Impact of the COVID-19 Pandemic on Developmental Vulnerabilities and Mental Health: Implications for Children and Adolescents in Alberta Using an Evidence-Based Approach

by

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Abstract

This paper-based thesis presents a comprehensive investigation into developmental vulnerability and mental health-related utilization in young individuals, including physicians' office visits, emergency department visits, and hospitalizations, utilizing population-level data. The primary objectives include identifying risk factors contributing to developmental vulnerability in children, developing a machine learning-based approach for early detection of Attention-Deficit/Hyperactivity Disorder (ADHD) based on early developmental vulnerability domains and social-environment-biological variables, and exploring the impact of the COVID-19 pandemic on the mental health of young individuals.

The first section focuses on early childhood development using the Early Development Instrument (EDI). The first paper identifies risk factors for developmental vulnerability among kindergarten children using the 2016 EDI combined with linked population-wide administrative health datasets. The study reveals significant associations between developmental vulnerability and mental illness, biological male sex, and poor socioeconomic status. The second paper applies machine learning techniques to prospectively detect ADHD in kindergarten-aged children, developing a model that reliably predicts case-defined ADHD, emphasizing the potential for early diagnosis and intervention.

The second section explores the impact of the COVID-19 pandemic on the mental health utilization of young individuals and changes in the pattern of mental health utilization in Alberta. The first paper of this section, the third paper of the thesis, investigates the association between developmental vulnerability and healthcare utilization among children in Alberta from 2016 to 2022. Vulnerable children exhibited, on average, more mental health-related healthcare service utilization compared to non-vulnerable children. Moreover, a consistent linear increase in the utilization of mental health-related services is observed, particularly among male vulnerable children. The fourth paper highlights the impact of the COVID-19 pandemic on mental health among Albertans. A retrospective, cohort study using administrative health records in Alberta revealed a rise in mental health service utilization in the post-pandemic onset era, particularly among adolescents, with anxiety and mood disorders-related utilization being the most prominent contributor diseases. The fifth and final paper of the thesis investigates the seasonal patterns in mental health utilization, identifying altered seasonal patterns after the pandemic onset, especially during the first months of the pandemic.

Altogether, this work contributes to the field of mental health and public health by identifying population-level risk factors, utilizing machine learning for the early detection of ADHD, and addressing the impact of the COVID-19 pandemic on young individuals' mental health. The implications extend to policy, practice, and future research, emphasizing the need for targeted interventions, support for mental health services, and continued exploration of childhood developmental vulnerability.

Preface

The completion of this thesis was made possible through a collaborative research effort between the University of Alberta and the Government of Alberta, Ministry of Health. Non-public domain data were used with permission from the host organization and in compliance with the approved purpose of use from that organization. The research conducted for this thesis received research ethics approval from the Health Research Ethics Board – Health Panel at the University of Alberta (Pro00104650_REN1).

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The studies presented in Section 1 and the first paper from Section 2 represent collaborative studies with Magdalena Janus and Ashley Gaskin from the Department of Psychiatry and Behavioural Neuroscience at McMaster University, Canada. The study designs were a joint effort by Mengzhe Wang, Magdalena Janus, Ashley Gaskin, Yang Liu, and me. The analysis of the first paper was conducted collaboratively with Dan Metes, and I contributed to the writing process alongside Yang Liu. While Yang Liu primarily led the second paper, my contributions involved discussing results, generating figures, and collaborating on the manuscript writing process.

Data preparation and analysis, results interpretation and discussion, generation of figures, and writing of papers 3 and 4 were done by me. For paper 5, Yipeng Song conducted the primary analysis. I integrated more recent data and reanalyzed the results based on Song's code, contributing to the refinement and augmentation of the study's findings.

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Introduction

Early childhood is pivotal in shaping an individual's lifelong trajectory, establishing the foundational groundwork that has gained extensive recognition in human development studies (D'Angiulli et al., 2009; Goncalves et al., 2019; Guhn et al., 2016 (A)). During these formative years, children undergo significant cognitive, emotional, and social growth, which profoundly influences their future prosperity, educational attainment, and overall achievement (D'Angiulli et al., 2009; Williamson et al., 2019). This aspect has been consistently emphasized in the literature, highlighting the critical role of effective social and emotional maturation during the early years. This developmental phase is closely linked to a smooth transition to school, fostering outcomes that promote healthy growth, thereby contributing to long-lasting well-being across the lifespan of an individual (Goncalves et al., 2019; Williamson et al., 2019; Woolfson, et al., 2013).

Central to the context of early childhood is the notion of developmental vulnerability, representing a state where children engage with challenges across key developmental domains, including physical health, language acquisition, emotional regulation, and social competence. Such vulnerability accentuates the risk of academic struggles, difficulties in social interactions, and long-term health issues (D'Angiulli et al., 2009; Guhn et al., 2016 (B); Woolfson, et al., 2013). Developmental vulnerability often emerges within the broader context of social determinants, including socioeconomic status, family dynamics, and community environment. These determinants interact in ways that can either magnify or mitigate their combined influence on developmental outcomes (Lloyd & Hertzman, 2009). For instance, a child raised in a socioeconomically advantaged household often benefits from access to quality education and healthcare. These positive factors can act as buffers against adversities and stressors that might arise during development, creating an environment conducive to optimal cognitive, emotional, and social growth (Guhn et al., 2016 (B); Lloyd & Hertzman, 2009). Conversely, a child from a disadvantaged socioeconomic background may face resource limitations, reduced access to healthcare, and fewer opportunities for enrichment. These challenges can exert additional pressure on the family dynamics, potentially straining the caregiving environment and diminishing the child's overall developmental prospects. In this case, the interaction between socioeconomic disadvantage and family dynamics may amplify the risk of developmental vulnerabilities (Guhn et al., 2016 (B); Taylor et al., 2020).

In recent years, administrative data has emerged as a robust method to obtain information on child development and its implications (Saunders et al., 2021). The routine collection of electronic health records offers an expansive database that advises healthcare system delivery and policy formulation (Harron et al., 2017). The integration of cross-sectoral data linkages that combine developmental, biological, and social services records provides a more comprehensive understanding of the multifaceted elements influencing child development (D'Angiulli et al., 2009; Guhn et al., 2016 (B); Janus et al., 2021; Saunders et al., 2021; Taylor et al., 2020). For instance, Canada has an extensive collection of health data for each health system interaction of all its legal residents. Analyzing linked datasets offers a unique opportunity to explore the complex interaction among maternal and child health, social well-being, and early childhood development. Despite the potential promise of this approach, it is essential to acknowledge the presence of methodological challenges that warrant consideration, such as concerns relating to data quality, missing data, and bias (Harron et al., 2017; Saunders et al., 2021). Furthermore, administrative data are primarily collected for operational purposes rather than research, which might lead to inconsistent records and incomplete information, possibly introducing discrepancies and inaccuracies in analyses (Saunders et al., 2021). Nevertheless, the cost-effectiveness of this approach further enhances its appeal over traditional methods like surveys (Saunders et al., 2021).

One widely used population-level health surveillance tool for addressing early childhood vulneravilities is the Early Development Instrument (EDI), providing a holistic view of a child's early developmental status by assessing various developmental domains (Janus & Offord, 2007). Its significance lies in its predictive ability for school preparedness, future academic performance, and physical and mental health concerns (D'Angiulli et al., 2009). Through tracking developmental progress and outcomes, including academics and mental health, the EDI reveals how early strengths shape lifelong trajectories. By observing the same cohort over time, the EDI uncovers the interplay between early experiences, socioeconomic factors, education, mental health, and overall well-being, thus revealing the enduring impact of identified protective and risk factors from early childhood (D'Angiulli et al., 2009; Guhn et al., 2016 (B)).

Children's mental health, a critical aspect of their overall development and well-being, has come to the forefront during the COVID-19 pandemic. This challenging period has brought about unique stressors and uncertainties, impacting children's emotional and psychological states. The disruptions in daily life, the prolonged periods of isolation, and concerns about the virus's spread profoundly influenced children's mental health and overall development (Khan et al., 2023; Racine et al., 2021; Cielo et al., 2021; Santomauro et al., 2021) and have all contributed to changes in mental health service utilization (Khan et al., 2023; Cielo et al., 2021; Santomauro et al., 2021).

The onset of the COVID-19 pandemic has sparked both a primary public health crisis and a secondary mental health crisis, affecting individuals of all ages. Studies have shown a significant rise in global rates of major depressive disorder and anxiety disorders in 2020 Alshammari & Alshammari, 2021; Davico et al., 2021; Khan et al., 2023; Madigan et al., 2023; Shankar et al., 2022; Tanaka & Okamoto, 2021). Initially, there was a decrease in mental health service utilization, followed by a concerning surge, particularly in suicide rates among women and younger populations by October 2020. This disparity underscores the pandemic's unequal impact on different demographic groups. The fluctuating trend in mental health service utilization highlights the intricate relationship between psychological distress and access to mental health resources. Addressing this multifaceted mental health crisis requires comprehensive strategies that address both immediate needs and systemic barriers to care. However, a comprehensive understanding of the pandemic's exacerbation of specific mental health conditions and their lasting implications remains an ongoing exploration.

Based on the summary of evidence discussed above, there exist a few research and knowledge gaps within the domain of early childhood development, such as:

- <u>Relationship between developmental vulnerability and social determinants</u>: Although the concept of developmental vulnerability and its interplay with broader social determinants are well acknowledged, it remains as an area that needs further exploration. Understanding how socioeconomic status, family dynamics, and community environment intersect to amplify or mitigate developmental vulnerability's impact is crucial for targeted interventions.

- Comprehensive understanding of the COVID-19 pandemic impact: The pandemic has substantially disrupted daily life and altered healthcare utilization patterns, with its consequences continuously evolving. So, it is essential to maintain an ongoing, thorough examination of the specific mental health conditions worsened by the pandemic and their long-term implications. This examination should consider various relevant factors, perspectives, and details to understand fully how these disruptions have affected children's mental health and overall development.
- Comprehensive framework for early childhood development: Although the EDI has emerged as a valuable tool for assessing various dimensions of child development, further exploration of the interaction between physical, cognitive, emotional, and social development and its implications for lifelong outcomes is crucial. Understanding these interactions is vital for predicting and addressing lifelong outcomes, presenting an area where further research and development are warranted.

This paper-based thesis aims to take major steps forward in addressing the research gaps. The objectives of this study were to explore developmental vulnerability in children and its association with psychiatric diseases, to develop machine learning-based approaches for the early detection of ADHD, and to examine the influence of the COVID-19 pandemic on the mental health issues of children, adolescents, and young adults. More specifically, the following research questions guided the progress of this thesis:

1) What are the population-level risk factors associated with developmental vulnerability in kindergarten-aged children? Can a comprehensive understanding of these risk factors inform targeted intervention strategies for vulnerable children?
2) Can machine learning approaches enhance the early detection of ADHD in kindergarten-aged children using population-level administrative health data and developmental vulnerability assessment? How accurate and reliable is the model in

predicting case-defined ADHD? What key predictors drive the model's performance, and how can they contribute to early diagnosis and intervention?

3) How has the COVID-19 pandemic affected mental health outcomes among young individuals? Does developmental vulnerability influence the impact of the COVID-19 pandemic? To what extent has there been a change in mental healthcare utilization patterns during the pandemic?

By addressing these questions, my overarching goal with this thesis is to contribute substantively to informed policymaking, foster proactive interventions, and advocate for the comprehensive promotion of children's well-being. In doing so, this work aspires to play a role in advancing a healthier and more equitable society.

Literature review

In the introduction, I discussed the influence of cognitive, emotional, and social growth during the first few years of age, emphasizing its crucial role in shaping future prosperity and achievement. This exploration revealed significant gaps in the comprehension of childhood development, accentuated by the impact of the COVID-19 pandemic. The pandemic's disruption of daily life and healthcare patterns has uncovered new aspects of childhood mental health, requiring further investigation. This chapter transitions to a conceptual review, exploring the existing literature and examining different aspects of childhood development, mental health, administrative health data, and the implications of the COVID-19 pandemic in an effort to help address the research questions stated in the introduction.

Developmental vulnerability and its significance

Developmental vulnerability refers to the elevated susceptibility of a child's neurobiological and psychophysiological development to adverse environmental exposures during critical periods of growth (Schweiger, 2019). The initial years of children's lives are particularly sensitive to disruptions triggered by environmental stressors, which can have profound and enduring effects across various dimensions of human development (Graham et al., 2021; Kalra & Shah, 2023). The vulnerability concept acknowledges that certain individuals possess a greater predisposition than others to experience adverse outcomes due to these exposures, owing to the complex interaction between genetic predispositions and environmental factors, encompassing the prenatal and postnatal periods, maternal distress, and socioeconomic circumstances (Jelicic et al., 2022; Oberklaid et al., 2013).

Investigating children's developmental vulnerability carries profound implications for public health, clinical practice, and policymaking. By exploring the intricate mechanisms through which life experiences impact neurodevelopment, researchers can formulate potential intervention opportunities to mitigate the adverse consequences associated with developmental vulnerability (Oberklaid et al., 2013; Taylor et al., 2020). Early identification of individuals at risk of developmental vulnerabilities has demonstrated its capacity to enhance children's health and well-being (Young & Richardson, 2007). This timely support can redirect developmental trajectories, guiding them away from unfavourable outcomes and towards more positive life paths. Early intervention is a proactive shield against potential adversities, helping at the right moment and in the most relevant context.

Brain development and the role of epigenetics

Human brain development involves cellular proliferation, migration, differentiation, and synaptogenesis (Graham et al., 2021; Sly et al., 2021). From the earliest stages of an embryo to adolescence, various phases mark the formation of neural structures and the establishment of functional connections (Graham et al., 2021; Kalra & Shah, 2023; Sly et al., 2021). The embryonic period spans approximately three to seven weeks of gestation, in which neural tube structure formation occurs that eventually evolves into the brain and spinal cord (Sly et al., 2021). As development progresses, neural precursor cells migrate to their designated regions, forming distinct brain regions and layers (Sly et al., 2021). This dynamic process continues through the fetal period and into late adolescence, as brain regions fine-tune their connections and establish complex neural networks (Sly et al., 2021).

The human brain's complexity emerges from its complex web of neural connections. Neurons communicate through synapses, forming neural circuits that underlie cognitive, emotional, and behavioural functions. Different brain regions specialize in distinct functions. For example, the prefrontal cortex is essential for executive functions like decision-making and impulse control (Bick & Nelson, 2017). The amygdala plays a pivotal role in emotion processing (Bick & Nelson, 2017). The hippocampus is critical for memory consolidation (Bick & Nelson, 2017). These brain regions collaborate and communicate, giving rise to the multifaceted abilities of the human mind.

Human brain development is subject to the complex relationship between genetic predisposition and environmental influences (Jelicic et al., 2022; Oberklaid et al., 2013). Prenatal exposure to stress, malnutrition, or toxins can result in persistent changes in brain structure and function (Kalra & Shah, 2023; Miguel et al., 2019). Such alterations can manifest as poor cognitive development, emotional dysregulation, and an increased risk of mental health disorders (Bick & Nelson, 2017; Jelicic et al., 2022; Kalra & Shah, 2023; Miguel et al., 2019; Wall-Wieler et al., 2020). The prefrontal cortex, amygdala, and hippocampus are particularly sensitive to these influences (Graham et al., 2021; Jelicic et al., 2022; Miguel et al., 2019).

The social and environmental conditions interact with the genetic predisposition through epigenetics, which provides a molecular framework for translating environmental experiences into changes in gene expression (Jelicic et al., 2022; Sly et al., 2021). DNA methylation, histone modification, and microRNA expression are pivotal in mediating how environmental exposures shape gene expression and subsequently impact brain structure and function. For example, maternal exposure to stress and adversities during pregnancy can lead to transgenerational effects, impacting not only the developing child but also future generations (Jelicic et al., 2022; Sly et al., 2021). These transgenerational effects can be mediated through epigenetic modifications that impact gene expression patterns in the developing fetus, extending to the maternal great-granddaughter. Epigenetic modifications induced by maternal experiences can affect genes critical for brain development, particularly in regions like the prefrontal cortex and hippocampus. These modifications can compromise the fine balance of neural circuits involved in emotional regulation, memory processing, and cognitive flexibility (Jelicic et al., 2022; van den Bergh et al., 2020).

In conclusion, the interaction between brain structure, development, and epigenetics shapes the trajectory of human neurodevelopment. Neural connections and brain regions collaborate to give rise to complex cognitive and emotional functions. Epigenetic mechanisms serve as a bridge between environmental exposures and changes in gene expression, underscoring their pivotal role in developmental vulnerability. Understanding how disruptions in normal brain development contribute to poor child development is crucial for identifying strategies to mitigate the impact of adverse experiences and promote healthy brain development.

Prenatal, maternal, and intrauterine adversities

The period spanning from conception to birth is a critical window of vulnerability. Various prenatal factors exert a significant influence on a child's developmental trajectory during this time. This phase is characterized by the potential for exposure to adverse intrauterine environments and maternal adversities (Jelicic et al., 2022; van den Bergh et al., 2020). Adverse exposures during the embryonic and fetal periods can have distinct effects on a child's development's structural and functional aspects (Graham et al., 2021; Miguel et al., 2019; Sly et al., 2021; van den Bergh et al., 2020).

Exposure to harmful substances during pregnancy can result in structural abnormalities in the developing fetus, having enduring consequences (Graham et al., 2021; Miguel et al., 2019). These substances encompass a range of factors, including outdoor and indoor air pollution, maternal smoke exposure, pesticide use, contaminants in food and water, as well as various environmental pollutants. Previous research has consistently shown a strong link between exposure to these substances and adverse developmental outcomes in children (Graham et al., 2021; Harris et al., 2023; Miguel et al., 2019; Oberklaid et al., 2013; Sly et al., 2021). When it comes to intrauterine exposure to nicotine and tobacco, studies have revealed that it can lead to significant alterations of specific fetal brain regulatory gene expression that play pivotal roles in critical processes such as brain growth, myelination, and neuronal migration (Graham et al., 2021; Miguel et al., 2019). Such changes disrupt normal cognitive and motor functioning while impairing mental development in affected children (Jelicic et al., 2022). These prenatal exposures have been associated with an increased risk for various conditions among the offspring, including bipolar disorder, depression, addiction, and attention-deficit/hyperactivity disorder (ADHD) (Miguel et al., 2019; Nakama et al., 2023).

The impact of prenatal adversities on fetal development is mediated, in part, through the intricate machinery of the hypothalamo-pituitary-adrenal (HPA) axis. Maternal stress can induce increased transplacental transfer of maternal cortisol to the fetal compartment (Jelicic et al., 2022; Nakama et al., 2023; van den Bergh et al., 2020). This surge in fetal cortisol levels can have far-reaching implications, disrupting the normal synthesis of neuropeptides and the regular development of the fetal HPA axis itself (Jelicic et al., 2022). The effects of this dysregulation extend well into adulthood, giving rise to a spectrum of abnormalities encompassing neuroendocrine, behavioural, autonomic, and metabolic function disturbance (Jelicic et al., 2022; Oberklaid et al., 2013).

Another critical factor to consider is maternal age at childbirth. The association between maternal age and child development follows a reverse J-shaped curve, where the risk of developmental vulnerability varies across maternal age groups (Falster et al., 2018). Children born to both the youngest and oldest mothers appear to face elevated risks of developmental vulnerability.

Understanding the profound effects of intrauterine exposures, maternal stress, and maternal age on fetal development emphasizes the need for targeted interventions and support systems. Recognizing the long-reaching consequences emphasizes the critical role of the early postnatal environment in shaping enduring developmental outcomes. This comprehension is vital for enriching our understanding of developmental vulnerability and for informing strategies that promote healthier beginnings and resilient life paths for children.

Postnatal adversities

The postnatal period is equally important to the prenatal and maternal environments in shaping a child's health and developmental trajectory. The initial few years are a critical phase for brain development as it undergoes remarkable growth and refinement (Graham et al., 2021; Kalra & Shah, 2023; Sly et al., 2021), continuing maturation into adolescence (Graham et al., 2021; Jelicic et al., 2022; Sly et al., 2021; van den Bergh et al., 2020). Exposure to stressors during infancy and early childhood can cause alterations in neuronal structure and function, thereby affecting synaptic connectivity and neural plasticity (Nakama et al., 2023; van den Bergh et al., 2020). Subsequent delays in various developmental domains, such as cognitive, speech-language, and motor skills may manifest (Bick & Nelson, 2017; Kalra & Shah, 2023; Jelicic et al., 2022; Janus et al., 2021; Miguel et al., 2019). Behavioural and learning difficulties often emerge, significantly impacting socioemotional development (Jelicic et al., 2022; Kalra & Shah, 2023).

The interplay between early stressors and neurodevelopment continues into infancy and early childhood. Exposure to maternal depression during this period is associated with specific forms of developmental vulnerability, particularly those related to social competence and emotional maturity (Jelicic et al., 2022; Wall-Wieler et al., 2020). Mothers experiencing postpartum depression may encounter difficulties in forming strong bonds with their infants, potentially leading to challenges in breastfeeding (Jelicic et al., 2022). This, in turn, can impact the emotional well-being of the child and their nutritional intake.

The effects of postnatal adversities are not limited to the immediate developmental period, extending into adulthood. Exposure to violence, neglect, and abuse have been linked to enduring effects on developmental outcomes (Bick & Nelson, 2017; Goncalves et al., 2019; Kalra & Shah, 2023; Miguel et al., 2019). These distressing experiences can disrupt the formation of secure attachments, impede cognitive development, and contribute to emotional and behavioural challenges (Bick & Nelson, 2017; Miguel et al., 2019; Sly et al., 2021).

The HPA axis, a key player in the body's stress response system, can also be dysregulated by postnatal stressors. Chronic stress experienced during infancy and childhood can trigger excessive cortisol production, throwing the HPA axis off its usual equilibrium (Jelicic et al., 2022). This dysregulation has far-reaching consequences for neurodevelopment. It can lead to alterations in neurotransmission, affecting glutamate regulation, and signalling systems like dopamine and serotonin (Holz et al., 2023; Ochi & Dwivedi, 2023). These modifications can negatively impact neural development and plasticity, potentially increasing the susceptibility to psychiatric disorders in adulthood (Graham et al., 2021; Nakama et al., 2023).

The impact of postnatal adversities, ranging from maternal depression to exposure to violence and neglect, is profound and enduring, leaving lasting imprints on a child's developmental trajectory. These challenges profoundly shape crucial aspects such as attachment formation, cognitive maturation, and emotional well-being. Recognizing the importance of these postnatal dynamics is essential for understanding the roots of developmental vulnerabilities and guiding effective interventions and support systems. By exploring the nuances of postnatal influences, we gain insights that extend beyond the immediate developmental period, providing a foundation for cultivating the well-being of children and laying the groundwork for healthier, resilient generations.

Social determinants

A child's development is significantly influenced by the social environment in which they are raised. Socioeconomic status (SES) is a critical determinant in a child's developmental path and involves aspects such as income, education, occupation, and resource access (Guhn et al., 2016 (B); Janus et al., 2021; Oberklaid et al., 2013). Several factors, including teenage motherhood, low maternal education, harsh parenting, maternal health problems, family conflict, and household unemployment, are intricately linked to a poor developmental trajectory (Bick & Nelson, 2017; Janus et al., 2021; Oberklaid et al., 2013; Wall-Wieler et al., 2020). Extensive research consistently demonstrates that growing up in families with lower SES can have adverse effects on a child's physical and cognitive development, carrying long-term consequences (Guhn et al., 2016 (B); Janus et al., 2021; Oberklaid et al., 2013).

For families with limited financial resources, regular medical check-ups, early intervention programs, and therapeutic services, all crucial for addressing developmental challenges, can be limited. Children lacking access to regular medical care and preventive interventions are at a heightened risk of experiencing developmental challenges. The importance of equitable access to healthcare services in mitigating developmental vulnerability is emphasized by research (Racine et al., 2021; Goncalves et al., 2019).

The neighbourhood and community in which a child grows up profoundly impact their developmental trajectory. Neighbourhood safety and access to quality schools and recreational facilities are vital (Deyessa et al., 2020; Goncalves et al., 2019; Janus et al., 2021; Oberklaid et al., 2013). Children raised in unsafe neighbourhoods are at higher risk of exposure to violence and trauma, which can lead to emotional and psychological vulnerabilities (Goncalves et al., 2019; Kalra & Shah, 2023; Miguel et al., 2019). Disparities in the quality of education across neighbourhoods can significantly affect a child's educational attainment and future opportunities. A lower level of parental education has been linked to decreased cognitive stimulation and educational opportunities for children (Janus et al., 2021; Kalra & Shah, 2023; Oberklaid et al., 2013). On the other hand, strong social networks and community support systems act as protective factors for children (Deyessa et al., 2020; Goncalves et al., 2019). Positive neighbourhood characteristics, including safety, availability of green spaces, and low exposure to pollution, have been associated with reduced vulnerabilities (Kalra & Shah, 2023; Sly et al., 2021).

Cultural and ethnic background emerge as another crucial determinant of developmental vulnerability, influencing family dynamics, cultural practices, and access to healthcare and education (Deyessa et al., 2020). Cultural norms and practices can influence parenting styles and early childhood experiences. Understanding the cultural factors is essential for tailoring interventions and support to diverse populations.

Government policies and social support systems play a substantial role in either alleviating or exacerbating developmental vulnerabilities. Policies that endorse paid parental leave allow caregivers to spend more time with their infants, fostering early bonding and attachment. Accessible and high-quality early childhood education programs can provide children with essential cognitive and social skills. Income assistance programs can help ease financial stress for families, reducing the negative impact of economic hardships on children's development.

In conclusion, social determinants are powerful influencers of developmental vulnerability. Understanding how SES, neighbourhood environments, cultural factors, and policy decisions relate to and affect children's development is essential for developing effective strategies and interventions. These endeavours are vital to promoting resilience and mitigating the impact of social disparities on vulnerable populations.

The Early Development Instrument

A comprehensive understanding of population-level risk factors for childhood developmental vulnerability is essential for a thorough assessment of vulnerabilities. In this context, the Early Development Instrument (EDI) is an invaluable tool (D'Angiulli et al., 2009; Guhn et al., 2016 (B)). It aids in comprehending and evaluating the extent to which children meet age-appropriate developmental expectations, an assessment grounded in their experiences during the crucial first five years of life (Janus & Offord, 2007; Janus et al., 2021). The EDI was conceived to offer a population-level snapshot of children's developmental health as they embark on their formal schooling journey (Janus & Offord, 2007; Janus et al., 2021).

The questionnaire is completed by kindergarten teachers and encompasses 103 questions grouped into five areas: physical health and well-being, social competence, emotional maturity, language and cognitive development, and communication skills (Janus & Offord, 2007). The physical health and well-being domain examines a child's overall health, including physical fitness, general health status, and chronic health conditions. The social competence domain assesses a child's ability to interact positively with peers and adults, manage emotions, and engage in prosocial behaviours. The emotional maturity domain focuses on emotional regulation, self-control, and coping skills, exploring how well a child can express emotions and adapt to various situations. Language skills, numeracy, problem-solving abilities, and knowledge acquisition are all evaluated in the language and cognitive domain. A child's communication abilities, vocabulary, and general knowledge about the world are accounted for in the communication skills and general knowledge domain.

Each child's scores in these areas are averaged, ranging from 0 to 10, where a higher score means a better developmental status. To identify developmental vulnerability, we compare individual scores in each domain to the 10th percentile of all children. If a child's score is at or below this threshold, it indicates a risk for difficulties in that specific area. If a child scores as "developmentally vulnerable" in one or more domains, they are considered vulnerable overall (for more details please visit https://edi.offordcentre.com/resources/edi-cohort-reports/). This helps provide a comprehensive view of a child's developmental health, guiding interventions, and support strategies.

The EDI shows its relevance by allowing for the early identification of children at risk for developmental challenges or delays (D'Angiulli et al., 2009; Janus et al., 2021). This early detection is crucial as it enables timely interventions, potentially preventing more significant issues later in a child's life (Bick & Nelson, 2017; Deyessa et al., 2020; Graham et al., 2021; Taylor et al., 2020). Also, the EDI is administered at a population level, providing a comprehensive view of the developmental health of children in a particular community, demographic group, or region. Research using the questionnaire can reveal patterns, trends, and disparities in developmental vulnerability and allows the exploration of the association between developmental outcomes and various risk factors, including SES, maternal health, access to early childhood services, prenatal adversities, and postnatal adversities. Furthermore, the EDI can be used to assess the effectiveness of intervention programs aimed at reducing developmental vulnerabilities in at-risk populations. By analyzing EDI data, research can identify disparities in developmental outcomes among different demographic groups, helping to elucidate areas where additional support is needed.

In conclusion, the EDI is a valuable tool for assessing and understanding developmental vulnerability in young children. Its ability relies on collecting population-level data and identifying children at risk of developmental vulnerabilities. Utilizing the EDI contributes to a better understanding of the factors related to developmental vulnerability and informs strategies to support children's healthy development.

Mental health

The World Health Organization (WHO) defines mental health as a state of well-being in which individuals realize abilities, cope with everyday stresses, work productively and fruitfully, and contribute to their community (WHO, 2022). This definition underscores that good mental health extends beyond the mere absence of mental disorders. A key element in fostering good mental health is mental health literacy, which includes knowledge about mental disorders and their treatments, reducing stigma, and effectively seeking help (Nobre et al., 2021; Fusar-Poli et al., 2020). Mental health literacy encompasses understanding how to attain and maintain good mental health. This includes factors like cultivating stable relationships, receiving support from family, ensuring adequate sleep, engaging in regular exercise, nurturing positive thinking, avoiding substance misuse, participating in meaningful activities, and practicing relaxation techniques (Nobre et al., 2021; Fusar-Poli et al., 2020). Insufficient mental health literacy reduces the utilization of mental health services, hinders personal development, and elevates the risk of psychiatric disorders (Nobre et al., 2021; Fusar-Poli et al., 2020).

Mental illness and substance use disorders have now become the leading causes of disability in Canada, significantly hampering an individual's capacity to lead a healthy and fulfilling life (CAMH, 2023 (A)). The implications are severe, as mental illnesses alone can curtail life expectancy by 10 to 20 years, contributing to approximately 67,000 fatalities annually in Canada (CAMH, 2023 (A)). Within the country, over 6.7 million people have already encountered or will encounter a mental illness by the time they reach 40 years of age, underscoring its pervasive impact on society (CAMH, 2023 (B)).

Suicide continues to be a pressing public health issue, resulting in approximately 4,000 fatalities among Canadians each year, equivalent to almost 11 lives lost daily (CAMH, 2023

(B)). Although overall suicide rates have demonstrated a decline over the last couple of years, they continue to be a leading cause of death among specific demographic groups, particularly young individuals aged 15 to 24 (CAMH, 2023 (A); CAMH, 2023 (B)). The impact is especially pronounced in Indigenous communities, where suicide rates are alarmingly high. First Nations youth aged 15 to 24 face a suicide rate approximately six times higher than their non-Indigenous counterparts, while Inuit youth confront rates nearly 24 times the national average (CAMH, 2023 (A); CAMH, 2023 (B)).

Biological sex differences are also notable in the prevalence of mental health conditions, with men exhibiting higher rates of substance use disorders, like alcohol or drug addiction (CAMH, 2023 (A)). In contrast, women face higher rates of mood and anxiety disorders (CAMH, 2023 (A)). A profound interconnection exists between mental and physical health. Individuals grappling with chronic physical conditions, like chronic pain, confront a heightened risk of experiencing mood disorders, such as depression (CAMH, 2023 (A)).

Stigma and discrimination against individuals with mental health conditions have severe, toxic effects that exacerbate marginalization and social exclusion (Thornicroft et al., 2022). Stigma can deter individuals from seeking help, resulting in delayed or inadequate treatment (CAMH, 2023 (A)). It also impacts various aspects of an individual's life, including education, employment, and overall quality of life (Thornicroft et al., 2022). The stigma surrounding mental illness in the workplace remains a significant challenge. Many Canadians express reluctance to disclose their mental health conditions to employers or colleagues due to fear of being stigmatized, treated differently, or facing negative consequences, such as job loss (CAMH, 2023 (A)).

The economic toll of mental illness in Canada is substantial, with estimated costs surpassing $50 billion annually (CAMH, 2023 (A)). This encompasses expenses related to healthcare, lost productivity, and diminished health-related quality of life. Substance use disorders similarly impose a considerable economic burden, totalling nearly $40 billion (CAMH, 2023 (A)). These costs encompass healthcare expenses, involvement with the criminal justice system, and lost productivity, with alcohol and tobacco contributing the most. Furthermore, employment rates among individuals contending with mental illnesses are significantly lower. For those grappling with the most severe mental illnesses, unemployment rates can soar to as high as 70% to 90%, underscoring the necessity for workplace support and accommodations (CAMH, 2023 (A)).

Investments in promotion and prevention

Initiatives focusing on mental health promotion and prevention and ensuring accessible and effective treatment for those in need are instrumental in reducing the overall burden of mental illnesses (CAMH, 2023 (A)). Mental health is closely intertwined with physical health, lifestyle, and social factors (CAMH, 2023 (A); CAMH, 2023 (B)). Therefore, investments in mental health should encompass holistic approaches that address the broader determinants of health. This includes supporting stable relationships, promoting family and community support, advocating for healthy lifestyles (e.g., exercise and nutrition), and combating substance misuse (CAMH, 2023 (A)). Public policy and advocacy efforts are essential in securing resources and support for mental health initiatives. These policies can influence everything from funding allocation to insurance coverage for mental health services (CAMH, 2023 (A)).

Investing in research and innovation is crucial for advancing the field of mental health. Research leads to the development of new treatments, interventions, and technologies that can revolutionize mental healthcare. It helps the early identification of children and families experiencing mental health challenges. Programs that provide support to at-risk families, offer parenting guidance, and deliver early therapeutic interventions are essential in reducing the long-term impact of mental health problems on children's development (CAMH, 2023 (A); Harris et al., 2023; Purtle et al., 2020; Saunders et al., 2021). By targeting risk factors and enhancing protective factors at the population level, these programs help mitigate the development of mental health issues (CAMH, 2023 (A); Fusar-Poli et al., 2020; Graham et al., 2021; Harris et al., 2023). Examples include anti-stigma campaigns, community resilience-building programs, and educational campaigns promoting mental health literacy.

Community-based mental health programs, including peer support networks and local mental health services, provide a lifeline for individuals facing mental health challenges. These programs foster a sense of belonging, reduce isolation, and offer practical support (Khan et al., 2023; Nobre et al., 2021; Racine et al., 2021). Another example is digital mental health solutions. With the rise of digital technology, smartphone apps and online therapy platforms are becoming increasingly important. They offer accessibility, convenience, and anonymity, making mental health support available to a broader audience (Keyes et al., 2022; Panchal et al., 2021; Racine et al., 2021).

Therefore, investments in mental health are not just about financial resources; they also involve societal commitment and a recognition of the profound impact of mental health on individuals and communities. The returns on such investments are substantial, including improved quality of life, increased productivity, reduced healthcare costs, and a more inclusive and compassionate society (CAMH, 2023 (A); Deyessa et al., 2020; Guhn et al., 2016 (B)). We can foster a mentally healthier and more resilient society by prioritizing mental health at all levels, from individual well-being to public policy.

Social determinants

It is important to recognize that mental health is influenced by broader social determinants. Population-based approaches aim to address the root causes of mental health disparities and promote mental well-being at a community level. By considering social justice, equity, and human rights, population-based approaches have the potential to enhance mental health on a societal scale, moving beyond the narrow focus on clinical interventions (Purtle et al., 2020).

Socioeconomic factors, including income, education, occupation, and resource access, play a substantial role in shaping mental health outcomes (CAMH, 2023 (A)). Factors such as teenage motherhood, low maternal education, harsh parenting, maternal health issues, family conflict, and household unemployment intricately relate to poor mental health (Oberklaid et al., 2013). In Canada, those in the lowest income groups are disproportionately affected, being three to four times more likely to report poor to fair mental health (CAMH, 2023 (A)). Homelessness is another critical concern. A significant percentage of homeless individuals in Canada, ranging from 23% to 67%, may be living with mental illnesses (CAMH, 2023(A)).

Stressors encountered during critical developmental periods, such as prenatal, infancy, and childhood phases, can have a profound and enduring impact on mental health. Exposure to stressors during these formative stages disrupts the balance of neurodevelopment (Graham et al., 2021; Jelicic et al., 2022; Kalra & Shah, 2023; Oberklaid et al., 2013; Woolfson, et al., 2013). It can lead to structural and functional alterations in neuronal systems, affecting synaptic connectivity and neural plasticity (Graham et al., 2021; Kalra & Shah, 2023; van den Bergh et al., 2020). Chronic stress during infancy and childhood, particularly in the context of maternal stress during pregnancy, can lead to alterations in systems like the central nervous system, autonomic nervous system, HPA axis, cardiovascular system, and immune system, ultimately increasing susceptibility to somatic diseases and mental health problems (Graham et al., 2021; Jelicic et al., 2022; Miguel et al., 2019; van den Bergh et al., 2020). The impact of stressors can be manifested in the form of psychiatric disorders. These include, but are not limited to, post-traumatic stress disorder (PTSD), major depressive disorder, anxiety disorders, and substance use disorders (Kalra & Shah, 2023; Miguel et al., 2019; Nakama et al., 2023).

The impact of natural disasters

Natural disasters, ranging from hurricanes and earthquakes to floods and wildfires, can have profound and lasting effects on mental health. The psychological toll of such events extends beyond immediate physical harm, often leaving individuals and communities grappling with long-term mental health challenges (Saeed & Gargano, 2022). The unpredictable nature of natural disasters and the uncertainty about the future contribute to heightened anxiety. Individuals may develop generalized or acute stress anxiety disorders because of ongoing stress and fear. This is a natural response to the stress of a traumatic event and normally lasts for a short duration (Saeed & Gargano, 2022). However, some individuals may experience a more severe anxiety response, which may lead to the development of PTSD (Saeed & Gargano, 2022). Symptoms include intrusive memories, flashbacks, nightmares, and severe anxiety.

Exposure to a natural disaster can influence an individual's resilience to future stressors. Those with a history of trauma may find it challenging to cope with subsequent adversities (Purtle et al., 2020). Adolescents may grapple with identity issues and an increased risk of substance use (Miguel et al., 2019; Saeed & Gargano, 2022).

Mental health issues may not manifest immediately after an event and can develop or intensify over time (McDaid, 2021). This delayed onset necessitates long-term mental health support and monitoring. However, immediate access to mental health support and interventions is critical. Establishing community-based mental health programs that address the collective trauma and foster resilience is essential for long-term recovery (Purtle et al., 2020; Saeed & Gargano, 2022). Future disaster preparedness plans should incorporate mental health components to minimize the psychological impact of such events.

Understanding the intricate relationship between natural disasters and mental health is crucial for designing comprehensive and effective interventions. A holistic approach, involving mental health professionals, community leaders, and policymakers, is essential for supporting individuals and communities in the aftermath of such traumatic events.

The impact of the COVID-19 pandemic

The COVID-19 pandemic has not only led to a primary public health crisis but has also given rise to a secondary mental health crisis, leaving profound implications for individuals across all ages (Alshammari & Alshammari, 2021; Graham et al., 2021). Research in this field has indicated a substantial increase in the global prevalence of major depressive disorder and anxiety disorders during the year 2020 (Santomauro et al., 2021; Davico et al., 2021). This surge was closely linked to the rise in SARS-CoV-2 infection rates and the implementation of measures to limit the virus's spread, such as lockdowns and school closures (Alshammari & Alshammari, 2021; Deng et al., 2022; Davico et al., 2021; Khan et al., 2023; Panchal et al., 2021; Santomauro et al., 2021). However, it is crucial to recognize that experiencing poor mental health outcomes does not always translate into a proportional increase in the utilization of mental health-related services. Despite the escalating mental health concerns, individuals faced barriers to accessing professional care. For example, the fear of infection presented impediments for those seeking psychological support (Alshammari & Alshammari, 2021; Campion et al., 2020; Davico et al., 2021; Kola et al., 2021; Madigan et al., 2023; Maulik et al., 2020; Moreno et al., 2020; Racine et al., 2021).

The initial months of the COVID-19 pandemic brought forth a transient decrease in the utilization of mental health services (Davico et al., 2021; Madigan et al., 2023; Tanaka &

Okamoto, 2021). This downturn could be attributed to several factors, including implementing stringent measures, such as lockdowns and social distancing, which may have inadvertently discouraged individuals from seeking professional help (Maulik et al., 2020; Moreno et al., 2020; Santomauro et al., 2021). The fear of contracting the virus, coupled with the logistical challenges posed by restrictions, likely created a hesitancy to engage with mental health services (Davico et al., 2021; Madigan et al., 2023).

The initial dip in mental health service utilization was followed by a notable and, in some regions, alarming surge. By October 2020, suicide rates not only rebounded to pre-pandemic levels but escalated (Madigan et al., 2023; Tanaka & Okamoto, 2021), with women and younger populations experiencing a disproportionate increase (Tanaka & Okamoto, 2021; Yard et al., 2021). This disparity underscores the pandemic's differential impact on various demographic groups.

This nuanced trend in mental health service utilization (i.e., initially decreasing, then surging) highlights the complex interplay between psychological distress and the accessibility of mental health resources. It serves as a reminder that addressing mental health challenges during a global crisis involves not only bolstering mental health infrastructure but also strategically dismantling barriers that impede individuals from seeking the care they need.

As the adverse mental health effects of the COVID-19 pandemic continue to reverberate, it is paramount to comprehend the relationship between pre-pandemic and pandemic-related factors in shaping poor mental health outcomes in young individuals. Governments and policymakers across the globe are being called to reassess and fortify existing mental health system plans (Santomauro et al., 2021). Crafting recovery strategies for the post-pandemic era becomes essential, ensuring that mental health services are not only available but also accessible to everyone. The COVID-19 pandemic has unveiled a multifaceted mental health crisis, demanding comprehensive strategies that encompass both immediate needs and the systemic intricacies contributing to this complex challenge (Alshammari & Alshammari, 2021; Graham et al., 2021).

The role of artificial intelligence

In Canada, a substantial disparity exists between the demand for mental health services and the resources available to meet it (CAMH, 2023 (B)). Bridging this gap is a complex and multifaceted challenge, encompassing strategies like augmenting the number of mental health professionals, enhancing access to care, diminishing stigma, elevating mental health literacy, and giving prominence to mental health within healthcare policy and budgeting considerations (Fusar-Poli et al., 2020; Nobre et al., 2021; Thornicroft et al., 2022). Furthermore, it is essential to acknowledge that dedicating resources to mental health has exhibited favourable returns on investment, underscoring the economic and societal advantages of a robust, accessible mental healthcare system (CAMH, 2023 (A); Deyessa et al., 2020).

Artificial Intelligence (AI) has emerged as one of the possible solutions to address the shortage of mental healthcare resources. AI refers to the development of computer systems that can perform tasks that typically require human intelligence. Machine Learning, a subset of AI, empowers systems to learn and improve from experience, enhancing their ability to make data-driven predictions or decisions. AI can streamline tasks, enhance diagnostic accuracy, and provide complementary support to clinicians, ultimately improving the efficiency and accessibility of mental health services (Lee et al., 2021). However, challenges, such as data privacy and the complexity of mental health data must be addressed to integrate AI into mental healthcare effectively.

AI excels in the early detection and diagnosis of mental health issues through predictive analytics (Lee et al., 2021). AI algorithms can analyze extensive datasets, encompassing behavioural patterns, social media activity, and physiological data to identify early signs of mental health concerns (Lee et al., 2021). AI can also assist in identifying individuals at risk for mental health conditions by analyzing, for example, large administrative health records (Lee et al., 2021). This capability enables proactive interventions and the development of personalized treatment plans tailored to an individual's unique needs. Aligned with everyone’s unique requirements, precision medicine is a promising approach to mental health treatment.

Virtual mental health support, facilitated by AI-driven chatbots and virtual assistants, provides immediate and scalable assistance (Keyes et al., 2022; Lee et al., 2021; Panchal et al., 2021; Thornicroft et al., 2022). These systems engage users in conversations, offering coping strategies, disseminating information, and monitoring well-being. Such virtual support can be especially valuable in scenarios where access to in-person mental health services is limited. However, integrating AI into mental health care comes with important considerations. Data privacy and confidentiality are paramount as AI processes sensitive health data. Implementing robust privacy measures, including encryption and anonymization, is crucial to safeguard individuals' health information. Adherence to data protection regulations is essential and ethical considerations are central. Developers must actively address biases in algorithms to ensure that AI systems do not perpetuate or exacerbate existing disparities in mental health care. Ensuring fairness and equity in AI-driven mental health solutions is essential.

In conclusion, AI has ushered in a new era in mental health care, offering a range of applications that enhance early detection, diagnosis, treatment, and support. While the potential benefits are vast, careful attention to data privacy and ethical considerations is essential to harness the full potential of AI while ensuring that it aligns with the principles of patient care and well-being. The collaboration between technologists, mental health professionals, policymakers, and ethicists will be pivotal in navigating these complex challenges and fostering the effective use of AI in mental health care. As AI continues to evolve, its integration into mental healthcare holds immense potential to transform the field, making services more accessible, personalized, and responsive to the diverse needs of individuals seeking mental health support (Lee et al., 2021).

Administrative health data

In the exploration of childhood vulnerabilities and mental health issues, the utilization of administrative health data (AHD) proves to be a pivotal asset. This type of data, routinely collected from healthcare interactions in Canada, provides a rich source of insights into the real-world manifestation of population-level risk factors for children's vulnerabilities and mental health concerns (Saunders et al., 2021; Taylor et al., 2020). By offering a systematic understanding of pathways leading to these issues, AHD allows for the identification of high-risk groups, aiding in the recognition of children and families in need (Harron et al., 2017).

Administrative health data provides instrumental insights for the development of targeted healthcare services. It can inform the creation of interventions and policy decisions designed specifically to address vulnerabilities in children and support the development of early mental health interventions (Harron et al., 2017; Janus et al., 2021; Madigan et al., 2023; Taylor et al., 2020). Interventions can be customized to provide timely support to youth and families exposed to psychiatric conditions during crucial developmental phases (Deng et al., 2022; Deyessa et al., 2020; Taylor et al., 2020). AHD empowers governments to tailor policies to the specific needs of at-risk populations, optimizing the impact of interventions and facilitating the development of targeted, effective strategies.

Evidence-based policies, support for early intervention efforts, and the optimization of resource allocation can all benefit from collaborative research. AHD catalyzes research partnerships, enabling multidisciplinary studies that generate insights, driving informed, effective, and interconnected approaches to addressing childhood vulnerabilities and mental health issues (Bando et al., 2023; D'Angiulli et al., 2009; Saunders et al., 2021; Taylor et al., 2020). Through collaborative research, experts can generate robust evidence and identify vulnerable children and families early in their developmental journey. This early identification is pivotal for designing precise, timely interventions (Bando et al., 2023; Bick & Nelson, 2017; Deyessa et al., 2020).

The use of AHD extends beyond the healthcare domain into various aspects of society, offering significant economic benefits and opportunities for cross-sectoral collaboration. Early identification of at-risk populations enables targeted interventions, preventing the escalation of issues and the need for more extensive and costly interventions later. For example, early intervention for developmental delays or mental health issues can reduce the long-term economic burden on the healthcare system (CAMH, 2023 (A); Goncalves et al., 2019; Guhn et al., 2016 (B); Woolfson, et al., 2013). This, in turn, contributes to a more robust and capable labour force, enhancing economic productivity and reducing the need for social assistance programs (CAMH, 2023 (A); Taylor et al., 2020). Furthermore, using AHD can help tailor education and employment programs to the specific needs of vulnerable populations (Taylor et al., 2020; Saunders et al., 2021). This might lead to better educational outcomes and improved employment prospects, reducing the economic disparities associated with childhood vulnerabilities and psychiatric diagnoses (Deyessa et al., 2020; Goncalves et al., 2019; Guhn et al., 2016 (B); Taylor et al., 2020).

The utilization of AHD also facilitates data linkage, through which various datasets from different domains, such as healthcare, education, and social services, can be combined to enhance research and intervention efforts (D'Angiulli et al., 2009; Harron et al., 2017; Madigan et al., 2023; Taylor et al., 2020). This interdisciplinary approach refines our understanding of the multifaceted factors influencing childhood outcomes and mental health issues. For example, researchers can gain insights into how health conditions may impact a child's school performance and the role of family and community support systems in mitigating developmental vulnerabilities (Wall-Wieler et al., 2020; D'Angiulli et al., 2009; Taylor et al., 2020). Moreover, healthcare providers, educators, and social workers can work together to design and implement interventions that target at-risk populations more precisely (Bando et al., 2023; D'Angiulli et al., 2009; Saunders et al., 2021; Taylor et al., 2020). This collaborative synergy maximizes the impact of interventions, ensuring that children and families receive the most appropriate support when needed.

While it is important to understand the strengths of AHD, including detailed information, large sample sizes, minimal loss to follow-up, and high external validity, it is important to consider its limitations. One of the primary limitations pertains to data quality. AHD may contain inaccuracies or inconsistencies due to errors in recording or data entry, potentially compromising the integrity of research findings (Harron et al., 2017). Missing data is another significant concern. Incomplete or absent information can hamper the comprehensiveness of analyses and can introduce biases in research results (Harron et al., 2017). Also, the process of linking information across multiple sources can be hindered by insufficient identifying information, leading to data that is either missing or incorrectly linked. Additionally, the absence of data on individuals who did not interact with specific services may introduce biases and gaps in the dataset, affecting the overall quality of research (Harron et al., 2017).

The exchange and integration of information between diverse healthcare entities and sectors are pivotal for the optimal utilization of AHD. Interoperability, referring to the capability of computer systems to efficiently share and use information, plays a vital role in enhancing the utility of AHD (Torab-Miandoab et al., 2023; Turbow et al., 2021). Achieving true interoperability enables the fluid movement of data across healthcare settings, improving the accessibility and comprehensiveness of AHD (Torab-Miandoab et al., 2023). This is particularly crucial for ensuring the accuracy and relevance of the data, addressing some of the challenges related to incomplete information and data quality that may arise in siloed systems. Moreover, interoperability fosters collaborative research initiatives by facilitating data linkage across various domains, such as healthcare, education, and social services. The COVID-19 pandemic has underscored the importance of interoperability, exposing gaps not only between disparate health systems but also between health systems and public health infrastructure (Turbow et al., 2021). The pandemic has heightened the urgency to reject the status quo and accelerate efforts toward achieving robust interoperability in healthcare, especially in times of crises (Turbow et al., 2021).

In conclusion, the utilization of AHD, derived from routine healthcare interactions in Canada, is a powerful tool for identifying population-level risk factors, allowing for the targeted recognition of high-risk groups and the development of tailored interventions. Its impact extends beyond healthcare, influencing evidence-based policies, supporting early interventions, and optimizing resource allocation through collaborative research efforts. The economic benefits are substantial, with AHD guiding cost-effective resource allocation, reducing long-term economic burdens. The usage of AHD also represents a cornerstone in fostering comprehensive, effective, and interconnected approaches that promote the well-being of children and families.

Section 1. Early childhood development

Risk factors in early childhood development

This section assessed developmental vulnerability among kindergarten children using the 2016 Early Development Instrument (EDI) and identified risk factors of developmental vulnerability using EDI data cross-linked to a population-wide administrative health dataset. We chose to focus on the EDI questionnaire as a metric for vulnerability because we had the opportunity to collaborate with one of the founders of the EDI program in Canada. Additionally, the EDI's significance lies in its application by teachers. Given that children spend a significant amount of time in schools, teachers often serve as the first individuals to observe any symptoms associated with developmental vulnerability. The results of this study contribute to addressing the first research question of this thesis by identifying population-level vulnerability risk factors using combined social and biological/health information. The findings enhance our comprehension of developmental vulnerability in Canada and offer insights for policymakers, guiding strategies for risk reduction and prevention, and advocating for a comprehensive, multilevel approach that targets individuals, families, and communities collectively.

Paper 1. Risk factors for developmental vulnerability using the Early Development Instrument

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Introduction

In the area of determinants of health and disease (DOHaD), there is a growing body of knowledge that can inform policy and action plans to increase the human potential for a healthy life (Hoffman DJ et al., 2017). Early childhood development from birth to eight years old is multifaceted, including physical, socioemotional, cognitive, and motor development (Chan M et al., 2017). The prenatal period and the first five years of a child's life are especially important due to rapid brain development, which is sensitive to biological and environmental influences. Prenatal and postnatal care, and early detection and treatment of health concerns are important when considering children's developmental health. From both child development and economic perspectives, preventive strategies are most effective when they are proportionately tailored to specific risk factors and timing in the development (Heckman JJ et al., 2006). Concerning health economics impact, there is an estimated doubling of return on investment to society for every dollar paid toward supporting healthy early childhood development (Heckman JJ et al., 2006).

Understanding the most important risk and protective factors for child development is important to inform decisions and policy development for the deployment of programs and services to support vulnerable children and their families. Vulnerability in children can be broadly defined as the outcome of the interaction between biological and social factors that make children prone to certain risks in their development (Schweiger G, 2009). In utero exposure to substances, prenatal exposure to maternal diabetes (2019; Mackay DF et al., 2017; Molino AR et al., 2020; Novak CM & Graham EM; Tobon AL et al., 2017), and lack of essential nutrients during pregnancy (Schwarzenberg SJ et al., 2018) are examples that may negatively impair children's development, whereas breastfeeding during infancy is a well-known protective factor for children's optimal neurodevelopment (Turner S et al., 2019). However, based on our rapid literature review, among the studies focusing on understanding how early life events may shape children's development (N = 25), only around half of those (N = 12) focus on prenatal and neonatal risk/protective factors, while only a fifth (N = 5) investigated prenatal, neonatal, and early childhood determinants (Appendix 1 Table 1). Also, the 2019 Canadian Health Survey on Children and Youth reported a need for additional information for those individuals under the age of 12. This calls for more converging evidence for the potential prenatal, neonatal, and early childhood factors related to early childhood development.

Studies across Canada often use the Early Development Instrument (EDI) to assess developmental vulnerability by identifying children whose skills and behaviors are below the levels exhibited by most of their peers (Comaskey B et al., 2017; Singal Det al., 2020; Wall-Wieler E et al., 2020). The EDI is a kindergarten-teacher-completed questionnaire that provides information about children's ability to meet age-appropriate developmental expectations, as shaped by their experiences in the first five years of their life (Janus M & Offord DR, 2007).

Studies using administrative health data already confirmed common risk factors of developmental vulnerability, yet individual studies are usually limited in scope, for example focusing only on social (Toit M et al., 2020) or biological/health (Molino AR, et al., 2020; Wall-Wieler E et al., 2020) information, or lack a population-level representative sample (Page KA et al., 2019; Symington EA et al., 2018). Linking data from different sources including both biological and social factors may help to reduce this current knowledge gap by generating evidence with enhanced external validity, providing a more comprehensive perspective of social economics and health utilization, which in turn can promote a better involvement of policymakers (Harron K et al., 2017). In this study, we sought to understand how prenatal, neonatal, and early childhood factors are associated with kindergarten-aged children's vulnerability in the Canadian province of Alberta and to compare these results with other provinces in Canada and other countries, within the broader context of known social and biological determinants of health.

The primary goal of the study is to bridge the knowledge gap in the literature by the development of a cross-linked dataset by linking multiple population-level province-wide health administrative databases to the 2016 collection of EDI data. A secondary goal is to confirm the association between the important prenatal, neonatal, and early childhood factors that contribute to early development specifically in the Alberta population, which have not been explored in the literature, and to enable comparison of the results to other jurisdictions in Canada and other countries. The study results may facilitate a better understanding of developmental vulnerability in Canada and other countries and could inform policymakers and guide vulnerability risk reduction and prevention.

Methods

Study population and variable extraction

The province-wide collection of EDI data for Alberta, sponsored by the Alberta Ministry of Education, was carried out in February and March 2016. This data collection process involved obtaining active consent from parents. During that period, Alberta had a total of 69,486 children aged five and six years old; 31,128 (44.8%) of them did not participate in the EDI data collection due to being homeschooled, living in remote areas, or due to school opt-outs. An additional 7,677 questionnaires did not meet eligibility criteria (e.g., missing data, under 30 days in the classroom, parental consent was missing, incorrect completion of the questionnaire) and were excluded. Then, data from the EDI were linked with the administrative databases from the Ministry of Health, Government of Alberta based on identifiable information (i.e., name, biological sex, and date of birth) and unique provincial health number, resulting in a cohort size of 28,952. Eight databases were linked with EDI data, including Alberta Health Care Insurance Plan Physician Claims, the National Ambulatory Care Reporting System, the Canadian Institute of Health Information–Discharge Abstract Database, the Alberta Health Care Insurance Plan Population Registry Database, Alberta Pharmaceutical Information Network database and Alberta Human Services Drug Supplement Plan database, Alberta Notice of Live Birth or Stillbirth database, Statistics Canada Census Data (2016). For a description of the databases, please see Appendix 1. Only linked records were used in the study.

Finally, we retrieved neonatal and prenatal information from the Alberta Notice of Live Birth or Stillbirth records. Children not born in Alberta do not have records from this database and were excluded from the analysis. The final analytical study sample consisted of 23,494 children (mean age = 5.68 years and SD = 0.33; 48.0% females). The flowchart of the sample exclusions is shown in Figure 1.1.

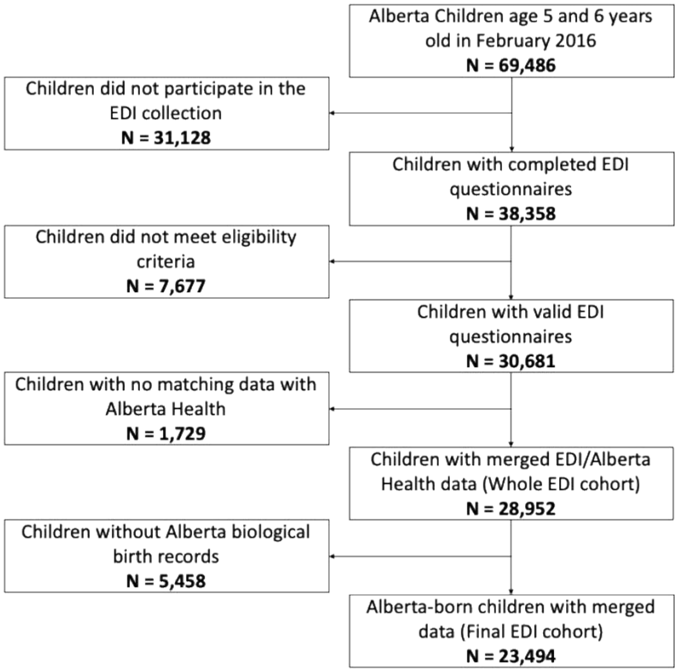

Figure 1.1. Study cohort flow chart.

This study was approved by the Health Research Ethics Board—Health Panel at the University of Alberta (Pro00104650_REN1). Informed consent was waived by the institutional review board due to the secondary analysis nature of the study. Given the anonymization of the data, the researcher's access to it presents minimal risks.

Outcome measures

The EDI's validity, reliability, and consistency have been reported, showing a high degree of consistency across several countries (Janus M et al., 2011). The questionnaire includes 103 items grouped into five relevant developmental domains: physical health and well-being, social competence, emotional maturity, language and cognitive development, and communication and general knowledge (Janus M & Offord DR., 2007). Each child's domain summary scores were derived by averaging scores from domain-specific questions with a range from 0 to 10, where a higher score indicates a higher developmental status. Each domain score was then categorized as "developmentally vulnerable" when the range for a specific domain fell on or below the 10th percentile of the distribution in that domain, which indicates risk for difficulties (for more details, please visit https://edi.offordcentre.com/resources/edi-cohort-reports/). Children who score in the "developmentally vulnerable" range in one or more domains are considered vulnerable overall. This was the study's main outcome measure, as it encompasses all areas of development and is strongly predictive of poor academic and behaviour outcomes in later grades (Toit M et al., 2020), often more so than a domain-specific vulnerability (Davies S et al., 2016). As most of the research published using EDI data uses the same Canadian baseline threshold (i.e., 10th percentile of the Canadian normative distribution), it is reasonable to compare them among different locations. Analyses using domain-specific outcomes were also conducted and are presented in the supplementary material (Appendix 1 Tables 6-10).

Study predictors

To facilitate study interpretation and reduce multicollinearity bias, raw variables with duplicated meanings, or moderately and highly correlated ($r > 0.5$) were excluded from the study. A total of 28 variables were included as predictors (see Appendix 1 Tables 2 and 11). They included biological factors, such as sex assigned at birth and the child's and mother's chronic and mental conditions, and socioenvironmental factors, such as history of health services utilization, mother's drug and multivitamin use, socioeconomic status (SES) as measured by whether the child was part of a subsidy group and community sociodemographic characteristics. For a complete list of variables included in the regression model and details on the predictor variables please refer to Appendix 1.

Statistical analysis

Alberta-born cohort characteristics were compared between the vulnerable and non-vulnerable children across several selected variables with Chi-square tests (Table 1.1). See Appendix 1 Table 4 for a comparison of all variables. Likewise, we compared children for whom EDI data were available (n = 28,952) with those without EDI data (n = 40,534) to investigate whether these groups had similar demographic characteristics and patterns of health service utilization (see Appendix 1 Table 3).

Multivariate logistic models were used to identify risk factors associated with vulnerability in children using SAS, version 9.4. Statistical tests with p-values lower than 0.05 were considered statistically significant. This analysis was performed for Alberta-born children with vulnerability in one or more domains and with vulnerability in each of the five domains as outcomes. Numeric variables with highly skewed distributions were converted to binary equivalents (1 = high risk, 0 = low risk) to ease the interpretation of results. The cut-offs for these dichotomous variables were chosen at the 90th percentile to code the high-risk groups as 1s, and the cut-offs were sometimes rounded to facilitate interpretation (for more details, see Appendix 1 Table 2).

Odds ratios from logistic regression models tend to overestimate the relative risks when the outcome is common (e.g., > 10%) (Vieira AJ, 2008). For more accurate relative risk interpretation, risk ratios were computed (Zhang J & Yu KF, 1998) to assess the effects risk factors had on the vulnerability risk in conjunction with adjusted p-values (using a false discovery rate at 0.05). Dichotomous variable categories were chosen so that the baseline group was the one that received no treatment (e.g., breastfeeding = "No," preterm pregnancy = "No"). Due to the high number of variables included in the regression model, only those variables that reached statistical significance are reported in the results; all variables are reported in Appendix 1).

Among all data sources, biological data collected via the administrative health data Alberta Notice of Live Birth or Stillbirth form at the child's birth in a hospital had the highest proportions of missing data. To explore the risk factor potential of those data, missing values were replaced via imputation methods either based on medians (for continuous variables) or modes (for categorical variables), when less than 30% of the original variable was missing. Logistic models were applied to the data after imputation.

Results

Descriptive statistics

Our analyses found statistically significant differences between the group of children with EDI data (whole EDI cohort) and the group of children without EDI data (non-EDI) in

SES/subsidy and mental health utilization in physician claims (Appendix 1 Table 3). Children who did not participate in the EDI assessment have a higher rate of subsidy (12.43%) than children who did take part in the survey (8.33%). We found a slightly higher proportion of children without EDI data had mental health utilization in physician claims (88.9%, compared to 88.2% of children with EDI data). No statistically significant between-group differences were found in demographic characteristics and patterns of health service utilization.

A total of 6,702 children (28.5%) were developmentally vulnerable. Relative to non-vulnerable children (n =16,792), a higher proportion of the vulnerable children were males (21% of girls were vulnerable compared to 35% of boys), belonged to a subsidy group (54% of those who received subsidy were vulnerable), and were part of a drug benefit plan for at least one year (51% of children that were part of the plan were vulnerable). The results for all variables can be seen in Table 1.1 and Appendix 1 Table 4. Definitions of all variables are in Appendix 1 Table 2.

Table 1.1. Characteristics of the study cohort by vulnerability in one or more domains.

Variable Name	Variable Label	Non-Missing N	Non-Vulnerable Children (n = 16,792) N (%)	Vulnerable Children (n = 6,702) N (%)	p-value[#]
Age – mean (SD)	Years	23,494	5.70 (0.32)	5.63 (0.34)	<0.001
Child's Biological Sex	Female	23,494	8869 (52.8%)	2420 (36.1%)	<0.001
	Male		7923 (47.2%)	4282 (63.9%)	
Socioeconomic/ Subsidy Status (Child)	Subsidy	23,339	900 (5.4%)	1042 (15.7%)	<0.001
	No Subsidy		15,800 (94.6%)	5597 (84.3%)	
Mother's Smoker Status	Yes	18,689	1237 (9.1%)	1014 (19.7%)	<0.001
	No		12,304 (90.9%)	4,134 (80.3%)	
Years Child had Human Service Drug Benefit Plan Enrollment	0	23,494	15,776 (93.9%)	5674 (84.7%)	<0.001
	1		498 (3.0%)	405 (6.0%)	
	2		281 (1.7%)	322 (4.8%)	
	3		237 (1.4%)	301 (4.5%)	
Preterm Pregnancy	Yes	23,494	1066 (6.4%)	610 (9.1%)	<0.001
	No		15,726 (93.6%)	6092 (90.9%)	
Breastfeeding Status	Yes	18,603	13,014 (96.2%)	4745 (93.4%)	<0.001
	No		510 (3.8%)	334 (6.6%)	
Years Child had Asthma	0	23,242	15,147 (91.0%)	5874 (89.0%)	<0.001

	1		239 (1.4%)	107 (1.6%)	
	2		248 (1.5%)	109 (1.6%)	
	3		1006 (6.1%)	512 (7.8%)	
Child's Chronic Disease Status	Yes	23,339	2327 (13.9%)	1536 (23.1%)	<0.001
	No		14,373 (86.1%)	5103 (76.9%)	
Years Child had Mental Health Diagnosis	0	23,243	14,481 (87.0%)	4667 (70.7%)	<0.001
	1		1590 (9.5%)	1081 (16.4%)	
	2		462 (2.8%)	551 (8.3%)	
	3		108 (0.7%)	303 (4.6%)	
Child's Emergency Visits	ED Visits≥4	23,242	2010 (12.1%)	1127 (17.1%)	<0.001
	ED Visits<4		14,630 (87.9%)	5475 (82.9%)	
Not Speaking English or French - mean proportion (SD)	Proportion of individuals	23,477	1.6 (1.6)	1.9 (1.8)	<0.001
Individuals with Higher Education - mean proportion (SD)	Proportion of individuals	23,477	65.1 (11.3)	61.5 (10.8)	<0.001

Note. # χ^2 test was used for categorical variables. T-test was used for continuous variables.

Vulnerable vs. non-vulnerable children

The results of the logistic regression examining the contribution of potential risk factors to vulnerability are presented in Table 1.2 (see Appendix 1 Table 5 for the results for all variables). Overall, children who experienced socioeconomic adversity had 1.58 times the risk of being vulnerable than non-subsidy children. Similarly, after adjusting for other risk factors, the risk for vulnerability among males relative to females is 1.51 times higher, 1.30 times higher for prenatal exposure to nicotine, and 1.46 times higher for every additional year of mental health diagnosis.

Table 1.2. Logistic regression model results for children with one or more vulnerabilities at ages five and six (n = 23,494).

Predictors	Risk Ratio	Standardized Estimate	P-Value*
Biological Factors			
Child’s Biological Sex (Male)	1.51	0.18	<0.001
Child’s Chronic Disease Status	1.13	0.04	<0.001
Mother’s Diabetes Status	1.10	0.03	<0.001
Years Child had Asthma	0.96	-0.02	0.010
Years Child had Mental Health Diagnosis	1.46	0.20	<0.001
Social and Environmental Factors			
Breastfeeding Status	0.87	-0.02	0.021
Child's Emergency Visit	1.01	0.03	0.001
Individuals with Higher Education	0.99	-0.09	<0.001
Living in Rented Dwellings	1.01	0.01	<0.001
Mother's Pregnancy History Count	1.04	0.03	<0.001
Mother's Smoker Status	1.30	0.07	<0.001
Mother’s Drug Use Status	1.18	0.02	0.046
Not Speaking English or French	1.05	0.07	<0.001

Preterm Pregnancy	1.16	0.03	0.001
Socioeconomic/Subsidy Status (Child)	1.58	0.10	<0.001
Years Child had Human Service Drug Benefit Plan Enrollment	1.16	0.07	<0.001

Note. *Adjusted p-value based on false discovery rate (FDR) correction at 0.05. All p-values presented in this table are significant at $p < 0.05$, see Appendix 1 Table 5 for the full table.

Breastfeeding at birth was associated with a 13% lower risk of vulnerability compared to children who were not breastfed. Further, a 4% reduction of risk was observed for every additional year the child had asthma. Finally, a 1% increase in the proportion of individuals in the community with higher education reduced the risk of vulnerability by 1%.

Follow-up analyses explored the association of these risk factors with vulnerability in each EDI domain (Appendix 1 Tables 6-10). Increased risk of vulnerability in each domain was associated with the child's socioeconomic/subsidy group, years of mental health diagnosis, and prenatal exposure to smoking and other addictive substances. There were no substantial differences in terms of the identified risk factors between Alberta-born children and all children cohorts.

Discussion

In this comprehensive, population-level linked dataset including perinatal and birth data as well as child development at school entry in the Canadian province of Alberta, we confirmed the universality of key risk factors associated with the highest risk of vulnerability: SES, biological sex, and children's mental health. Studies including such a broad range of perinatal, neonatal, and early childhood variables, both biological and social, as predictors of child development outcomes are rare, and so far, come only from a few in Canada (Cabaj JL et al., 2014; Cronin P & Goodall S, 2021; Grace T et al., 2016; Mughal MK et al., 2019; O'Meagher S et al., 2017; Razaz N et al., 2019; Santos R et al., 2012; Saunders NR et al., 2021; Wall-Wieler E et al., 2020) and Australia (Pearce A et al., 2016). By conducting our study in the Canadian province of Alberta, we both confirm the previous findings and add a unique contribution of extended universality to this body of knowledge. These results call for further research and practical guidelines in diminishing the negative impact of mental diseases and poor SES on child development and focusing on sex-specific developmental vulnerability.

Biological sex at birth might be indicative of vulnerability as our analysis shows that boys have a 50% greater risk of being developmentally vulnerable than girls. Similar results were found in other studies in Canada (Cabaj JL et al., 2014; Dea C et al., 2019; Mughal MK et al., 2019) and Australia (Dea C et al., 2019; O'Meagher S et al., 2017; Veldman SL et al., 2020; Williamson Aet al., 2019). Dea and colleagues reported almost twice the risk for developmental vulnerability in boys when compared to girls by using the EDI data in Quebec, Canada. Using different data sources, Cabaj and colleagues and Mughal and collaborators reported that boys have a higher risk of problem behaviours at age eight and are more prone to develop communication and personal-social delays at age three, respectively. In Australia, previous reports showed that male children are at higher risk of developmental vulnerability, motor gross delay, and executive function difficulties at age five (O'Meagher S et al., 2017).

Several components of SES were associated with vulnerability, as previously reported by studies using the EDI data in Canada (Dea C et al., 2019; Lloyd JE & Hertzman C, 2009; Saunders NR et al., 2021) and the Australian version data (Australian Early Development Census, AEDC; Dea C et al., 2019; Dhamrait GK et al., 2021; Williamson A et al., 2019). Our results suggest that living in an area with a higher proportion of people with higher education was a protective factor for child vulnerability. This finding is consistent with the known compounding effect of low SES and education (O'Meagher S et al., 2017; Williamson A et al., 2019), where children from low SES families are more likely to demonstrate poor outcomes, with limited exposure to stimulating environment and the lack of family resources to stimulate education suggested as a possible mechanism (Lloyd JE & Hertzman C, 2009; van Bergen E et al., 2017) which can later affect their school attendance and transfer to high school (Sheridan MA & McLaughlin KA, 2016). Relatedly, we identified a higher proportion of individuals who do not speak English/French in the child's neighbourhood. This higher proportion may contribute to poor outcomes in education and is associated with higher vulnerability risks.

The present study showed an association between a child's poor mental health and school readiness difficulties (i.e., children's ability to successfully engage in the task demands of school). By analyzing the AEDC data, Green and colleagues showed that childhood developmental vulnerability indicators at age five are a major contributor to children's mental illness at age 13. Together, these findings add insights to the current knowledge of the association between mental health issues at early ages and increased psychiatric diagnosis and symptom severity later in life (Luby JL et al., 2014). Interestingly, maternal and paternal mental illnesses are also associated with developmental vulnerability in children. Studies led by Saunders, Wall-Wieler, and Bell and colleagues, all of them using the EDI data or the Australian version data (AEDC), showed that exposure to parents with a psychiatric diagnosis increases the risk of developmental vulnerability, difficulties in social competence, physical health and wellbeing, and emotional maturity. In addition to the psychiatric diagnosis of parents, the mental health history in children also had a similar impact on vulnerability. Mental illness is one of the global leading causes of years lived with disability (YLDs, i.e., years of life lost due to time lived in states of less than full health), accounting for almost 15% of global YLDs (Collaborators GBDMD, 2022). The burden due to mental disorders is seen across all age groups and emerges even before five years of age (Collaborators GBDMD, 2022). This highlights the need for early identification and intervention to support children in their mental health, particularly as young individuals with psychiatric disorders often face challenges in obtaining an accurate diagnosis (Reimherr JP & McClellan JM, 2004).

We also identified other risk factors for children's vulnerability, confirming previous studies in the field. For example, exposure to tobacco, opioids, and other substances during pregnancy are contributors to poor developmental outcomes in children (Mackay DF et al., 2017; Molino AR et al., 2020; Tobon AL et al., 2019; Tzoumakis S et al., 2018; Williamson A et al., 2019). In addition, in-utero exposure to these substances can result in preterm birth (Mackay DF et al., 2017; Tobon AL et al., 2019), further contributing negatively to early childhood development as shown by previous studies (Saunders NR, et al., 2021). On the other hand, breastfeeding and multivitamins and folic acid intake showed a significant trend ($p = 0.050$, see Appendix 1 Table 5) and are associated with lower risks for childhood development. Those are important factors of neurodevelopment since many important brain formation events are dependent on folic acid and vitamins, such as the proliferation and growth of glial and neuronal cells and the synthesis of neurotransmitters (Valera-Gran D et al., 2014). Also, breastfeeding is beneficial for all infants as it has important nutrients that influence the development of cognitive and motor abilities and socioemotional competencies in children (Turner S et al., 2019).

Despite many strengths, our study also has limitations. The EDI data privacy impact assessment did not allow us to link EDI scores with parent or family information. Due to this limitation, we did not have access to the original family environment or the parents' health status (chronic disease conditions and mental health issues), which are known to impact children's early development and their vulnerabilities (Comaskey B et al., 2017; Singal D et al., 2020; Wall-Wieler E, et al., 2020). Also, our final cohort covered approximately 30% of Alberta children due to the mandatory informed consent process and the options for school boards to opt out of the program, and EDI data were not collected for First Nation Band-operated schools. Thus, results need to be interpreted with caution due to a potential sample selection bias. The representativeness of the study sample is further impacted by reducing the cohort to Alberta-born children with valid EDI data. A sizable proportion of the sample (n = 5,458) had missing Alberta Notice of Live Birth or Stillbirth form data, which may be due to the busy schedule of health providers in hospitals and the low priority for nurses to record answers thoroughly on the form, enforcing the use of imputation methods that could potentially underestimate variability due to repetition of the same value within variables. In addition, since we found a significant difference in the proportion of people receiving subsidies (Appendix 1 Table 3), in conjunction with imputing systematically missing data, there are likely group differences in other unmeasured factors between the study cohort and the larger EDI cohort. All considered, the study sample selection may have underestimated the proportion of vulnerable children. In addition, the study was designed to explore risk factors associated with vulnerability, not to establish causality. Thus, even though the dataset collected may imply causality, due to the temporal separation between variables and outcome, the modelling results should be interpreted with caution (Hernán MA et al., 2019; Shmueli G, 2010; Westreich D & Greenland S, 2013).

Conclusion

The current findings from the analysis of a large cohort of Albertan children are a significant contribution to our body of knowledge concerning the vulnerability of Canadian children in the context of DOHaD. By linking data on child development at school entry with a variety of health administrative data including data collected from birth and by using a population-level sample from Alberta, we included both social and health information in a representative sample of Alberta, Canada. Our results are in line with existing findings that the mother's substance use, the child's chronic and mental disease status, male biological sex, and socioeconomic status are the main risk factors of developmental vulnerability, while breastfeeding and multivitamins with folic acid supplementation are associated with lower risk of developmental vulnerability. Our results confirm evidence established in other geographic regions and jurisdictions and demonstrate the association of perinatal risk factors for Alberta children. Although it is extremely important to know risk factors for policymakers and prevention, our top risk factors may be challenging to address. It would take time to change at a population level, making it difficult to make informed decisions for developing programs and services aimed at supporting specifically vulnerable children and their families. The current health system is designed to treat diseases and to invest in procedural interventions instead of focusing on preventive care. Our results are in favour of long-term multilevel intervention, in which individuals, families, and communities are targeted together.

Disclaimer

This study is based in part on data provided by Alberta Health. The interpretation and conclusions contained herein are those of the researchers and do not necessarily represent the views of the Government of Alberta. Neither the Government nor Alberta Health expressed any opinion about this study.

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Machine learning for early detection of ADHD

This section explores a machine learning-based approach for the prospective detection of ADHD among kindergarten-aged children by linking population-level administrative health data with the 2016 EDI dataset. We chose to focus on ADHD due to its classification as a neurodevelopmental disorder and the EDI's inclusion of questions directly related to hyperactive and inattentive behaviors. This raised the question of whether the EDI alone, health administrative data alone, ADHD symptoms alone, or a combination of them could accurately predict future ADHD diagnoses. The study uses a cohort of 23,247 children born in Alberta without an ADHD diagnosis in 2016. After a four-year follow-up period, a set of machine learning models was trained and tested to identify children with ADHD. Our findings suggest that this approach could be a valuable tool for informing about ADHD risks and has the potential to promote early diagnosis and intervention.

Paper 2. Early detection of ADHD using the Early Development Instrument

Paper 1 enhances our understanding of the vulnerability of Canadian children within the framework of DOHaD, confirming the universality of critical risk factors linked to heightened vulnerability. Paper 2 extends this exploration by delving into the integration of the EDI with machine learning methods for the early detection of ADHD. The following paper was submitted to PLOS Digital Health on October 5th, 2023, and is presently undergoing the peer-review process.

Introduction

ADHD (Attention-Deficit/Hyperactivity Disorder) is characterized by developmentally inappropriate, persistent, and pervasive inattention and/or hyperactivity-impulsivity that interferes with daily functioning at home, school, or work (American Psychiatric Association, 2013; Centre for ADHD Awareness Canada, 2017). It is associated with emotional dysregulation (Shaw P et al., 2014), neuropsychological dysfunction (Pauli-Pott U & Becker K, 2011), poor social relationships and cognitive skills (Thomaidis L et al., 2017), academic underachievement (DuPaul GJ & Stoner G, 2014), risky sexual behaviour, early pregnancy, (Meinzer MC et al., 2020) and criminal activities (Baggio S et al., 2018;

Sebastian A et al., 2019). The economic impact of ADHD is significant, with disease-associated costs estimated to be $74 billion and $6 to $11 billion annually in the United States and Canada, respectively, due to losses in productivity (Centre for ADHD Awareness Canada, 2017).

Early interventions in preschool (Diamond A & Lee K, 2011) and school-aged children (DuPaul GJ et al., 2018; Rimestad ML et al., 2019), such as behavioural training and stimulant medications, have proven effective in mitigating downstream negative consequences of untreated ADHD. However, diagnosing ADHD in the preschool years poses challenges, leading to delayed intervention in nearly all cases. Most children do not receive a diagnosis until the age of seven. For example, in 2016, among the 6.1 million ADHD cases diagnosed before 18 years of age in the United States, only 2-6% were diagnosed before the age of four (Lavigne JV et al., 2009), with over half diagnosed between 12 and 17 years (Danielson ML et al., 2016; DuPaul GJ et al., 2018; Lavigne JV et al., 2009; Olivia F et al., 2020). This delay is more prevalent in girls (Sayal K et al., 2018). Factors contributing to delayed diagnosis may include a lack of awareness of ADHD signs/symptoms among parents and teachers. Early identification of children at a heightened risk of ADHD at a young age can increase parental awareness, prompting them to seek clinical diagnostic clarification and facilitating early intervention.

Ideally, if ADHD cases can be accurately identified at a population level, building predictive models for early detection and targeted interventions has the potential to reduce the burden associated with ADHD on patients and society. However, clinical diagnoses are often not directly captured in population-level data, and the risk of ADHD can only be estimated. One means of identifying probable ADHD cases is through administrative health data. In Canada, the health care system is publicly funded, universally available, and administered at the province/territory level. Administrative data are routinely collected and widely used for population health surveillance, holding the potential to estimate the risk of clinical ADHD diagnoses using specific case definitions. The validity of using case definitions of ADHD to approximate clinical diagnoses and population-level prevalence was previously explored, demonstrating high confidence using International Classification of Disease (ICD) codes from physician claims, ambulatory records, and drug dispensation history (Daley MF et al., 2017; Gruschow SM et al., 2019; Mohr-Jensen et al., 2016; Morken R et al., 2020).

In addition to administrative health data, cross-sector data, such as population surveillance within the educational system, is routinely collected and may facilitate the identification and estimation of ADHD risk. One widely used population-level surveillance tool in the education sector is the Early Development Instrument (EDI) (Janus M & Offord DR, 2007; Janus M et al., 2011). The EDI assesses developmental health by identifying children's vulnerability to poor developmental outcomes based on teacher-completed questionnaires. It provides information about the ability of kindergarten-aged children (four to six years old) to meet age-appropriate developmental expectations shaped by their experiences in the first five years of life (Janus M & Reid-Westoby C, 2016).

The questionnaire comprises 103 questions covering five domains: physical health and well-being, social competence, emotional maturity, language, and cognitive development, and communication skills and general knowledge (Janus M & Offord DR, 2007). These domains include 16 subdomains, such as physical readiness for the school day, physical independence, gross and fine motor skills, overall social competence, responsibility and respect, approaches to learning, readiness to explore new things, prosocial and helping behaviour, anxious and fearful behaviour, aggressive behaviour, hyperactivity and inattentive behaviour, basic literacy, interest literacy/numeracy and memory, advanced literacy, basic numeracy, and communication and general knowledge (Liu YS et al., 2022; Ostergaard SD et al., 2016). Also, the EDI contains parent-reported and teacher-recorded medical and developmental diagnoses, including parent-reported formal ADHD diagnosis (Liu X et al., 2019). Cross-linkage of datasets across the health and education sectors provides an enriched context for interdisciplinary research focussed on identifying risk factors of developmental disorders and developing data-driven, high-performance health risk predictive models (Lavebratt C et al., 2019).

The literature has reported various risk factors for ADHD, encompassing demographic factors such as family size and low socioeconomic status (Engelhard MM et al., 2020), as well as health history factors like asthma (Hall HA et al., 2020), early exposure to antibiotics

(Bzdok D et al., 2018), increased health utilization (Tibshirani R, 1996), and prenatal maternal health (Cassie S & Hoouwelingen JC, 1992). The existing literature has predominantly investigated these risk factors using conventional statistical analysis methods, primarily focused on data description, with less emphasis on the performance and generalizability of the models themselves. In contrast, machine learning-based algorithms go beyond traditional statistical approaches. They employ sophisticated algorithms to construct predictive models, with the primary aim of making precise individual-level forecasts that may be extrapolated to real-world contexts. For instance, machine learning models are developed using training data, and a separate hold-out test set is used to assess their real-world performance in predicting future outcomes (Friedman JH, 2001). The insights derived from the underlying mechanisms of a successful predictive model can offer valuable data on the individual-level likelihood of ADHD risk.

This paper aims to develop a high-performing predictive model for identifying individuals with childhood ADHD by applying machine learning algorithms to population-level administrative health data cross-linked with EDI. We also evaluated the contributing predictive risk factors. Receiving a positive ADHD flag based on a case definition indicates a higher risk of ADHD (refer to Appendix 2 Table 1). Then, we used cross-linked administrative health data and the EDI questionnaire collected in Alberta, Canada, to predict children with ADHD in a four-year follow-up window. By utilizing machine learning, we aim to investigate the combined and individual utility of administrative health and EDI data in predicting the elevated risk of future ADHD.

Methods

Data sources

The 2016 EDI data was collected between February and March and was provided by the Ministry of Education, Government of Alberta, Canada. The EDI implementation was offered to all publicly funded schools. Unlike other Canadian jurisdictions, opting out was possible for Alberta schools, and individual families, resulting in capturing 55.2% (38,358 out of 69,486) of the population. Other administrative health datasets were used in this study, including the Alberta Health Care Insurance Plan (AHCIP) Physician Claims, National

Ambulatory Care Reporting System (NACRS), Discharge Abstract Database (DAD), the Alberta Health Care Insurance Plan (AHCIP) Population Registry Database, Alberta Pharmaceutical Information Network (PIN) database and Alberta Human Services Drug Supplement Plan database (AHSDSP), Alberta Notice of Birth database, and Statistics Canada Census Data (2016). These datasets contain children's health utilization history, prenatal records, and demographic information.

This study was approved by the ethics committee at the University of Alberta (Pro00104650).

Linking procedure and database development

The EDI dataset was linked with health administrative datasets from the Ministry of Health, Government of Alberta (Alberta Health) based on identifiable information (i.e., name, biological sex at birth, date of birth) and unique provincial health number. Except for demographic information, all predictive variables were developed based on a three-year historical window before enrollment. Personally identifiable information was used for data linkage only and excluded from the analysis.

Sample derivation

In Alberta, there were 69,486 children between the ages of five and six in 2016. Of those, 38,358 (55.2%) completed the EDI questionnaire. The reasons EDI data was not collected for all children aged five and six included: homeschooling, living in remote areas, or school authority and family opt-outs. After applying our exclusion criteria to the EDI dataset, including the removal of children with missing data, those who attended less than 30 days in the classroom, and a lack of parental or guardian consent records, 7,677 children were removed from the analysis. After linking the EDI data with the health administrative data, 7,187 children were further excluded due to mismatch (i.e., children not having an Alberta biological birth record – N= 5,458 – or the birth record did not match the information in the health administrative data – N = 1,729). To ensure prospective prediction, children with prior ADHD diagnoses before March 31st, 2016 (N = 247) were further eliminated from the remaining cohort. Therefore, the final cohort for analysis included 23,247 children (Figure 2.1).

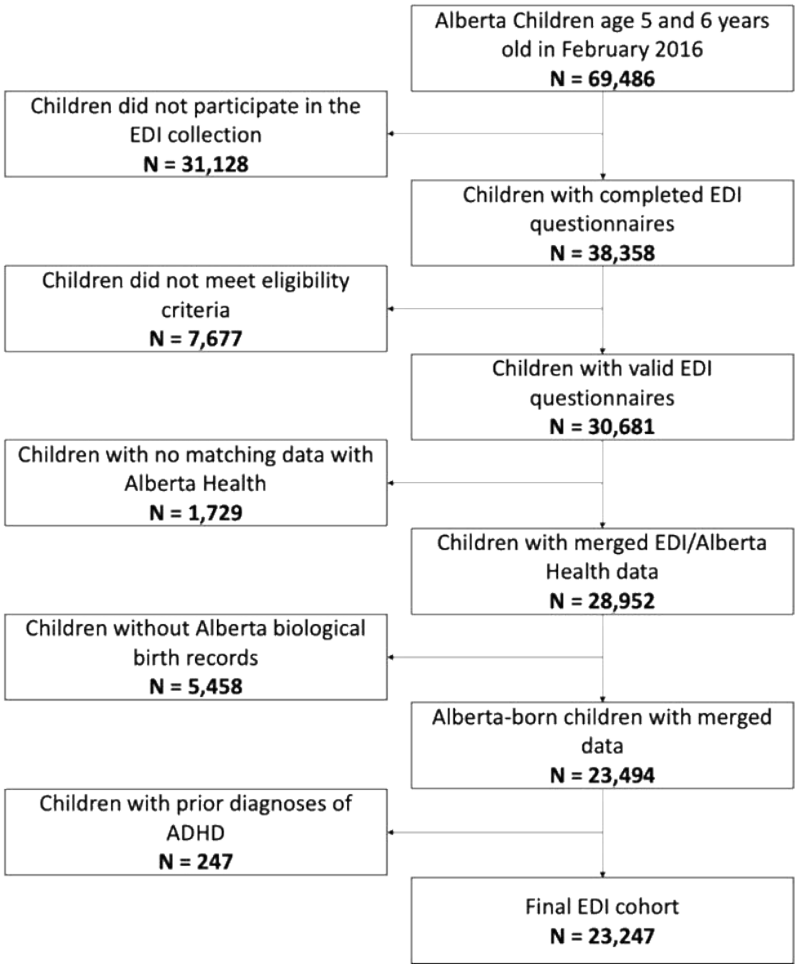

Figure 2.1. Study cohort flow chart.

Outcome definition

The target outcome is whether a subject has ADHD in the four-year follow-up window, operationally defined as a binary outcome (1 – ADHD, 0 – No ADHD). ADHD cases were determined based on administrative health data-derived case definition. This included ICD-9 and ICD-10 codes related to inpatient and outpatient visits, psychiatric and mental health facility outpatient visits, physician claims, or a history of stimulant drug use based on Anatomical Therapeutic Chemical (ATC) Classification drug codes (see Appendix 2 Table

1 for ADHD case definition). Incidence of ADHD was noted for the cohort in the four years between March 2016 and March 2020.

Data analysis

Python 3.6 with the *scikit-learn* 0.22.1 package was used for data pre-processing and machine learning (ML) analysis. A total of 58 features were used (Table 2.1). The EDI features included in the analysis were based on the categorical subdomain scores, in which groups of scores were identified as representing children who met: 1) few/none of the developmental expectations, 2) some developmental expectations, or 3) all/almost all developmental expectations. This helped the model be more interpretable and helped drive actionable findings. Twenty-six features with categorical responses (e.g., 'Yes', 'No') were dummy coded with the first redundant level dropped.

We tested a set of machine learning models, both linear and non-linear models, to explore the combined and individual predictive utility of administrative and EDI data. We also sought to identify important individual predictive factors driving the results. For linear models, we included the standard Logistic Regression model and Logistic regression model with regularizations, i.e., Logistic Lasso Regression (Ho TK, 1995) and Logistic Ridge Regression (Tachimori H et al., 2003). We included Gradient Boosting (Kessler RC et al., 2005) and Random Forest (Storebo OJ et al., 2019) for non-linear models. All models were optimized for the area under the receiver operating characteristic curve (AUC) and evaluated using 10-fold cross-validation (CV), with hyperparameter tuning. All numeric features were standardized using the StandardScaler function to a mean of 0 and a unit standard deviation after training and testing data splitting.

The optimal model for interpretation were selected based on a performance on AUC. For each machine learning algorithm, we run three models, 1) Administrative health data only (36 features), 2)EDI data only (23 features), and 3) ADHD symptoms (3 features) as the baselines for performance comparison.. Age and biological sex at birth were included in all baseline models. For all linear models, frequency-based weight adjustments were applied to control the class-imbalance effect (1,680 ADHD cases versus 21,567 No ADHD). The AUC confidence interval was derived based on 30 times of repeats of the 10-fold CV. Non-overlapping confidence intervals were interpreted as statistically different at $p < 0.05$.

Unlike the standard logistic regression model with equal weights for samples from minority and majority classes, the coefficients' p-values and t-test statistics cannot be derived parametrically from the logistic regression model with weight adjustments. Thus, we accounted for the uncertainty of the coefficients using a nonparametric method. The distributions of the coefficients were derived from logistic regression models with weights adjustment built on 100 times of bootstrapping using randomly selected data, each representing 90% of the original samples. Then, t-tests were used to evaluate if the observed coefficients were significantly different from zero, with the p-value adjusted using an FDR at $\alpha < 0.05$. To reduce the computational complexity of the study pipeline, no feature selection algorithm was used for modeling. Feature importance was estimated based on ranked average coefficient values from bootstrapping.

Results

Cohort description

The final cohort included 23,247 children, with a mean age of 5.68 (SD = 0.33). Most children were males (52.0% male; 48.0% female) and 8.3% of them belonged to a socioeconomic subsidy group. Based on our case definition, the prevalence rate of ADHD for children aged four and five years is 1.1%, which is in line with Canadian reports of 0.8%, 2.0%, and 2.1% prevalence rates for the age group of five to nine years old in Ontario, Nova Scotia, and Quebec, respectively (Vasiliadis HM et al., 2017). During the follow-up period, 1,680 children (7.2%) were found to have case-defined ADHD. See Table 2.1 for the descriptive analysis.

Table 2.1. Dataset variable summary.

	ADHD (n = 1,680)			No ADHD (n = 21,567)			
Continuous Variables	**mean**	**std**	**range**	**mean**	**std**	**range**	**t**
Years with Asthma	0.33	0.91	0.00 - 3.00	0.23	0.76	0.00 - 3.00	5.35*
High Health Utilization[a] (Number of years)	0.14	0.46	0.00 - 3.00	0.07	0.32	0.00 - 3.00	8.30*
Past mental health records of the child (Number of years)	0.58	0.87	0.00 - 3.00	0.21	0.55	0.00 - 3.00	25.65*
Years on Human Service Drug Benefit Plan	0.22	0.67	0.00 - 3.00	0.15	0.55	0.00 - 3.00	5.36*
≥30% of Owner Income Spent on Housing (%)	15.38	3.75	0.00- 29.60	15.6	4.11	0.00 - 29.60	-2.15*
≥30% of Renter Income Spent on Housing (%)	34.88	6.86	0.00 - 64.60	34.24	7.29	0.00 - 64.60	3.47*
Not Speaking English or French (%)	1.5	1.53	0.00 - 8.35	1.68	1.7	0.00 - 8.35	-4.14*
Immigrants Arriving Within the Last 5 Years (%)	5.48	3.87	0.00 - 20.13	5.75	4.21	0.00 - 20.66	-2.48*
Percentage of Individuals with Higher Education	64.41	11.32	32.46 - 87.60	64.08	11.26	24.58 - 87.60	1.16
Lone Parent Families (%)	14.66	5.11	5.44 - 43.28	14.33	5.15	5.44 - 51.08	2.47*
Average Household Size	2.71	0.36	1.50 - 4.50	2.74	0.39	1.50 - 5.00	-3.16*
Families with Low After-Tax Income (%)	8.89	4.04	1.60 - 32.00	8.82	4.09	1.60 - 32.00	0.64
Age	5.69	0.34	4.89 - 6.88	5.67	0.33	4.55 - 7.13	1.97
Communication skills and general knowledge	1.86	0.86	1.00 - 3.00	2.22	0.86	1.00 - 3.00	-16.48*
Prosocial and helping behaviour	1.7	0.8	1.00 - 3.00	2.07	0.83	1.00 - 3.00	-17.51*
Anxious and fearful behaviour (R)	1.23	0.51	1.00 - 3.00	1.14	0.41	1.00 - 3.00	7.85*
Aggressive behaviour (R)	1.59	0.83	1.00 - 3.00	1.16	0.49	1.00 - 3.00	32.31*
Hyperactive and inattentive behaviour (R)	2.05	0.9	1.00 - 3.00	1.32	0.65	1.00 - 3.00	42.59*
Basic literacy	2.24	0.83	1.00 - 3.00	2.55	0.7	1.00 - 3.00	-17.23*
Interest in literacy/numeracy and memory	2.32	0.84	1.00 - 3.00	2.65	0.67	1.00 - 3.00	-18.65*
Advanced literacy	2.13	0.92	1.00 - 3.00	2.5	0.79	1.00 - 3.00	-18.52*
Basic numeracy	2.25	0.9	1.00 - 3.00	2.57	0.75	1.00 - 3.00	-16.66*
Physical readiness for school day (R)	1.15	0.53	1.00 - 3.00	1.07	0.36	1.00 - 3.00	8.69*
Physical independence	2.42	0.91	1.00 - 3.00	2.77	0.64	1.00 - 3.00	-20.95*
Gross & fine motor skills	1.89	0.87	1.00 - 3.00	2.28	0.86	1.00 - 3.00	-18.12*
Overall social competence	1.88	0.71	1.00 - 3.00	2.43	0.65	1.00 - 3.00	-32.91*
Responsibility and respect	2.27	0.78	1.00 - 3.00	2.78	0.51	1.00 - 3.00	-37.58*
Approaches to learning	1.98	0.75	1.00 - 3.00	2.6	0.63	1.00 - 3.00	-38.77*
Readiness to explore new things	2.66	0.57	1.00 - 3.00	2.81	0.45	1.00 - 3.00	-13.02*

Binary Variables	ADHD (n = 1,680) %Yes	ADHD (n = 1,680) %No	No ADHD (n = 21,567) %Yes	No ADHD (n = 21,567) %No	χ^2
Mother's alcohol use status	4.94	95.1	2.93	97.1	20.45*
Total Doctor Visits >15	33.5	66.5	23.1	76.9	99.05*
Emergency Department Visits >=4	18.8	81.2	12.7	87.2	48.17*
Inpatient Hospital Days>=1	5.8	94.2	3.7	96.3	18.32*
Total public health cost >=5K	20.2	79.8	10.5	89.5	146.00*
APGARS 5 Score >=8	94.7	5.3	96.4	3.6	12.48*
Mother has diabetes	5.2	94.8	5.6	94.4	0.42
Mother >=4 pregnancies	14	86	13.5	86.5	0.24
Mother has hypertension	6.5	93.5	5	95	6.60*
Communicate adequately in first language	90.1	9.9	92.4	7.6	10.62*
Mother's drug use	4.2	95.8	1.7	98.3	52.62*
English/French as second language	4.9	95.1	1.7	98.3	100.68*
Mother has mental health issues at childbirth	14.6	85.4	7.6	92.4	103.8*
Preterm birth	10.1	89.9	6.8	93.2	225.22*
Repeat school grade	5.5	94.5	2.8	97.2	38.59*
Mother's smoking status	15.1	84.9	8.9	91.1	69.36*
Special need status	8.3	91.7	1.8	98.2	293.2*
Prenatal visits >=9	73	27	6.8	93.2	5.97*
Breastfeeding	95.2	4.8	96.5	3.5	7.21*
Biological sex at birth	26	74	50.1	49.9	361.33*
Chronic Disease Status (2015-2016)	25.8	74.2	14.9	85.1	138.69*
Socioeconomic/Subsidy Status (2015-2016)	11.4	88.6	7.8	92.2	26.99*

Note: All variables presented were collected before Marth 31st, 2016. T-tests and were used for comparisons between groups with numerical measure. Two by two $\chi 2$ tests were used for comparison between groups with binary measures. * denotes $p < 0.05$, after a false discovery rate (FDR) correction at $\alpha = 0.05$. R in parentheses denotes reverse coding of the original EDI score, higher score is associated with mo re problem behaviour. a High health utilization indication is assigned if the patient had more than 15 visit to primary health care physician or 10 or more specialist visits or 10 or more ED visits during a fiscal year.

Model performance

The standard Logistic Regression model without regularisation had a CV-AUC of 0.811, representing the best model performance. In contrast, other more complex ML models offered no enhancement of predictive performance (Appendix 2 Table 2). As a result, we focused on the outputs of the Logistic Regression model without regularisation to assess the model's performance (i.e., balanced accuracy) and to determine the top 10 predictive features based on feature importance ranking. The Receiver Operating Characteristic (ROC) of the best fitting and baseline models are plotted in Fig 2.2. The logistic model achieved a cross-validated balanced accuracy of 0.745, with a sensitivity of 0.717 and a specificity of 0.773, presenting a 9.5% increase in balanced accuracy compared to the model with only administrative health features (balanced accuracy = 0.650). When compared to a model using features exclusively from EDI, we found a 0.4% balanced accuracy difference (balanced accuracy = 0.741). When compared to ADHD symptoms model using EDI Hyperactive and Inattentive Behaviour score, biological sex and age as features, we found a 4.3% balanced accuracy difference (balanced accuracy = 0.702). To facilitate the interpretability of the analysis, a logistic regression model with frequency weight adjustment for equal class weight was fitted to the raw data to generate odds ratios corresponding to the raw data units and FDR-adjusted p-value (based on $\alpha < 0.05$).

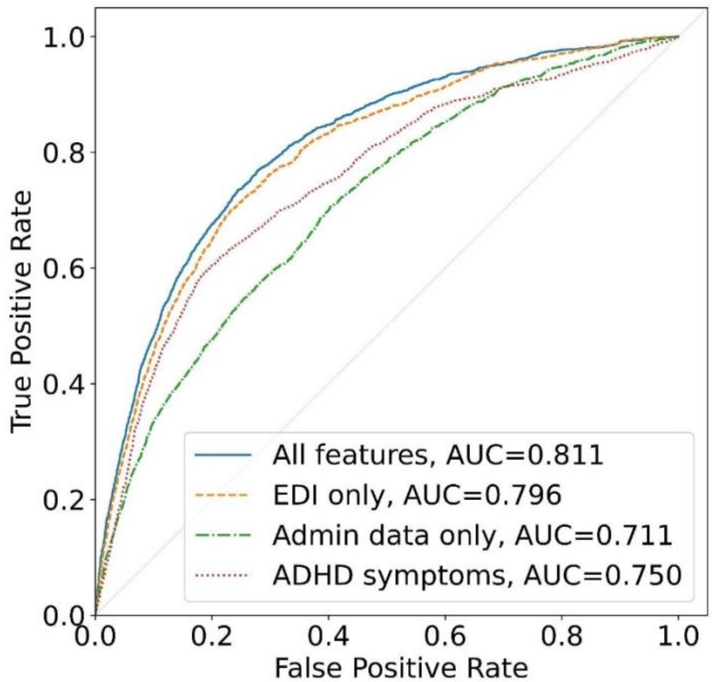

Figure 2.2. ROC curves

Predictive variables

Table 2.2 presents the top 10 predictive variables for case-defined ADHD, including four features from EDI. The variable 'Approaches to learning' helps to assess how well children work neatly and independently, solve problems, adhere to rules and routines in class, and readily adapt to changes. 'English/French as 2nd language' indicates whether a child is not a native speaker of the classroom's instruction language. 'Hyperactive and inattentive behaviour' evaluates the degree to which children show hyperactive behaviours: the ability to concentrate, settle in chosen activities, wait their turn, and think before acting. 'Note scores' have been reverse coded, so a higher number indicates more problem behaviours. 'Overall social competence' evaluates the degree to which children have good or excellent overall social development, an ability to get along with other children and to play with various children, cooperative play, and self-confidence.

Table 2.2. Top 10 predictive features for children with ADHD.

Predictive Variable	Odds Ratio	95% CI Lower	95% CI Upper	p adjusted
EDI: Approaches to learning	0.58	0.54	0.62	<0.001
EDI: English/French as a 2nd language (yes)	0.35	0.31	0.40	<0.001
EDI: Hyperactive and inattentive behaviour (R)	1.62	1.54	1.70	<0.001
EDI and Admin: Biological sex at birth (female)	0.52	0.49	0.56	<0.001
EDI: Overall social competence	0.63	0.59	0.67	<0.001
Admin: Past mental health records of the child (Number of years) [1]	1.52	1.44	1.60	<0.001
Admin: Percentage of individuals with postsecondary education	1.02	1.01	1.02	<0.001
Admin: Mother has mental health issues at childbirth (yes)	1.73	1.57	1.92	<0.001
Admin: ≥30% of owner income spent on housing (yes)	1.02	1.01	1.02	<0.001
Admin: Average household size	1.37	1.17	1.61	<0.001

Note: Odds ratios and confidence intervals of odds ratios were calculated based on regular logistic regression fit on raw data with class-balance weight adjustments. Feature importance was ranked based on the magnitude of the bootstrapped coefficients from the ML pipeline. Adjusted p-value based on an FDR correction at $\alpha < 0.05$. The intercept of the model has a standard estimate of -1.62, with adjusted p = 0.004. CI stands for Confidence Interval. EDI stands for Early Development Instrument. Odds ratios presented are associated with a higher numerical score of the predictor, or "yes" if the predictor is a binary indicator. R in parentheses (R) denotes reverse coding of the original EDI subdomain score, where a higher score indicates more problem behaviour.

[1]Number of years the child was flagged with mental health-related problems between 2013 and 2016.

A high score on learning strategies, learning English or French as a second language (i.e., not being fluent in the language of instruction), having a female biological sex at birth, and having a high overall social competence are protective against an increased risk of ADHD, according to the multivariate model. A longer history of past mental health records, more hyperactive and inattentive behaviour, and a mother's history of mental health concerns at childbirth were all linked to higher probabilities of ADHD. In addition, demographic data including a higher percentage of individuals with postsecondary education in the neighbourhood, greater than or equal to 30% of income spent on housing, and a higher average household size in the neighbourhood were associated with increased risk of ADHD.

Discussion

Using cross-linked data from administrative health and a population surveillance tool, the EDI, we investigated a machine learning approach to identify and validate the increased risk of ADHD in kindergarten-aged children. We report an AUC of 0.811 and a balanced accuracy of 0.745, demonstrating an increase of 9.5% when compared to the use of administrative health data alone. The EDI-only model is also performing close to the comprehensive model (AUC = 0.796, balanced accuracy = 0.741). The result suggests that EDI, although designed to be a population surveillance tool for children's vulnerability, may offer insights to facilitate identifying heightened risk of ADHD. Our results also further contribute to the literature on confirming key risk factors of ADHD that may be used to improve early identification and intervention to reduce the burden associated with ADHD.

Early identification of children with a heightened risk of ADHD often starts with parents' and teachers' suspicion and is confirmed by physicians later. However, earlier signs of ADHD are often overlooked, even though reliable patterns to identify ADHD may have already emerged. Our study supports that machine learning application on population-level data may offer a practical tool to identify the overlooked early warning signs and therefore raise the red flags for parents, teachers, and physicians, which in turn may translate to early diagnoses and intervention. Although there is currently a lack of comparable studies utilizing similar methods on population data for children's ADHD risk screening and a lack of general clinical tools to facilitate early childhood ADHD screening, our model's performance is comparable to those studies aiming to retrospectively identify other developmental disorders and childhood ADHD. A clinical scale used for screening autism, the Childhood Autism Rating Scale (Saunders NR et al., 2021), achieved a sensitivity of 0.71 and specificity of 0.75 in a large sample validation study. In a meta-analysis, pooled sensitivity and specificity of ADHD screening tools ranged from 0.72 to 0.84 (Granziera H et al., 2021), with the Conners Abbreviated Symptom Questionnaire reaching a balanced accuracy of 0.83. However, the scales are not designed to identify ADHD in a future time window.

The top four contributing features of our best-performing model are consistently EDI-based features. Higher scores on approaches to learning are protective against ADHD risk (OR =

0.58) and may indicate that children with ADHD echo early signs of learning disabilities at kindergarten age (Thomaidis L et al., 2017). Children learning English or French as a second language have a significantly reduced risk of ADHD (OR = 0.35). To the authors' knowledge, there's a lack of empirical findings on the impact of children not fluent in the language of instruction in class on ADHD. However, a lack of English structural skills has been shown to be positively associated with ADHD behaviour (53), thus it is likely children not fluent in the language of instruction have higher risk of ADHD. The reduced risk of ADHD for English and French as a second language children in our model may indicate this is a group of children vulnerable for underdiagnoses of ADHD, a hypothesis warrant future research. Further, it is not surprising that early observations of hyperactive and inattentive behaviour are associated with a 1.62 OR increase for future diagnoses of ADHD, recognized as a primary symptom of the disease.

ADHD diagnoses in females are normally delayed and they experience higher levels of underdiagnosis compared to males (Sayal K et al., 2018). Consequently, females with ADHD in our sample of young children were less likely to receive a diagnosis. In our model, the female sex reduces the odds of ADHD by half (OR = 0.52). In addition, ADHD children suffer from social incompetency (Hauck TS et al., 2017), coinciding with our finding that a higher social competency score reduces the ADHD odds by 37% (OR = 0.63).

For a list of significant risk factors derived from health data-based predictors, children with a greater number of past mental health visits and mothers with poor mental health at birth are associated with largely increased odds of future ADHD (OR of 1.52 per year and 1.73, respectively). This aligns with existing literature where both children (Bzdok D et al., 2018; Hall HA et al., 2020; Tibshirani R, 1996) and maternal health (Cessie S & Houwelingen JC, 1992) are recognized as ADHD risk factors. While the results do not provide insights into the causes of increased odds, some plausible explanations may involve poor mental health in both the child and mother, potentially leading to attachment issues. This notion is supported by the observation of a high prevalence of insecure attachment among ADHD children and their mothers (Darling RP et al., 2019; Ozcan NK et al., 2018). This finding may inform mental health service providers and policymakers to allocate more resources to parents with mental disorders, such as mothers suffering from post-partum depression or psychosis.

For census-based predictors, a higher average household size in the neighbourhood increases the risk of ADHD, in line with evidence that poor socioeconomic environments are associated with ADHD diagnosis (Engelhard MM et al., 2020). The odds ratio of the percentage of individuals with postsecondary education greater than or equal to 30% of owner income spent on housing was very low, at 1.02. The average percentage difference between the ADHD and No ADHD groups for those variables was also small in magnitude (e.g., < 1%). Thus, we could not draw a meaningful interpretation based on such a small magnitude effect.

In general, the identified risk factors may have limited clinical utility. Nevertheless, the model's predictions could serve as a red flag for clinicians, prompting more thorough screening for ADHD and aiding in the early identification of potential missed diagnoses.

Our results support the hypothesis that linking administrative health data with population surveillance data may facilitate accurate individual-level prediction of ADHD. This opens opportunities for harm reduction strategies, including promoting awareness of ADHD among teachers, parents, and clinicians, and encouraging early access to healthcare for at-risk children. In the recent literature, EDI data has been linked with administrative data records for the purpose of studying medical and social risk factors of non-specific developmental vulnerabilities. One study reported a reasonable concordance between ADHD case definition and EDI records, with a positive predictive value of 61.9% and a negative predictive value of 96.7% (Saunders NR et al., 2021). In another study, EDI data was cross-linked with census data to develop behavioural self-regulation profiles of children, showing that children with a high-risk profile were more likely to be associated with a subsequent clinical diagnosis of ADHD up to five years later (Liu X et al., 2019).

Another insight from the current study is that administrative health and EDI data both have the potential to facilitate the identification of ADHD even without data crosslinking. Administrative data alone, even though performing subpar to models including EDI data, can be used to perform crude prediction of heightened ADHD risks (AUC = 0.711). It's also not surprising that EDI data alone performed well in ADHD screening, as parent-reported and school-reported symptom data are often critical to making a diagnosis of ADHD. The current findings set a stage for future follow-up studies to refine predictive modelling algorithms and explore potential real-world applications of big data and ML to inform heightened ADHD risks.

In this study, we intentionally excluded children already diagnosed with ADHD or those with a case-defined ADHD label at the time of data collection. This was done to apply cross-validation specifically to the prediction of a future ADHD label, ensuring the model is trained for prospective forecasting. Had this group of children with dual labels (currently confirmed ADHD and case-defined ADHD in a four-year window) been included in the training samples, the algorithm might have achieved a higher classification accuracy, given the ML model access to more examples of ADHD children for differentiation from non-ADHD children.

The relatively short four-year follow-up window in our data extraction process introduces the possibility of mislabeling children with ADHD identified after this period, incorrectly categorizing them as not having ADHD. This mislabeling during model training might have compromised the classification performance in identifying ADHD cases. Similarly, the model may have flagged individuals with a higher likelihood of ADHD who, within our timeframe, hadn't received a diagnosis. While considered false positives in our model, these instances could represent true positive cases given a more extended time window. Therefore, false positive predictions from our model could serve as an indicator of an elevated risk of ADHD. Recognizing this, we anticipate that future studies with a more extended longitudinal follow-up may produce improved classification results and validate whether a model prediction based on a shorter time window can indeed be employed for early ADHD identification.

One limitation of the study is that the identification of ADHD is based on a case definition derived from administrative health data. This may be a good proxy for true ADHD diagnoses, or a heightened risk, but not equivalent to a confirmed clinical diagnosis. The surveillance case definition usually has limited specificity but is sensitive and has a high degree of confidence in identifying true cases. When considering the total number of children with case-defined ADHD from five to 10 years of age, the identified ADHD rate is higher than expected, at 7.2%. As a comparison, the prevalence rate of ADHD in Ontario, Canada has been estimated to be at 5.6% (Hauck TS et al., 2017). The higher prevalence of ADHD identified in our data suggests the case definition used in our study may have introduced more false positive cases, where children with no ADHD risk could have been identified as ADHD cases. Also, the modelling did not extract diagnoses of specific mental disorders and use them as predictive factors and cannot inform if predicted ADHD had comorbid diagnoses. Future studies should use clinical diagnoses of ADHD if such data becomes accessible and explore subtypes of ADHD and ADHD with comorbidity.

Conclusion

The result of this study suggests that children at risk of ADHD could be identified prospectively at kindergarten age through machine learning adaptation of administrative health and population-level surveillance data. The novel application of machine learning on cross-linked population-level data may have the potential to systematically improve awareness, reduce delayed diagnoses, and promote early intervention to minimize the negative impact of ADHD.

Disclaimer

This study is based in part on data provided by Alberta Health. The interpretation and conclusions contained herein are those of the researchers and do not necessarily represent the views of the Government of Alberta. Neither the Government nor Alberta Health expressed any opinion about this study.

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Section 2. The COVID-19 pandemic

Impact on mental health utilization

Given the onset of the COVID-19 pandemic and its impact on the mental well-being of children and adolescents, this section continues to investigate the connection between early developmental vulnerability and healthcare utilization in children spanning from 2016 to 2022 using the population-wide administrative health data. It also examines the impact of the pandemic on mental health-related utilization in youth. The results indicate that vulnerable children had more interactions with the health system than their non-vulnerable counterparts. Despite the COVID-19 pandemic not disrupting overall utilization patterns, male children consistently exhibited higher utilization rates than females, particularly among those identified as vulnerable. In the context of the pandemic, our findings highlight a decrease in non-mental health-related utilization, while the proportion of individuals seeking professional mental health care increased, especially among adolescents. These outcomes raise concerns about a significant upswing in mental health service utilization among adolescents, hinting at a potential decline in youth mental well-being since the pandemic. Drawing insights from kindergarten data, we underscore the imperative for early and targeted intervention strategies, particularly for at-risk children. This emphasis offers a pathway to mitigate the burden of childhood mental health disorders.

Paper 3. Six-year longitudinal patterns of mental health service utilization rates among children developmentally vulnerable in kindergarten and the COVID-19 pandemic disruption

This paper was submitted to PLOS Digital Health on December 11th, 2023, and is presently undergoing the peer-review process.Introduction

The escalating global prevalence of mental health disorders in children and adolescents has emerged as a pressing issue of our time (Vasileva et al., 2021). Recent research has unveiled high rates of depression, anxiety, sleep disturbances, and posttraumatic stress symptoms, particularly in the aftermath of the COVID-19 pandemic (Dragioti et al., 2022; Ma et al., 2021; Schroeder et al., 2022). The interplay of factors such as social isolation, disrupted routines, and economic uncertainties has exacerbated mental health problems, necessitating a re-evaluation of interventions spanning the developmental continuum from early childhood to adolescence (Barbieri et al., 2022; Deolmi & Pisani, 2020; Ma et al., 2021).

The impact of early life adversities on mental health stands as a central concern warranting exploration. Pivotal experiences such as childhood maltreatment and socioeconomic hardships have been linked to an elevated risk of psychiatric conditions, including depression, anxiety, and substance use disorders (Black et al., 2017; Britto et al., 2017; Miguel et al., 2019). Early life adversities not only have immediate mental health outcomes but also contribute to persistent neurobiological alterations with lifelong implications (Aboud & Yousafzai, 2015; Black et al., 2017; Miguel et al., 2019; Mulraney et al., 2021).

Early intervention and prevention strategies become increasingly imperative in the achievement of alleviation of the burden of mental health disorders and promotion of optimal development (Britto et al., 2017; Moran et al., 2022; Mulraney et al., 2021). While conventional approaches often target high-risk populations, emerging evidence highlights the potential of population-level interventions and early screenings to prevent the onset of more severe mental health challenges (Gross et al., 2021; Kato et al., 2015).

In this context, comprehending service utilization patterns and evaluating disparities in mental health-related service access among children holds paramount importance for informed policymaking and targeted interventions. This study aims to analyze the existing disparities in service utilization, mainly related to mental health, within the context of children's developmental characteristics. Specifically, we examine children who were recognized by kindergarten teachers as developmentally vulnerable, aiming to explore whether such vulnerabilities are associated with distinct service utilization patterns. We hypothesize that developmentally vulnerable children exhibit heightened levels of mental health-related service utilization compared to their non-vulnerable counterparts. Furthermore, considering the impact of the COVID-19 pandemic on healthcare utilization (Dragioti et al., 2022; Ma et al., 2021; Schroeder et al., 2022), the secondary hypothesis posits that the pandemic has led to an increase in mental health-related services utilization among both vulnerable and non-vulnerable children.

To comprehensively investigate the interplay between early developmental characteristics and mental health service utilization patterns, this study employs an established tool, the Early Development Instrument (EDI) questionnaire (M. Janus, & Offord, D. R., 2007). By integrating the EDI with healthcare utilization data, this study seeks to provide a nuanced understanding of how children's developmental profiles predict patterns of mental health-related service utilization.

Methods

Study design

This was a six-year longitudinal cohort study, linking teacher ratings of kindergarten children's development with subsequent administrative health records, specifically physician's office claims, emergency department visits, and hospitalizations.

The records are accessible through the databases available on the Alberta Ministry of Health website (www.alberta.ca/health-research.aspx).

Participants

The study participants were drawn from the cohort of all five to six-year-old children who participated in the 2016 Early Development Instrument (EDI) (Janus M, & Offord DR, 2007) assessment in Alberta, Canada and were covered by public Alberta Health insurance from 2016 to 2022 (N = 38,358). After applying exclusion criteria (more than 30% of missing data, under 30 days in the classroom, missing parental consent, incorrect questionnaire completion) and data cleaning (no matching data with other administrative databases, children without Alberta biological records), 14,864 individuals were removed from the analysis. Thus, the eligible population for inclusion in the study comprises 23,494 (33.8% of the initial sample) children, which represents 21.4% of the age cohort in Alberta. More information on the inclusion and exclusion criteria is published elsewhere (Talarico et al., 2023).

A prior analysis conducted by our research team highlighted significant differences between the final cohort of children (N = 23,494) and those excluded from the analysis, particularly regarding socioeconomic status and mental health utilization (Talarico et al., 2023). Specifically, children excluded from the analysis due to non-participation in the EDI data collection or exclusion based on the defined criteria, demonstrated exhibited a higher rate of subsidy (12.43%) in comparison to the cohort included in the final analysis (8.33%). Additionally, a slightly larger proportion of the excluded group demonstrated mental health utilization in physician claims (88.9%), compared to 88.2% among the final cohort of children. Importantly, no statistically significant differences were observed between these two groups concerning demographic characteristics and patterns of health service utilization.

The EDI assessment data collection in Alberta was conducted in February and March 2016. This instrument, widely recognized for its reliability and validity, offers an assessment of children's developmental vulnerabilities across multiple domains, including physical health and well-being, social competence, emotional maturity, language and cognitive development, and communication skills (Shelley Hymel, 2011; Zumbo, 2011).

The study was approved by the Ethics Board – Health Panel at the University of Alberta (Pro00104650_REN1).

Exposure

Teacher ratings on the EDI were used to categorize the children into those who were developmentally vulnerable and those who were not. The EDI is a widely used and well-validated assessment tool in Canada that measures developmental vulnerability in children by identifying those whose skills and behaviours fall below the levels exhibited by most of their peers (Shelley Hymel, 2011; Zumbo, 2011). The assessment is completed by kindergarten teachers and consists of 103 items grouped into five developmental domains: physical health and well-being, social competence, emotional maturity, language and cognitive development, and communication and general knowledge. The summary scores for each domain were calculated by averaging scores from domain-specific questions, with a range of 0 to 10, where higher scores indicate higher developmental status. A score falling on or below the 10th percentile of the distribution in a specific domain is considered "developmentally vulnerable," indicating a risk for difficulties. Children who scored in the "developmentally vulnerable" range in one or more domains are considered vulnerable overall (M. Janus, & Duku, E., 2007).

Outcome

The primary variable of interest in this study is the number of all conditions and mental health-related services utilized during the study period (2016 to 2022). We used diagnosis codes from the International Classification of Diseases 9th and 10th revisions (ICD-9 and ICD-10) available for service utilization records to identify mental health disorders and their sub-conditions. We selected the top three mental health disorders in reference to the highest number of children seeking treatment (namely anxiety disorders, mood disorders, and ADHD). A complete list of the diagnosis codes used is available in Appendix 2 Table 1.

To account for changes in population size over time in Alberta, we calculated crude rates per 1,000 population. Specifically, we divided the total number of all events and mental health-related events by the corresponding population size in each group (i.e., vulnerability and biological sex groups). We then multiplied the resulting value by 1,000 to obtain the crude rate per 1,000 population for each group in each year.

Analysis

Linear regression models with vulnerability group (yes or no), biological sex (male or female), and year as predictor variables were used to investigate the association between the number of all events and mental health-related events (i.e., dependent variables). The interaction term between vulnerability and sex was also included as an independent variable. Separate models were conducted to assess vulnerability specific to each developmental domain, as well as vulnerability across multiple domains (i.e., vulnerability in one or more domains). We adjusted the p-values using a false discovery rate (FDR) and models with adjusted p-values lower than 0.05 were considered statistically significant.

Additionally, we compared service utilization between the pre- and post-pandemic onset periods. The mean value of service utilization from January 2016 to February 2020 was computed and defined as the 'pre-pandemic' period, while the mean value from March 2020 until December 2022 was classified as the 'post-pandemic onset' period. To analyze the variability within each group, the standard deviation was calculated for each time point and compared between the pre- and post-onset periods.

The statistical analyses and graphical representations were performed using R version 4.1.1 .

Results

Among the 23,494 children, there were 11,289 (48.1%) females and 6,702 were classified as vulnerable in one or more developmental domains. Among vulnerable children, 9.75% of all utilization was related to a mental health problem (N = 3,719). This number rose to 24.2% in 2022 (n = 7,050).

Table 3.1. Cohort characteristics.

Variable Name	Variable Label	Non-Vulnerable Children (n = 16,792) - N (%)	Vulnerable Children (n = 6,702) -N (%)	p-value#
Age – mean (SD)	Years	5.70 (0.32)	5.63 (0.34)	<0.001
Child's Biological Sex	Female	8869 (52.8%)	2420 (36.1%)	<0.001
	Male	7923 (47.2%)	4282 (63.9%)	
Socioeconomic/ Subsidy Status (Child)	Subsidy	900 (5.4%)	1042 (15.7%)	<0.001
	No Subsidy	15,800 (94.6%)	5597 (84.3%)	

There is a statistically significant difference in biological sex distribution between the two groups in all years. Despite there being more females in the overall cohort, males represent the majority among the vulnerable group across all years. The percentage of mental health utilization increased over time for all groups, with vulnerable children exhibiting a consistently higher rate than their non-vulnerable peers across all years (Table 3.2)

Table 3.2. Descriptive of service utilization by sex and year.

Year	Vulnerability (1 or more domain	Sex N (% Female)	chi^2 p-value	MH utilization N (%)	All utilization N
2016	Y	8233 (29.7%)	< 0.01	3713 (9.75%)	38068
	N	19018 (53.3%)		1792 (2.44%)	73451
2017	Y	8088 (36.5%)	< 0.001	5130 (14.2%)	36057
	N	18734 (53.3%)		5130 (4.61%)	69470
2018	Y	7999 (36.4%)	< 0.001	6021 (17.7%)	34060
	N	18541 (53.3%)		4123 (6.31%)	65344
2019	Y	7888 (36.4%)	< 0.001	6526 (19.8%)	32989
	N	18373 (53.3%)		5354 (8.10%)	66122
2020	Y	7765 (36.5%)	< 0.001	5986 (23.6%)	25413
	N	18134 (53.2%)		5863 (11.3%)	51778
2021	Y	7678 (36.5%)	< 0.001	6634 (24.5%)	27113
	N	17997 (53.2%)		7365 (12.9%)	56964
2022	Y	7638 (36.5%)	< 0.001	7050 (24.2%)	29145
	N	17994 (53.3%)		8186 (13.5%)	60787

Note: Y = yes (vulnerable children); N = no (non-vulnerable children).

All conditions

The results indicate a significant linear decrease in all health services utilization from 2016 to 2020. Utilization slowly increased thereafter, reaching levels similar to those observed pre-pandemic by 2022 (Figure 3.1A). Vulnerable children, on average, had 648 more events than non-vulnerable children ($\beta_{vulneravility}$ = 647.9; p-value = 0.013). Almost all utilization involved office visits (Figure 3.1A and B) and therefore the results of these two variables are similar: there is a linear decrease in utilization (β_{time}= -85.7; p-value = 0.018) and vulnerable children, on average, had 670 more events than non-vulnerable children ($\beta_{vulneravility}$= 569.9; p-value = 0.010).

Similar to office visits, emergency visits exhibited a linear decrease (βtime = -28.7; p-value = 0.003) from 2016 to 2020, and a gradual increase thereafter (Figure 3.1C). The hospitalization patterns of vulnerable children were similar to those observed in emergency visits, with a linear decrease from 2016 to 2020. However, in 2022, there was a sharp increase in hospitalizations among females, surpassing the number of hospitalizations in males, as illustrated in Figure 3.1D. Non-vulnerable children, on the other hand, exhibited a slight decrease in hospitalizations from 2016 to 2021. In 2022, while the hospitalization rate of males continued to decrease, that of females increased, exceeding the rate of males.

Vulnerable children had, on average, eight more hospitalization events than their non-vulnerable peers, which was statistically significant (βvulnerability = 8.1; p-value = 0.008).

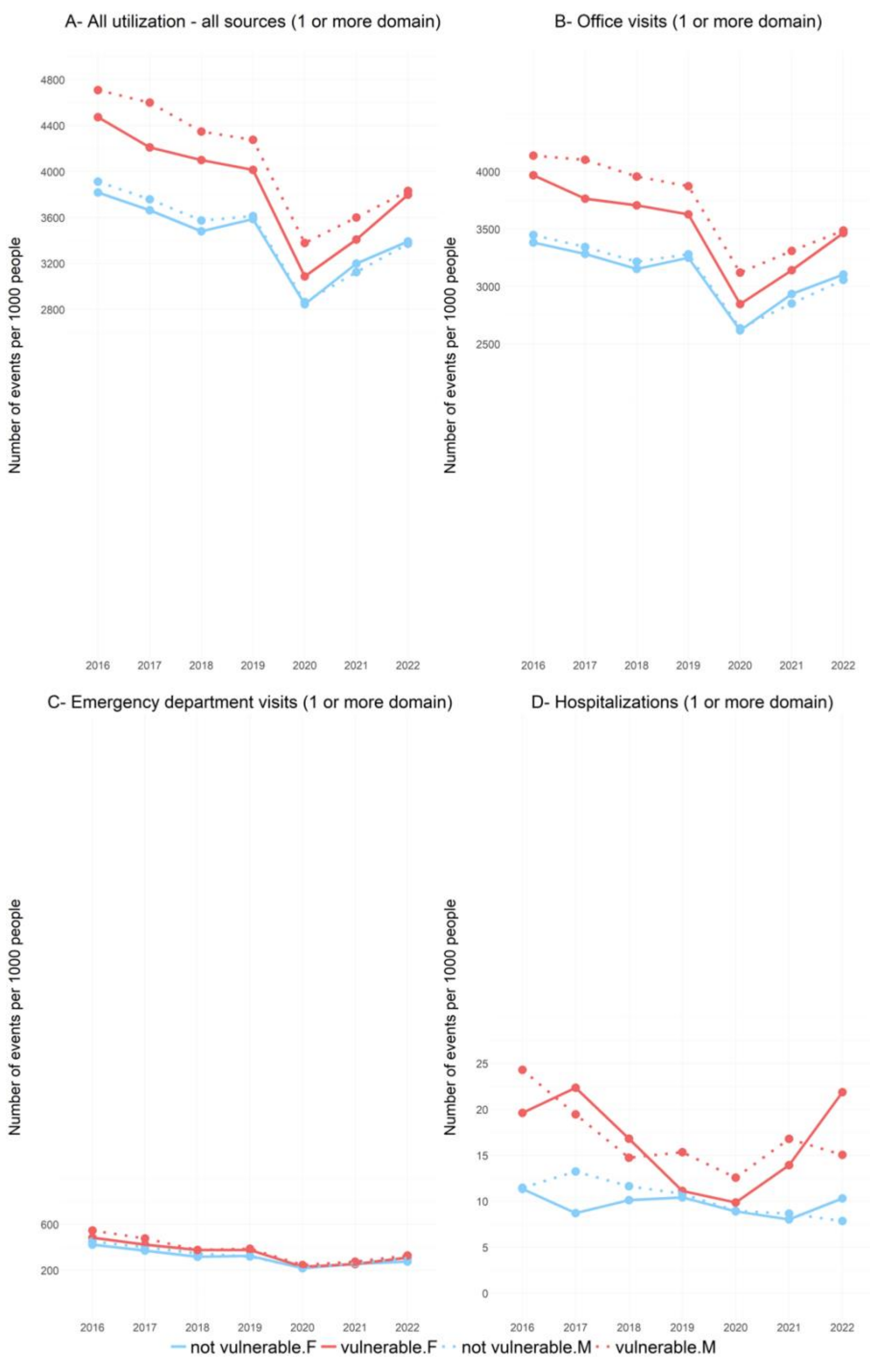

Figure 3.1. Trend of all health services utilization between 2016 and 2022.

Note: M = male, F = female. D is not on the same scale as A, B, and C.

Consistent patterns of association were observed across distinct developmental domains. Generally, children classified as vulnerable in areas such as communication and general knowledge (CG), emotional maturity (EM), language and cognitive development (LC), physical health and well-being (PH), and social competence (SOC) had a higher number of office visits compared to non-vulnerable children. Children with vulnerabilities in EM, LC, PH, and SOC domains had higher rates of emergency department visits and hospitalizations. For a more comprehensive breakdown of the findings, indicating the domain-specific beta and p-values for office visits, emergency department visits, and hospitalizations, please consult Appendix 3 Table 2.

We also analyzed the average number of events that occurred during the pre-pandemic period (2016-2019) and post-onset period (2020-2022), along with their corresponding standard errors (SEs). As shown in Appendix 3 Figure 1, both vulnerable and non-vulnerable children experienced a decline in healthcare services utilization after the onset of the COVID-19 pandemic. During the post-onset period, there were no substantial differences in utilization between the two groups, except for hospitalizations, in which vulnerable children continued to have higher rates than non-vulnerable children. In terms of biological sex differences, male children had slightly higher utilization rates than females for all utilization sources and emergency department visits in both periods. However, females showed slightly higher utilization rates than males for office visits and hospitalizations in the post-onset period.

Mental health conditions

Our findings demonstrate a consistent linear increase in the utilization of all mental health-related services between 2016 and 2022. Throughout the years, male children consistently displayed higher utilization rates than females, particularly among vulnerable children (Figure 3.2A). Overall, the results of the linear regression analysis indicated that, on average, male vulnerable children had 209 more events than non-vulnerable males, which was statistically significant ($\beta_{vulnerability*sex(M)} = 209.4$; p-value = 0.002).

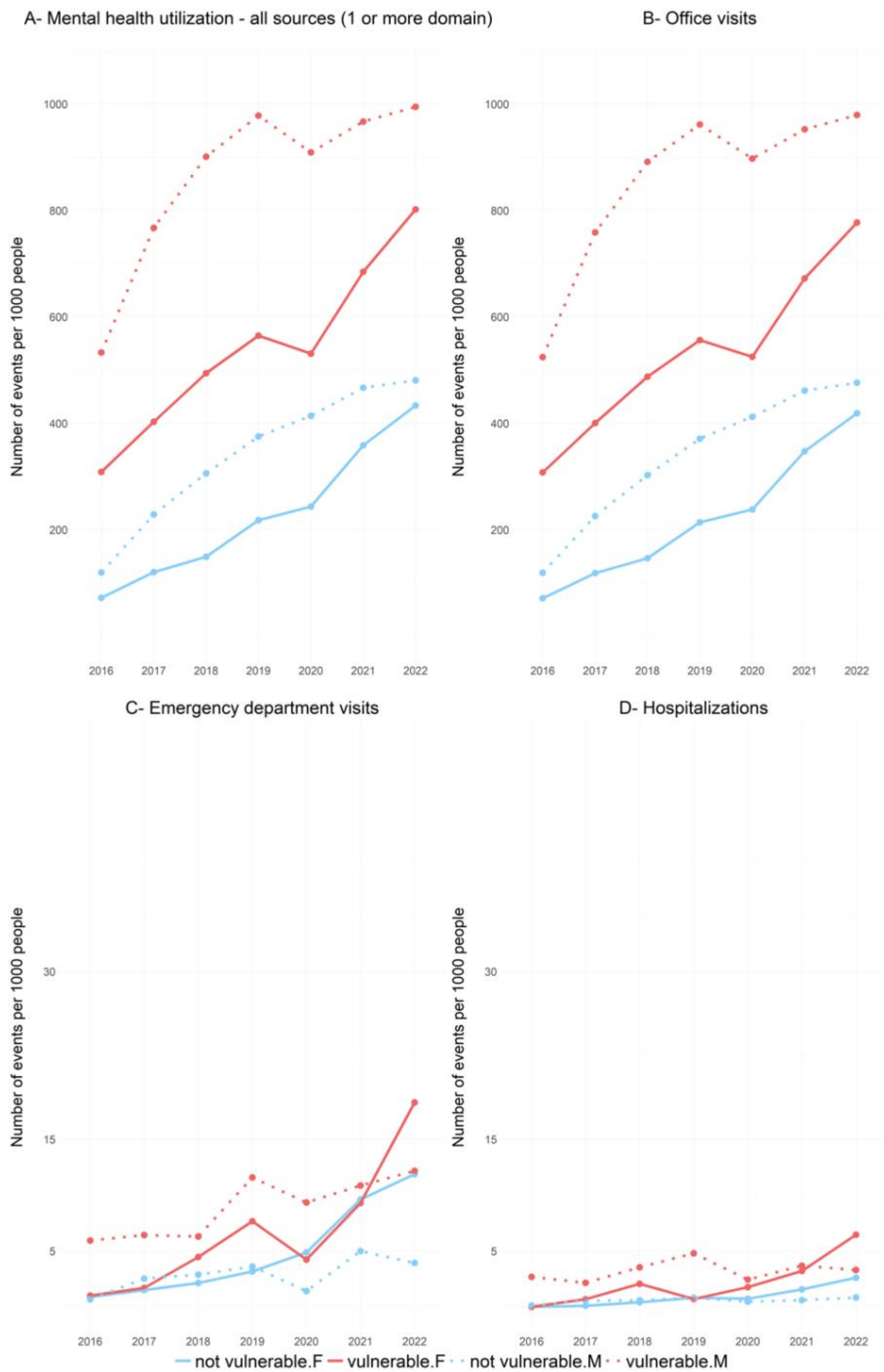

Figure 3.2. Trend of mental health-related services utilization between 2016 and 2022.

Note: M = male, F = female. A and B are in different scales than C and D.

The data indicates that office visits constitute most of the mental health-related utilization (Figure 3.2B) and the findings are consistent with the overall mental health utilization results. Specifically, the analysis revealed that vulnerable male children had, on average, 204 more events than non-vulnerable males, which was statistically significant (βvulnerability*sex(M) = 203.7; p-value = 0.002).

There was also a consistent increase in mental health-related emergency visits between 2016 and 2022. Although there was a slight decline in 2020 for male vulnerable children, their emergency visits resumed a steady increase until 2022 (Figure 3.2C). In contrast, female vulnerable children exhibited a significant increase in emergency visits in both 2021 and 2022, surpassing the male vulnerable values. There were relatively stable emergency visit rates among non-vulnerable males throughout the years, with a slight decrease in mental health-related visits in 2020 and a small increase in 2021. In contrast, among female non-vulnerable children, there was a consistent increase in emergency visits from 2016 to 2020, with a sharp increase in subsequent years. In 2020 and 2021, their numbers were comparable to those of female vulnerable children, and in 2022, they were comparable to those of male vulnerable children, as demonstrated in Figure 3.2C.

The linear regression analysis revealed that the increasing trend of mental health-related emergency visits was significant for male vulnerable children, who had an average of four more visits than their peers (βvulnerability*sex(M) = 4.3; p-value = 0.035). Although the mental health-related hospitalization pattern was similar to those observed in emergency visits, it was not statistically significant.

Different outcomes were observed across various developmental domains. Children identified as vulnerable in the language and cognitive development (LC) and social competence (SOC) domains exhibited elevated frequencies of office visits, emergency department visits, and hospitalizations. Vulnerability in the emotional maturity (EM) and physical health (PH) domains was associated with higher numbers of office visits. Additionally, vulnerability in the communication and general knowledge (CG) domain was linked to increased office visits and emergency department visits. For details of the results of this analysis, please refer to Appendix 3 Table 3.

To better understand the impact of the COVID-19 pandemic on mental health utilization rates, we analyzed the average number of events that occurred during the pre-pandemic (2016-2019) and post-onset (2020-2022) periods, along with their corresponding standard errors (SEs). Our results revealed that among both vulnerable and non-vulnerable children, there was an increase in healthcare services utilization (Figure 3.3A-D). Specifically, for all sources and office visits, both groups and sexes demonstrated a similar increase, with male vulnerable children consistently exhibiting the highest utilization rates. However, there were notable sex differences in the rates of emergency department visits and hospitalizations. While male utilization remained relatively stable between the pre- and post-onset periods, female utilization increased significantly. Both female vulnerable and non-vulnerable children displayed a similar increase in emergency department visits, but the hospitalizations among female vulnerable children increased at a higher rate compared to female non-vulnerable children. Thus, our findings suggest that the COVID-19 pandemic had a similar impact on healthcare utilization rates for both vulnerability groups, except for hospitalizations.

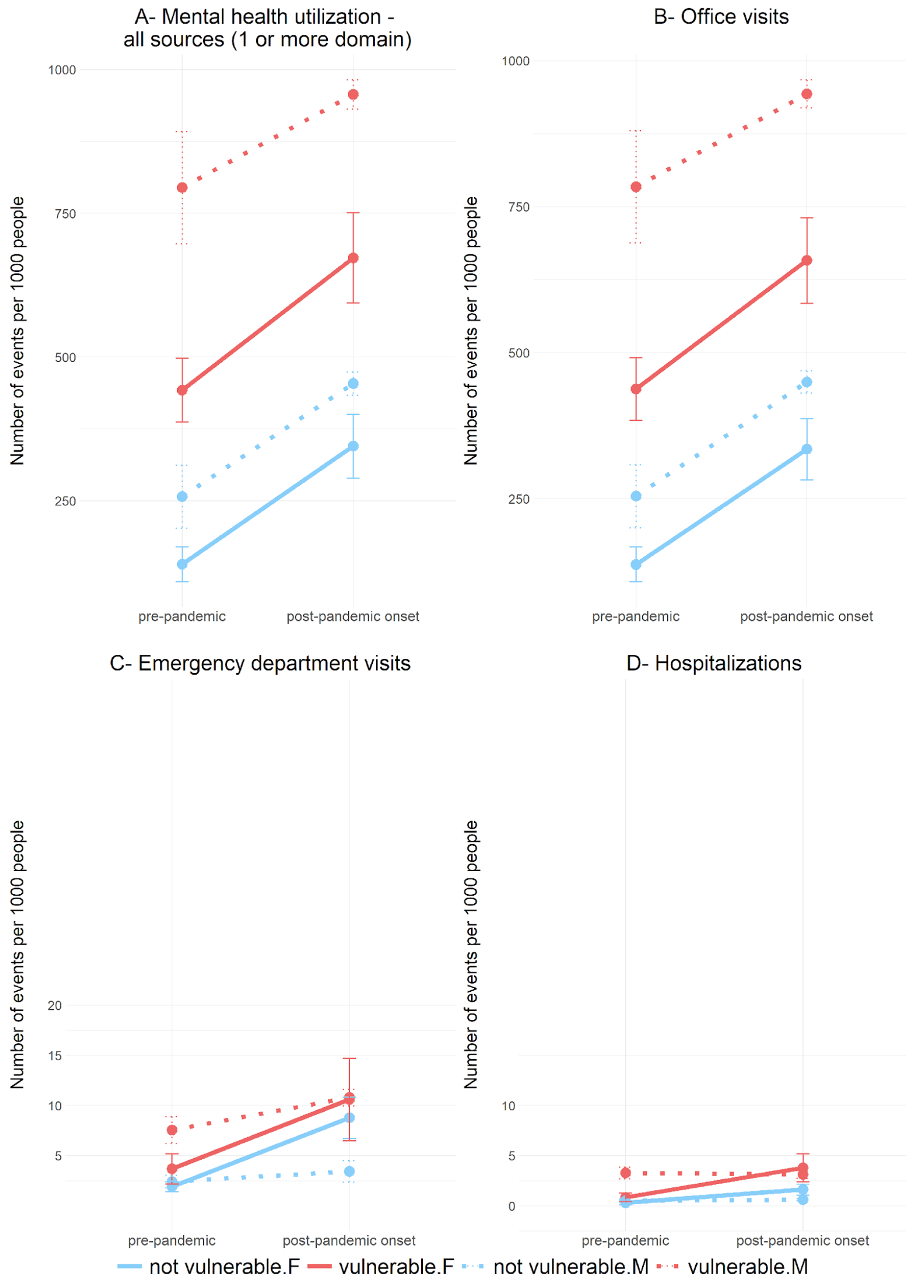

Figure 3.3. Comparison of mental health-related services utilization between the pre (2016-2019) and post (2020-2022) pandemic onset periods.

Note: M = male, F = female. A and B are on different scales than C and D. Error bar indicates standard error.

Specific mental health conditions

There is a consistent linear increase in the utilization of anxiety-related services by vulnerable and non-vulnerable children from 2016 to 2022, as shown in Figure 3.4A. A similar trend was observed among both male and female children between 2016 and 2020. However, the slope for females increased in 2021 and they surpassed males in utilization rates. Our linear regression analysis indicated that males had, on average, 25 fewer anxiety-related events than females over the years (βsex(M) = -25.2; p-value = 0.032). Additionally, vulnerable children had, over time, nine more events than their peers (βvulnerability*time = 9.0; p-value = 0.032).

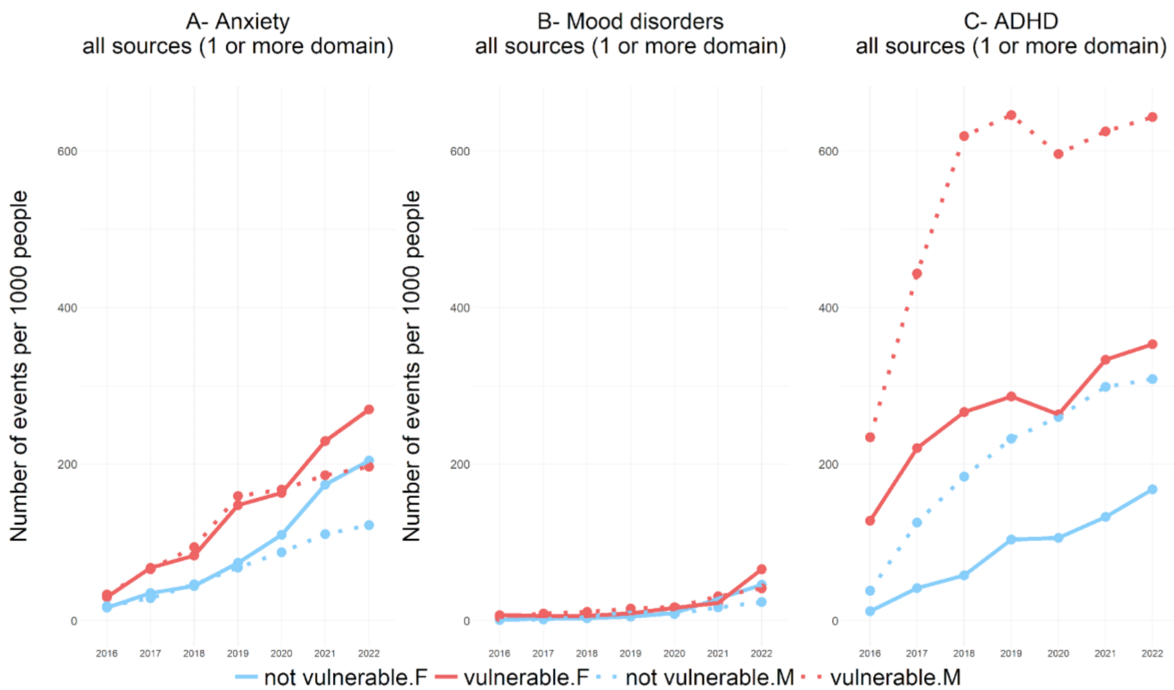

Figure 3.4. Trend of specific mental health disorders for all services utilization between 2016 and 2022.

Note: M = male, F = female.

There was a consistent and gradual rise in mood disorders-related utilization from 2016 to 2020, which was followed by a significant increase in subsequent years. This increase was particularly pronounced among female vulnerable children (Figure 3.4B), but there were no statistically significant differences observed between groups.

The utilization of ADHD-related services showed different patterns for each group. There was a stable increase for females between 2016 and 2022; while vulnerable males had a sharp increase between 2016 and 2018 and then stabilized. Non-vulnerable males showed a steady linear increase throughout the years, which was similar to vulnerable females' pattern (Figure 3.4C). Our analysis further revealed that male vulnerable children had, on average, 161 more events related to ADHD than their peers (βvulnerability*sex(M) = 161.5; p-value = 0.002).

The analysis based on specific developmental domains revealed an association between all domains and ADHD, indicating a higher utilization rate among vulnerable children as well as male children. Among vulnerable children, only the physical health (PH) domain exhibited a significant association with increased utilization. For more detailed information, please refer to Appendix 3 Table 4.

Our analysis of healthcare utilization rates before and after the onset of the COVID-19 pandemic found that rates of utilization increased after the pandemic for all children with all three mental health conditions (Figure 3.5A-C). The rate of increase was similar across all groups, indicating that the pandemic did not affect the service use patterns of vulnerable and non-vulnerable children differentially.

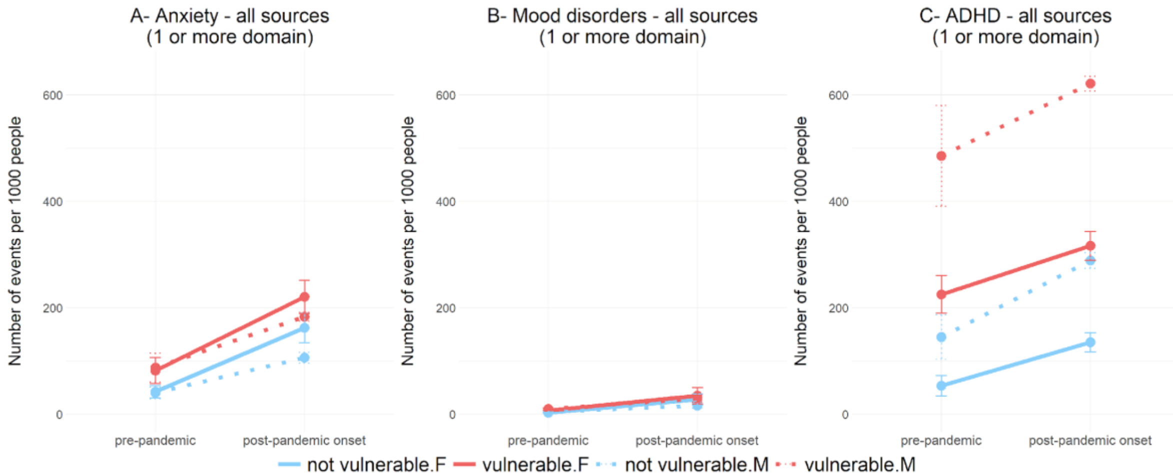

Figure 3.5. Comparison of mental health-related services utilization between the pre (2016-2019) and post (2020-2022) pandemic onset periods. The error bar indicates standard error.

Note: M = male, F = female.

Discussion

Our study explored the utilization patterns of mental health-related services among five–12-year-old children in Alberta, with known kindergarten teacher-rated developmental vulnerability status, before and after the onset of the COVID-19 pandemic. Our findings suggest that the COVID-19 pandemic had a similar impact on healthcare utilization rates for both vulnerability groups, except for hospitalizations. We observed that developmentally vulnerable children demonstrated higher engagement with mental health-related services compared to their non-vulnerable counterparts. These findings underline the demand for targeted interventions and comprehensive support for vulnerable populations, underscoring the imperative of equitable access to mental health services. There is a need for tailored interventions and comprehensive support strategies that account for the unique challenges faced by developmentally vulnerable children. This includes measures to bridge potential sex and vulnerability disparities in access, such as fortifying community-based support networks and enhancing mental health programs within educational institutions. Our study highlights the importance of ensuring that vulnerable populations have the same opportunities to benefit from these services as their non-vulnerable counterparts.

Furthermore, we demonstrated a COVID-19 pandemic-related disruption in utilization patterns among both vulnerable and non-vulnerable children, which is in line with the evidence of the global surge in mental health disorders among children and adolescents, including depression, anxiety, sleep disorders, and posttraumatic stress symptoms, reflects the pandemic's consequences (Dragioti et al., 2022; Ma et al., 2021; Schroeder et al., 2022; Vasileva et al., 2021). Our study not only adds to this evidence but also reveals how early developmental vulnerabilities can interact with such a disruption, thereby creating distinct challenges in accessing mental health services.

The role of age emerges as a crucial factor in comprehending the increased patterns of mental health issues observed among children. As children progress through developmental stages, specific disorders become more evident and diagnosable. Advancing age exposes them to an array of stressors and complexities, potentially contributing to the emergence of additional health concerns, which in turn may explain the increasing patterns of utilization observed in our study. This perspective aligns with existing research that accentuates the role of age in influencing mental health outcomes (Jones, 2013; Solmi et al., 2022).

Our findings align with established literature that depicts a consistent upward trend in mental health challenges among children (Dragioti et al., 2022; Vasileva et al., 2021). The high prevalence of depression, anxiety, and other mental health issues during the pandemic is well-documented (Barbieri et al., 2022; Dragioti et al., 2022; Ma et al., 2021).

Our study’s unique contribution to the understanding of the pandemic’s association with children and adolescent mental health is the ability to distinguish between groups of children who were rated as vulnerable in their developmental health, broadly reflecting school readiness, at school entry. While patterns showed some variation to type of service, in general, children who were developmentally vulnerable at five years of age, experienced higher engagement with health services prior to, but especially after the pandemic onset, than those who were not vulnerable. By identifying sex disparities in utilization, our study supplies insights for policymakers and healthcare providers in addressing the unique service needs of these vulnerable populations.

Our study was conducted using a large population-wide dataset on health service utilization, with a unique link to data on children's early vulnerability. Nevertheless, it has some important limitations. First, no socioeconomic data were available, which can influence patterns of health service utilization, especially in vulnerable populations. Poor socioeconomic status, represented as low income and poorer education, is known to be associated with reduced healthcare access and utilization. Second, we were unable to distinguish between rural and urban areas in our analysis. This is a significant limitation because healthcare access and service availability can vary considerably between the two settings. Also, we excluded children who did not participate in the EDI collection based on specific criteria. As noted in our previous study, these children presented different patterns of service utilization. Finally, while the linkage of EDI data with health service utilization revealed important associations, it limited the sample size, affecting the generalizability of our findings.

Conclusion

In sum, we believe that despite its limitations, by demonstrating the sex-related differences in mental health utilization at the population level, our study contributes meaningfully to the growing literature on the impacts of the COVID-19 pandemic on children and youth. Based on our findings, we suggest that tailored interventions aimed at vulnerable populations are essential. This may encompass strategies such as broadening telehealth options, fortifying community-based support networks, and enhancing mental health programs within educational institutions. Future studies should examine the impact of these strategies on children's outcomes. Due to its data linkage from kindergarten, our study highlights the potential opportunities for early intervention and prevention strategies, especially for children at an elevated risk (Black et al., 2017; Britto et al., 2017; Moran et al., 2022; Mulraney et al., 2021; Richter et al., 2017). By prioritizing these recommendations, policymakers can take substantial steps toward reducing the burden of mental health disorders among children.

Disclaimer

This study is based in part on data provided by Alberta Health. The interpretation and conclusions contained herein are those of the researchers and do not necessarily represent the views of the Government of Alberta. Neither the Government nor Alberta Health expressed any opinion about this study.

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Paper 4. Impact of the COVID-19 pandemic on youth's mental health-related utilization

Paper 3 explored the utilization patterns of mental health-related services among five to 12-year-old children in Alberta, examining periods both before and after the onset of the COVID-19 pandemic. This study makes a significant contribution to the growing body of literature on the impact of the pandemic on children. Paper 4 extends this exploration to adolescents, providing a more in-depth analysis of how the pandemic has affected this demographic. Currently pending submission, the following paper is intended for publication in a peer-reviewed scientific journal.

Introduction

The age of onset for most mental disorders is between 14 and 24 years old (Kessler et al., 2005), a period in which social and emotional experiences are crucial for healthy brain development (Beharry, 2022; Foulkes & Blakemore, 2021). During the COVID-19 pandemic, school closures and social distancing mandates were disruptive for many children and youth, limiting their contact with peer support groups. Although these measures may have reduced the spread of COVID-19, they may have also negatively impacted mental health as barriers to the optimal social, psychological, and academic development of the younger population (Hards et al., 2022). Recent studies point out higher than pre-pandemic levels of mental health problems in children, adolescents, and youths (Bera et al., 2022; Chang et al., 2021; Foulkes & Blakemore, 2021; Ma et al., 2021; Racine et al., 2021; Viner et al., 2022). During the pandemic, children and youth may have experienced higher anxiety, depression, and stress rates (Cielo et al., 2021; Dragioti et al., 2022; Samji et al., 2022), while adults experienced increased PTSD and substance use (Dragioti et al., 2022; Lundahl & Cannoy, 2021). However, the long-term consequences of the pandemic on younger individuals' mental health are unknown and should be prioritized (Holmes et al., 2020).

Longitudinal studies on children and adolescents have shown that the proportion of mental health-related (MH-related) emergency department (ED) visits increased globally during the pandemic (from March to October 2020) when compared to the same period of 2019, while

ED visits for injury and non-COVID-19-related diseases decreased (CIHI; Leeb et al., 2020; Meade, 2021). Interestingly, studies looking only at the overall count of MH-related ED visits rather than the proportion showed a reduction in MH-related ED utilization (Bothara et al., 2021; Díaz de Neira et al., 2021; Ferrando et al., 2020; Leff et al., 2021), especially during the first three months after lockdown (i.e., from March to May 2020).

COVID-19 had complex effects on health services utilization, and it is important to better understand the possible impacts of the pandemic on child and youth mental health, both in the short and long term (Ma et al., 2021; Meade, 2021; Racine et al., 2021). Unfortunately, most published studies focus on one or a few hospitals and may not be generalizable to the general population (Samji et al., 2022). To provide a valid broad perspective, we analyzed MH-related health service utilization with a unique approach of analyzing physician visits, ED visits, and hospitalization for six years for over 1.6 million individuals living in Alberta, Canada. The Province of Alberta has a universal health system and all physician and ED visits as well as hospitalizations are recorded, along with demographic and diagnostic information entered by the physicians. Our study focused on MH-related health services utilization for children, adolescents, and young adults, comparing utilization during the pandemic period (2020 and 2022) to the pre-pandemic period (2016 to 2019).

Methods

Data source and study sample

We conducted a retrospective, observational cohort study using administrative health records, including office/clinic visits (from physician's office claims), emergency department visits (EDs), and hospitalization (from inpatient records). We included all children (six to 11 years old), adolescents (12 to 17 years old), and young adults (18 to 34 years old) living in Alberta, Canada, and covered by Alberta Health insurance from 2016 to 2022. Those records are accessible through the databases available on the Alberta Ministry of Health website (www.alberta.ca/health-research.aspx).

Outcomes

The main variable of interest in this analysis was the number of unique individuals within each age group (children, adolescents, and young adults) that utilized health services during the study period. The following MH conditions were extracted based on the International Classification of Mental and Behavioral Disorders codes - ICD) (Appendix 4 Table 1): anxiety disorders, attention deficit hyperactivity disorder (ADHD), eating disorder, mood disorder, depression, bipolar disorder, obsessive-compulsive disorder, psychotic disorders, self-harm, and substance use disorders (e.g., cannabis abuse/dependence, alcohol use/dependence, and opioid use/dependence). We also created an MH indicator for whenever an individual accessed the healthcare system for any of the above conditions. We also extracted data for non-mental health (non-MH) diseases if the individuals have accessed health services for anything, but the conditions listed above. Finally, we calculated the percentage of individuals accessing MH-related services to understand whether the utilization trend was specific to MH.

The number of individuals living in any jurisdiction typically changes over time, affecting population sizes for different age groups. To account for population change over time in Alberta, in addition to the total number of individuals who have accessed the healthcare system, we calculated rates per 1,000 population. To do this, we divided the total number of individuals with an MH and non-MH utilization event in each age group by the population size and multiplied the results by 1,000. These results are reported in Appendix 4.

Analysis

We compared yearly aggregate data for 2020 to 2022 with the equivalent data for 2016 to 2019 to reveal any differences in utilization between the pandemic and pre-pandemic eras.

Our exploratory data analysis and previous results (GBD Collaborators, 2022) indicate that MH utilization has been increasing over the last decades. To understand whether the COVID-19 pandemic had an impact on this trend, we computed the expected number of individuals with MH utilization events for 2020 to 2022 based on the values from 2016 to 2019 and compared them to the observed values for 2020 to 2022. To do that, we performed linear regressions with the percentage of unique individuals' population change with MH-related physician visits, EDs, and hospitalizations as the outcome variables. The variable year was transformed into smaller units of time by subtracting 2016 from the year of interest and adding it as a predictor to the model. The interaction term between time and age groups was also added to the model as a predictor variable. Based on this model, we calculated the predicted values for 2020, 2021, and 2022 and the percentage difference between the observed health utilization values for 2020 to 2022 and their predicted values (i.e., ([observed value - predicted value] / predicted value) *100). The difference may reflect the impact of the COVID-19 pandemic on MH health utilization. Although the calculation for the expected numbers comes from only 4 data points before the pandemic period (i.e., 2016 to 2019), the results we presented are robust due to the highly linear relationship between time and the outcome and because we have data for the whole population covered by Alberta Health Services, excluding the need for statistical inference. We also added 95% confidence intervals of the predicted values (calculated using the standard error from the prediction regressions) to infer whether it is different from the observed value.

Data extraction and preparation were performed in SAS version 9.4; data analysis and visualizations were performed in the ggplot2 package in R version 4.1.2.

Results

Sample characteristics

The estimated population size in Alberta for 2016 was 318,038 children (from six to 11 years old), 292,008 adolescents (from 12 to 17 years old), and 1,071,700 young adults aged 18 to 34 years old (Table 4.1). In 2021, the estimated numbers were 335,338 children, 322,828 adolescents, and 1,031,620 young adults (Table 4.1). So, the population grew by 5%, 10%, and -0.4% for children, adolescents, and young adults, respectively. The numbers of females and males are relatively equal in all age groups across all years (Table 4.1).

A total of 27,695 children, 35,248 adolescents, and 187,879 young adults went to a physician's office with mental health complaints in 2016 (Appendix 4 Table 2). In 2021, these numbers rose to 39,611 children (43% increase), 58,912 adolescents (67% increase), and 235,934 (26% increase) for young adults (Appendix 4 Table 2). Between 2016 and 2021, the number of individuals with emergency visits related to mental health increased by 19% in adolescents and remained stable in children (2% increase) and young adults (1% decrease). Individuals with MH-related hospitalizations decreased by 35% in children but increased by 13% and 12% in adolescents and young adults, respectively. Interestingly, people with non-MH-related utilization were stable or decreased during the study period for all age groups (Appendix 4 Table 2). The only exception was adolescents' physician visits, which increased by 7%.

Before the pandemic, the mean percentage of children with MH-related utilization was 10.55%, 1.71%, and 10.09%, respectively, for physician's office visits, emergency visits, and hospitalizations, compared to 13.02%, 2.01%, and 9.12% during the pandemic, respectively (Figure 4.1). An increase in the percentage of MH-related utilization was also seen in adolescents and young adults. Before the pandemic, the percentage of adolescents with MH-related physician's office visits, emergency visits, and hospitalizations was 14.36%, 8.70%, and 25.85%, compared to 18.06%, 10.36%, 27.69%, respectively, during the pandemic. For young adults, these numbers were 20.66%, 9.81%, and 11.86% before the pandemic, and 24.06%, 10.78%, and 13.56% during the pandemic (Figure 4.1).

Table 4.1. Demographic information of children, adolescents, and young adults between 2016 and 2021 in Alberta.

Age group	**Year**	**Population size N (% Female)**
6-11 (Children)	2016	318038 (48.9%)
	2017	324806 (48.9%)
	2018	330807 (48.8%)
	2019	334332 (48.8%)
	2020	335820 (48.8%)
	2021	335338 (48.8%)
12-17 (Adolescents)	2016	292008 (48.8%)
	2017	294781 (48.9%)
	2018	299226 (48.9%)
	2019	306567 (49.0%)
	2020	315956 (49.0%)
	2021	322828 (49.0%)

18-34 (Young adults)	2016	1071700 (48.5%)
	2017	1061319 (48.6%)
	2018	1057475 (48.6%)
	2019	1055444 (48.6%)
	2020	1050742 (48.6%)
	2021	1031620 (48.6%)

Overall mental health

There was a steady increase in the percentage of individuals with MH-related physician visits between 2016 and 2019 in all age groups, however, a sharper rise was noticed in 2020 and 2021, especially in adolescents (Figure 4.1 and Appendix 4 Figure 1). The percentage of adolescents with MH-related physician office visits increased from 15.5% in 2019 to 19.1% in 2021, 12% higher than expected based on the trend of observed values before the pandemic (Figure 4.1 and Table 4.2). Similar trends were observed in emergency visits during the pandemic period. Although the percentage of adolescents with MH-related emergency visits remained stable between 2016 and 2019 (around 8%), there was an increase in 2020 and 2021 (9.9% and 10.8%, respectively), peaking at 17% higher than expected. Likewise, the percentage of adolescents with MH-related hospitalizations was stable during the pre-pandemic period but reached almost 10% above expected in 2021 (Table 4.2). Although the percentage of adolescents with mental health utilization decreased slightly in 2022, it remained higher than the predicted values for office visits.

Table 4.2. Observed and predicted values of mental health utilization.

		Office visits			Emergency visits			Hospitalizations		
Year	**Age group**	**Actual value**	**Predicted value#1**	**Percentage difference#2**	**Actual value**	**Predicted value#1**	**Percentage difference#2**	**Actual value**	**Predicted value#1**	**Percentage difference#2**
2020	6-11 children	12.5	12.2	2.12	1.83	2	-6.27	9.41	9.14	2.94
	12-17 adolescents	17	16.3	4.81	9.95	9.04	10.15	27	25.8	4.5
	18-34 adults	23.3	22.7	2.79	10.7	10.4	3.04	13.3	13.1	1.76
2021	6-11 children	13.5	12.9	4.98	2.14	2.11	1.29	8.85	8.76	0.96
	12-17 adolescents	19.1	17	12.00	10.8	9.17	17.51	28.4	25.8	9.81
	18-34 adults	24.8	23.5	5.25	10.8	10.7	1.02	13.8	13.6	1.08
2022	6-11 children	13.4	13.8	-1.41	1.36	2.22	-39.00	6.17	8.38	-26.4
	12-17 adolescents	19	17.8	6.74	7.93	9.3	-14.76	25.6	25.8	-0.87
	18-34 adults	24.4	24.4	0.37	9.15	10.9	-16.28	12.9	14.1	-8.88

#1 Predicted values were calculated based on a linear regression of MH-related utilization from 2016 to 2019. #2 Percentage differences were calculated as: ([actual value - predicted value] / predicted value) *100.

For young adults, the percentage of MH-related physician visits increased from 19.2% in 2016 to 24.8% in 2021, 5% greater than expected based on the pre-pandemic values (Figure 4.1 and Table 4.2). Although there was an increase in the percentage of MH-related emergency visits and a small decrease in hospitalizations between the pre-pandemic period and the pandemic era, it was not as pronounced (Figure 4.1). The numbers recorded in 2022 were similar (office visits) or lower (EDs and hospitalizations) than predicted based on the years before the pandemic (Table 4.2).

The age group with the smallest increase in MH-related physician visits was children, ranging from 9.6% in 2016 to 11.6% in 2019 and 13.5% in 2021 (Figure 4.1 and Table 4.2). Similarly to young adults, the observed percentage of children with MH-related emergency visits and hospitalizations during the pandemic was somewhat similar to the expected values (Figure 4.1), except for 2022 in which the utilization was lower than expected (Table 4.2).

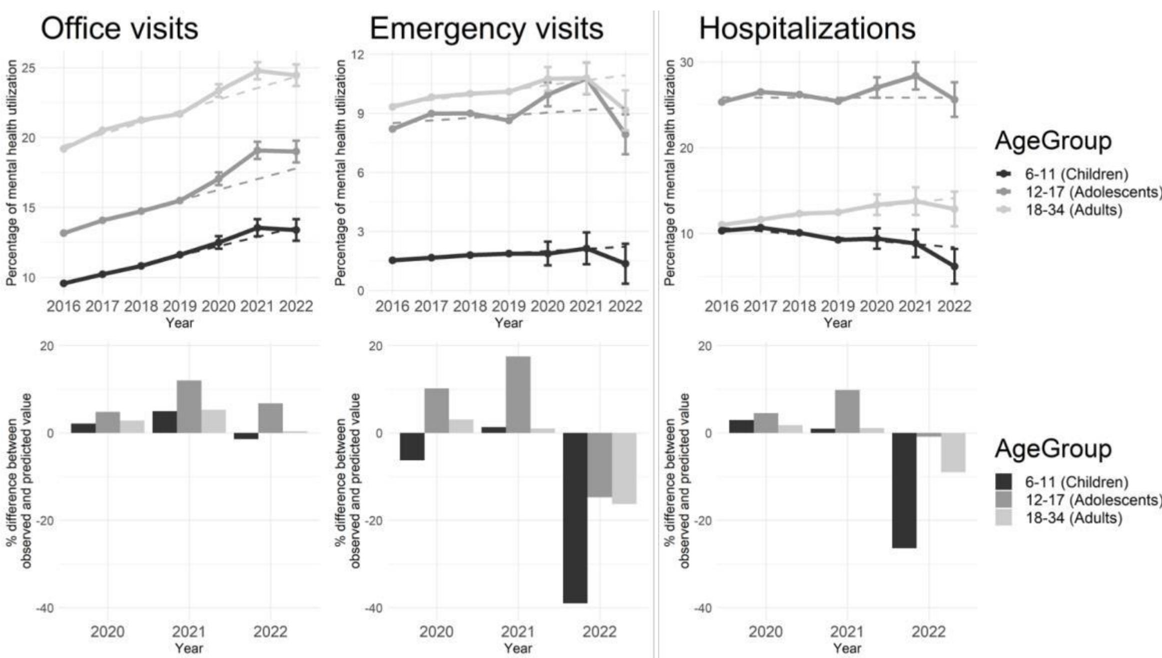


Figure. 4.1 Observed and predicted percentage of children, adolescents, and young adults with mental health service utilization between 2016 and 2022

Note: top: Dashed lines represent the fitted linear regression model for the years 2016 to 2019 and the predicted percentage of mental health service utilization for 2020 and 2022 based on that model;

the solid lines represent the observed values; the error bar represents the 95% confidence interval; bottom: Percentage difference between the actual value and the predicted value# for the percentage of mental health service utilization in the post-pandemic period. #predicted value derived by linear regression for the years 2016-2019.

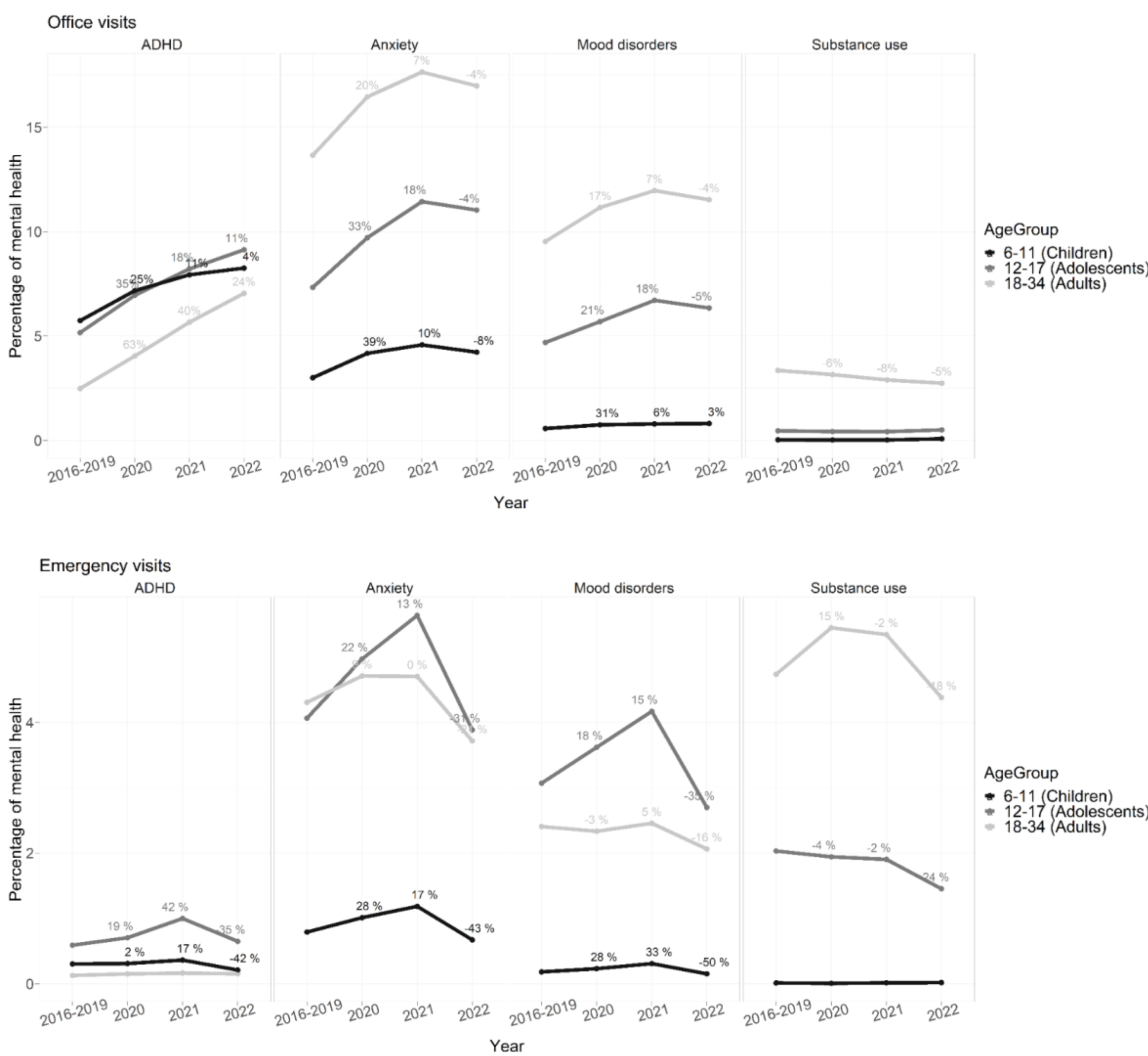
The health utilization for major mental health disorders.

To understand which psychiatric conditions were driving the rise in the number of individuals seeking professional care due to mental health concerns, we selected those with the most utilization across the years. The decision was based on the utilization rate in Appendix 4 Figure 2. Thus, we specifically analyzed the percentage of adolescents with ADHD, anxiety, mood disorders, and substance use utilization. Overall, there was an increase in the number of individuals utilizing the system concerning the four psychiatric conditions in all age groups in 2020, 2021, and 2022 compared to the pre-pandemic period (Figure 4.2).

The percentage of adolescents who visited a physician's office with ADHD increased sharply in 2020 compared to the previous year (35% increase) and continued to increase in 2021 (18% additional growth) and 2022 (11% additional growth) (Figure 4.2). An increase of 33% and 21% in adolescents was observed in anxiety and mood disorders-related physician visits in 2020, respectively, followed by a further 18% rise in 2021 (Figure 4.2). Although the percentage of utilization decreased in 2022, they are still higher than pre-pandemic. A similar utilization pattern was seen in emergency visits and hospitalizations related to these diseases (Figure 4.2). Interestingly, the percentage of adolescents utilizing the health system because of substance use problems remained similar or decreased during the pandemic years compared to the pre-pandemic period (Figure 4.2). We also observed a spike in the proportion of emergency visits and hospitalizations related to self-harm in 2020 and 2021 (Appendix 4 Figure 4). The percentage of adolescents with self-harm-related emergency visits almost doubled in 2020 compared to pre-pandemic levels and increased an additional 25% in 2021 (Appendix 4 Figure 4). Similar to other diseases, the numbers appear to be coming back to pre-pandemic levels in 2022.

The percentage of young adults who visited a physician's office because of problems related to ADHD, anxiety, and mood disorders was similar to that of adolescents: a significant increase in utilization during the two first years of the pandemic (Figure 4.2). However, emergency visits and hospitalizations remained stable. Particularly in this age group, the percentage of young adults utilizing emergency departments or hospitalized with problems related to substance use grew by 15% and 20% in 2020, respectively (Figure 4.2), but decreased to similar levels to pre-pandemics in 2022. Also unique to this age group was the rise in the proportion of emergency visits and hospitalizations related to schizophrenia (SCZ) in the pandemic years (Appendix 4 Figure 4).

The mental health diagnoses with the most significant increases in children were ADHD and anxiety, which presented a 25% and 39% increase in physicians' office visits in 2020, respectively (Figure 4.2).



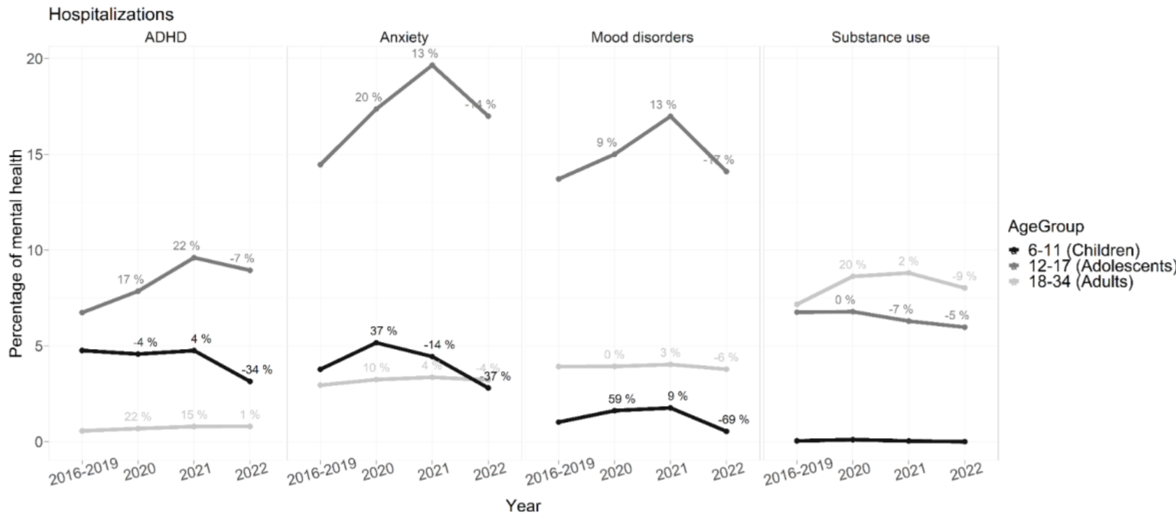


Figure. 4.2 The percentage of children, adolescents, and young adults with mental health service utilization between 2016 and 2022 for specific mental health conditions

Note: The values shown in 2016-2019 represent the mean value between 2016 and 2019. The percentage numbers within each plot represent the percentage difference from the previous year.

Discussion

The COVID-19 pandemic may give rise to a longer-term mental health crisis because of its direct impact, or secondary to health policies aiming to limit the spread of the virus, such as lockdowns and quarantine (Díaz de Neira et al., 2021; Hards et al., 2022; Nearchou et al., 2020). In this population-level analysis of health utilization, we observed a considerable increase in the number of youths utilizing mental health services, which may be positively correlated with increases in mental health problems or disorders, especially ADHD, anxiety, and depression. Also, the results of this study suggest that the COVID-19 pandemic has had a significant impact on the mental health of young individuals in Alberta, Canada, particularly among adolescents. The findings also highlight the importance of continued monitoring and support for mental health after the pandemic onset.

We observed an increase in the overall percentage of individuals with MH-related healthcare utilization during the pandemic. Based on the four years before the COVID-19 pandemic (i.e., from 2016 to 2019), we expected a slight increase in those numbers after 2020. Still, we observed a rise well beyond this prediction in 2021, especially for adolescents. Previous studies also show that MH-related emergency department visits increased in adolescents more than in other age groups (Leeb et al., 2020; Racine et al., 2021; Samji et al., 2022). Interestingly, some studies that analyzed data only a few months into the pandemic (i.e., from March 2020 to May 2020) observed a reduction in MH-related emergency visits (Bothara et al., 2021; Díaz de Neira et al., 2021; Ferrando et al., 2020; Leff et al., 2021). This might reflect patients being discouraged from going to the emergency unless necessary and the fear of patients being exposed to the virus. Thus, suffering from mental health was not immediately reflected in patterns of health service utilization and MH-related utilization may continue to change as demonstrated by the decrease in numbers in 2022 and should be monitored closely. Accordingly, some authors have claimed that longitudinal studies analyzing the long-term mental health implications of the pandemic in younger populations should be a priority, especially those with a representative population sample (Ma et al., 2021; Racine et al., 2021). Our study fills a current gap by analyzing overall population-level data before and after three years of the pandemic onset.

The number of individuals with non-MH-related utilization decreased during the pandemic relative to previous years. This may reflect people going less often to physician offices for checkups and avoiding going to the emergency because of fear of being infected with COVID-19 unless they were experiencing unmanaged chronic issues, like mental health. This alone would have increased the proportion of individuals with MH-related utilization during the same period without changing the actual numbers of MH utilization. However, we observed that the number of individuals utilizing the system specifically for mental health problems grew during the pandemic, especially among adolescents, increasing the proportion even more. Pandemics are stress-inducing situations and the numbers we observed might reflect that (Meade, 2021). Indirect effects of the pandemic may also contribute, these include school closures, self-isolation, the restriction of mental health services and peer support groups during the pandemic, and lack of interaction with teachers, school staff and the overall community might have limited access to mental health support (Antonelli-Salgado et al., 2021; Beharry, 2022; Hards et al., 2022; Viner et al., 2022). Individuals with medium and low levels of social support during the COVID-19 outbreak, those with previous mental health problems, and those who have parents with poorer mental health are at higher risk of mental health symptoms during the pandemic (GBD Collaborators, 2022; Viner et al., 2022). As adolescence is a stage of life in which complex and hierarchical peer relationships and certain social cognitive processes occur (Kilford et al., 2016), it is reasonable that the social implications of the pandemic have a deeper impact on adolescents.

The mental health symptoms with the highest increase overall were anxiety and depressive symptoms (Borel et al., 2022), especially in the young population (Cielo et al., 2021). Limited social contact during the COVID-19 pandemic may be a key factor in that increase (Bera et al., 2022; Shensa et al., 2018; Simone et al., 2019). Other factors such as the challenges of remote learning, (Cielo et al., 2021) including longer screen time (Chang et al., 2021; Cielo et al., 2021), and living in a household with a low socioeconomic level (Bera et al., 2022; Singh et al., 2020) also might have played an important role. Studies also showed that physical activity, reduced during physical isolation lockdowns, is a protective factor for anxiety symptoms, especially in children (Borel et al., 2022).

An interesting result was the reduction in MH utilization related to substance use in adolescents. In this context, online surveys conducted on teens (aged 13 to 18) living in Canada and Iceland showed a drop in alcohol, cannabis, and vaping consumption during the lockdown (Bera et al., 2022). The authors argued that the difficulty in accessing substances while in lockdown with their parents might have accounted for that.

Finally, we would like to address how these results might help policymakers focus on supporting the mental health of young individuals in Alberta, Canada. First, there should be an increase in funding and resources for mental health services to meet the increased demand for office and emergency visits and hospitalizations observed during the pandemic. Targeted mental health interventions for adolescents, who were found to have the highest rates of emergency visits and hospitalization, should be developed. Also, it is important to ensure that mental health services remain accessible and affordable for all individuals, including those who may be experiencing financial hardship because of the pandemic. By focusing on these areas, policymakers can help to mitigate the impact of the pandemic on the mental health of young individuals in Alberta and support their overall well-being.

This study has a few limitations. First, because physicians are only required to enter three digits in the physician billing data, it is difficult to achieve diagnostic precision, for example, it is not always possible to distinguish bipolar from unipolar mood disorders. Second, it is necessary to acknowledge that 2020 was an unusual year since it included three pre-pandemic months (from January to March), followed by three to six months in which the population was asked not to go to the ED unless necessary. However, with schools and community services closed, clinics and EDs became the first point of care for many young individuals dealing with mental health issues. Therefore, one would expect the observed increase in the percentage of individuals seeking help for mental health concerns because students had fewer resources to seek help from and provincial mental health services may represent an alternative source of support under those circumstances. Third, the increased use of mental health services since the pandemic does not necessarily mean that younger individuals are suffering from major mental disorders. It may be related to the intensification of temporary daily-life stress that might not lead to, or be related to, mental health disorders. Finally, veterans and some first responders are covered by Veteran's Affairs health services and Indigenous Peoples in Alberta are covered by the federal healthcare FNIB and therefore were not included in the analysis.

Conclusion

The number of adolescents with MH-related utilization increased during the months after the COVID-19 pandemic onset when compared to pre-pandemic years. This age group's proportion of mental health utilization increased beyond that expected during 2020 and 2021. The most significant rise was seen specifically for anxiety and mood disorders but was less prominent for substance use disorders and other mental health conditions. It is important to continue monitoring MH-related utilization closely, especially in the younger population, because there might be changes in MH-related utilization in the upcoming months and years. Future studies are necessary to elucidate whether the increase in the proportional use of mental health services may be due to the closure of other services that youth used access for care/help or because youth did suffer from mental health problems or mental disorders more since the pandemic onset.

Disclaimer

This study is based in part on data provided by Alberta Health. The interpretation and conclusions contained herein are those of the researchers and do not necessarily represent the views of the Government of Alberta. Neither the Government nor Alberta Health expressed any opinion about this study.

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Seasonal patterns in mental health utilization

This section analyzed the impact of the COVID-19 pandemic on the seasonal trends of mental health utilization among different biological sex and age groups. Understanding these impacts is crucial for informing government and policymaker decisions, ensuring that appropriate support and resources are provided in a timely manner over the year. The findings highlight the disruption of the seasonality patterns by the pandemic, but the number of COVID-19 cases alone does not explain the observed differences. Variations were observed among different age groups, with children displaying the most difference in utilization patterns in the post-pandemic onset era. These results suggest the need for tailored strategies to address evolving mental health needs, equitable access to services across age groups, and sex-sensitive approaches in service provision.

Paper 5. Seasonal and pandemic-related patterns in mental health-related utilization

Paper 4 showed a rise in mental health-related utilization among adolescents in the months following the onset of the COVID-19 pandemic, surpassing the anticipated levels for 2020 and 2021. To comprehensively assess the changes in mental healthcare utilization patterns during the pandemic, paper 5 delves into the seasonal patterns of mental health-related utilization, comparing the periods before and after the pandemic onset. The following paper was submitted to the Journal of Affective Disorders on April 17th, 2024, and is presently undergoing the peer-review process.

Introduction

The COVID-19 pandemic has caused significant psychological distress across the population due to measures taken to prevent the virus's spread. These measures, such as restrictions and closures, have disrupted people's daily lives and isolated many from their required support. This poses a challenge for people with pre-existing mental health conditions and has also increased mental health-related symptoms in individuals without any previous mental health conditions (Cullen et al., 2020). Recent studies have highlighted the pandemic's profound effect on global mental health and the subsequent surge in mental health service utilization (Beaudry et al., 2022; Dragioti et al., 2022; Lee et al., 2022; Ma et al., 2021).

Studies have shown that the frequency of psychiatry admissions to hospitals and emergency departments varies seasonally (Ayers et al., 2013; Marshall et al., 2021; Pelletier et al., 2021; Thiessen et al., 2020; Törmälehto et al., 2022; Yao et al., 2023; Zerón-Rugerio et al., 2022). Prior to the COVID-19 pandemic, there were established patterns of seasonal variation in mental health service utilization. Research indicated higher rates of emergency department visits and hospitalization due to issues related to ADHD, depression, schizophrenia, and mood disorders during the winter months and lower rates during the summer (Ayers et al., 2013; Marshall et al., 2021; Törmälehto et al., 2022; Yao et al., 2023; Zerón-Rugerio et al., 2022). However, the impact of the pandemic on these patterns remains largely unknown, representing a gap in the literature. For this reason, it is valuable to investigate the seasonal and pandemic-related patterns in mental health service utilization to better understand mental health needs and develop appropriate interventions. The present study aims to address this gap by providing insights into mental health service utilization trends in Alberta, such as physician office visits, emergency department (ED) visits, and hospitalizations, both before and following the COVID-19 pandemic onset (defined as March 2020 in this study). Alberta's healthcare system covers all residents with information about physician visits, ED visits, and hospitalizations recorded. This includes demographic details and diagnosis information recorded by treating physicians.

The objective of this study is to explore the seasonal patterns in mental health service utilization from various sources and compare them across different ages and biological sex in Alberta, and to provide insights into the impact of COVID-19 on the utilization of mental health services. Understanding these changes is valuable for providing appropriate and timely support and resources for those in need.

Methods

This descriptive study utilizes comprehensive administrative healthcare data from the Ministry of Health, Government of Alberta, to investigate mental health utilization trends in different age and sex groups while controlling for confounding factors. The records are accessible through the databases available on the Alberta Ministry of Health website (www.alberta.ca/health-research.aspx).

Data source and cohort

This study utilized administrative healthcare database records from the Ministry of Health in Alberta. These records included claims from physician office visits, ED visits, and hospitalizations. The cohort comprised all Alberta residents with active health insurance coverage from January 2014 to December 2022. The 'post-pandemic onset' period started in March 2020, coinciding with the initiation of the lockdown in Alberta, Canada. Any period preceding March 2020 was classified as 'pre-pandemic'.

Outcome

We used diagnosis codes from the International Classification of Diseases 9th and 10th revisions (ICD-9 and ICD-10) to identify mental health, neurodevelopment, and neurocognitive disorders-related utilization. Please see Appendix 5 Table 1 for the complete list of diagnosis codes used for feature extraction. We analyzed the data for each service separately and performed subgroup analyses to evaluate mental health service utilization trends among different biological sex and age groups, such as children (0-11 years old), adolescents (12-17 years old), young adults (18-24 years old), adults (25-64 years old), and seniors (65 years old or older). For this analysis, we combined all utilization sources.

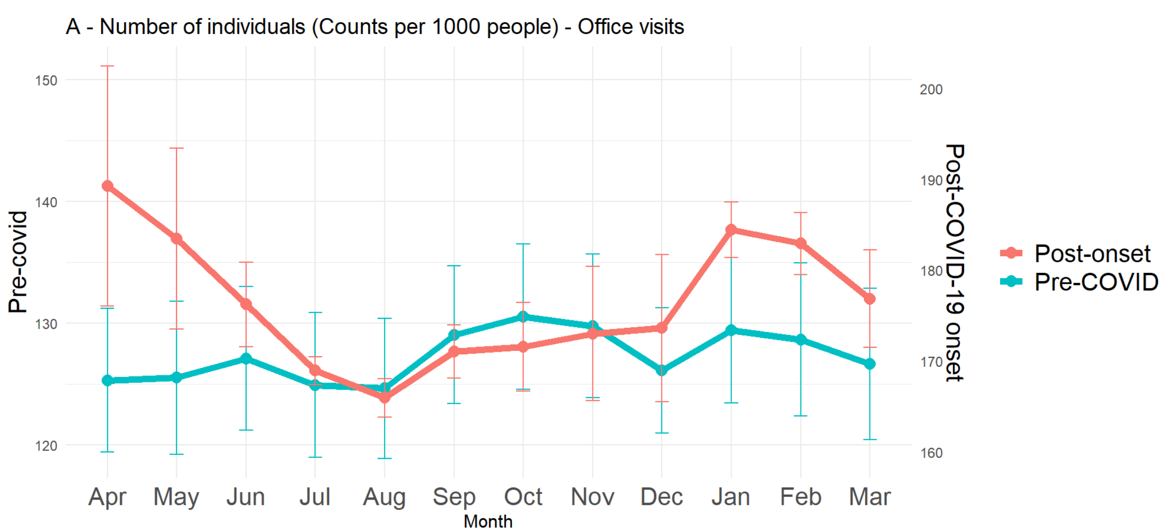
To account for the confounding effects of changes in healthcare utilization due to the COVID-19 pandemic and other factors, we scaled the number of unique patients with mental health service utilization by the monthly healthcare utilization size. This allowed us to calculate the number of unique patients per 1000 people each month. We extracted the monthly number of unique patients with mental health records from January 2014 to December 2022. As of the time of writing, the data for 2023 was not yet available.

COVID-19 cases in Alberta

Additionally, we also conducted a visual analysis of mental health-related utilization and the monthly COVID-19 cases in Alberta. The data for COVID-19 cases is available at https://www.alberta.ca/stats/covid-19-alberta-statistics.htm#data-export. By plotting mental health utilization alongside the COVID-19 cases, we gained insights into a potential correlation.

Results

Before the COVID-19 pandemic (i.e., January 2014 to February 2020), the number of patients with mental health-related office visits displayed a pattern of seasonal variation, (Figure 5.1A). Patients with mental health-related physician office visits remained low and stable between April and August, with a slight increase noted in June, followed by an upward trend starting in September. Patient numbers peaked in October and gradually decreased until March (Figure 5.1A). Following the COVID-19 pandemic onset (i.e., March 2020), the seasonal pattern of mental health-related office visits was altered during the initial months of the pandemic but subsequently returned to a similar trend during the summer months. The most notable distinction between the pre- and post-pandemic onset periods is the overall increase in mental health-related patients observed in the latter (Figure 5.1A).



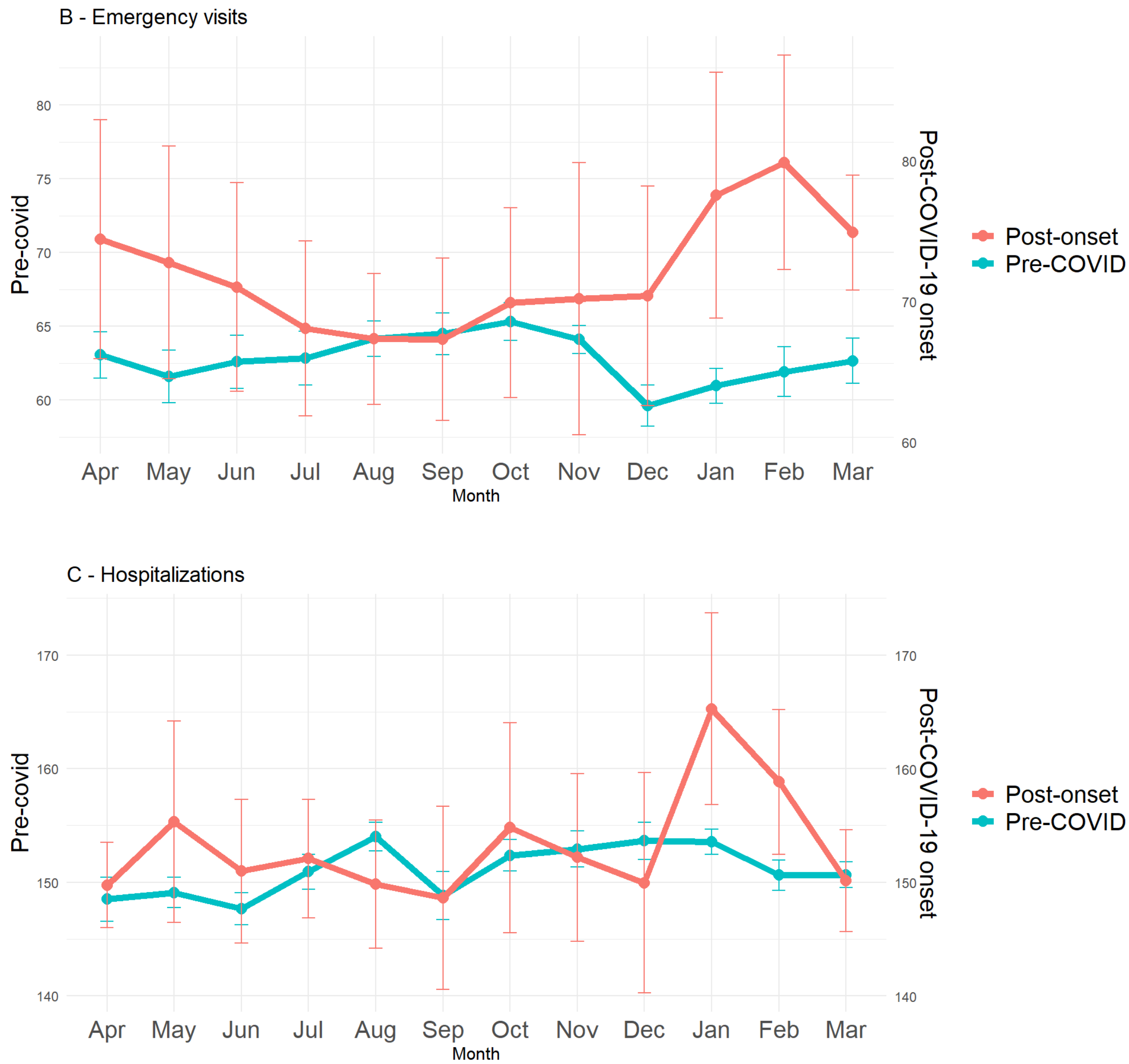


Figure 5.1. Pre- and post-pandemic onset mental health utilization trends, scaled to active healthcare insurance numbers, showcasing monthly averages with standard error bars.

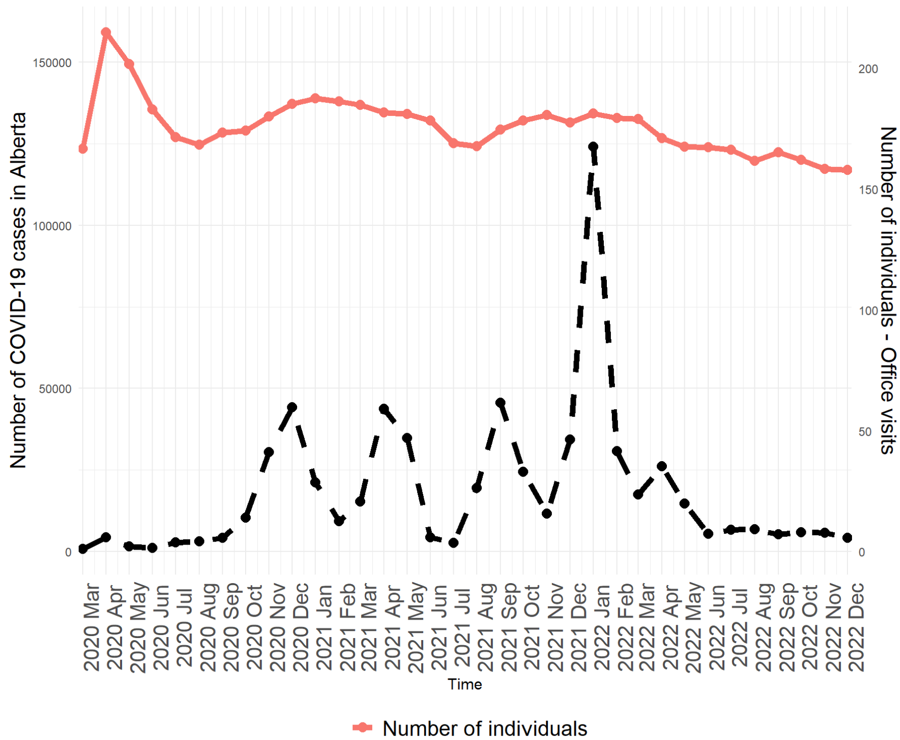
Note: Blue: Jan 2014-Feb 2020; Red: Mar 2020-Dec 2022. A. Office visits B. Emergency visits C. Hospitalizations.

Before the COVID-19 pandemic, mental health-related ED patients also followed a seasonal pattern. There was a minor decline in May and the number of patients remained stable and low until July, with a slight uptick leading up to the peak in October. The lowest number of visits was recorded in December, followed by a slight increase from January to April (Figure 5.1B). However, it appears the onset of the COVID-19 pandemic disrupted this pattern, manifesting a shift in utilization trends. Notably, the highest utilization occurred in January and February, deviating from the previous pattern. Moreover, there was lower utilization observed in August and September. In contrast to office visits, the number of individuals seeking mental health-related care remained relatively consistent after the onset of the pandemic (Figure 5.1B).

Before the COVID-19 pandemic, no discernible seasonal pattern was observed in mental health-related hospitalizations (Figure 5.1C). The number of hospitalizations remained relatively consistent, ranging from 145 to 155 patients per 1000 individuals. The lowest number of individuals hospitalized due to mental health-related issues occurred between April and June, followed by a gradual increase leading up to the peak in August. This was followed by a decline in September, with another increase in October. The number of hospitalized patients remained stable until January before decreasing again in February (Figure 5.1C). However, following the onset of the pandemic, distinct fluctuations in hospitalization patterns became evident throughout the year. Peaks in hospitalizations were observed in January, followed by a significant decline until April. Subsequently, fluctuations occurred, with increased utilization in May and October and the lowest point reached in December (Figure 5.1C).

MH utilization vs COVID-19 cases

Despite the substantial increase in the number of COVID-19 cases between March 2020 and December 2022, it appears that this factor does not sufficiently explain the observed differences in seasonality patterns for physician office visits, ED visits, and hospitalizations related to mental health (Figure 5.2 and Appendix 5 Figure 1). This suggests that other factors related to the pandemic may have played a more prominent role in altering the temporal distribution of mental health-related healthcare utilization.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Number of COVID-19 cases in Alberta
Number of individuals - Office visits
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2020 Jun
2020 Jul
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2020 Dec
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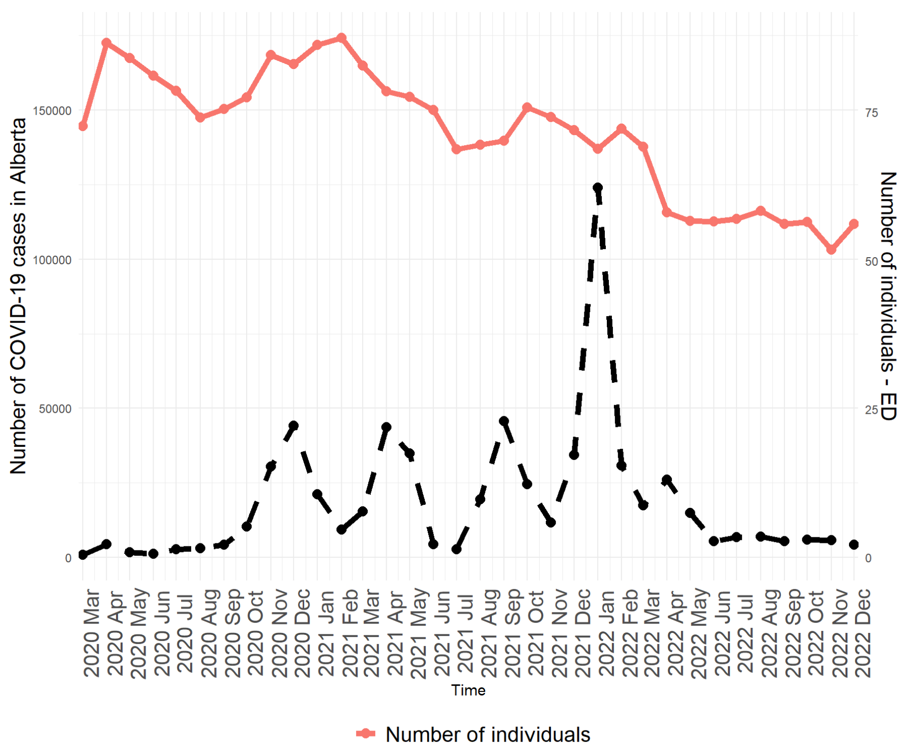
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100000
50000
0
75
50
25
0
Number of COVID-19 cases in Alberta
Number of individuals - ED
2020 Mar
2020 Apr
2020 May
2020 Jun
2020 Jul
2020 Aug
2020 Sep
2020 Oct
2020 Nov
2020 Dec
2021 Jan
2021 Feb
2021 Mar
2021 Apr
2021 May
2021 Jun
2021 Jul
2021 Aug
2021 Sep
2021 Oct
2021 Nov
2021 Dec
2022 Jan
2022 Feb
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2022 May
2022 Jun
2022 Jul
2022 Aug
2022 Sep
2022 Oct
2022 Nov
2022 Dec
Time
Number of individuals

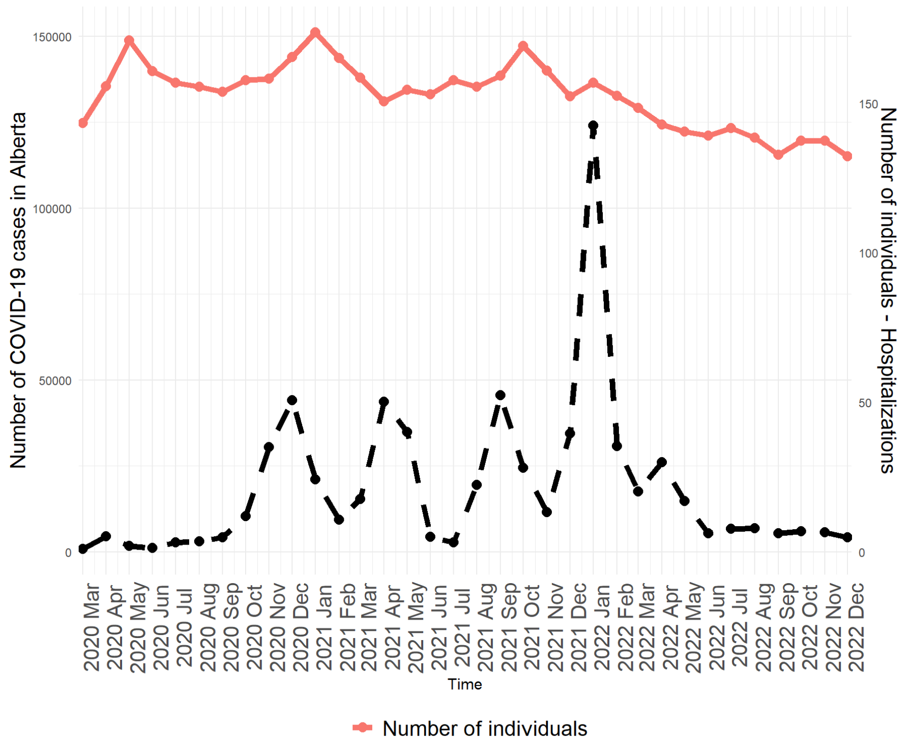


Figure 5.2. COVID-19 cases in Alberta versus mental health-related office visits (A), emergency visits (B), and hospitalizations (C), scaled to monthly active insurance holders (red solid line) in the post-pandemic onset period.

Subgroup analysis

The results of our analysis showed no significant seasonal differences between females and males in mental health service utilization, both before and after the onset of the COVID-19 pandemic (Figure 5.3). However, a notable disparity in the pattern of mental health utilization emerged between the pre- and post-pandemic onset periods. Before the pandemic, a consistent pattern was observed, with utilization rates increasing from September to November and gradually declining until August. In contrast, during the post-pandemic onset period, there was a peak in utilization in April followed by a decline leading into the summer months. Moreover, the number of individuals hospitalized due to mental health concerns continued to increase in November and December. These divergent trends underscore the potential correlations between the pandemic and temporal patterns of mental health service utilization.

Furthermore, our findings revealed an intriguing selective increase in female utilization compared to males. Specifically, before the pandemic, males utilized mental health services more frequently than females, maintaining a consistently higher proportion throughout the year. However, after the pandemic onset, the utilization rates of females approached those of males, with equal utilization observed from July to September.

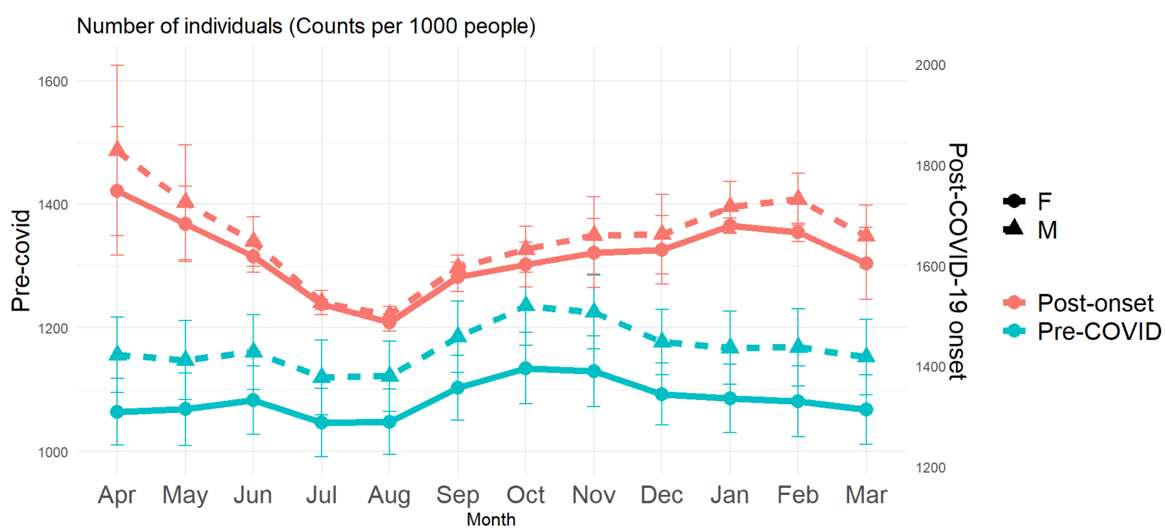
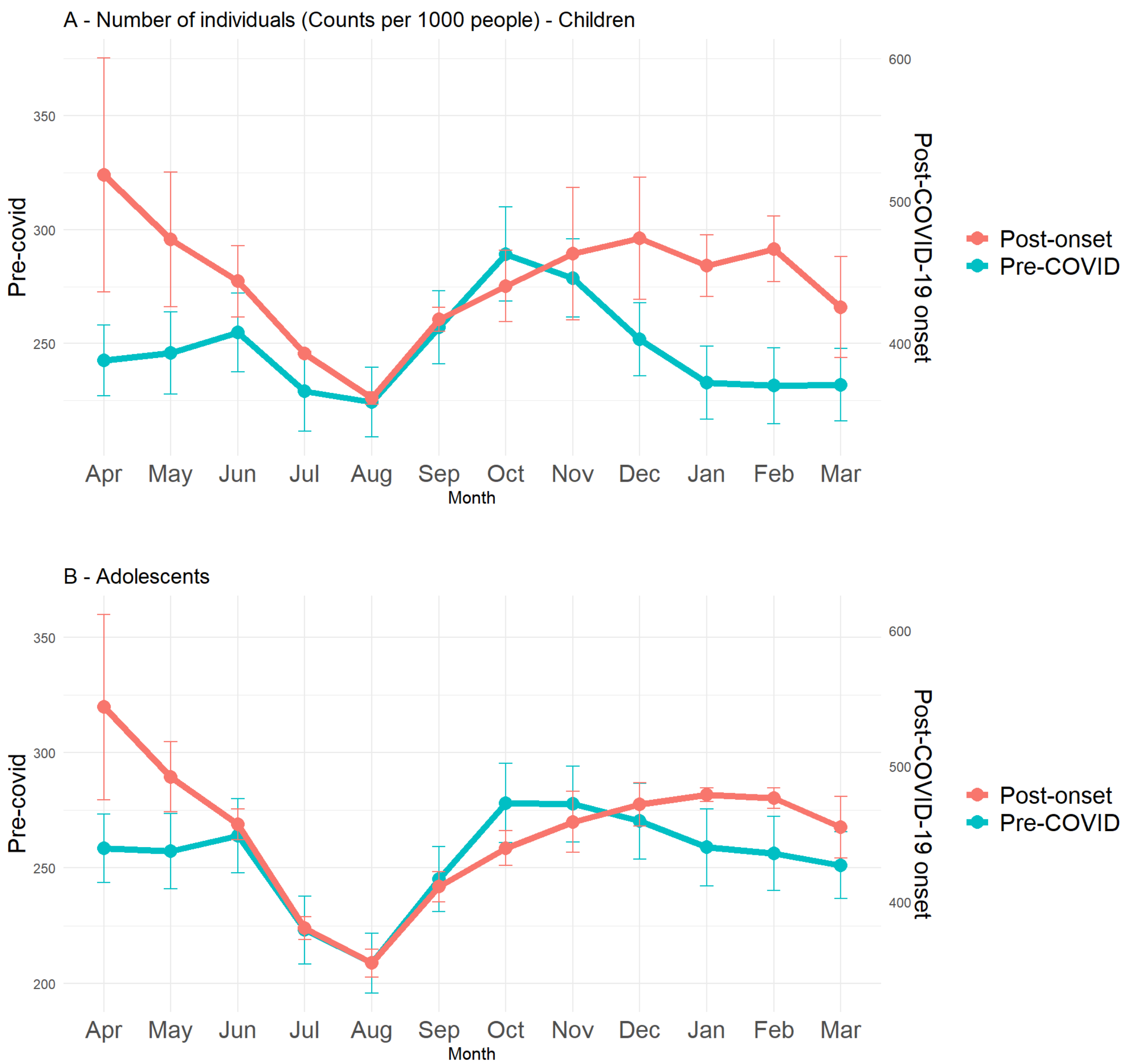


Figure 5.3. Pre- and post-COVID-19 onset mental health utilization trends for females and males, scaled to monthly active insurance holders, showing average monthly utilization with standard errors.

Note: Blue: Jan 2014-Feb 2020; Red: Mar 2020-Dec 2022.

Our analysis uncovered varying seasonal patterns of mental health service utilization among different age groups during the pre-pandemic period (Figure 5.4). Children, adolescents, and young adults exhibited a prominent seasonality trend with the highest number of mental health-related service utilization during the fall months and lowest during the late summer months (Figure 5.4A-C). Adults demonstrate a steady rise in utilization from April to

September, which then declines until reaching the lowest point in December, followed by a slight increase in January before declining again (Figure 5.4D). Seniors also exhibit a linear pattern, with utilization increasing from April to October, followed by a slight decrease before reaching the highest point in January (Figure 5.4E).



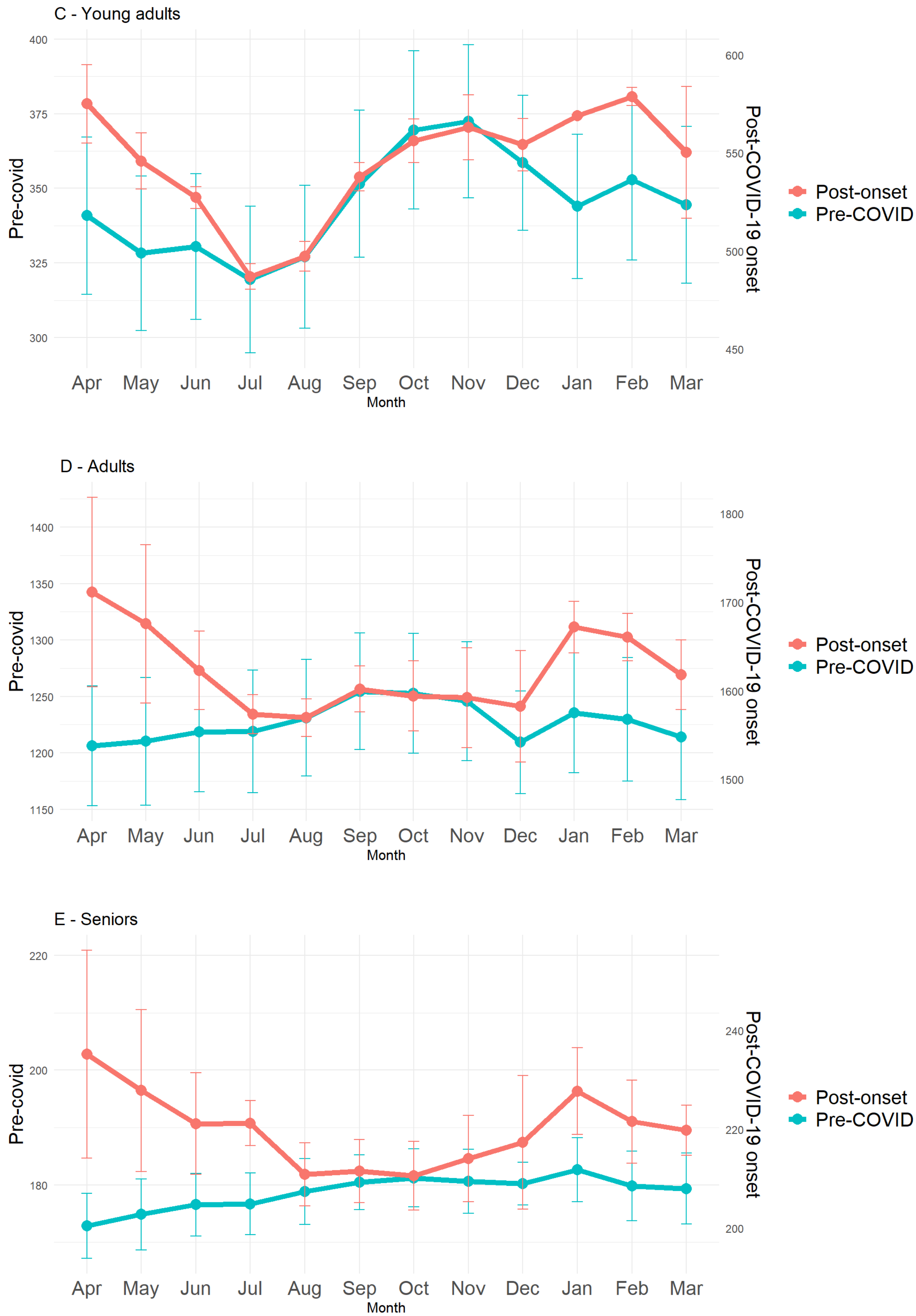

C - Young adults
Pre-covid
Post-COVID-19 onset
400
375
350
325
300
600
550
500
450
Apr May Jun Jul Aug Sep Oct Nov Dec Jan Feb Mar
Month
Post-onset
Pre-COVID
D - Adults
Pre-covid
Post-COVID-19 onset
1400
1350
1300
1250
1200
1150
1800
1700
1600
1500
Apr May Jun Jul Aug Sep Oct Nov Dec Jan Feb Mar
Month
Post-onset
Pre-COVID
E - Seniors
Pre-covid
Post-COVID-19 onset
220
200
180
240
220
200
Apr May Jun Jul Aug Sep Oct Nov Dec Jan Feb Mar
Month
Post-onset
Pre-COVID

Figure 5.4. Pre- and post-COVID-19 onset mental health utilization trends by age group, scaled to monthly active insurance holders, displaying average monthly utilization with standard errors.

Note: Blue: Jan 2014-Feb 2020; Red: Mar 2020-Dec 2022) A. Children B. Adolescents C. Young adults D. Adults E. Seniors.

When comparing the seasonal patterns between the pre- and post-pandemic onset periods, we found a consistent pattern for adolescents, young adults, adults, and seniors (Figure 5.4). The only notable difference was the abrupt change in the number of individuals seeking mental health-related services during the initial months of the pandemic. Specifically, there was a significant surge in utilization observed in April, May, and June, which can be attributed to the onset of the pandemic in 2020 (Figures 5.4B, C, D). However, children exhibited distinct utilization patterns in the post-pandemic onset era. Notably, there was a sharp increase in utilization starting from September, with peaks observed from November to February (Figure 5.4A).

Discussion

This study examined the seasonal patterns of mental health-related office visits, ED visits, and hospitalizations before and after the COVID-19 pandemic onset. Overall, we found that mental health service utilization in Alberta, Canada, showed seasonal patterns before the COVID-19 pandemic, with declines in the spring and summer months and peaks observed in the fall and winter months. After the onset of the pandemic, the seasonal patterns for mental health-related office visits and ED visits were altered, but the overall trend remained similar, with an increase in overall mental health service utilization during the pandemic period.

Our study's findings are consistent with previous research indicating an increase in mental health-related ED visits during the academic year for children and adolescents (Beaudry et al., 2022; Copeland et al., 2022; Marshall et al., 2021). However, the observed pattern of increased utilization during the pandemic period suggests that factors beyond academics, such as pandemic-related stressors, may have contributed to the rise in mental health service utilization (Copeland et al., 2022). An additional aspect to consider is how academic stressors changed after the pandemic onset, with students encountering difficulties such as a lack of social support due to remote schooling or having to attend classes from unfavourable home conditions (Viner et al., 2022). This is particularly noteworthy since if academics appeared to have been the sole stressor, we would have expected to see an increase in utilization during the early months of the academic year, which was not observed in our analysis. Also, the number of COVID-19 cases does not appear to be a significant explanatory factor for the observed differences in seasonality patterns for mental health-related utilization. These findings suggest that while the pandemic likely impacted mental health (Beaudry et al., 2022; Dragioti et al., 2022; Lee et al., 2022; Ma et al., 2021), other underlying factors independent of the direct influence of COVID-19 cases may have contributed to the changes in seasonality patterns.

The study also uncovered varying seasonal mental health service utilization patterns among different age groups during the pre-pandemic period. Children, adolescents, and young adults exhibited a prominent seasonality trend, with the highest number of mental health-related service utilization in the fall and winter months, whereas adults and seniors did not show varying seasonal trends. However, we observed a similar seasonal pattern when comparing the pre- and post-pandemic onset periods among adolescents, young adults, and adults.

Interestingly, we observed no significant seasonal differences between females and males in mental health service utilization, both before and after the onset of the COVID-19 pandemic. This finding is consistent with some previous studies (Patten et al., 2017), but contrasts with others that have reported sex differences in mental health service utilization (Jahan et al., 2020; Thiessen et al., 2020). Additionally, our analysis revealed a slight divergence in healthcare utilization patterns associated with the pandemic. Females displayed utilization rates that closely aligned with males during the pandemic period. These findings imply that the impact of the pandemic on mental health service utilization may have varied between males and females.

This study's findings have important implications for service providers and policymakers, particularly during the COVID-19 pandemic. The significant increase in mental health-related utilization during the pandemic highlights the need for increased mental health services and support. Mental health service providers could anticipate and prepare for increased utilization during specific periods and adapt their resources and services accordingly. The slight difference in utilization patterns between males and females during the pandemic is also noteworthy. It suggests the need for tailored interventions and approaches to address the unique challenges faced by different populations. Additionally, the inconsistent utilization patterns across different age groups after the pandemic onset underscore the importance of comprehensive and inclusive mental health support across the lifespan. The allocation of resources to ensure equitable access to mental health services for individuals of all ages should be prioritized. By considering diverse populations' unique needs and experiences, mental health service providers and policymakers can better address the complex and changing mental health landscape shaped by the pandemic.

Further research is warranted to explore the potential influence of pandemic-related stressors, such as social isolation, which could have altered the patterns of mental health-related utilization during this period. Understanding these additional drivers is valuable for formulating effective interventions and policies to mitigate the negative consequences of disrupted seasonality on mental health in the context of ongoing and future public health crises. By pursuing these avenues, future research can enhance the understanding of the complex relationship between the pandemic, seasonality patterns, and mental health service utilization, guiding evidence-based interventions, and policies to support mental health during and beyond public health crises.

Conclusion

Our study highlights the importance of understanding seasonal mental health service utilization patterns to optimize healthcare delivery and resource allocation. The pandemic appears to have brought about significant changes in mental health service utilization patterns, with increased overall utilization and disruptions to previously observed seasonal patterns.

Disclaimer

This study is based in part on data provided by Alberta Health. The interpretation and conclusions contained herein are those of the researchers and do not necessarily represent the views of the Government of Alberta. Neither the Government nor Alberta Health expressed any opinion about this study.

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Conclusion

Summary of the main findings

In this exploration of developmental vulnerability and mental health outcomes, my research addresses fundamental questions shaping the understanding of childhood development, machine learning applications, and repercussions of the COVID-19 pandemic. The key findings provide a nuanced perspective on these critical issues.

Section 1 delves into the use of the EDI linked with other healthcare administrative data to investigate vulnerabilities in children. The first paper of the section highlights the population-level risk factors linked to developmental vulnerability in kindergarten-aged children. This answer to the first research question emphasizes the pivotal roles of prenatal, neonatal, and early childhood factors, mental health conditions, biological sex, and socioeconomic status. These findings lay the foundation for targeted intervention strategies, advocating for multilevel prevention and intervention strategies targeting individual, family, and community aspects.

The second paper of Section 1 exemplifies one potential application of the EDI questionnaire by applying different machine learning algorithms for early ADHD prediction, identifying both protective and risk factors.. Answering the second research question, this study shows the efficacy of machine learning models and the importance of linking administrative datasets in predicting case-defined ADHD. The results revealed that learning English or French as a second language, having female biological sex at birth, and having a high overall social competence are protective against an increased risk of ADHD, while a longer history of past mental health records, more hyperactive and inattentive behaviour, and a mother's history of mental health concerns at childbirth are related to higher probabilities of ADHD.

With the onset of the COVID-19 pandemic, our interest turned to understanding its effects on the mental well-being of vulnerable children compared to their non-vulnerable counterparts. Section 2 delves into the pandemic's influence,, revealing its exacerbation of existing mental health issues and vulnerabilities. Paper 3 reinforces the association between developmental vulnerability and healthcare utilization, revealing an escalating trend in mental health-related service use, particularly among vulnerable children. This result addresses the first research question, emphasizing the importance of early intervention strategies even amid pandemic disruptions. Moreover, this paper emphasizes the association between developmental vulnerability and healthcare utilization, showing higher rates of health service utilization, including mental health services, among vulnerable children. This observation answers the third research question on the influence of the pandemic on developmental vulnerabilities.

Expanding the exploration of the impact of the COVID-19 pandemic on mental health issues among young individuals and its significance for policymakers, Paper 4 underscores a notable increase in mental health service utilization among adolescents. This surge suggests a potential decline in the mental well-being of youth.This aligns with the third research question on the pandemic's impact on young individuals' mental health outcomes. Finally, paper 5 also explored changes in mental healthcare utilization, broadening the investivation to different age groups, revealing disruptions of seasonal patterns. These findings address the third research question, emphasizing the need for timely and targeted support and resources for mental health services during crises.

In summary, this thesis harmonizes the multifaceted factors contributing to developmental vulnerability with the realities of the pandemic's impact on mental health. It addresses the research questions that guided the progress of this thesis, reinforcing the critical need for targeted interventions, particularly for vulnerable populations. It advocates for a holistic approach that combines social, biological, and technological elements in addressing childhood developmental challenges and their mental health ramifications. There is an urgent need for policymakers to prioritize robust mental health system plans, considering both immediate and broader societal and systemic factors in the post-pandemic era. This research significantly contributes to the ongoing discourse on childhood development and mental health, urging a proactive and comprehensive response to ensure the well-being of future generations.

Contributions to the field and future research directions

This thesis contributes significantly to the field of child development and mental health by shedding light on the complex interplay between developmental vulnerability and mental health outcomes, particularly in the context of the COVID-19 pandemic. These contributions offer valuable insights into understanding and addressing the challenges faced by children and adolescents, providing a foundation for future research and policy development.

The findings from this research underscore the need for a holistic approach to understanding and addressing developmental vulnerability and its impact on mental health. It emphasizes the interconnectedness of various factors, including prenatal and postnatal adversities, social determinants, and healthcare utilization patterns. This holistic perspective should inform the interpretation of findings in future studies, encouraging researchers to consider the broader context in which children develop.

The research highlights the importance of early intervention and support for vulnerable populations. Policymakers and healthcare providers should consider the long-term consequences of developmental vulnerability, especially in the wake of the COVID-19 pandemic. These findings emphasize the need for targeted interventions that address the specific needs of vulnerable children and adolescents.

While this research provides valuable insights, there are limitations that future studies can address to further advance the field. First, there is a need for more research on the long-term effects of developmental vulnerability. Understanding how developmental challenges in childhood impact individuals as they transition into adulthood can provide critical insights into the lifelong consequences of these vulnerabilities. Second, future research should evaluate the effectiveness of targeted interventions aimed at mitigating the impact of developmental vulnerability on mental health outcomes. This includes assessing the outcomes of interventions implemented at different developmental stages, from early childhood through adolescence. Such research can inform evidence-based intervention strategies that can be applied on a broader scale.

Several areas warrant further investigation in the realm of child development and mental health. For example, future research should delve deeper into the long-term effects of developmental vulnerability, exploring how these challenges impact individuals' mental health, educational attainment, and overall life outcomes as they age into adulthood. This longitudinal perspective can provide crucial insights into the enduring consequences of childhood vulnerabilities. While this thesis has focused on risk factors associated with developmental vulnerability, future studies can explore protective factors and resilience mechanisms that help children overcome adversity. Understanding what enables some children to thrive, despite challenging circumstances, can inform the development of resilience-focused interventions.

Building on the importance of early intervention highlighted in this research, future studies should rigorously evaluate the effectiveness of targeted interventions. This includes interventions designed to support children and adolescents facing developmental challenges and those aimed at enhancing mental health outcomes during and after crises like the COVID-19 pandemic. Another aspect to consider is whether the observed increase in mental health utilization among vulnerable children is attributable to the passage of time, as children grow older and become more susceptible to psychiatric disorders, or if it is influenced by heightened awareness of mental health issues that accompany the pandemic.

Further research should also investigate healthcare access barriers faced by vulnerable populations, particularly in the context of mental health services. Identifying these barriers and developing strategies to overcome them can enhance the delivery of mental health care to those in need.

In conclusion, this research contributes significantly to our understanding of developmental vulnerability and its implications for mental health in children and adolescents. By considering the interconnectedness of various factors and emphasizing the importance of early intervention, this work sets the stage for future research and policy initiatives aimed at improving the well-being of vulnerable populations. Future studies should explore long-term effects, evaluate interventions, identify resilience factors, and address healthcare access barriers to further advance the field and support the mental health needs of children and adolescents.

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Appendix

1. Risk factors for developmental vulnerability using the Early Development Instrument

Methodology

Study population and variable extraction

The EDI is a kindergarten teacher-completed assessment of child development. Unlike other Canadian provinces, Alberta required active consent for the EDI, meaning that each child's guardian was sent an information letter and consent form for signature. Only children with a signed consent form were included in the study. For the 2016 EDI data collection process, each of Alberta's school boards had the option to opt out from participating. EDI data were not collected for First Nation Band-operated schools and so the lack of data for Indigenous children attending those schools is a limitation of the EDI dataset.

Study predictors

Below are details of some of the predictor variables used in the regression model. The complete list of the predictors is shown in Table 1.

Chronic disease status. The chronic disease status measure was derived based on Clinical Risk Groupers (CRG), a population classification system that uses a range of healthy to palliative care groupings (see Table 1). In this study, children with minor chronic conditions, major chronic conditions, cancer, or catastrophic conditions in palliative care were labelled as "having a chronic illness," while those with health status or minor acute conditions were considered as "generally healthy children."

Diagnosis and procedure codes, pharmaceutical data, and functional/mental health status information from the two most recent years were used to assign each child to a severity-adjusted homogeneous group, thereby indicating everyone's health status (Table 1) (Health Information Systems, 2016).

Mental health status. Individuals who utilized any mental health service and/or were prescribed any psychiatric drug were considered to have mental health activity ('yes' for mental health status).

Mental health service utilization indicator. The mental health activity indicator was defined based on the Ministry of Health, mental health registry. This registry included individuals who had mental health service utilization records with diagnostic codes for mental health conditions (as per the International Classification of Diseases Codes) and/or were provided drug dispensations related to mental health issues for fiscal years 2013/2014 to 2015/2016

In-utero environmental factors and biological information at birth. We extracted children's health information at prenatal and time of birth from the Notice of Birth form recorded in Alberta hospitals. Available health information included prenatal exposure to tobacco, alcohol, and drugs (for a full list of drugs, please refer to Table 1); prenatal interventions of multivitamin supplements and folic acid; maternal factors such as number of previous pregnancies and chronic disease as well as indicators of health at birth including Apgar scores (American Academy & American College, 2015), prematurity and access to breastmilk (Table 1). Of the 72 variables available from Notice of Birth Data, 15 were kept for analysis, and 57 were excluded from analysis due to poor data quality caused by inconsistent completion of form fields.

Controls

Since health and early developmental outcomes are strongly linked (MCormack & Verdon, 2015), socioeconomic status (SES), child demographics, and community sociodemographic characteristics were included as control variables in the study (Table 1). Variables were selected based on literature review, practical content expertise, and data availability.

Child- and community-level control variables were obtained from various data sources. Area-level education, income, housing, single-family, and ethnicity information were obtained from the 2016 Statistics Canada Census at an aggregated dissemination area (community) level matched to the child's home address using the postal code. Therefore, all children in the same dissemination area shared these characteristics. There were 527 aggregated dissemination areas with an average population of 8,021 (Interquartile Range (IQR): [5,942; 10,211]). These variables were calculated for each child based on their home residency as of March 31, 2016. Enrollment of Alberta Health Child Benefit Program which covers children's health expenses for low-income families was coded as a continuous variable presenting the number of years in the program.

Tables

Table 1. Rapid literature review of studies on early life events and children's development.

Study	Data source	Linkage data	Variables			
			Demographic	Prenatal	Neonatal	Early childhood
Piek J.P. et al., 2008[1]	NR	No	Yes	No	Yes	No
Lloyd J.E.V. & Hertzman C., 2009[2]	EDI	Yes	Yes	No	No	Yes
Cabaj J.L. et al., 2014[3]	CPC	No	Yes	Yes	Yes	Yes
Grace T. et al., 2015[4]	WAPC	No	Yes	Yes	Yes	No
Bell M.F. et al., 2016[5]	AEDC	Yes	Yes	-	No	Yes
Guthridge S. et al., 2016[6]	AEDC	Yes	Yes	Yes	Yes	No
Laurens K.R. et al., 2016[7]	AEDC, NSW-CDS	Yes	Yes	No	No	No
McDonald S. et al., 2016[8]	AOB	No	Yes	Yes	Yes	Yes
O'Meagher S. et al., 2017[9]	Royal Hobart Hospital	No	Yes	No	Yes	No
Bell M.F. et al., 2018[10]	AEDC	Yes	Yes	-	No	No
Falster K. et al., 2018[11]	AEDC	Yes	Yes	Yes	No	No
Bell M.F. et al., 2019[12]	AEDC	Yes	Yes	Yes	Yes	Yes
Dea C. et al., 2019[13]	EDI and AEDC	No	Yes	No	No	No
Mughal M.K. et al., 2019[14]	AOB	No	Yes	Yes	Yes	Yes
Razaz N. et al., 2019[15]	EDI	Yes	Yes	No	Yes	No
Veldman S.L.C. et al., 2019[16]	Low-income and remote communities in Australia	No	Yes	No	Yes	Yes

Williamson A. et al., 2019[17]	AEDC	Yes	Yes	Yes	Yes	No
Hanly M. et al., 2020[18]	AEDC	Yes	Yes	Yes	No	No
Taylor C.L. et al., 2020[19]	AEDC	Yes	Yes	Yes	Yes	No
Wall-Wieler E. et al., 2020[20]	EDI	Yes	Yes	Yes	Yes	Yes
Cronin P. & Goodal S., 2021[21]	LSAC	No	Yes	Yes	Yes	No
Dhamrait G.K. et al., 2021 (1) [22]	AEDC	Yes	Yes	Yes	Yes	No
Dhamrait G.K. et al., 2021 (2) [23]	AEDC	Yes	Yes	No	Yes	No
Saunders N.R. et al., 2021[24]	EDI	Yes	Yes	No	Yes	No
Dhamrait G.K. et al., 2022[25]	AEDC	Yes	Yes	Yes	Yes	No

Note: The rapid review was undertaken by searching articles that included the following keyword on MEDLINE database: Early life events and children development. Examples of demographic variables include children's age and sex, maternal age, and socioeconomic status. Prenatal variables included but were not limited to, maternal smoking and drug use during pregnancy. Neonatal variables included gestational age, preterm birth, birth weight, and others. AEDC = Australian Early Development Census, AOB = All our Babies, CPC = Community Perinatal Care, EDI = Early Development Instrument, LSAC = Longitudinal Study of Australian Children, NR = not reported, NSW-CDS = New South Wales Child Development Study, WAPC = Western Australian Pregnancy Cohort.

Table 2. Variables Used in the Study.

Variable Name	**Definition**
Child's Biological Sex	Child's biological sex (Male vs. Female).
Socioeconomic/Subsidy Status (Child)	Whether the child was part of a subsidy group (Aboriginal, Subsidy, Welfare) or not, in 2015/16 (Subsidy vs. No Subsidy).
Years Child had Human Service Drug Benefit Plan Enrollment	Number of years the child was part of a human services drug benefit plan between 2013/14, 2014/15, and 2015/16.
Child's Chronic Disease Status	Binary variable (Yes="Minor/Major Condition(s), Malignancy, or Catastrophic" vs. No="Healthy or Acute"). Based on clinical risk groupers (CRG). CRG 9 - Catastrophic condition status, CRG 8 - Dominant and metastatic malignancies, CRG 7 - Dominant chronic disease in 3 or more organ systems, CRG 6 - Significant chronic disease, CRG 5 - Single dominant or moderate chronic disease, CRG 4 - Minor chronic disease in multiple organ systems, CRG 3 - Single minor chronic disease, CRG 2 - History of significant acute disease, CRG 1 - Healthy/Non-Users.

Child’s Emergency Visits	Number of child’s emergency visits in 2013/14, 2014/15, and 2015/16. The variable was turned into a binary variable (ED Visits≥4 vs. ED Visits<4).
Child’s Hospitalization Days	Number of days the child was hospitalized between 2013/14, 2014/15, and 2015/16. The variable was turned into a binary variable (Hospital Days≥1 vs. Hospital Days<1).
Years Child was a High Health System User	Number of years within which the child was flagged as a high user, between 2013/14, 2014/15, and 2015/16. High user = 15 or more GP visits, 10 or more specialist visits, or 10 or more emergency visits during a fiscal year.
Years Child had Asthma	Number of years the child was diagnosed with asthma between 2013/14, 2014/15, and 2015/16.
Years Child had COPD	Number of years the child was diagnosed with Chronic Obstructive Pulmonary Disease (COPD) between 2013/14, 2014/15, and 2015/16.
Years Child had Mental Health Diagnosis	Number of years the child was flagged with mental health related problems between 2013/14, 2014/15, and 2015/16. The flagging of mental health issues was based on utilization patterns derived from three major health administrative databases (provider claims, ambulatory care and inpatient, drug dispensations).
APGARS 5 Score at Birth	Apgar 5 is a quick test performed on a baby at 5 minutes after birth, indicating how well the baby is doing outside the mother's womb. The score ranges from 1 to 10 and was transformed into a binary variable (Score<8 vs. Score>=8).
Breastfeeding Status	Binary variable indicating whether the baby was being breastfed at birth (Yes vs. No).
Phototherapy at Birth	Binary variable indicating whether phototherapy was used during the pregnancy or not (Yes vs. No).
Preterm Pregnancy	Binary variable indicating whether the baby was delivered preterm (Yes vs. No).
Mother's Alcohol Use Status	Binary variable indicating whether the mother consumed alcohol during pregnancy (Yes vs No).
Mother's Diabetes Status	Binary variable indicating whether the mother suffered from diabetes before/during pregnancy (Yes vs. No).
Mother's Drug Use Status	Binary variable indicating whether the mother consumed drugs (cocaine, crystal meth, ecstasy, heroin, marijuana, methadone) during pregnancy (Yes vs. No).
Mother's Hypertension Status	Binary variable indicating whether the mother suffered from hypertension before/during pregnancy (Yes vs. No).
Mother's Mental Health Status	Binary variable showing the overall mother’s mental health status in NOB data (Yes vs. No)
Mother's Pregnancy History	Number of pregnancies the mother had to date. The variable was transformed into a binary one (≥4 pregnancies vs. <4 pregnancies).
Mother's Smoking Status	Binary variable indicating whether the mother smoked during pregnancy (Yes vs. No).
Mother’s Multivitamin with Folic Acid Intake	Binary variable indicating whether the mother took multivitamins with folic acid at least one month prior to pregnancy or during pregnancy (Yes vs. No).
Number of Prenatal Visits During Pregnancy	Number of prenatal visits the mother had during the pregnancy. The variable was transformed into a binary one (≥9 Visits vs. <9 Visits).

≥30% of Renter Income Spent on Housing	Proportion of individual renters (0-100%) who spent 30% or more of their income on housing in the aggregated dissemination area (527 Alberta ADAs) that the child resides in. This is a Statistics Canada Census 2016 derived variable.
Individuals with Higher Education	Proportion of individuals (0-100%) with higher education certificates or degrees living in the aggregated dissemination area (527 Alberta ADAs) that the child resides in. This includes individuals with apprenticeship or trades certificate or diploma, college, CEGEP, or other non-university certificate or diploma, and university certificate or diploma below bachelor level AND university certificate, diploma, or degree at bachelor level or above. This is a Statistics Canada Census 2016 derived variable.
Living at the Same Address as 5 Years Ago	Proportion of immigrants (0-100%) living at the same address as five years ago, in the aggregated dissemination area (527 Alberta ADAs) that the child resides in. This is a Statistics Canada Census 2016 derived variable.
Living in Rented Dwellings	Proportion of individuals (0-100%) living in rented dwellings in the aggregated dissemination area (527 Alberta ADAs) that the child resides in. This is a Statistics Canada Census 2016 derived variable.
Not Speaking English or French	Proportion of individuals (0-100%) excluding institutionalized persons that did not speak an official language (i.e., English, or French) in the aggregated dissemination area (527 Alberta ADAs) that the child resides in. This is a Statistics Canada Census 2016 derived variable.

Table 3. Comparison between children with and without EDI data available

Variable		**N**	**Non-EDI Sample = 40,534 N (%)**	**Whole EDI cohort Sample = 28,952 N (%)**	**Chi-square p-value**
Age	Age <5	69,486	0 (0%)	667 (2.30%)	0.238
	Age 5-6		31,340 (77.32%)	21,705 (74.97%)	
	Age 6-7		9,194 (22.68%)	6,571 (22.7%)	
	Age >=7		0 (0%)	9 (0.03%)	
Child's biological sex	Female	68,827	19,522 (48.16%)	13,611 (48.11%)	0.888
	Male		21,012 (51.84%)	14,682 (51.89%)	
Socio Economic/Subsidy Status (Child)	No Subsidy	68,887	35,491 (87.57%)	25,999 (91.67%)	<0.001
	Subsidy		5,036 (12.43%)	2,361 (8.33%)	
Child's Mental Health Utilization	No	64,423	37,620 (99.57%)	26,542 (99.64%)	0.169
	Yes		164 (0.43%)	97 (0.36%)	
Child's Mental Health Utilization - Physician claims	No	64,423	33,591 (88.9%)	23,501 (88.22%)	0.007
	Yes		4,193 (11.1%)	3,138 (11.78%)	

Note. non-EDI: Children without EDI data; Whole EDI cohort: Children with EDI data; SES: Socioeconomic status.

Table 4. Characteristics of the study cohort by vulnerability in one or more domains - all variables

Variable Name	Variable Label	Non-Missing N	Non-Vulnerable Children (n = 16,792) N (%)	Vulnerable Children (n = 6,702) N (%)	p-value[#]
Years Child had Asthma	0	23,242	15,147 (91.0%)	5874 (89.0%)	<0.001
	1		239 (1.4%)	107 (1.6%)	
	2		248 (1.5%)	109 (1.6%)	
	3		1006 (6.1%)	512 (7.8%)	
Years Child had Mental Health Diagnosis	0	23,243	14,481 (87.0%)	4667 (70.7%)	<0.001
	1		1590 (9.5%)	1081 (16.4%)	
	2		462 (2.8%)	551 (8.3%)	
	3		108 (0.7%)	303 (4.6%)	
Child's Chronic Disease Status	Yes	23,339	2327 (13.9%)	1536 (23.1%)	<0.001
	No		14,373 (86.1%)	5103 (76.9%)	
Mother's Diabetes Status	Yes	18,505	862 (6.5%)	443 (8.6%)	<0.001
	No		12,498 (93.5%)	4,702 (91.4%)	
Mother's Drug Use Status	Yes	22,859	228 (1.4)	220 (3.4%)	<0.001
	No		16,127 (98.6%)	6,284 (96.6%)	
Child's Emergency Visits	ED Visits ≥4	23,242	2010 (12.1%)	1127 (17.1%)	<0.001

	ED Visits <4		14,630 (87.9%)	5475 (82.9%)	
Mother's Pregnancy History	Pregnancies ≥4	19,373	2064 (14.8%)	1130 (20.9%)	<0.001
	Pregnancies <4		11,916 (85.2%)	4,263 (79.1%)	
Mother's Smoking Status	Yes	18,689	1,237 (9.1%)	1014 (19.7%)	<0.001
	No		12,304 (90.9%)	4,134 (80.3%)	
Mother’s Multivitamin with Folic Acid Intake	Yes	18,489	12,770 (95.5%)	4,744 (92.6%)	<0.001
	No		597 (4.5%)	378 (7.4%)	
Preterm Pregnancy	Yes	23,494	1066 (6.4%)	610 (9.1%)	<0.001
	No		15,726 (93.6%)	6092 (90.9%)	
Breastfeeding Status	Yes	18,603	13,014 (96.2%)	4745 (93.4%)	<0.001
	No		510 (3.8%)	334 (6.6%)	
Individuals with Higher Education - mean proportion (SD)	Proportion of individuals	23,477	65.1 (11.3)	61.5 (10.8)	<0.001
Living in Rented Dwellings - mean (SD)	Proportion of individuals	23,477	22.7 (13.2)	25.6 (14.0)	<0.001
Mother's Alcohol Use Status	Yes	18,948	451 (3.3%)	285 (5.4%)	<0.001
	No		13,235 (96.7%)	4,977 (94.6%)	
Years Child was a High Health System User	0	23,242	15,822 (95.1%)	5,977 (90.5%)	<0.001
	1		676 (4.1%)	434 (6.6%)	
	2		109 (0.6%)	136 (2.1%)	

	3		33 (0.2%)	55 (0.8%)	
Not Speaking English or French - mean proportion (SD)	Proportion of individuals	23,477	1.6 (1.6)	1.9 (1.8)	<0.001
≥30% of Renter Income Spent on Housing - mean proportion (SD)	Proportion of individuals	23,468	34.19 (7.3)	34.6 (7.2)	<0.001
Mother's Mental Health Status	Yes	17,887	1286 (9.9%)	635 (12.9%)	<0.001
	No		11,693 (90.1%)	4,273 (87.1%)	
Child's Hospitalization Days	Days≥1	23,242	549 (3.3%)	364 (5.5%)	<0.001
	Days <1		16,091 (96.7%)	6,238 (94.5%)	
Number of Prenatal Visits During Pregnancy	Visits≥9	16,676	8,063 (66.5%)	2,853 (62.7%)	<0.001
	Visits<9		4,062 (33.5%)	1,698 (37.3%)	
Phototherapy at Birth	Yes	16,903	437 (3.5%)	199 (4.3%)	0.019
	No		11,866 (96.5%)	4401 (95.7%)	
Years Child had COPD	0	23,242	16,602 (99.8%)	6,586 (99.8%)	0.490
	1		2 (0.0%)	0 (0.0%)	
	2		3 (0.0%)	0 (0.0%)	
	3		33 (0.2%)	16 (0.2%)	
Mother's Hypertension Status	Yes	18,880	852 (6.2%)	360 (6.9%)	0.113
	No		12,792 (93.8%)	4,876 (93.1%)	
APGARS 5 Score at Birth	Score≥8	18,764	12,976 (95.7%)	4,916 (94.5%)	0.001

	Score<8		586 (4.3%)	286 (5.5%)	
Socio Economic/ Subsidy Status	Subsidy	23,339	900 (5.4%)	1042 (15.7%)	<0.001
	No Subsidy		15,800 (94.6%)	5597 (84.3%)	
Mother's Smoker Status	Yes	18,689	1237 (9.1%)	1014 (19.7%)	<0.001
	No		12,304 (90.9%)	4,134 (80.3%)	
Child's Biological Sex	Female	23,494	8869 (52.8%)	2420 (36.1%)	<0.001
	Male		7923 (47.2%)	4282 (63.9%)	
Years Child had Human Service Drug Benefit Plan Enrollment	0	23,494	15,776 (93.9%)	5674 (84.7%)	<0.001
	1		498 (3.0%)	405 (6.0%)	
	2		281 (1.7%)	322 (4.8%)	
	3		237 (1.4%)	301 (4.5%)	
Living at Same Address as 5 Years Ago - mean proportion (SD)	Proportion of individuals	23,477	54.0 (12.8)	54.1 (12.0)	<0.001

Note. # χ^2 test was used for categorical variables. T-test was used for continuous variables.

Table 5. Logistic regression model results for all variables (n = 23,494).

Predictors	Risk Ratio	Standardized Estimate	P-value#
≥30% of Renter Income Spent on Housing	1.00	0.01	0.244
APGARS 5 Score	0.99	0.20	0.368
Breastfeeding Status	0.87	-0.02	0.021*
Child's Biological Sex (Male)	1.51	0.18	<0.001*
Child's Chronic Disease Status	1.13	0.04	<0.001*
Child's Emergency Visits	1.01	0.03	0.001*
Child's Hospitalization Days	1.01	0.01	0.123
Individuals with Higher Education	0.99	-0.09	<0.001*
Living at the Same Address as 5 Years Ago	1.00	0.01	0.193
Living in Rented Dwellings	1.01	0.01	<0.001*
Mother's Multivitamin With Folic Acid Intake	0.89	0.07	0.050
Mother's Alcohol Use Status	1.12	0.09	0.101
Mother's Diabetes Status	1.10	0.03	<0.001*
Mother's Drug Use Status	1.18	0.02	0.046*
Mother's Hypertension Status	1.01	0.04	0.671
Mother's Mental Health Status	1.02	0.06	0.671
Mother's Pregnancy History	1.04	0.03	<0.001*
Mother's Smoking Status	1.30	0.07	<0.001*
Not Speaking English or French	1.05	0.07	<0.001*
Number of Prenatal Visits During Pregnancy	1.00	0.04	0.931
Phototherapy	1.03	0.09	0.700
Preterm Pregnancy	1.16	0.03	0.001*
Socio Economic/Subsidy Status (Child)	1.58	0.10	<0.001*

Years Child Had Asthma	0.96	-0.02	0.010*
Years Child Had COPD	0.97	0.11	0.726
Years Child had Human Service Drug Benefit Plan Enrollment	1.16	0.07	<0.001*
Years Child Had Mental Health Diagnosis	1.46	0.20	<0.001*
Years Child was a High Health System User	1.05	0.05	0.244

Note. #Adjusted p-value based on false discovery rate (FDR) correction at 0.05. * Variables that reached statistical significance.

Table 6. Odds ratios for the Alberta-born (notice of birth) EDI children with physical and well-being domain vulnerabilities at ages five and six.

Predictors	**Odds Ratio**	**Confidence Interval**	**Standardized Estimate**	**P-Value***
Mother's Diabetes Status	1.26	1.07 - 1.48	0.03	0.015
Mother's Pregnancy History	1.32	1.16- 1.49	0.05	<.001
Preterm Pregnancy	1.35	1.18 - 1.56	0.04	<.001
Mother's Smoking Status	1.63	1.44 - 1.84	0.08	<.001
Child's Biological Sex (Male)	1.71	1.58 - 1.86	0.15	<.001
Child's Chronic Disease Status	1.29	1.15 - 1.45	0.05	<.001
Socioeconomic/Subsidy Status (Child)	2.28	2.01 - 2.58	0.12	<.001
Years Child was a High Health System User	1.25	1.11 - 1.40	0.04	<.001
Years Child had Mental Health Diagnosis	1.57	1.48 - 1.66	0.15	<.001
Child's Physician Visits	0.88	0.77 - 0.99	-0.03	0.068
Years Child had Human Service Drug Benefit Plan Enrollment	1.11	1.05 - 1.19	0.03	0.002
≥30% of Owner Income Spent on Housing	1.03	1.01 - 1.04	0.06	0.002
Immigrants Arriving Within Last 5 Yrs	0.98	0.96 - 1.00	-0.05	0.067
Individuals with Higher Education	0.98	0.98 - 0.99	-0.09	<.001
Lone Parent Families	1.03	1.02 - 1.04	0.08	<.001

Note. * p-value adjusted using false discovery rate (FDR).

Table 7. Odds ratios for the Alberta-born (Notice of Birth) EDI children with emotional maturity domain vulnerabilities at ages five and six.

Predictors	**Odds Ratio**	**Confidence Interval**	**Standardized Estimate**	**P-Value***
Mother's Alcohol Use Status	1.27	1.03 - 1.58	0.02	0.061

Child's Physician Visits	0.88	0.78 - 0.99	-0.03	0.078
Child's Emergency Visit	1.27	1.11 - 1.45	0.04	0.001
Mother's Drug Use Status	1.43	1.11 - 1.84	0.03	0.015
Mother's Mental Health Status	1.30	1.26 - 1.49	0.04	0.001
Mother's Smoking Status	1.69	1.48 - 1.92	0.08	<.001
Child's Biological Sex	3.00	2.72 - 3.29	0.30	<.001
Child's Chronic Disease Status	1.28	1.13 - 1.4	0.05	<.001
Socioeconomic/Subsidy Status (Child)	1.71	1.49 - 1.97	0.08	<.001
Years Child had Asthma	0.91	0.8 - 0.97	-0.04	0.006
Years Child had Mental Health Diagnosis	1.89	1.78 - 2.00	0.22	<.001
Years Child had Human Service Drug Benefit Plan Enrollment	1.10	1.02 - 1.17	0.03	0.021
Living at Same Address as 5 Yrs Ago	0.99	0.99 - 1.00	-0.05	0.021
Individuals with Higher Education	0.99	0.98 - 0.99	-0.08	<.001
Lone Parent Families	1.03	1.01 - 1.04	0.07	<.001
Immigrants Arriving Within Last 5 Yrs	0.97	0.95 - 0.99	-0.06	0.017

Note. * p-value adjusted using false discovery rate (FDR) at 0.05.

Table 8. Odds ratios for the Alberta-born (Notice of Birth) EDI children with language and cognitive development domain vulnerabilities at ages five and six.

Predictors	**Odds Ratio**	**Confidence Interval**	**Standardized Estimate**	**P-Value***
Child's Emergency Visit	1.22	1.07 - 1.40	0.04	0.012
Child's Public Health Care Cost	1.11	0.88- 1.40	0.03	0.069
Mother's Pregnancy History	1.21	1.05 - 1.39	0.03	0.025
Number of Children at Home	1.29	1.04 - 1.59	0.03	0.051
Mother's Drug Use Status	1.31	1.01 - 1.70	0.02	0.093
Mother's Multivitamin with Folic Acid Intake	0.81	0.6 - 0.98	0.02	0.072
Preterm Pregnancy	1.25	1.07 - 1.46	0.03	0.015
Mother's Smoking Status	1.32	1.15 - 1.51	0.04	<.001
Child's Biological Sex	1.51	1.38 - 1.65	0.11	<.001
Socioeconomic/Subsidy Status (Child)	2.15	1.88 - 2.45	0.12	<.001
Years Child had Mental Health Diagnosis	1.55	1.46 - 1.66	0.15	<.001
Years Child had Human Service Drug Benefit Plan Enrollment	1.17	1.09 - 1.24	0.05	<.001
≥30% of Owner Income Spent on Housing	1.04	1.02 - 1.06	0.09	<.001
Individuals with Higher Education	0.98	0.98 - 0.99	-0.10	<.001
Lone Parent Families	1.03	1.02 - 1.04	0.09	<.001
Child's Chronic Disease Status	1.17	1.02 - 1.33	0.03	0.054

Note. * p-value adjusted using false discovery rate (FDR) at 0.05.

Table 9. Odds ratios for the Alberta Born (Notice of Birth) EDI Children with Social Competence domain vulnerabilities at ages five and six.

Predictors	Odds Ratio	Confidence Interval	Standardized Estimate	P-Value*
Child's Emergency Visit	1.22	1.06 - 1.39	0.04	0.015
Preterm Pregnancy	1.32	1.13 - 1.5	0.04	0.001
Mother's Smoking Status	1.67	1.45 - 1.90	0.08	<.001
Child's Biological Sex	2.38	2.16 - 2.62	0.24	<.001
Child's Chronic Disease Status	1.28	1.23 - 1.46	0.05	<.001
Socioeconomic/Subsidy Status (Child)	1.81	1.57 - 2.09	0.09	<.001
Years Child had Mental Health Diagnosis	1.88	1.77 – 2.00	0.21	<.001
Years Child had Human Service Drug Benefit Plan Enrollment	1.10	1.03 - 1.18	0.03	0.019
≥30% of Owner Income Spent on Housing	1.04	1.02 - 1.06	0.09	<.001
Individuals with Higher Education	0.98	0.98 - 0.99	-0.10	<.001
Lone Parent Families	1.03	1.01 - 1.04	0.08	<.001
Immigrants Arriving Within Last 5 Yrs	0.98	0.96 - 1.00	-0.05	0.109
Child's Physician Visits	0.88	0.77 - 0.99	-0.03	0.109

Note. * p-value adjusted using false discovery rate (FDR) at 0.05.

Table 10. Odds ratios for the Alberta-born (Notice of Birth) EDI children with Communication Skills and General Knowledge domain vulnerabilities at ages five and six.

Predictors	Odds Ratio	Confidence Interval	Standardized Estimate	P-Value*
Child's Hospitalization Days	0.77	0.62 - 0.96	-0.03	0.039
Child's Public Health Care Cost	1.03	0.85 - 1.27	0.06	<.001
Years Child had Mental Health Diagnosis	1.90	1.80 - 2.01	0.22	<.001
Mother's Diabetes Status	1.32	1.13 - 1.54	0.03	0.002
Mother's Pregnancy History Count	1.16	1.02 - 1.32	0.03	0.046
Number of Children at Home	1.38	1.13 - 1.67	0.04	0.003
Mother's Multivitamin with Folic Acid Intake	0.72	0.60 - 0.86	-0.03	0.001
Mother's Mental Health Status	0.73	0.61 - 0.87	-0.04	0.004
Child's Biological Sex	1.68	1.55 - 1.82	0.14	<.001
Child's Physician Visits	0.86	0.80 - 0.96	-0.03	0.009
Breastfeeding Status	0.74	0.62 - 0.90	-0.03	0.005
Child's Chronic Disease Status	1.20	1.07 - 1.35	0.04	0.005
Socioeconomic/Subsidy Status (Child)	1.88	1.66 - 2.14	0.10	<.001
Years Child had Asthma	0.93	0.88 - 0.98	-0.03	0.018
Years Child had Human Service Drug Benefit Plan Enrollment	1.17	1.10 - 1.24	0.05	<.001
≥30% of Owner Income Spent on Housing	1.03	1.02 - 1.05	0.07	<.001
Not Speaking English or French	1.06	1.01 - 1.11	0.06	0.018
Individuals with Higher Education	0.99	0.98 - 0.99	-0.07	<.001
Lone Parent Families	1.03	1.01 - 1.04	0.07	<.001

Note. * p-value adjusted using false discovery rate (FDR) at 0.05.

Table 11. Correlation matrix of variables.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
1	1																										
2	-.03	1																									
3	.00	-.01	1																								
4	.00	-.02	-.01	1																							
5	-.02	.03	.01	-.07	1																						
6	-.09	.01	-.02	.04	-.21	1																					
7	.00	-.03	.00	.00	-.12	.16	1																				
8	.08	-.03	.06	.00	-.01	-.14	-.02	1																			
9	-.23	.01	-.01	.01	.02	.03	.00	-.24	1																		
10	.23	-.01	-.02	-.01	.00	.00	.00	-.25	-.30	1																	
11	.01	.01	.08	.00	.00	-.02	-.01	.08	-.03	-.02	1																
12	.01	-.03	-.04	.00	-.01	.02	.00	-.03	.00	.03	-.04	1.00															
13	.01	-.02	-.01	.00	-.01	-.01	.00	.02	-.01	.02	.00	.00	1														
14	.02	-.03	-.04	.00	-.01	.01	.00	-.05	.01	.06	-.05	.20	.00	1													
15	.01	-.07	.00	-.01	-.03	-.01	.00	.02	.00	-.02	.00	.01	.09	.00	1												
16	.01	-.04	-.03	.00	-.02	.03	.01	.00	.02	.00	-.03	.07	.03	.07	.02	1											
17	-.02	.03	-.08	.01	.02	.00	.01	-.06	.05	.01	-.09	.00	.04	.03	-.04	.10	1										
18	.00	-.01	-.12	.01	-.02	.06	.00	-.15	.05	.09	-.11	.15	.01	.24	-.01	.10	.13	1									
19	.10	.01	.03	-.01	-.02	-.09	.00	-.19	-.09	.08	.03	-.04	.03	-.02	-.02	-.06	-.02	-.07	1								
20	.03	.01	.04	-.02	.00	-.02	-.01	.02	-.03	.01	.06	-.04	-.03	-.02	-.01	-.04	-.07	-.07	.07	1							
21	.01	-.06	-.02	.01	-.02	.00	.00	.01	.00	.01	-.01	.02	.04	.01	.05	.00	-.02	.01	.00	-.02	1						
22	.01	-.11	-.02	.02	-.06	.03	.02	-.01	.00	.01	.00	.01	.05	.02	.12	.01	.02	.03	.03	-.05	.14	1					
23	-.01	-.01	.05	.00	.04	-.06	-.02	.14	-.02	-.14	.09	-.07	.01	-.11	.02	-.04	-.13	-.18	-.04	.01	.00	-.01	1				
24	.00	-.02	.00	.09	-.36	.17	.04	.00	.00	.01	.01	-.01	.01	.01	.02	.02	.00	.02	.02	-.01	.01	.05	-.03	1			
25	.00	-.01	.01	.01	-.03	.02	.06	.00	.00	.00	.01	.00	.00	.00	-.01	.00	.00	.00	.01	.01	.00	.00	.00	.05	1		
26	.06	.00	-.05	.01	-.09	.06	.03	-.14	.01	.14	-.04	.03	.01	.07	-.02	.04	.10	.10	.16	.01	-.01	.02	-.33	.08	.01	1	
27	.01	-.05	-.02	.11	-.33	.10	.08	.00	-.01	.01	-.02	.02	.01	.04	.03	.05	.00	.04	-.01	.00	.01	.06	-.06	.06	.01	.07	1
28	-.01	-.02	-.02	.03	-.33	.37	.31	-.02	-.01	.02	.00	.01	.01	.00	.01	.02	.00	.01	.04	.01	.01	.05	-.05	.18	.01	.10	.25

Note: Variable names map: 1) ≥30% of Renter Income Spent on Housing, 2) APGARS 5 Score at Birth, 3) Breastfeeding Status, 4) Child's Biological Sex, 5) Child's Chronic Disease Status, 6) Child's Emergency Visits, 7) Child's Hospitalization Days, 8) Individuals with Higher Education, 9) Living at the Same Address as 5 Years Ago, 10) Living in Rented Dwellings, 11) Mother's Multivitamin with Folic Acid Intake, 12) Mother's Alcohol Use Status, 13) Mother's Diabetes Status, 14) Mother's Drug Use Status, 15) Mother's Hypertension Status, 16) Mother's Mental Health Status, 17) Mother's Pregnancy History, 18) Mother's Smoking Status, 19) Not Speaking English or French, 20) Number of Prenatal Visits During Pregnancy, 21) Phototherapy at Birth, 22) Preterm Pregnancy, 23) Socioeconomic/Subsidy Status (Child), 24) Years Child had Asthma, 25) Years Child had COPD, 26) Years Child had Human Service Drug Benefit Plan Enrollment, 27) Years Child had Mental Health Diagnosis, 28) Years Child was a High Health System User.

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2. Early detection of ADHD using the Early Development Instrument

Tables

Table 1. ADHD case definition.

Rule	ICD-9	ICD-10	Drug Code	
>=1 inpatient visits (1st diagnostic position)	314,	F90,	Stimulants:	
OR	314.0,	F90.0,	methylphenidate	N06BA04
>=2 outpatient visits (1st diagnostic position)	314.00,	F90.1,	dexamphetamine	N06BA02
OR	314.01,	F90.2,	amphetamines	N06BA01
>=1 outpatient visits in a psychiatric or MH	314.01.a,	F90.8,		
facility	314.01.b	F90x.9	Non-stimulants:	
OR			guanfacine	C02AC02
>=2 physician claims (1st diagnostic position)			atomoxetine	N06BA09
OR			clonidine	C02AC01
Use ADHD medication 2 times a year				

Note: Case definition was applied to Alberta residents (as at fiscal year end), individuals were flagged with ADHD/no-ADHD within each year.

Table 2. Model cross-validation performance.

	Logistic	Lasso	Ridge	Gradient Boosting	Random Forest	Baseline (Admin data only)	Baseline (EDI only)
AUC	0.811	0.801	0.806	0.811	0.803	0.711	0.796
Lower Bound	0.810	0.800	0.806	0.810	0.800	0.709	0.796
Upper bound	0.812	0.801	0.807	0.814	0.805	0.712	0.797

Note: AUC stands for the area under receiver operating characteristic curve. EDI stands for Early Development Instrument.

3. Six-year longitudinal patterns of mental health service utilization rates among children developmentally vulnerable in kindergarten and the COVID-19 pandemic disruption

Tables

Table 1. List of ICD 9 and 10 codes for mental health conditions.

Disease	ICD-9 (used for physicians' office visits)	ICD-10 (used for emergency visits and hospitalizations)
All mental health	'290','291','292','293','294','295','296','297','298','299','300','301','302','303','304','305','306','307','308','309','310','311','312','313','314','315','316','317','318','319', '331','341'	'F','G30','X60','X61','X62','X63','X64','X65','X66','X67','X68','X69','X70','X71','X72','X73','X74','X75','X76','X77','X78','X79','X80','X81','X82','X83','X84','Y87','T51','G210','G211', 'G240', 'G251', 'G259', 'T740', 'T741', 'T742', 'T509', 'Y870', 'Z004', 'Z046'
Anxiety	'300','308','300.1','300.4','300.5','300.6','300.7','300.8','300.9'	'F40','F41','F42','F43','F93'
Mood disorders	'296','311','300.4'	'F30','F31','F32','F33','F34','F38','F39'
ADHD	'314'	'F90'

Table 2. Results of linear regression models for domain-specific analysis of all utilization.

		Office visits		Emergency department visits		Hospitalizations	
Domain	**Variable**	**Beta**	**P-value**	**Beta**	**P-value**	**Beta**	**P-value**
General knowledge (CG)	Vulnerability	762.6	0.004	not significant		not significant	
Emotional maturity (EM)	Vulnerability	676.7	0.006	129.8	0.009	6.2	0.040
Language and cognitive development (LC)	Vulnerability	780.5	0.004	93.8	0.040	10.8	0.040
Physical health and well-being (PH)	Vulnerability	751.6	0.004	122.4	0.015	12.9	0.021
Social competence (SOC)	Vulnerability	794.1	0.004	117.1	0.018	7.6	0.040

Note: the variable Sex and the interaction term Vulnerability*Sex was not significant in any domain.

Table 3. Results of linear regression models for domain-specific analysis of mental health-related utilization.

		Office visits		Emergency department visits		Hospitalizations	
Domain	**Variable**	**Beta**	**P-value**	**Beta**	**P-value**	**Beta**	**P-value**
General knowledge (CG)	Vulnerability	306.2	0.002	-	-	not significant	
	Vulnerability*Sex	not significant		4.1	0.020	not significant	
Emotional maturity (EM)	Vulnerability*Sex	196.4	0.012	not significant		not significant	
Language and cognitive development (LC)	Vulnerability	373.6	0.002	3.6	0.046	2.6	0.046

Physical health and well-being (PH)	Vulnerability	427.9	0.002	not significant		not significant	
	Sex	194.1	0.002	not significant		not significant	
Social competence (SOC)	Vulnerability	-	-	-	-	2.7	0.020
	Vulnerability*Sex	191.6	0.005	8.4	0.002	not significant	

Note: Non-significant variables are omitted in this table.

Table 4. Results of linear regression models for domain-specific analysis of specific mental health disorders.

		Mood disorder		Anxiety		ADHD	
Domain	**Variable**	**Beta**	**P-value**	**Beta**	**P-value**	**Beta**	**P-value**
General knowledge (CG)	Vulnerability	not significant		not significant		152.8	0.002
	Sex (M)	not significant		not significant		193.9	0.002
Emotional maturity (EM)	Vulnerability*Sex	not significant		not significant		158.5	0.024
Language and cognitive development (LC)	Vulnerability	not significant		not significant		160.6	0.005
	Sex (M)	not significant		not significant		188.1	0.002
Physical health and well-being (PH)	Vulnerability	not significant		42.2	0.040	202	0.002
	Sex	not significant		not significant		173.9	0.002
Social competence (SOC)	Vulnerability*Sex	not significant		not significant		138.1	0.027

Note: Non-significant variables are omitted in this table.

Figures

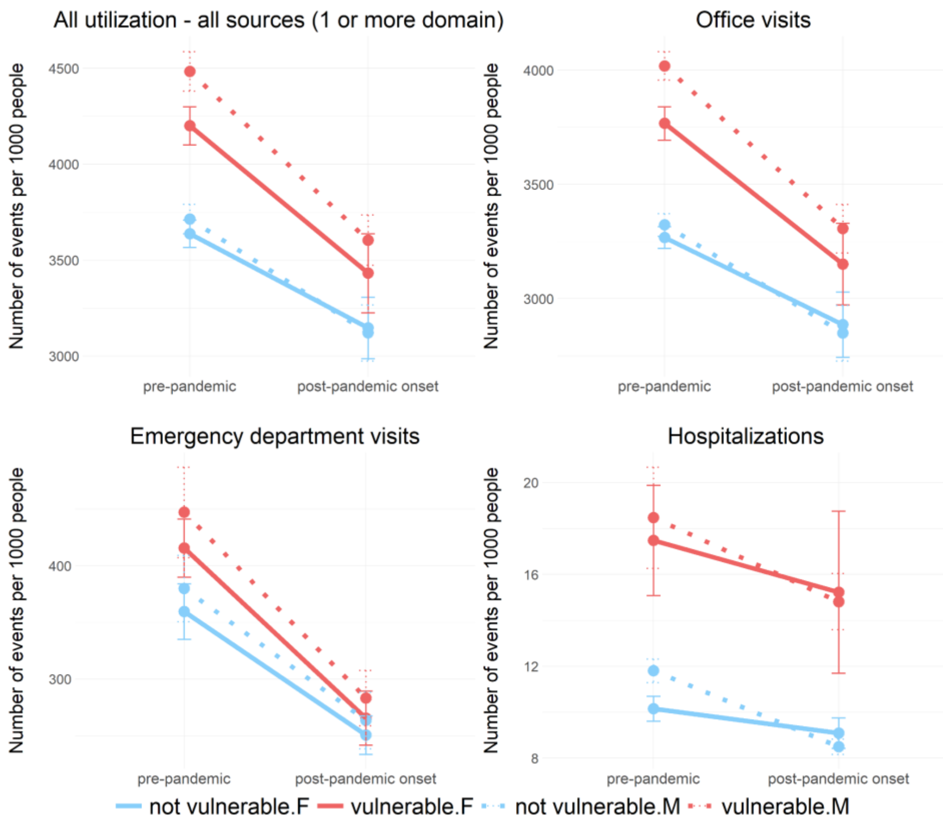


Figure 1. Comparison of health services utilization between the pre (2016-2019) and post (2020-2022) pandemic onset periods. The error bar indicates standard error.

Note: M = male, F = female.

4. Impact of the COVID-19 pandemic on youth's mental health-related utilization

Tables

Table 1. List of International Classification of Mental and Behavioral Disorders 9 and 10 codes for mental health conditions.

Disease	ICD-9 (used for physician's office visits)	ICD-10 (used for emergency visits and hospitalizations)
Anxiety	'300','308','300.1','300.5','300.6','300.7','300.8','300.9'	'F40','F41','F42','F43','F93'
Mood disorders	'296','311','300.4'	'F30','F31','F32','F33','F34','F38','F39'
Depression	'311','296.2','296.3','296.5','300.4'	'F32','F33','F341','F381'
Bipolar disorder	'296.0','296.1','296.4','296.5','296.6','296.7','296.8','296.9'	'F30','F31','F340'
Psychotic disorder	'295','297','298'	'F20','F22','F23','F24','F25','F28','F29'
Substance use	'291','292','303','304','305'	'F10','F11','F12','F13','F14','F15','F16','F17',’F18','F19','F55'
Alcohol dependence and abuse	'303','305.0'	'F102','F103','F106','F107','F108','F109','F100','F101'
Cannabis dependence and abuse	'304.3','305.2'	'F122','F123','F126','F127','F128','F129','F120','F121'
Opioid dependence and abuse	'304.7','305.5'	'F112','F113','F116','F117','F118','F119','F110','F111'
Self-harm	'950','951','952','953','954','956','957','959','958.0','958.1','958.2','958.3','958.4','958.5','958.6','958.7','958.8','958.9'	'X60','X61','X62','X63','X64','X65','X66','X67','X68','X69','X70','X71','X72','X73','X74','X75','X76','X77','X78','X79','X80','X81','X82','X83','X84','Y870'
ADHD	'314'	‘F90'
Eating disorders	'307.1','307.5'	'F50','F982','F983'
OCD	'300.3'	‘F42’

Table 2. Sample size and counts of children, adolescents, and young adults who utilized the health system in Alberta from 2016 to 2021 .

			Physician's office visits		Emergency visits		Hospitalizations	
Age group	**Year**	**Population size**	**MH-related**	**non-MH- related**	**MH-related**	**non-MH- related**	**MH-related**	**non-MH- related**
6-11 Children	2016	318038	27695	261648	1203	77363	433	3760
	2017	324806	30538	268430	1336	78821	445	3716
	2018	330807	33080	272632	1394	76397	414	3689
	2019	334332	36662	279137	1494	78504	374	3664
	2020	335820	35457	248364	1070	56054	317	3051
	2021	335338	39611	252759	1232	56366	282	2909
12-17 Adolescents	2016	292008	35248	232597	6893	77184	2168	6394
	2017	294781	38730	236338	7652	77569	2282	6327
	2018	299226	41257	239020	7369	74552	2157	6079
	2019	306567	45515	248424	7367	77923	2106	6185
	2020	315956	48190	234456	6574	59486	2058	5563
	2021	322828	58912	249977	8215	68020	2442	6166
18-34 Young adults	2016	1071700	187879	791268	28045	272582	8134	65697
	2017	1061319	202002	782820	28844	264852	8359	63587
	2018	1057475	209037	775114	28867	259599	8674	61688
	2019	1055444	214030	772791	28967	257894	8578	60224
	2020	1050742	218934	718693	26693	221467	8710	56506
	2021	1031620	235934	716442	27652	228466	9084	56873

Figures

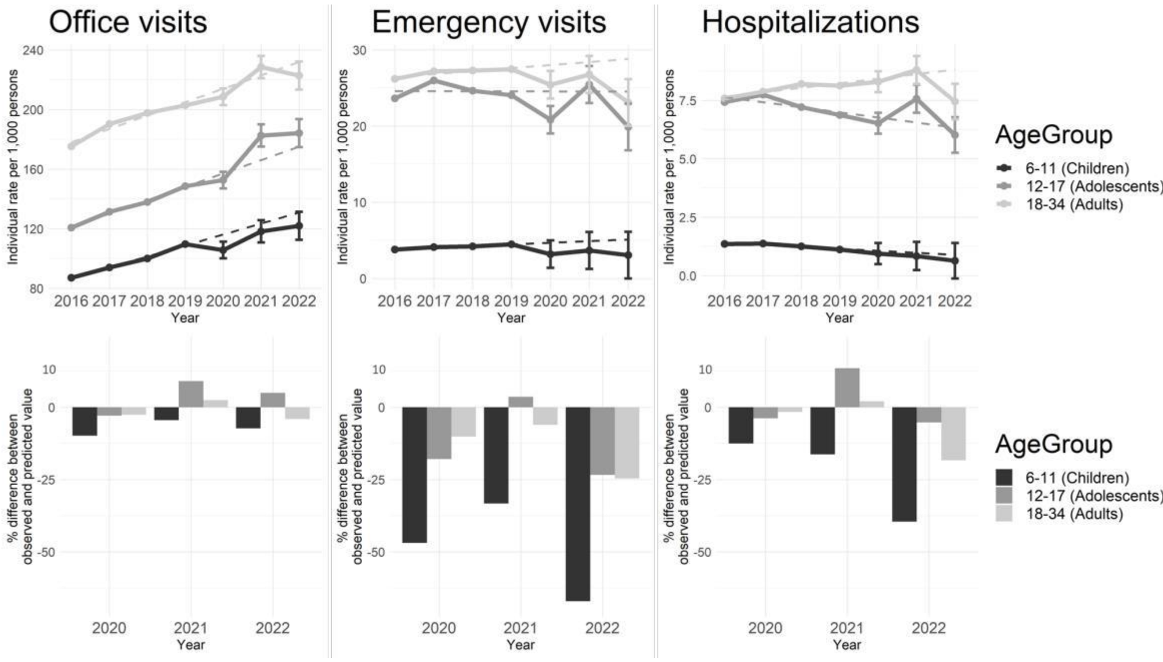
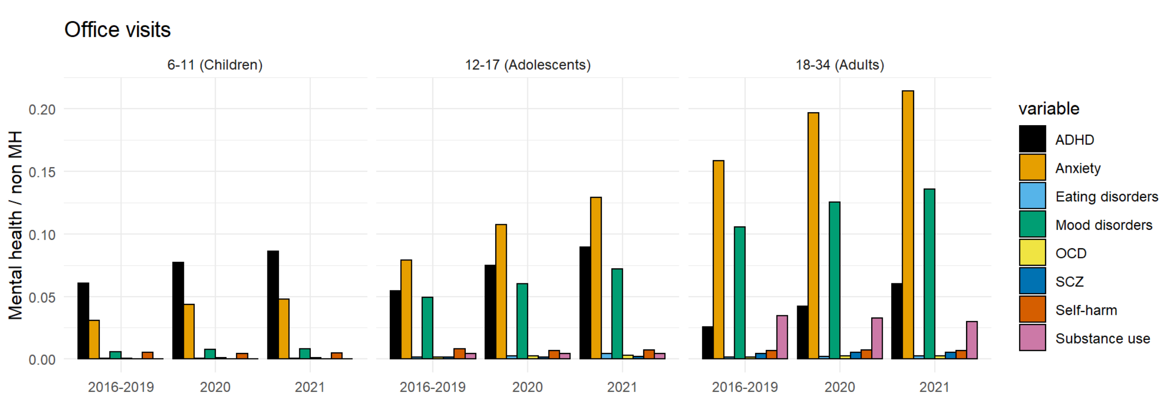


Figure 1. Observed and predicted values of the percentage of mental health service utilization corrected by population size and growth by age groups (children, adolescents, and young adults) between 2016 and 2021.

Note: top: Dashed lines represent the fitted linear regression model for the years 2016 to 2019 and the predicted percentage of mental health service utilization for 2020 and 2021 based on that model; the solid lines represent the observed values; error bar represents the 95% confidence interval; bottom: Percentage difference between the actual value and the predicted value# for the percentage of mental health service utilization in the post-pandemic period. #predicted value derived by linear regression for the years 2016-2019.



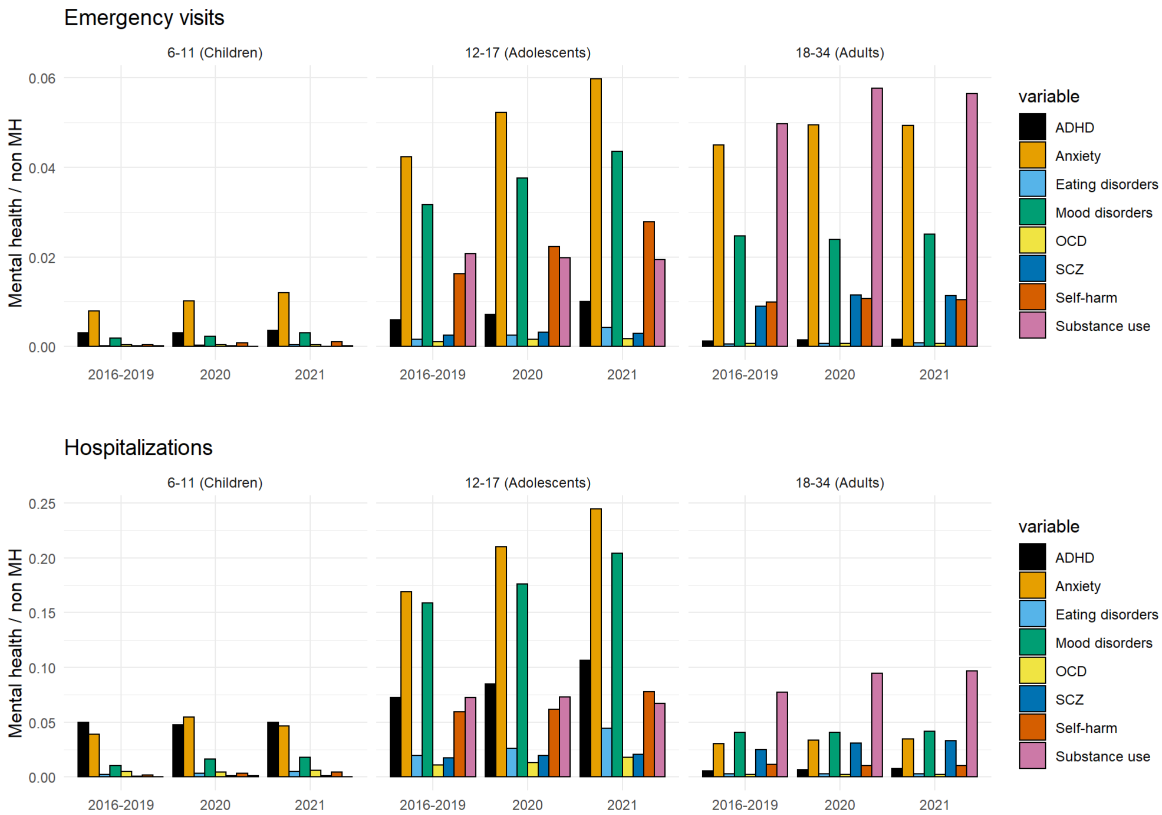
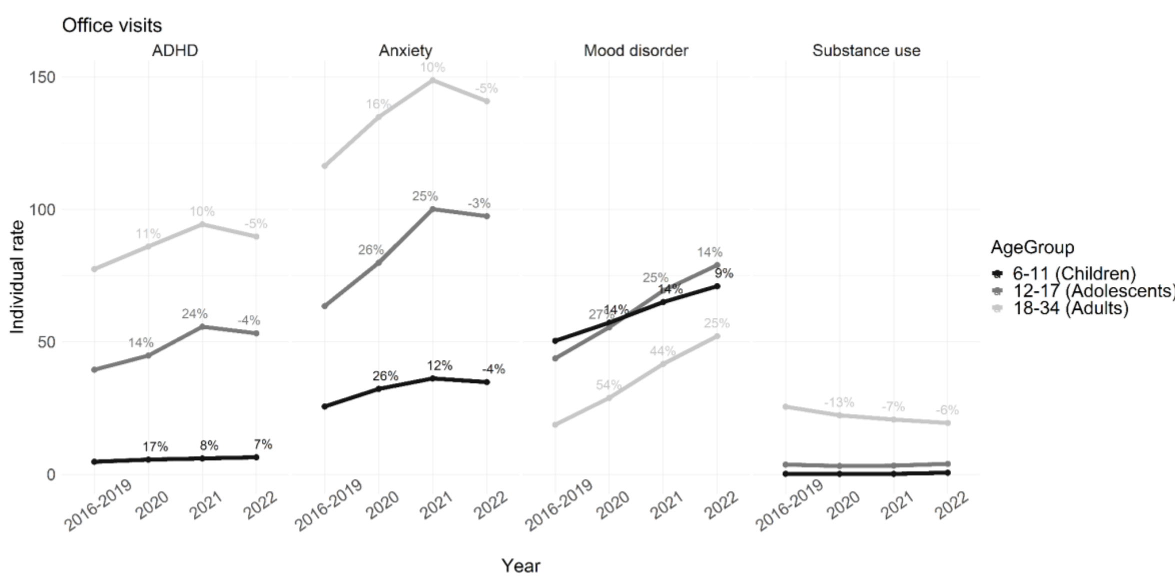


Figure 2. The proportion of specific mental health-related service utilization by age groups (children, adolescents, and young adults). The 2016-2019 values represent the mean value between 2016 and 2019.



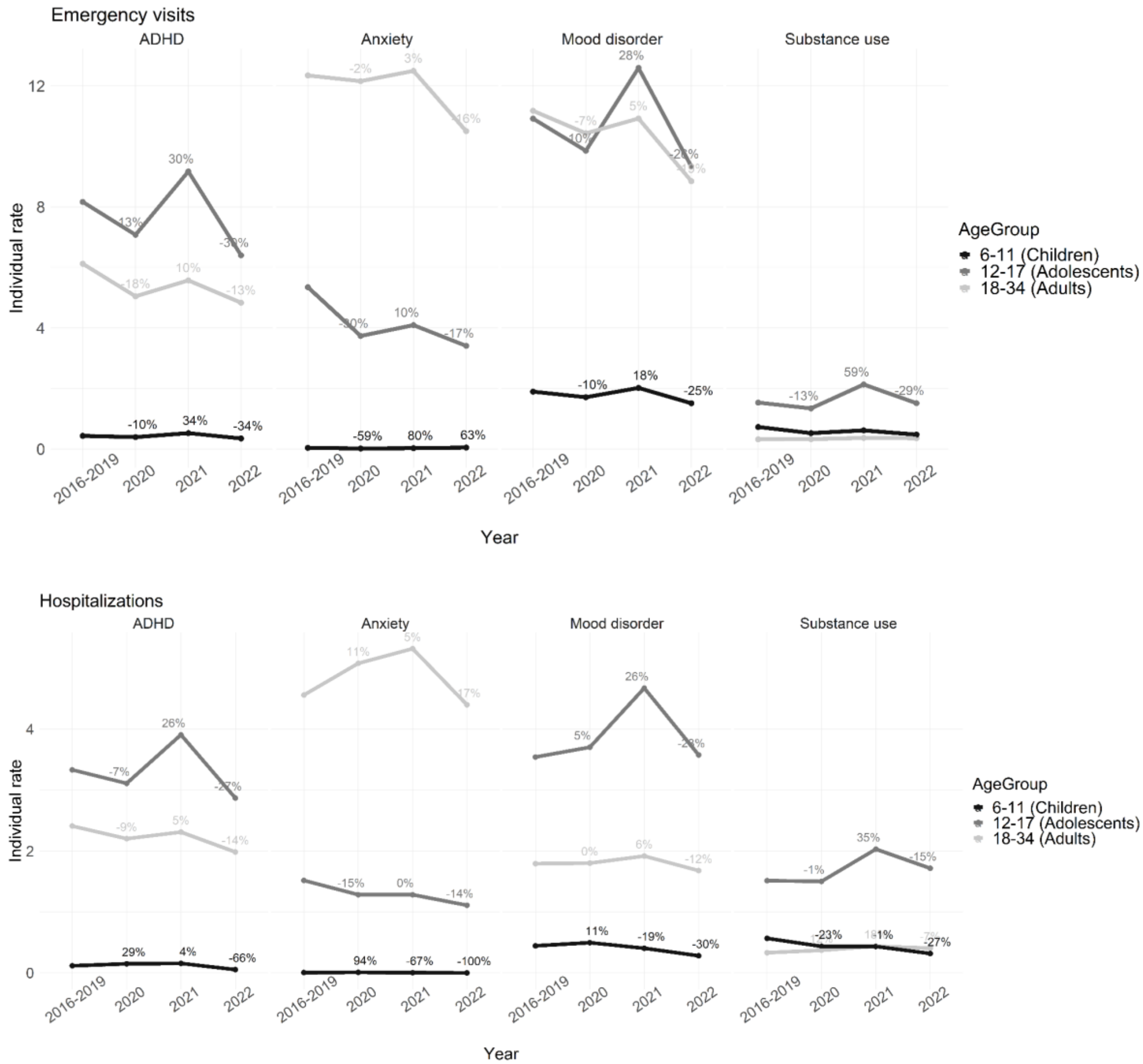


Figure 3. The percentage of children, adolescents and young adults with mental health utilization corrected by population size for specific mental health conditions. The 2016-2019 values represent the mean value between 2016 and 2019.

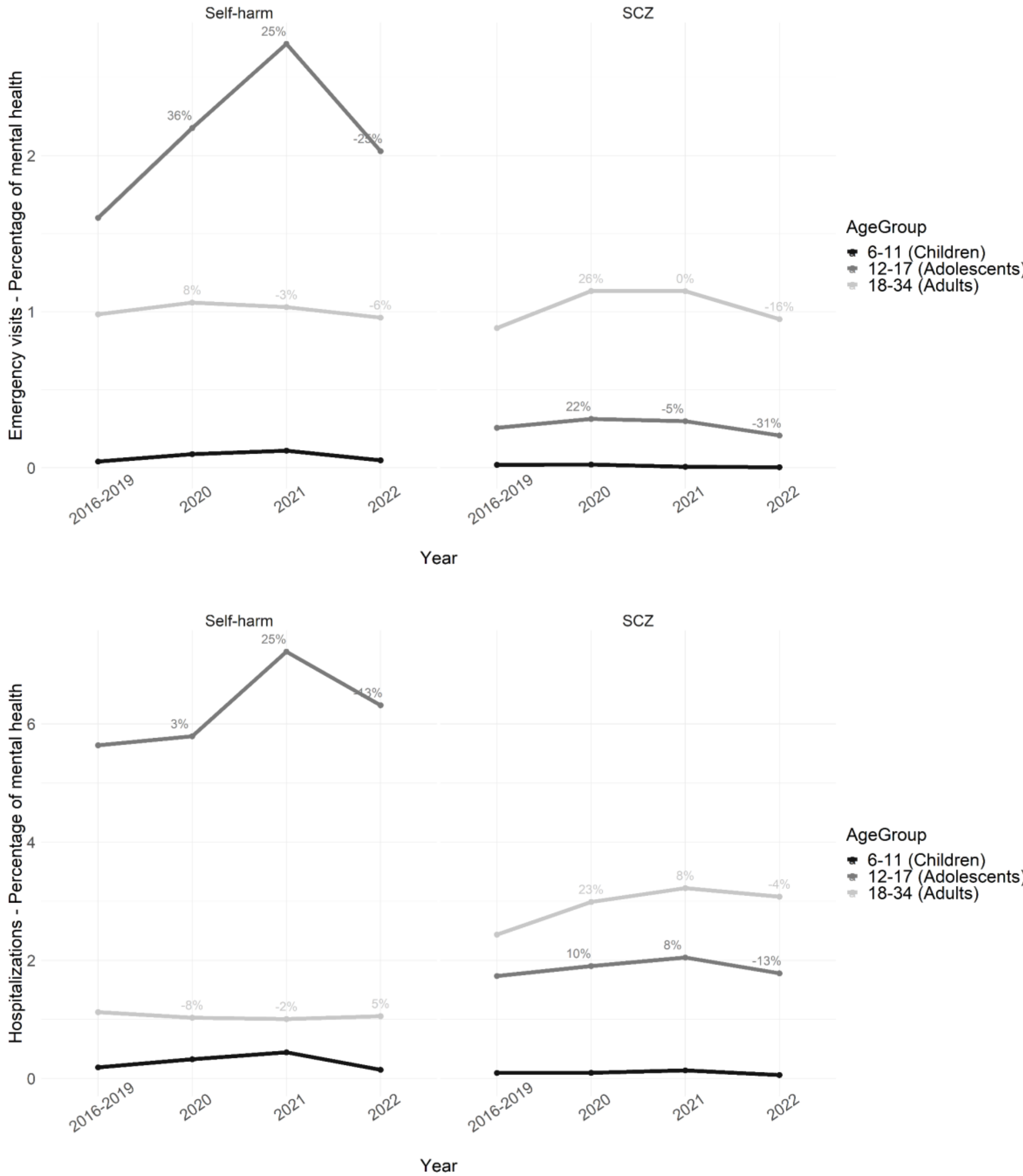


Figure 4. The percentage of children, adolescents and young adults with mental health service utilization corrected by population size for self-harm and schizophrenia (SCZ). The 2016-2019 values represent the mean value between 2016 and 2019.

5. Seasonal and pandemic-related patterns in mental health-related utilization

Tables

Table 1. List of mental health-related ICD-9 and ICD-10 codes.

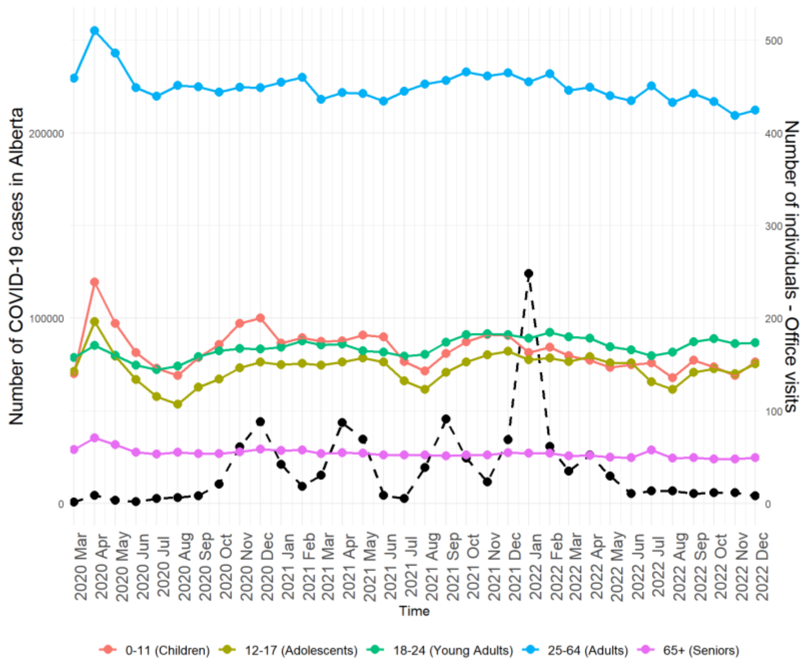
Disease	ICD-9 (used for physician's office visits)	ICD-10 (used for emergency visits and hospitalizations)
Neurocognitive disorders (Alzheimer, Dementia, Delirium, Organic Alzheimer, Organic)	290, 290.1, 290.11, 290.12, 290.13, 290.2, 290.21, 290.3, 290.4, 290.41, 290.42, 290.43, 290.8, 290.9, 293, 293.1, 293.8, 293.89, 293.9, 294, 294.1, 294.11, 294.8, 294.9, 331, 331.1, 331.2, 331.3, 331.4, 331.7, 331.8, 331.9, 341	F00, F000, F001, F002, F009, F01, F010, F011, F012, F013, F018, F019, F02, F020, F021, F022, F023, F024, F028, F03, F04, F05, F050, F051, F058, F059, F06, F060, F061, F062, F063, F064, F065, F066, F067, F068, F069, F07, F070, F071, F072, F078, F079, F09, G30, G300, G301, G308, G3080, G3081, G3082, G3088, G309
Substance use disorders (Alcohol psychosis, dependence, and abuse; Drug psychoses, dependence, and abuse; Opioid dependence and abuse; Cannabis dependence and abuse; Other)	291, 291.1, 291.2, 291.3, 291.4, 291.5, 291.8, 291.81, 291.89, 291.9, 292, 292.1, 292.11, 292.12, 292.2, 292.8, 292.81, 292.82, 292.83, 292.84, 292.89, 292.9, 303, 303.74, 303.9, 303.91, 303.93, 304, 304.01, 304.03, 304.1, 304.11, 304.13, 304.2, 304.21, 304.23, 304.3, 304.31, 304.33, 304.4, 304.41, 304.5, 304.6, 304.61, 304.7, 304.71, 304.73, 304.8, 304.81, 304.83, 304.9, 304.91, 304.93, 305, 305.01, 305.03, 305.1, 305.2, 305.21, 305.23, 305.3, 305.31, 305.33, 305.4, 305.43, 305.5, 305.51, 305.53, 305.6, 305.61, 305.63, 305.7, 305.71, 305.73, 305.8, 305.9, 305.91, 305.93	F10, F100, F101, F102, F103, F104, F105, F106, F107, F108, F109, F11, F110, F111, F112, F113, F114, F115, F116, F117, F118, F119, F12, F120, F121, F122, F123, F124, F125, F126, F127, F128, F129, F13, F130, F131, F132, F133, F134, F135, F136, F137, F138, F139, F14, F140, F141, F142, F143, F144, F145, F146, F147, F148, F149, F15, F150, F151, F152, F153, F154, F155, F156, F157, F158, F159, F16, F160, F161, F162, F163, F164, F165, F166, F167, F168, F169, F17, F170, F171, F172, F173, F174, F175, F176, F177, F178, F179, F18, F180, F181, F182, F183, F184, F185, F186, F187, F188, F189, F19, F190, F191, F192, F193, F194, F195, F196, F197, F198, F199, F55

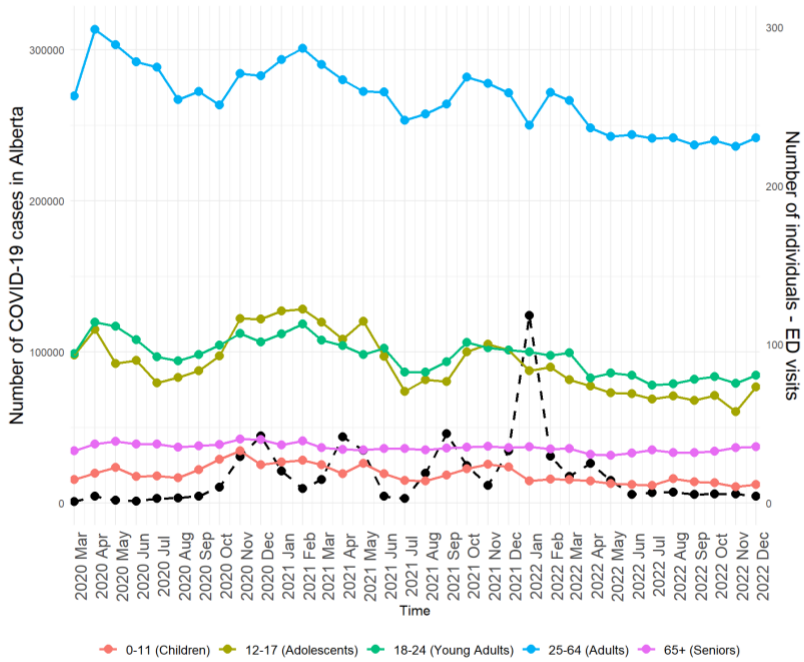
Psychotic disorders (Delusional, Psychoses, Schizophrenia)	295, 295.01, 295.02, 295.03, 295.04, 295.05, 295.1, 295.11, 295.12, 295.13, 295.14, 295.15, 295.2, 295.21, 295.22, 295.23, 295.24, 295.25, 295.3, 295.31, 295.32, 295.33, 295.34, 295.35, 295.4, 295.41, 295.42, 295.43, 295.44, 295.45, 295.5, 295.51, 295.52, 295.53, 295.54, 295.55, 295.6, 295.61, 295.62, 295.63, 295.64, 295.65, 295.7, 295.71, 295.72, 295.73, 295.74, 295.75, 295.8, 295.81, 295.82, 295.83, 295.84, 295.85, 295.9, 295.91, 295.92, 295.93, 295.94, 295.95, 297, 297.1, 297.2, 297.3, 297.8, 297.9, 298, 298.1, 298.2, 298.3, 298.4, 298.8, 298.9	F20, F200, F201, F202, F203, F204, F205, F206, F208, F209, F21, F22, F220, F228, F229, F23, F230, F231, F232, F233, F238, F239, F24, F25, F250, F251, F252, F258, F259, F28, F29
Mood disorders (Bipolar, Depression, Bipolar depression, Other)	296, 296.01, 296.02, 296.03, 296.04, 296.05, 296.06, 296.1, 296.11, 296.12, 296.13, 296.14, 296.15, 296.16, 296.2, 296.21, 296.22, 296.23, 296.24, 296.25, 296.26, 296.3, 296.31, 296.32, 296.33, 296.34, 296.35, 296.36, 296.4, 296.41, 296.42, 296.43, 296.44, 296.45, 296.46, 296.5, 296.51, 296.52, 296.53, 296.54, 296.55, 296.56, 296.6, 296.61, 296.62, 296.63, 296.64, 296.65, 296.66, 296.7, 296.76, 296.8, 296.81, 296.82, 296.89, 296.9, 296.99, 300.4	F30, F300, F301, F302, F308, F309, F31, F310, F311, F312, F313, F314, F315, F316, F317, F318, F319, F32, F320, F321, F322, F323, F328, F329, F33, F330, F331, F332, F333, F334, F338, F339, F34, F340, F341, F348, F349, F38, F380, F381, F388, F39
Anxiety disorders (Anxiety disorder, OCD, Panic disorder, Phobias, Stressors and Trauma, PTSD, Other)	300, 300.01, 300.02, 300.09, 300.2, 300.21, 300.22, 300.23, 300.29, 300.3, 308, 308.1, 308.2, 308.3, 308.4, 308.9	F40, F400, F401, F402, F408, F409, F41, F410, F411, F412, F413, F418, F419, F42, F43, F430, F431, F438, F439, F930, F931, F932

Developmental disorders (ADHD, Autism, Communication disorder, Conduct disorder, Coordination disorder, Intellectual disability, Specific learning disorder, Tics, Other)	299, 299.01, 299.1, 299.11, 299.8, 299.81, 299.9, 299.91, 307, 307.2, 307.21, 307.22, 307.23, 307.3, 307.9, 311, 312, 312.1, 312.2, 312.8, 312.81, 312.82, 312.89, 312.9, 313, 313.1, 313.2, 313.23, 313.3, 313.8, 313.81, 313.89, 313.9, 314, 314.01, 314.1, 314.2, 314.8, 314.9, 315, 315.1, 315.2, 315.3, 315.31, 315.32, 315.39, 315.4, 315.5, 315.8, 315.81, 315.9, 317, 318, 318.1, 318.2, 319	F70, F700, F701, F708, F709, F71, F710, F711, F718, F719, F72, F720, F721, F728, F729, F73, F730, F731, F738, F739, F78, F780, F781, F788, F789, F79, F790, F791, F798, F799, F80, F800, F801, F802, F803, F808, F809, F81, F810, F811, F812, F813, F818, F8181, F819, F82, F83, F84, F840, F841, F842, F843, F844, F845, F848, F849, F88, F89, F90, F900, F901, F908, F909, F91, F910, F911, F912, F913, F918, F919, F92, F920, F928, F929, F94, F940, F948, F949, F95, F950, F951, F952, F958, F959, F98, F984, F985, F986, F988, F989
Somatoform disorders	300.7, 300.8, 300.81, 300.82, 307.8, 307.81, 307.89	F444, F445, F446, F447, F448, F449, F45, F450, F451, F452, F453, F454, F458, F459
Personality disorders	301, 301.1, 301.2, 301.22, 301.3, 301.4, 301.5, 301.51, 301.6, 301.7, 301.8, 301.81, 301.82, 301.83, 301.84, 301.89, 301.9	F60, F600, F601, F602, F603, F604, F605, F606, F607, F608, F609, F61, F62, F620, F621, F628, F629, F68, F680, F681, F688, F69
Eating disorders (Anorexia, Bulimia, Other)	307.1, 307.5, 307.51, 307.52, 307.53, 307.59	F50, F500, F501, F502, F503, F504, F505, F508, F509, F982, F983
Sleep disorders	307.4, 307.42, 307.44, 307.45, 307.46, 307.47	F51, F510, F511, F512, F513, F514, F515, F518, F519
Self-harm	-	X60, X61, X62, X63, X64, X65, X66, X67, X68, X69, X70, X71, X72, X73, X74, X7400, X7401, X7408, X7409, X75, X76, X77, X78, X79, X80, X81, X82, X83, X84, Y870
Other mental health conditions	300.1, 300.11, 300.12, 300.13, 300.14, 300.15, 300.16, 300.19, 300.5, 300.6, 300.9, 302, 302.1, 302.2, 302.3, 302.4, 302.5, 302.6, 302.7, 302.71, 302.72, 302.73, 302.74, 302.75, 302.76, 302.79, 302.8, 302.81, 302.82, 302.83, 302.84, 302.85, 302.89, 302.9, 306, 306.1, 306.2,306.3, 306.4, 306.5, 306.51, 306.6, 306.7, 306.8, 306.9,	F432, F44, F440, F441, F442, F443, F48, F480, F481, F488, F489, F52, F520, F521, F522, F523, F524, F525, F526, F527, F528, F529, F53, F530, F531, F538, F539, F54, F59, F63, F630, F631, F632, F633, F638, F639, F64, F640, F641, F642, F648, F649, F65, F650, F651, F652, F653, F654, F655, F656, F658, F659, F66,

307.6, 307.7, 309, 309.1, 309.2, 309.21, 309.3, 309.4, 309.8, 309.9, 310, 310.1, 310.2, 310.8, 310.9, 316	F660, F661, F662, F668, F669, F93, F933, F938, F939, F980, F981, F99

Figures





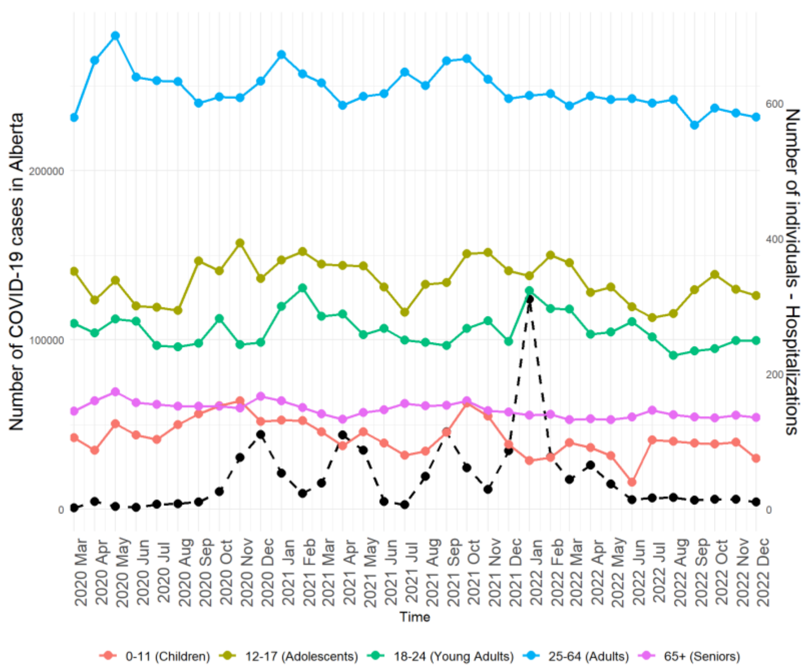


Figure 1. COVID-19 cases in Alberta (Mar 2020-Dec 2022; black dashed line) versus age-grouped mental health-related office visits (A), emergency visits (B), and hospitalizations (C), scaled to monthly active insurance holders (red line).