Artificial Intelligence Interventions in The Mental Healthcare of Adolescents

Pooria Ghadiri

Department of Family Medicine
McGill University, Montreal

October 2022

A thesis submitted to McGill University in partial fulfillment of the requirements of the degree of Master of Science

Copyright © Pooria Ghadiri, 2022

TABLE OF CONTENTS

ACKNOWLEDGEMENT

First and foremost, I want to express my deepest gratitude to my supervisors, Drs. Samira Abbasgholizadeh Rahimi and Mark J. Yaffe. They have provided me with outstanding supervision and assistance these past three years. I thank you immensely for sharing your wealth of knowledge, dedication, effort, time, and superb guidance and feedback, and I sincerely hope that I have made you proud with this work.

I am really grateful to Dr. Alayne Mary Adams for being a member of my thesis committee and for her insight and advice, particularly concerning the qualitative study's methodological aspect. I would like to thank Dr. Perry Samuel John Adler for serving as a collaborator in the qualitative study, particularly for assisting me with participant recruitment, and Dr. Pierre-Paul Tellier, who gave me input on the qualitative study design.

I am deeply grateful to my wife, Nazila, who has stood by me from day one. Thank you for your unwavering love and support not only during the completion of this project but throughout my academic, professional, and personal endeavours. Words on a page will never capture or express my true feelings. You are indeed an inspiration and my love of a lifetime. I love you! And my deepest gratitude to my lovely parents, Farideh and Hossein, my sister, Parnian, and in-laws, who have continually provided me with moral, personal, and emotional support, as well as to my family, Soodabeh Joolaee, and best friends, Abbas Mohammadi and Alireza Setarehaseman, for all the support you have given me during my three-year program.

I would also like to thank the Jewish General Hospital Foundation and Goldman-Herzl Family Practice Centre for providing one-time financial support for my work.

I would like to extend my appreciation to all those involved with the Scoping review study. Thank you, Geneviève Gore, for your help with developing the search strategy, Gauri Sharma and

Laura Pinkham for your tireless work and dedication as a second reviewer. I would also like to thank the administration and staff at the Department of Family Medicine, Sherrie Child, and Dr. Isabelle Vedel who went above and beyond their roles with helping me comprehend the logistics of completing the master’s program.

I would want to convey my joy and pleasure at being able to articulate and submit my thesis in a family medicine context. I am honoured to have a small but significant role in contributing to the vast universe of information, innovation, and education in Family Medicine.

DEDICATION

This thesis is dedicated to the memory of Dr. Siavash Jafari, MD, MSc, FRCPC, whose support, dedication to academic excellence, and perseverance inspired me throughout my personal and academic life. You are always alive, and your belief in me has made the impossible well possible. I love you and will miss you with all the pieces of my soul. "There are no goodbyes for us. Wherever you are, you will always be in my heart." —Mahatma Gandhi

CONTRIBUTION OF AUTHORS

As the MSc candidate, I wrote the first draft of all sections of this thesis under the supervision of Drs. Samira Abbasgholizadeh Rahimi (SAR) and Mark J. Yaffe (MJY).

I was the first author of the scoping review (manuscript 1) under the guidance of the supervisory team. I formulated the review question and eligibility criteria, identified and selected relevant studies from bibliographic databases (search strategy developed alongside specialized librarian, Genevieve Gore), appraised the quality of studies, extracted relevant data, analyzed and synthesized the data from the included studies, and wrote the manuscript. Drs. SAR and MJY assisted with formulating the review question, eligibility criteria, reviewing the selection of relevant studies— (I was the first reviewer and leader, and Laura Pinkham was the second reviewer who assisted in screening relevant citations, and Gauri Sharma in validating and extracting the AI-related data)—, appraisal of study quality, data analysis and interpretation of results, and the manuscript revisions and suggestions.

I was the lead author for the qualitative study (manuscript 2), while Drs. SAR and MJY contributed to the study's conception, planning, and design. Drs. MJY and Perry Samuel John Adler assisted me with finding the names and contact information of the potential participants. I analyzed the data and interpreted the results primarily with the assistance of Drs. SAR and MJY. Dr. Alayne Mary Adams (AMA) gave me some input on that. I prepared the first draft of the manuscript and Drs. MJY, SAR, and AMA revised the draft critically and provided editorial advice before approving the final draft.

LIST OF TABLES AND FIGURES

ABBREVIATIONS

AI: Artificial Intelligence

CBT: Cognitive Behavioral Therapy

FG: Focus Group

HCP: Healthcare professional

HCPs: Healthcare Professionals

ML: Machine Learning

NLP: Natural language Processing

PC: Primary Care

PCP: Primary Care Physician

PCPs: Primary care physicians

ABSTRACT

Background: Adolescence is a critical phase in a person's life since it might affect behaviors and conditions that impact physical and mental health and contribute to adulthood illnesses. Primary care physicians (PCPs) are increasingly acknowledged for their critical role in detecting and managing adolescents' mental health problems. PCPs however face several challenges when providing mental healthcare to this population. Artificial Intelligence (AI) interventions may provide some solutions if they are adapted for primary care use. Given the rise and importance of mental health problems among adolescents, it is critical to identify such interventions and assess PCPs potential interest in using them.

Objective: Two studies were conducted to respond to these objectives. The first sought to identify AI interventions tested and/or implemented in adolescents' mental healthcare. The second explored perceived challenges of primary care physicians in providing adolescents' mental healthcare, along with their perceived needs for AI interventions that would be helpful in dealing with adolescents' mental health issues.

Methods: In the first study a systematic scoping review was conducted to identify AI interventions tested and/or implemented in adolescents' mental healthcare. Using the Levac et al. framework, we searched five electronic databases (MEDLINE, Embase, Web of Science Core Collection, Compendex, INSPEC) from inception date until February 2020. Two independent reviewers identified articles based on title and abstract, and full text. Inclusion criteria were patients aged 10 to 19 receiving mental healthcare from healthcare professionals (HCPs) and any HCP that provides for this demographic and listing of AI interventions that were tested and/or implemented. Outcomes were any related to patients, HCPs, or the healthcare system. Setting: any healthcare setting.

The second study was a qualitative descriptive, based on focus group (FG) discussion with a sample of PCPs in the Montreal, Canada. Through purposeful sampling, we recruited four PCPs with specific interest in adolescent mental healthcare and AI interventions. FG discussions were conducted and audio-visually recorded through Zoom software and lasted 1 ¼ hours. The discussion was transcribed verbatim, followed by thematic analysis using A-priori and inductive coding.

Results: ***Scoping review****:* 30 papers were retained for analysis from 1044 retrieved. AI interventions were most commonly reported for Autism Spectrum Disorder (n=3), Unspecified Outcomes of Psychological Stress/Pressure Level (n=3), Substance Use Disorder (n=2) and Dysfunctional Behavior (n=2). The application of AI within the continuum of mental healthcare for adolescents was used for the mediation of diagnostic processes (n=23), monitoring and evaluation (n=8), treatment (n=5), and prognosis (n=2). ***Focus Group study****:* PCPs saw AI interventions as potentially cost-effective, able to handle large amounts of data, and relatively credible. They envisioned AI to assist in collecting patients' data, suggesting a diagnosis, and establishing a treatment plan. However, they were concerned about these interventions' performances and outcomes and feared losing clinical competency. Participants highlighted systematic challenges PCPs face while giving care to adolescents, including parental involvement and psychosocial influences. PCPs desired interventions that were user-friendly.

Conclusion: To implement AI appropriately, greater participation and critical understanding of patients', physicians', and data scientists' opinions on AI use in clinical processes is required, resulting in a feedback loop of co-designing future AI initiatives. It is predominantly believed that the promise of AI in adolescents' mental health was considerable. These first stages and analyses provide the foundation for future work examining the practical usability, application, and effectiveness of these interventions in adolescents' mental healthcare.

RÉSUMÉ

Contexte : L'adolescence est une phase critique dans la vie d'une personne, car elle peut affecter les comportements et les conditions qui ont un impact sur la santé physique et mentale et qui contribuent aux maladies à l'âge adulte. Les problèmes de santé mentale des adolescents peuvent entraîner une déficience fonctionnelle, une susceptibilité à la stigmatisation, des préjugés, de la discrimination, un risque accru de mortalité précoce et des dépenses de santé plus élevées. Les médecins de soins primaires (MSPs) sont de plus en plus reconnus pour leur rôle essentiel dans la détection et la gestion des problèmes de santé mentale des adolescents. Les MSPs sont cependant confrontés à plusieurs défis lorsqu'ils fournissent des soins de santé mentale à cette population. Les interventions d'intelligence artificielle (IA) peuvent apporter des solutions si elles sont adaptées à une utilisation en soins primaires. Compte tenu de l'augmentation et de l'importance des problèmes de santé mentale chez les adolescents, il est essentiel d'identifier de telles interventions et d'évaluer l'intérêt potentiel des MSPs à les utiliser.

Objectif : Deux études ont été menées pour répondre à ces objectifs. La première visait à identifier les interventions d'IA testées et/ou mises en œuvre dans les soins de santé mentale des adolescents. La seconde a exploré les défis perçus des médecins de soins primaires dans la prestation de soins de santé mentale aux adolescents, ainsi que leurs besoins perçus en matière d'interventions d'IA qui seraient utiles pour traiter les problèmes de santé mentale des adolescents.

Méthodes : Dans la première étude, une revue systématique de la portée a été menée pour identifier les interventions d'IA testées et/ou mises en œuvre dans les soins de santé mentale des adolescents.

En utilisant le Levac et al. Cadre, nous avons effectué des recherches dans cinq bases de données électroniques (MEDLINE, Embase, Web of Science Core Collection, Compendex, INSPEC) de la date de début à février 2020. Deux examinateurs indépendants ont identifié des articles en fonction du titre et du résumé, et du texte intégral. Les critères d'inclusion étaient les patients âgés de 10 à 19 ans recevant des soins de santé mentale de la part de professionnels de la santé et tout professionnel de la santé qui fournit cette démographie et la liste des interventions d'IA qui ont été testées et/ou mises en œuvre. Les résultats étaient liés aux patients, aux professionnels de la santé ou au système de soins de santé. Milieu : tout milieu de soins de santé. Nous avons évalué le risque de biais pour les études de pronostic et de diagnostic à l'aide de l'intervention PROBAST (Prediction model Risk Of Bias Assessment Intervention).

La deuxième étude était une étude descriptive qualitative, basée sur une discussion de groupe avec un échantillon de médecins de soins primaires (abréviation) à Montréal, Canada. Grâce à un échantillonnage ciblé, nous avons recruté quatre médecins de soins primaires ayant un intérêt particulier pour les soins de santé mentale des adolescents et avec des technologies innovantes telles que l'IA. Les discussions du groupe de discussion ont été menées et enregistrées de manière audiovisuelle via le logiciel Zoom et ont duré 1 heure et quart. La discussion a été transcrite textuellement, suivie d'une analyse thématique avec une combinaison de codage A-priori et inductif.

Résultats : Revue de cadrage : 30 articles ont été retenus pour analyse sur 1044 extraits. Les interventions d'IA ont été le plus souvent signalées pour les troubles du spectre autistique (TSA) (n = 3), les résultats non spécifiés du niveau de stress/pression psychologique (n = 3), les troubles liés à l'utilisation de substances (n = 2) et les comportements dysfonctionnels (n = 2).

L'application de l'IA dans le continuum des soins de santé mentale pour les adolescents a été utilisée pour la médiation des processus de diagnostic (n = 23), le suivi et l'évaluation (n = 8), le traitement (n = 5) et le pronostic (n = 2). Étude de groupe de discussion : les MSPs considéraient les interventions d'IA comme potentiellement rentables (temps, argent et ressources), capables de traiter de grandes quantités de données et relativement crédibles. Ils ont envisagé l'IA pour aider à collecter les données des patients, suggérer un diagnostic et établir un plan de traitement. Cependant, ils étaient préoccupés par les performances et les résultats de ces interventions et craignaient de perdre leur compétence clinique. Les participants ont souligné les défis structurels et systématiques auxquels les MSPs sont confrontés lorsqu'ils prodiguent des soins aux adolescents, notamment l'implication des parents et les influences psychosociales telles que le sexe et le genre, la famille, la culture, les pairs et les habitudes. Les MSPs souhaitaient des interventions conviviales (simples à utiliser, facilement opérationnelles, transparentes et soutenues par un support technique « juste à temps »).

Ils étaient disposés à aider à concevoir et à développer des interventions d'IA si cela relevait de leur champ de pratique, et ils étaient rémunérés par des incitations externes (crédits d'études de développement financier ou professionnel). Ils ont également souligné la nécessité pour les organismes de réglementation de traiter les aspects médico-légaux et éthiques des interventions d'IA (par exemple, la confidentialité et la responsabilité des données) pour la création de lignes directrices/cadres clairs pour réduire/éliminer les préjudices (le cas échéant) pour les patients résultant de l'utilisation de telles interventions.

Conclusion : Cette recherche fournit des informations pertinentes sur : (1) l'étendue et la variété des interventions d'IA testées et/ou mises en œuvre dans les soins de santé mentale des adolescents. Nous avons examiné de manière critique ces interventions et découvert des incohérences dans les rapports sur les participants, les formes de techniques d'IA, les analyses et les résultats, ainsi qu'une lacune importante dans le développement et la mise en œuvre réussis des soins de santé mentale des adolescents IA. (2) Besoins et défis perçus par les MSPs dans les soins de santé mentale des adolescents utilisant l'IA.

Pour intégrer et mettre en œuvre l'IA de manière appropriée, une plus grande participation et une compréhension critique des opinions des parties prenantes (patients, médecins et scientifiques des données) sur l'utilisation de l'IA dans les processus cliniques sont nécessaires. Cela se traduit par une boucle de rétroaction de co-conception de futures initiatives d'IA dans les soins de santé mentale des adolescents.

En combinant les deux études, on pense principalement que la promesse de l'IA dans la santé mentale des adolescents était considérable. Ces premières étapes et analyses fournissent la base de travaux futurs examinant la facilité d'utilisation pratique, l'application et l'efficacité de ces interventions dans la prise en charge des problèmes de santé mentale des adolescents et aident également les futurs chercheurs dans ce domaine à savoir quels sont les besoins et où investir.

CHAPTER 1 - BACKGROUND

1.1 Importance of adolescence in the human life span

The World Health Organization defines adolescence as a period of the life span that addresses individuals between ages of 10 and 19 (1). It is a period of dramatic psychological and social transition that occurs concurrently with puberty's hormonal and biological changes (2). It is a time when one is more vulnerable to mental health issues, with 75 percent of adults who have ever had a mental health problem reporting that symptoms initially appeared within adolescence (2, 3). It is associated with rapid physical growth, learning, adaptability, psychosocial, emotional, and formational neurobiological development (4). The brain's architecture, functions, and connectivity unique to this phase of life allow for a high level of developmental flexibility, making adolescents vulnerable to change (5). Such normal processes are necessary for the brain to prepare for the demands and difficulties of adolescence and adulthood, but they may also increase sensitivity to risk behavior and psychopathology (5). Adolescents' lives might take dramatic turns for worse or better in this period of fast development (6). As a crucial transitional period between childhood and adulthood, adolescence offers a unique chance for growth and transformation (7)); yet adolescents who do not get adequate mental health support are at a higher risk of developing mental health problems (1).

1.2 Mental health and its importance

The World Health Organization (WHO), views mental health as "a state of well-being in which the individual realizes his or her abilities, can cope with the normal stresses of life, can work productively and fruitfully, and can make a contribution to his or her community"(8). In the WHO model there are two essential components, positive emotions and positive functioning (9). Keyes (2014) has classified mental health into three categories: emotional, psychological, and social well-being (9). Emotional well-being is defined as the ability to generate pleasant emotions, moods, thoughts, and sentiments, and adaptation in the face of adversity and challenging conditions (9, 10). Psychological well-being contributes to positive connections, personal mastery, autonomy, a sense of purpose and meaning in life, and personal growth and development (9, 10). Social well-being is defined as a feeling of belonging to a community and contributing to society while maintaining a sense of self-coherence (9, 10). Mind, organism, and environment are all intertwined, and one's total sense of being in the world is inextricably bound up with how one's body feels in connection to the rest of its surroundings (11). Under certain situations disruptions in these connections may result in psychotic experiences, eating disorders, self-harm, body dysmorphic disorder, and poor physical health (11).

Mental health issues may significantly impact on a person's capacity to function normally in many aspects of life, including school or job performance, personal connections with loved ones, and community engagement (12). The consequences of ignoring and treating mental problems reach well beyond the person affected by the condition. As a result, when community members' mental health needs are satisfied, communities have greater potential to thrive (13).

1.3 Manifestations of adolescents' mental health problems

Mental health problems among adolescents are on the rise, and represent significant causes of morbidity and mortality (14, 15). This is increasing demand for mental health services (from 11.7% in 2011 to 17.0% in 2018 in Canada), along with an increase in the incidence of mental health consultations (same period) (16). However, there are inadequate services for these young people (17, 18). Around 20% of the world's children and adolescents have a mental health problem, with suicide being the second most significant cause of mortality among those aged 15 to 19 (19). In 2016, an estimation of 13.6% of 15-to 19-year-olds worldwide engaged in excessive episodic drinking, with males being the most engaged (20).

Since 2010, comprehensive screening studies in the United States on adolescents' psychological well-being (21) and suicide trends (22) have shown reductions in reported levels of happiness, life satisfaction, along with rises in loneliness, anxiety, and depressive symptoms (23). Hospitalizations for self-harm behaviors, suicidal thoughts, and attempts by poisoning have increased during the past two decades, as have severe depressive episodes (23). Given their age at the beginning of such problems, the delays and lost possibilities for care are concerning. Therefore, a pervasive need exists for early intervention and proper care of adolescents' mental health problems (24, 25).

1.4 Sources of adolescents’ mental health care

The high prevalence of adolescents with poor mental health puts burdens on health care delivery at primary, secondary, and tertiary levels worldwide (26). The primary level refers to the work of healthcare professionals who serve as the initial point of contact for patients throughout the healthcare system (27, 28). Despite the importance of primary care in detecting and treating adolescents with mental health problems, few adolescents get it at least once a year (29). Further, most primary care physicians have limited training in recognizing or treating mental health problems in adolescents, while time restrictions for in-office visits limit their capacity to screen such patients for problems (30). Even though not all adolescents will need extra care, the limited identification of mental health problems may impede or delay receiving appropriate care for those who do (30).

Secondary care comprises acute care, specialists' necessary treatment for a critical disease , injury, or complex health condition (27). This type of service is frequently encountered in hospitals and/or emergency rooms. Between 2006–2007 and 2013–2014, adolescent emergency department visits and inpatient admissions for mental health problems rose 45% and 37%, respectively (29). Early referral is sometimes necessary to recognize and address their mental health problems to provide enough treatment and management to avoid a negative spiral of problems that may be more difficult to address in adulthood (31, 32). However, given that not all adolescents with mental health problems require secondary care, of those who need it, only a minority get specialized treatment (32) due to the high demand for expert services, limited available provision, and extensive waiting lists (31).

Tertiary care refers to the specialized health care, usually for inpatients and on referral from a primary or secondary health professional, in a facility that has personnel and facilities for advanced medical investigation and treatment, such as tertiary referral hospitals (27). For complex mental health needs of adolescents some may require highly specialized trauma- and attachment-informed, multi-agency, collaborative services (33-35), and there is growing international evidence for the effectiveness of tertiary-level mental health intervention and program models for adolescents in care (35-37).

The alarming prevalence of adolescents with poor mental health affects all three levels of healthcare and can impose further damage beyond the healthcare system. This result in a cascade of short and long-term consequences such as learning problems (e.g., problems with inattention and deficits in executive functions), educational difficulties, social exclusion (e.g., peer rejection), internalizing symptoms (e.g., depression, anxiety, oppositional defiant disorder, conduct disorder, aggression), and post-traumatic stress disorder (PTSD) discrimination, stigma (affecting readiness to seek help), risk-taking behaviors, physical ill-health, and human rights violations (38, 39).

1.5 Adolescents' mental health care at the primary care level

Primary care (PC) is defined as "the provision of integrated, accessible healthcare services by clinicians who are accountable for addressing a large amount of individuals' healthcare needs, developing a sustained partnership with patients, and practicing in the context of family and community" (40). PC should prioritize strengthening health systems and accelerate progress towards achieving universal health coverage. Adolescents utilize a range of primary care services, including family medicine, maternal and child health outpatient clinics, immunization and growth monitoring outreach programs, HIV counseling and testing outpatient services, and family planning services (41). In adolescent medicine, physical issues appear to be addressed more often and more effectively than mental issues (42).

Primary care physicians (PCPs), including family doctors and primary care pediatricians, have the benefit of developing longitudinal and family-based views on adolescent patients that other providers might not have (43). Incorporating mental health into primary care is critical for adolescents since family doctors are commonly the only health care providers that potentially follow patients intermittently over their lifetime (43). While PCPs are often the first point of contact when early signs of mental health problems emerge among adolescents (29), often-busy PCPs may fail to recognize them correctly (44). Commonly perceived barriers for PCPs, who frequently act as 'gatekeepers' between families and specialist services, include difficulties identifying and managing mental health problems (e.g., confidence, time, lack of specific mental health knowledge) and making successful referrals for treatment (e.g. lack of providers and resources) (31).

Adolescent care may be problematic when they do not regularly seek out or attend medical care services (45). They may need help as they approach important developmental milestones, and adolescents gain a better understanding of who they are as they begin to form their own identities (46, 47). They grow increasingly self-sufficient and autonomous (47). They begin to recognize societal demands and seek ways to reconcile them with their desires, motivations, and sense of self (48, 49). As a result, some gradually begin to believe they are invincible and deny problems (50). They may not trust medical services or the individuals who provide such care (50). Adolescents may be hesitant historians therefore, making access to health-care services, adolescent-clinician dialogue, and clinical decision-making even more difficult (50).

There are inequities in access to primary care, and many adolescents confront hurdles that limit their access to services and raise their likelihood of poor health outcomes: barriers to scheduling appointments and complaints about long waiting lists to see PCPs (51); medical services not easily accessible geographically or temporally (50), with transportation-related barriers when adolescents want to visit PCPs (52); and a shortage of PCPs (53).

1.6 Role of Artificial Intelligence in health care

Artificial Intelligence (AI) is a field of engineering and computer science which focuses on creating intelligent machines (54). AI has become an integral part of modern life, to a great extent, with diverse applications, including media and entertainment, e-commerce, finance, and marketing (55).

AI is deemed an approach that might facilitate and/or enhance human work (56). It is generally shown that AI use has the potential to provide valuable improvements in many areas and levels of healthcare services (56). It may assist a range of tasks in forming automating medical devices, administrative planning, resource management to support prevention, screening, diagnostics, management and treatment (57).

Although healthcare, in general, has been slow in adopting/implementing AI compared to other service industries, AI technology gradually started to become more prevalent in primary care for physical health applications (58). AI has begun to demonstrate numerous intriguing applications in health care (59, 60). Researchers have suggested and developed many clinical decisions support systems since the mid-twentieth century (59). For example, rule-based AI approaches have shown promise in ability to read electrocardiograms, diagnose illnesses, identify suitable medications, offer interpretations of clinical reasoning, and help clinicians generate diagnostic hypotheses in difficult patient situations (61-64). Further, with AI visualizing live-cell biomarkers, risk stratification of prostate and breast cancer patients may be more easily accomplished in pathology assessments (65). AI has also shown promise in supporting primary care physicians with triage through tele-dermatology (66, 67).

1.7 Role of Artificial Intelligence in adolescents' mental health care

Within the mental health discipline, AI has been used at a slower pace and has yet to become commonly accepted (58, 68). However, newer technologies are emerging for adolescents' mental health care, showing potential in helping primary care providers take charge of adolescents' mental health care (53).

1.8 Medical manpower and AI

Studies have shown that increased investment in primary care physicians (PCPs) may alleviate workloads for existing clinicians (69). However, World Health Organization data suggests that there will be a global deficit of 18 million healthcare professionals by 2030 (69). As a result, to facilitate PCPs' services to adolescents with mental health problems, there may be a need to familiarize and consider new approaches, such as the use of AI interventions.

1.9 Exploring AI for adolescent's mental health in a primary care setting

In this manuscript-based thesis, we sought, through a scoping literature review, evidence-based AI s that have been implemented and/or tested in the mental health care of adolescents. This served, in part, as the foundation for a qualitative study aimed at looking at (1) perceived challenges for primary care physicians (PCPs)—specifically family physicians and general pediatricians—in providing adolescents' mental health care; and (2) primary care physicians' attitudes to, and knowledge of AI use in supporting adolescents' mental health, along with perceived needs in order to make this work.

1.9.1 Scoping review

A literature scoping review is a critical initial step in effectively identifying, integrating, and mapping existing information. Our review revealed gaps in the literature concerning tested and/or implemented AI interventions in adolescents' mental health care. We found no research that attempted to identify primary care physicians' (PCPs') perceived needs and challenges for AI interventions supporting adolescents' mental health. We therefore aimed to fill this gap in knowledge by conducting exploratory qualitative research to investigate this.

Together, both manuscripts add to the evidence-based potential use of AI interventions in adolescents' mental health care and identify PCPs ‘perceived needs and challenges for AI interventions. These first steps and assessments provide the groundwork for future research dedicated to assessing the practical utility, applicability, and effectiveness of AI interventions in adolescents' mental health care practice.

CHAPTER 2

MANUSCRIPT 1: USE OF ARTIFICIAL INTELLIGENCE IN ADOLESCENTS' MENTAL HEALTHCARE: A SCOPING REVIEW

Pooria Ghadiri [1,3,4], Samira A. Rahimi [1,3,4], Gauri Sharma [1], Laura Pinkham [1], Genevieve Gore[1], Perry SJ. Adler[1], Mark J. Yaffe [1,2]

Affiliations:

[1] Department of Family Medicine, McGill University, Montreal QC, Canada
[2] St. Mary's Hospital Center, Montreal, QC, Canada
[3] Mila-Quebec AI Institute, Montreal, QC, Canada
[4] Lady Davis Institute for Medical Research (LDI), Jewish General Hospital, Montreal, QC, Canada

2.1 Abstract

Background: Approximately 1 in 7 (14%) who do not see HPCs experience mental health problems, and of concern to public health is that some are either inadequately or never addressed. Artificial Intelligence (AI) interventions are potentially seen as useful in enhancing access to, and engagement with, services that facilitate diagnosis, treatment, and optimally improvement in mental health problems at all healthcare levels (primary, secondary and tertiary). There is a lack of evidence on the impact of AI in adolescents' mental healthcare.

Objective: To identify Artificial Intelligence (AI) interventions that have been tested and/or implemented for use in adolescents' mental healthcare.

Methods: We conducted a scoping review using Levac et al. and the Joanna Briggs Institute scoping review framework and followed PRISMA scoping review reporting standards. An information specialist conducted a comprehensive search of five electronic databases from inception date to February 2020 during the identification step. We included all adolescents (age 10-19) and any HCPs who provide care to adolescents with mental health problems. All AI interventions tested and/or implemented. Comparators: No restrictions. Outcome: Outcomes related to patients, HCPs and healthcare systems. Setting and study design: Studies in any healthcare setting and countries published in English. All research that used qualitative, quantitative, or mixed method studies were included. Two independent reviewers carried out the selection of studies and the subsequent data extraction, including study type, nature of population, AI interventions, mental health and outcomes characteristics. A third reviewer validated and resolved any AI-related data disagreements. We extracted data focusing on the characteristics of population and intervention. We used a narrative technique to synthesize data regarding studies' populations, interventions, and outcomes. We evaluated the risk of bias for prognosis and diagnosis-related studies using the Prediction model Risk of Bias Assessment Tool (PROBAST).

Results: The search process resulted in 1,044 records. After the removal of duplicates, 804 papers were screened for potentially relevant studies based on titles and abstracts and 30 peer-reviewed publications met our inclusion criteria. We found that the most frequently reported methods were Support-Vector Machines (n=10), Neural Networks (n=6), and Gaussian Mixtures and k-means (n= 6). Six studies specified mechanisms of AI delivery, with an fMRI scanner computer software being the most common. AI was used for the mediation of diagnostic processes (n=23), monitoring and evaluation (n=8), treatment (n=5), and prognosis (n=2). Diagnoses for which AI was used were as follows. Autism Spectrum Disorder (n=3) and Unspecified Outcomes of Psychological Stress/Pressure Level in adolescents (n=3), followed by Substance Use Disorder (n=2) and Dysfunctional Behavior in Adolescents (n=2). The most commonly reported AI performance metric was "Accuracy" (n=20, 70%-100%). The “overall” risk of bias for diagnosis/prognosis related models was unclear (84%), followed by high risk (16%) and low risk (0%). Although end users (adolescents and/or HCPs) were reported to be slightly/inadequately involved in testing AI interventions, (n = 1, 3%) no research was found describing their engagement in validating these interventions.

Conclusion: We found differences in how participants, types of AI models, analyses, and outcomes were reported, highlighting a considerable gap in AI's successful development and use in adolescent mental healthcare. More research is required to: (1) include meaningful and active involvement of end-users (patients and/or HCPs) in the design, development, and validation of AI interventions; (2) ensure the inclusivity and diversity of their population in data collection and analysis; and (3) provide better reporting of AI methods, data collections, and analyses.

Keywords: Adolescent health; Mental health; Artificial Intelligence; Machine Learning; Emerging technologies; scoping review

2.2 Introduction

2.2.1 Mental health among adolescents

According to the World Health Organization adolescents are defined as the age interval between 10 and 19 (1). It is a pivotal time of life when vulnerability to mental health issues increases (2) as it encompasses critical years for mental, social, and emotional growth (3). It is a period when questioning of one's identity is common, along with gradual assertion of independence (4). This may be accompanied by rebellion against parents, while self-expression within the world at large begins. During adolescence there are important hormonal shifts, and the brain undergoes significant developmental changes in neural pathways and behavioural patterns that will remain throughout adulthood and may impact on mental health (5). Certain mental diseases that begin in adolescence continue into adulthood, causing long-term morbidity and a significant burden on society (5, 6).

Globally, it is estimated that 1 in 7 (14%) 10-19 year-olds experience mental health problems, yet these remain largely unrecognized and untreated (7). Approximately 20% of all adolescents suffer from mood and behavioral disorders (2, 8). Worldwide Anxiety disorders, Depression, Attention deficit hyperactivity disorder are reported to affect 3.6%, 1.1%, and 3.1% of 10–14-year-olds, and 4.6%, 2.8% and 2.4% of 15–19-year-olds respectively (7, 9, 10). Eating disorders, such as Anorexia Nervosa, which has a peak occurrence around the age of 15–19 years (11), have a more remarkable fatality than any other mental condition, typically owing to medical problems or suicide (7). Suicide is the fourth most significant cause of death among older adolescents (15–19 years old) (12) accounting for 9.1% of all mortalities in this age range (13). In 2016, the incidence of excessive episodic drinking among adolescents aged 15 to 19 years was 13.6% globally, with men being the most vulnerable (14). Mental health problems that begin early mostly continue through adult life (15). Therefore, there are serious consequences from such illnesses during the adolescent period and later in life (16). This supports the need for early intervention and appropriate management of adolescents' mental health problems (15, 17).

2.2.2 General role of AI in healthcare

Artificial Intelligence (AI) is a field of engineering and computer science that focuses on creating intelligent machines and is deemed an approach that might facilitate and/or enhance work (18, 19). AI has been proven to have the ability to deliver significant benefits in a variety of sectors and levels of healthcare services (20), including automating medical devices (20), administrative planning (21), resource management (22), and prevention (23), screening (24), diagnostics (25), and treatment(26, 27). In oncologic radiology AI has transformed image analysis in oncology/radiology, resulting in the successful classification of organ lesion images (28). In pathology AI-based breast cancer and lung cancer subtype diagnostic interventions have been tried to analyze fine needle aspiration cytology images to distinguish presence or absence of malignancy (29). In cardiology, since echocardiogram interpretation is heavily reliant on operator skill, it is felt to be a suitable situation for use of AI to harmonize, unify and standardize medical diagnosis (30). Hence with increased life expectancy and heavier caseloads AI may be one solution to inadequate healthcare manpower.

2.2.3 Role of AI in adolescents' mental healthcare

Adolescents as a collective are deeply engaged with utilizing technology, particularly social media, and perceive it as a mainly positive experience (31). In light of this engagement, technology is often seen as a possible avenue for developing solutions to health problems (32). For example, it has been suggested that AI interventions at various levels of healthcare might aid adolescents who are suffering from conditions such as depression and anxiety, and suicide as a possible outcome (33):

1) Adolescents' level: A socialization intervention for autistic adolescents that combined wearable AI-assisted Google Glass helped them reflect on their moods and emotions, resulting in better socializing skills (34). Furthermore, when it comes to adolescent depression, AI-powered chatbots like Weobot may be able to help by expanding access to care and reducing depressive symptoms via self-management cognitive behavioral therapy techniques customized to its users (19).

2) Healthcare professional (HCP) level: Professional bodies recommend that people aged 11–21 be visited regularly for various health and lifestyle concerns (35). These recommendations, however, are being met by less than 2% of the targeted population (35), and underprivileged adolescents may fare worse (36). Early screening, diagnosis, treatment, and management, on the other hand, are acknowledged as critical aspects in limiting the effect of any potentially significant health problem. This occurs despite the fact that early screening, diagnosis, treatment, and management, are acknowledged as critical aspects in limiting the effect of any potentially significant health problem (37). AI interventions may open up the potential for earlier intervention for vulnerable adolescents, increased access to and engagement with therapeutic services, and greater awareness of mental health problems (38). AI interventions are being designed, tested, and deployed to address HCPs concerns for adolescents—particularly in the context of mental health — in the form of diagnostic interventions, therapeutic chatbots, and public health interventions, etc. (39).

3) A Healthcare system level: At the healthcare system level, AI could aid in the improvement of insufficient data systems for following patients through screening and surveillance

procedures, particularly in non-integrated healthcare settings (40). Colorectal cancer screening may be provided programmatically through integrated healthcare systems using AI, in which individuals who are at risk are approached and given screening from a population health management standpoint (40). In certain countries, such as Canada and the United Kingdom, national AI programmes have begun to be combined with goals to promote digital health technologies under provincial/territorial healthcare systems (41). For instance, the “Clinical governance” is a systematic approach to maintaining and improving the quality of patient care within the National Health Service (NHS) in England. AI could help address the health and mental wellbeing gap by predicting which individuals or groups of individuals are at risk of mental illness and allow the NHS to target treatment more effectively towards them (39). Furthermore, AI has broad usefulness to present practices and approaches in health systems throughout the globe in essential areas of the "infostructure," such as " patients' trust and privacy," and is seen as a viable instrument for safeguarding personal data privacy (41).

The goal of our research has therefore been to conduct a scoping review that addressed this topic to provide a focal point for understanding how AI is being tested and/or implemented to address adolescent mental health, and ultimately to serve as a stimulus for further work in this domain.

2.3 Method

2.3.1 Study design

Scoping review methodological framework was proposed by Levac et al. (42) and the Joanna Briggs Institute (JBI) methodological guidance for scoping reviews (43). The draft protocol was revised upon receiving feedback from the research team. We followed five steps: (1) defining the review topic, objective, and research questions; (2) identifying relevant publications; (3) choosing studies that matched our eligibility criteria; (4) extracting and charting data from included studies; (5) aggregating, summarizing, and reporting the findings, and (6) consult the findings with relevant stakeholders (HCPs and AI developers) .This protocol is registered and accessible on the Open Science Framework (OSF) website and can be accessed here.

Figure 2.1 depicts the screening process. We used the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analysis-Scoping Reviews) reporting guideline for reporting the study (44) (Appendix 1).

We deployed the PROBAST (Prediction Model Risk of Bias Assessment Tool) tool to examine the risk of bias. This tool evaluates the risk of all sorts of bias (ROB) and usability of diagnostic and prognostic predictions from studies that used AI models (45). PROBAST is classified into four domains: participants, predictors, outcomes, and analysis (45). The risk of bias is judged as low, high, or unclear (46).

2.3.2 Eligibility criteria

We used the Population, Intervention, Comparison, Outcomes, Setting, and Study (PICOS) design components to develop our search approach for peer-reviewed papers from all countries and settings published in English (47).

Population: Studies about 1) individuals between 10-19 years of age and 2) healthcare professionals (HCPs) who provide care to adolescents with mental health problems (e.g., nurses, social workers, dietitians, public health practitioners, Family physicians, (unregulated) community-based workers, clinical psychologists, pediatricians, psychiatrists, pediatric psychiatrists).

Intervention: Any AI intervention (AI is defined according to McCarthy) (48). We included studies that "tested" or "implemented" or "tested and implemented" AI methods, such as computer heuristics, expert systems, fuzzy logic, knowledge representation, automated reasoning, data mining, and machine learning (e.g., support vector machines, neural networks, and Bayesian networks) were included. We excluded studies related to robot-assisted care and simulated data (which is the use of to replicate real world situations) (49).

Comparators/control: No restriction,

Outcome: Our outcome of interest were outcomes related to 1) Adolescents 2) HCPs, and 3) Healthcare System

Setting and study design: We included studies in any healthcare setting. All study designs except reviews, opinion pieces, conference papers and abstracts, editorials, commentaries, news, and letters were included.

2.3.3 Information sources and search strategy:

An experienced information specialist developed and executed comprehensive literature searches. The systematic literature search was an iterative procedure and was conducted from inception of each database until February 2020 in five electronic bibliographic databases: MEDLINE (Ovid), EMBASE (Ovid), Web of Science Core Collection, Compendex and INSPEC. Retrieved records were managed with EndNote X9.3.3 (Clarivate) and imported into the DistillerSR review software (Evidence Partners, Ottawa, ON) to facilitate the selection process.

2.3.4 Publication selection process:

Title and abstract screening (level 1) and Full-Text Screening (Level 2): Two independent reviewers used DistillerSR software and screened the titles and abstracts of the initially identified records. Then, the same two reviewers separately examined the full texts selected at level 1 screening for their eligibility to be included in the review. The third reviewer addressed conflicting decisions. Finally, studies that matched the eligibility criteria were included for full data extraction.

2.3.5 Data Collection

A data extraction form was created and completed with team members' input which was informed by some aspects of the Cochrane Effective Practice and Organisation of Care Review Group (EPOC) data collection checklist (50). This checklist instructed reviewers on the types of relevant data that may be extracted from included papers (50). Particularly, we extracted study characteristics, population, intervention, and outcome characteristics.

Datasets in AI methods are divided into three categories: (1) training: data samples used to fit the AI method; (2) validation: tuning AI method parameters; and (3) testing: AI method performance (51).

2.3.6 Assessment of Risk of Bias in the Included Studies

One reviewer independently assessed the included studies using the PROBAST criteria to determine the risk of bias in each eligible study for PROBAST evaluation (46). A second reviewer validated the assessments.

2.3.7 Synthesis

The techniques used to build preliminary synthesis comprised textual descriptions of the studies, grouping, and clustering, and tabulation (52). We employed a narrative technique to synthesize the data after extracting it from the relevant studies. We particularly detailed the characteristics of AI interventions, the characteristics and conditions of adolescents' mental health, and whether or not end users were engaged in the development and/or validation process of these interventions. To manage data synthesis, we used Distiller software and Microsoft Excel.

2.3.8 Consultation

Throughout the review, we kept all study team members up to date and solicited their comments about the quality and accuracy of the ongoing data gathering process. We also presented our preliminary results to a multidisciplinary group of participants (primary care researchers, AI-healthcare researcher, family physician) at virtual symposiums (FMF 2021 (53), and AAAI 2021 Spring Symposium Series (54)) and received feedback.

2.4 Results

Through searching the identified bibliographic databases, we obtained 1044 papers (figure1), leading to 804 papers after deduplication. Finally, 30 papers were included in this scoping review for data charting and analysis.

2.4.1 Study Characteristics

Countries and Publication Dates: Considering the total of 30 included studies, despite a plateau trend from 1994 to 2012, the number of studies published annually on adolescents' mental health using AI has progressively increased until 2018 when a drop has been observed. This trend continued with the start of the COVID-19 pandemic in early 2020. Figure 2.2 depicts the timeline of AI-based studies (n=30). The four countries having a higher number of publications are the United States (n=9, 30%), China (n=8, 30, 27%) United Kingdom (n=3) and Spain (n=2). The remaining are Iran, Russia, Singapore, Canada, Sweden, Japan, Ireland and India-Portugal published one study each (n=1).

Aims of Studies: The 30 papers included in this review aimed to assess the use, test, and implementation of an AI model in mental healthcare for adolescents. The goals were explicitly stated in 23/30 (77%) of the papers.

2.4.2 Population Characteristics

Adolescents: The AI interventions were trained, validated, and tested on a total of 48,808 adolescent patients (female 20,048; male 27,645). 28 (93%) of the 30 studies stated their sample size, of which 21 (75%) of the 28 reported the sex distribution, but none addressed gender-relevant variables. The mean age of adolescents was 15.39 (+/-1.25). The race/ethnicity of the participants was reported in 9 (30%) of the 30 studies. It was impossible to provide a unified summary of all the included papers reviewed because of the failure of studies to break down and distinguish between race and ethnicity (Table 2.1).

Healthcare Professionals: No studies provided information regarding the total number, sex, gender, age and race/ethnicity of HCPs. Their only role was described as collaborators who assisted researchers in assigning the eligible adolescents to a study and/or confirming the adolescents' mental health disorder before using the AI interventions. Adolescent psychiatrists, child psychiatrists, mental health professionals, pediatric-psychiatric clinicians, and adolescent forensic psychiatrists are among the HCPs involved in the mentioned process.

2.4.3 Intervention

AI Methods:

Most of the studies (29/30, 97 %) reported on the testing and/or usage of an off-the-shelf AI model (also known as AI as a service). An off-the-shelf AI method is any method that is readily (or instantly) accessible or relevant to the specific context without modification, but it may also be applicable to a wide range of other contexts or issues (55). The number of AI methods has also been increased since 2010. Further, SVM was the most used AI method in papers published between 2012 and 2019 (12/30, 40%). For more information on AI methods (Appendix 2).

Performance of AI interventions:

Three out of 30 (10%) studies did not report the model performance; of the remaining 27 that did, 17 (77%) used two or more performance measures, and the other 13 (23%) reported only one. Of all the methods reported, Fuzzy Sets, Data Mining and Random Tree Classifier were the ones with the highest performance accuracy within the available data sets for the defined task (Accuracy: 90–100%). Among the 30 included studies, "Accuracy" was used as the only method of reporting performance metrics of AI methods in 10 (33%) of the studies. More details on included studies' AI methods and performance measures could be found in the Appendix 2. Table 2.2 shows the criteria to evaluate the performance of AI models.

2.4.4 Data Sets (Training, Validation, and testing)

Evaluating "Training," "Validation," and "Testing" parameters is crucial since it reveals the accuracy of the AI model's predictions and the possible ramifications of hyperparameter tuning (56). Among the 30 included studies, 10 (34%) reported on the training and testing data sets, 6 (20%) reported on all three data sets, one reported on the training and validation, one reported only on the validation, and one reported only on testing data sets. There were no descriptions of these data sets in 19 (64%) of the included studies.

2.4.5 Mental Health Disorder

The most frequent mental health disorders studied were Autism Spectrum Disorder (3/30, 10%) (57-59), unspecified outcomes of other psychological stress/pressure level (3/30, 10%) (60-62), Substance use disorder/behavior (2/30, 7%) (63, 64), and Dysfunctional Behavior in Adolescents (hopelessness) (2/30, 7%) (65, 66) (Table 2.3).

2.4.6 AI applications on the continuum of adolescents' mental healthcare

We retrieved data relevant to the uses of AI in adolescent mental healthcare, obtaining the input, discussion, and ensuring agreement on what each paper reported with the study team across numerous sessions. Included studies reported the following information regarding the applications of AI in adolescent mental healthcare (Table 2.3): (1) Facilitate and improvement of the mediation of diagnostic processes (23/30, 77%) such as more accurate diagnosis, enhancing disease pathogenesis knowledge, and identifying associated disease risk factors; (2) Improve treatment (5/30, 17%) by boosting treatment accuracy and implementing more targeted interventions; (3) Improve monitoring and evaluation (8/30, 27%); (4) Improve prognosis (2/30, 7%), for illustration, by discovering new disease biomarkers.

2.4.7 Legal Information and Data Privacy

The legal information on data privacy and security using AI was not reported in any of the 30 studies.

2.4.8 End users' involvement

Active involvement of the "end-users" refers to the active and effective involvement of patients and HCPs in the processes and choices that occur throughout the relevant stakeholders as appropriate (67). This might involve initiatives at key decision points and ongoing cooperation throughout the research and development process (67). We reviewed the degree to which "end users" were engaged in the "development," "testing," and "validation" of AI interventions in this review as follows: Development: 11/30 (37%) identified the AI developers, all of whom were engineers, and none reported the involvement of end-users in developing AI interventions. Testing and Validation: 11/30 (37%) and 7/30 (23%) identified those who participated in testing and validating the AI interventions, respectively, again engineers. Studies did not explicitly report the active involvement of "end users" in developing, validating, and testing AI interventions. However, our review revealed that "end users" were slightly/inadequately involved in AI intervention testing, with only one study involving an HCP in experimental testing and intervention setup (57).

2.4.9 AI delivery Mechanism

AI delivery mechanism refers to how the AI interventions developed were administered e.g., smartphone application, computer software, website, etc. Among all the studies, 10/30 (33%)

reported delivering the AI interventions using several different techniques, including Computer Software (7/10, 70%), Smartwatch T-sensor (1/10), and Micro-blog (1/10), and Virtual Reality Network Interface (1/10, 10%). The remaining studies (20/30, 67%), on the other hand, did not specify how the AI interventions were administered.

2.4.10 Type of data used to develop AI interventions

"Type of data" refers to the particular operational data acquired from patients as a result of their participation in the studies with the intent of utilizing intelligent models for a very specific process of tagging phrases, qualities, characteristics, and images (57). The "Type of data" reported in all of the included studies, to feed AI interventions, is reported in Table 2.4.

2.4.11 Risk of bias

We identified the studies that were eligible to be evaluated using PROBAST. Only 83 % (25/30) of our included studies were qualified to be analyzed via the PROBAST tool. Of those qualified, 16% (4/25) were at high risk of bias according to our assessment with PROBAST (Figure 2.3) and the remaining 84% (21/25) were at “unclear risk” of bias. Details for each domain are provided in the Figure 2.3. Appendix 3 shows the risk of bias table based on the authors’ judgments about each risk of bias item.

2.5 Discussion

We did a scoping study as a first step toward a complete evaluation of the literature on the use of AI in adolescents' mental healthcare because there are considerable knowledge gaps in how AI can be incorporated and influence adolescents' mental healthcare. This review comprised 30 studies on the application of AI interventions in adolescents' mental healthcare and gave a critical assessment of the current studies in this field. Our review leads to the following observations.

2.5.1 AI Models, Performance, and Risk of Bias

Machine Learnings were the most often employed AI methods used in adolescents' mental healthcare. Of all the methods reported, Fuzzy Sets, Data Mining and Random Tree Classifier were the ones with the highest performance accuracy within the available data sets for the particular task (Accuracy: 90–100%). The majority of the included studies (29/30, 97 %) reported on the testing and/or usage of an off-the-shelf AI model.

The findings are consistent with previous research indicating that off-the-shelf models cannot be used directly in all clinical and mental applications, given that models with extensive training data sets fail to reflect the complexities of clinical mental cohorts (68).

Obtaining representative training data is fundamental to excellent AI interventions' performance in clinical and mental settings. Otherwise, the data might be misinterpreted because of a lack of relevant information (69). We found poor reporting of AI techniques and their methodologies in our study's included papers. Further, there was no mention of adherence to a particular reporting framework/guideline in any of the studies included in this review. As a result, there was uncertainty in the included studies about various aspects, such as 1) whether or not the training dataset was representative, and 2) how potential (data and algorithm) bias and missing data were considered. Studies that report on the usage of AI methods in general and in the context of physical and mental healthcare should follow a verified framework/guideline to convey their findings (70). Overwhelming evidence has demonstrated that AI models in mental health and clinical research have poor reproducibility and reporting, implying the necessity for reports to be given in a clear, succinct, and accessible way to promote comprehension and critical review (71). The TRIPOD (Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis) Statement, which consists of a checklist of 22 items, is an example of such a helpful reporting framework/guideline. It aims to improve the reporting of a prediction model considered vital for transparent reporting (72) and is predominantly used for regression-based prediction models. Nevertheless, there is a need for the creation of a framework that can provide uniform reporting criteria for other AI methods such as machine learning. Complete and transparent reporting of AI models' data and methodologies helps discover mistakes and possible biases and promotes accurate assessment of the efficacy, reproducibility, and reuse of AI and machine learning methods in future research (70). This is crucial in the burgeoning usage and implementation of AI in clinical and mental health contexts. The clinical and mental utility of these AI methods capable of dealing with large amounts of data on adolescents' mental health requires more careful consideration, and investigations must adhere to more rigorous methodological standards.

In studies related to diagnosis and prognosis, we found a high degree of unclear overall bias, followed by a high risk. This shows that the AI models being developed were not considering the various parameters used to assess the risk of bias. Even if they were considering these parameters, then they were not sufficiently reporting it, which again leads to an unclear and/or high risk of bias. This pattern of results is consistent with the previous literature that indicated an unclear and/or high risk of bias resulted in escalating concerns about the AI model's applicability (45). The category/domain of included studies with the most significant risk of bias was analysis, outcome, and predictors; validation of the papers (external and internal) was poorly documented, and calibration was seldom addressed.

The risk of bias was the least in the participants category, whereas the most were in analysis. This shows that studies are not analyzing the models and their outcomes efficiently, although they are reporting and including the participants and ensuring less risk of bias. Given the substantial risk of bias in the studies included AI models employed in other circumstances for example with different data, may not achieve the same degree of prediction accuracy. Because these AI models have a significant risk of bias, their performance on a new dataset may not be as high as demonstrated in these studies. There's a high possibility that these models fail to perform accurately in different datasets.

The majority of research on AI and machine learning-based prognostic and diagnostic prediction models in our review were ambiguous or had a substantial "unclear" risk of bias. That might be due to insufficient/unclear 1) reporting of multivariable prediction models and 2) information about their study. In the development of AI models, acquiring high-quality data is a well-known difficulty (73). Nonetheless, while developing AI models, it is critical to keep this in mind. Improved efforts are required in the design, conduct, reporting, and validation of such research to increase the implementation of AI prediction models, which enhance adolescents' mental healthcare in clinical and mental practice settings. This may be assisted by a transparent and focused approach to developing AI models and ensuring the safe delivery of care to adolescents suffering from mental health problems in the future.

2.5.2 Mental health applications of AI in the continuum of care and practice

We discovered AI interventions in adolescents' mental healthcare in four major domains: (1) mediation of diagnostic process; (2) monitoring and evaluation; (3) treatment; and (4) prognosis. Our findings were consistent with the previous literature on the use of AI interventions to aid in mental health diagnosis, prognosis, treatment, and monitoring and evaluation (74). Today's AI interventions may assist with mental health diagnostic problems and processes in a variety of ways, including improving the capacity to distinguish between diseases with similar initial clinical manifestations yet vastly different treatment strategies. For illustration, identifying people with post-traumatic stress disorder (75), using speech data to predict psychosis beginning in high-risk youth and adolescents (76), or analyzing genetic profiles in schizophrenia (77). Additionally, studies have shown that applying AI methods to panel data (i.e., data collected in a series of repeated observations of the same subjects over some extended time frame to measure the change) might help improve the accuracy of prognoses for mental health patients (78). For instance, by combining imaging, electronic medical records, genetic, and speech data to predict depression patterns (79), risk of suicide (80), and future substance abuse among adolescents (81). Previous studies showed that AI interventions might enhance mental health treatments in several ways, including predicting treatment response (82), possibly avoiding or substituting impotent medication experiments (83), and invasive costly brain stimulation therapies or time-consuming psychotherapies (83). As for monitoring and evaluating mental health problems, AI was shown to remotely monitor and detect subjective and objective markers of psychotic recurrence (84). Predicting whether adolescents may develop mental health problems is essential for accurate and early intervention to avoid major unfavourable consequences in the future. Therefore, using innovative technologies, such as AI interventions, we may acquire ongoing, long-term tracking of individuals' distinct mental and physical profiles that affect their mental health.

The ensuing volume of complex, multidimensional data is too large for people to interpret meaningfully, but AI is perfectly adapted to the job. As AI interventions advance, it may become feasible to characterize mental health problems more realistically than the present DSM-5 categorization framework (85), detecting such problems in the initial phase and customizing recommended treatments for adolescents’ distinctive traits.

While our results showed that AI was used for the four main elements of diagnosis, prognosis, treatment, and monitoring and evaluation purposes in adolescents' mental healthcare, most articles were concerned with the diagnosis only, and much fewer employed AI in other elements. This can be a considerable gap to be addressed i.e., future studies. Lastly, using AI to generate insights from data may aid in the diagnosis, prognosis, monitoring, and treatment. However, it is critical to assess the practicality of these insights and if they can be translated, applied, and implemented in the mental care setting.

In general, AI exhibits the potential to improve the efficiency of clinical, mental, and research operations while also giving a unique insight into adolescents' mental health and well-being (86). Recent AI intervention advancements are highlighted to show growing capabilities and future potential. Therefore, there is considerable opportunity to investigate other mental health problems important and common among adolescents' period, such as anxiety, depressive, and behavioral disorders (87), to determine whether AI can achieve equivalent performance in detecting, prognosing, monitoring, and treating other mental health issues.

2.5.3 End users’ involvement

The AI line of research is transitioning from technology-oriented use, emphasizing enhancing output and overall performance, to humanity-oriented usage, focusing on supplementing human intellect with machine intelligence (88). The change in the direction of AI research has created new obstacles, namely related to the transition from broad sense to transfer intelligence, computation to cognition, tailoring to adaptability, discovering the unknown, universal and harmonizing to specificity, and technology to human values (89). As a result, the new strategy is to pursue greater amounts of human supervision as well as elevated concentrations of automation, which is more likely to occur in automated AI interventions that are secure, credible, and reliable (90). Our results indicate "end users" have been slightly/inadequately involved in AI interventions' development, validation, and testing in adolescents' mental healthcare. As a result, AI interventions fail to suit the needs of HCPs and patients; they suffer from poor usage scenarios and eventually fail during clinical practice adoption. While AI interventions must perform correctly and safely, they must also be usable to the end users in adolescents' mental healthcare settings. Involving end-users in designing and developing such interventions can help produce better applications and significantly boost the likelihood of adoption.

Our findings echoed earlier research on the need to keep humans in the loop when developing, testing, and validating AI interventions to screen for bias in algorithmic assessments (91, 92). The failure to incorporate human elements into previous technological paradigm changes resulted in poor usage and major accidental mistakes (93). To optimize the effectiveness and usability of the evolving paradigm shift of current AI interventions in adolescent mental healthcare, we should use human-oriented design in partnership with targeted end-users. This offers a mechanism of control in which neither the human nor the AI intervention is totally autonomous, making it simpler to uncover opportunities to keep results more comprehensive. Future research must also incorporate end-users into the design, development, and validation of AI interventions in a meaningful, active, and participatory manner.

2.5.4 Ethical and Legal Aspects/considerations

Despite the benefits, AI interventions' applications are not without challenges (94). It is critical to comprehend the dangers and hazards of this new technology; thus, we must apply AI to reflect long-established ethical and legal principles while maintaining patient safety (94).

Ethical challenges of applying AI in healthcare fall into four categories: 1) informed consent, 2) safety and transparency, 3) algorithmic fairness and bias, and 4) data privacy. There are also five legal challenges to consider and address in order to create a successful AI system, including 1) safety and effectiveness; 2) liability; 3) data protection and privacy; 4) cybersecurity; and 5) intellectual property law (94). These ethico-legal challenges are key factors that need to be considered and addressed to successfully create an AI-driven healthcare system (95). Our results indicate that ethico-legal aspects have rarely been addressed in AI-adolescents' mental health studies, as in a single study (96), two domains, 1) data safety and transparency; and 2) privacy and security issues, were hardly discussed. These results reflected evidence in the literature, underscored the importance of all AI stakeholders (i.e., HCPs, developers, and patients), irrespective of professional domain, remaining aware of and clearly reporting the ethical challenges involved, as well as being active participants in discussions about the existing and anticipated use of these technologies (97). Additionally, two related studies highlighted that AI interventions' use in mental healthcare was restricted due to a continuous lack of data and an appropriate report on model construction and transparency (69, 98).

Sex and gender interplay in the emergence of diseases (99) such as depression (100) coping mechanisms (101) and are sources of variability in mental health problems, influencing various factors such as prognosis, symptomatology expression, and therapeutic efficacy (102). They may assist in diagnosing a mental problem, assessing the effects of therapy, and forecasting a patient's prognosis to generate an accurate diagnosis and recommend a customized and more effective treatment for every unique patient (103). Recent studies on adolescents examined diagnostic disparities in mental and neurodevelopmental problems in relation to sex and gender effects (104, 105).

Our results indicated that the distinction between biologic sex and gender-related characteristics was not appropriately reported, and no research explicitly accounted for this when presenting demographic data. Additionally, these findings revealed that the sex distribution was specified in nearly three-fourths of the included studies, with just adolescents and none with HCPs. Besides, no study examined gender-related indicators with either patients or HCPs involved. These findings mirrored related research that highlighted the importance of gender and sex differences being reported explicitly as a potential source of mental and clinical heterogenicity among adolescents to reduce health disparities and identify the role of inter-individual variances when incorporating them with AI (105-107).

AI interventions are revolutionizing mental healthcare services, communities, and everyday lives (108). In the context of clinical and mental healthcare, expected gender and sex distinctions are sometimes neglected or underreported (107). Lack of specifics and transparency for sex and gender differences leads to bias and limits our capacity to systematically examine the robustness of AI interventions in adolescents' mental healthcare, which is an essential direction for future work. This bias may have a negative impact on the accuracy of predictions provided by AI interventions that HCPs may routinely employ, and failure to account for these differences will result in suboptimal findings, blunders, and misleading outcomes.

To promote the use of new technologies in adolescents' mental healthcare settings, all ethico-legal concerns and considerations must be addressed within mental health studies (109).

Defining instances in which informed consent is required could, for example, be valuable in increasing the use of AI interventions by HCPs, as it could clarify their duties for using such interventions. Furthermore, to what degree do HCPs have a responsibility to educate patients on the complexities of AI to avoid projecting unwanted biases, and under what circumstances must an HCP disclose to the patient that AI is being utilized at all? Therefore, a collaborative effort between AI developers, patients, HCPs and regulatory authorities is essential to ensure that AI can be applied ethically and legally while also meeting the needs of all parties involved.

2.5.5 Geographic distributions and Ethno-racial information

According to our results, most AI research in adolescent mental health was conducted in North American and East Asian contexts. Our findings also show that race/ethnicity was considered/reported in less than a third of the included studies reported on the races/ethnicities of patient participants, with no discussion of the races/ethnicities of participating HCPs. Furthermore, for those studies that included patient ethnicity, we discovered that the obtained data were primarily associated with Caucasian/White populations, raising concerns about the data set's representativeness, and perhaps leading to biases. Discussing and presenting detailed data regarding participants' race/ethnicity has significant importance as a clear description of data set characteristics in healthcare research (110). Similarly, in research evaluating the models' performance in predicting suicide, R. Yates Coley et al., 2021, underlined the relevance of how ethno-racial unrepresentative AI models would impact the forthcoming models' prediction results. They found that using two prediction models to guide suicide prevention interventions would provide less benefit and more risks to patients who are Black, American Indian/Alaska Native, or whose ethno-racial demographic is unknown, compared to White, Hispanic, and Asian patients

(111). This pattern of results has also been recorded in disciplines other than mental health. Recent studies signified a lack of dermatology-specific guidelines for defining and describing AI data set characteristics. Concerns regarding the exclusion of multiple skin tones have previously been voiced by dermatologists, and this effect was demonstrated in an example where the lesions on Caucasian versus Asian patients were dramatically different. In these data sets, analyzing the racial and ethnic variety of the patients was hindered by a lack of reporting of these characteristics (112, 113).

It is possible that the AI interventions could make predictions that discriminate against marginalized and vulnerable patient populations, leading to unsatisfactory patient outcomes (114). Given the clear ethnic and racial differences on disease biomarkers, prevalence, and outcomes, the inclusion of this information is likely to improve the accuracy and lessen biases of AI interventions (115). By ignoring ethno-racial distinctions from training and testing AI models, we are creating tools that do not match the features of average adolescents, resulting in less effective, biased, and poor representation of their usage. We can achieve advances in adolescent mental healthcare linked to the heterogeneous structures of a community if we take purposeful and substantial actions to train AI models to be ethno-racially inclusive. Therefore, we propose that future research clearly report ethno-racial differences to eliminate race/ethnicity-based disparities in adolescent mental healthcare using AI.

2.5.6 Limitations

There are some limitations to this study. First, since only English studies were considered, there may be publication bias. Second, our search strategy may not have collected all relevant studies because 1) we used the World Health Organization definition of adolescent to determine our inclusion criteria and 2) the definition of adolescent varies by country and charter, with possible overlaps in between (116). While terminology like "adolescent," "youth," and "young people" is commonly used interchangeably (117, 118) and may have distinct definitions in different settings/locations, this study focused mainly on the second decade (10–19) of life.

Third, limitations in the search methodology may have resulted in the omission of certain pertinent publications, e.g., the exclusion of gray literature (simulated data and robotics) and lower-level evidentiary records such as reviews, opinion pieces, editorials, comments, news, letters, and conference abstracts without full-text articles for more detailed information from the search. This is a common limitation observed in scoping review studies, and it is due to the trade-off between obtaining breadth and depth of analysis in a short period of time (119). The present study effectively mapped a large cross-section of the literature. It produced a valuable synthesis for researchers and HCPs to better understand the potential of AI in their various fields within the mental healthcare of adolescents. With that regard, compiling a more comprehensive review would be more difficult due to the fact that the subject is constantly evolving, and such a review would rapidly become outdated. assessment, and such a review would quickly become out-of-date as the field continues to evolve.

2.5.7 Conclusion

Many AI interventions are being tested and implemented in AI adolescents' mental healthcare. We critically examined these AI interventions and discovered inconsistencies in reporting the participants, forms of AI techniques, analyses, and results, as well as a significant gap in the successful development and use of AI in the mental healthcare of adolescents. The use of AI in various aspects of healthcare is relatively new, and HCPs, patients, and AI developers might 1) consider becoming more aware of the potential that AI may play in adolescents' mental healthcare and 2) the potential pros and cons of AI in this context. Further, to incorporate and implement AI in an appropriate way, it is critical to understand the end-users’ (patients and HCPs) opinions on AI utilization in mental health processes and expect that this strategy will result in a feedback loop of co-designing future AI initiatives in mental healthcare.

In future work, we advocate for a standard, accurate, and transparent report on AI interventions in adolescent mental healthcare. This requires reporting guidelines and frameworks for AI interventions in this context to be created to enhance the usage and development of these interventions and address bias and accuracy problems. Also, more research has to be done to understand how to make AI models generalizable while remaining patient-centred and retaining high accuracy.

2.6 Tables

Table 2.1. Adolescents' variable reported (N=30).

Adolescents' variable reported	N=30
Sex	23
Gender	0
Sample size	28
Race/ethnicities[1]	9
Other Sociodemographic[2]	14

[1] Race/ethnicities: Caucasian/White, Japanese, Chinese, Indian, Malay, Black, Oriental, African American, Asian-American, Hispanic, Native American/Alaskan, Asian, and Mixed
[2] Other Sociodemographic: parental marital status, parental educational level achieved, socioeconomic aspects (e.g., parental and household income), place of residence, criminal records, maternal history of depression, neighborhood level of deprivement, adolescents' traumatic events and their level of education

Table 2.2. Criteria to evaluate the performance of AI models

Criteria	Definition
True positive	A result in which the model predicts the positive class properly
True negative	A result in which the model predicts the negative class properly
False positive	Positive results that the model wrongly predicted
False negative	Negative results that the model wrongly predicted
Sensitivity	The metric that assesses a model's ability to predict true positives in each accessible category
Specificity	The metric that assesses a model's ability to predict true negatives in each accessible category
Precision or Positive Predictive Value	The proportion of cases labelled as positively that was genuinely positive);
Recall	The measure with which the model recognizes True Positives
F1 score	The weighted average of precision and recall);
Accuracy	A model's measurement's proximity to the standard or real value, calculated as the number of correct predictions divided by the total number of predictions

Table 2.3. AI application on the continuum of adolescents' mental healthcare

Authors' name	Illness/disease	Mediation of Diagnostic Process	Treatment	Monitoring and evaluation	Prognosis
Bekele E. et al., 2013	Autism Spectrum Disorder	Helps to identify certain emotions and differences in how processing emotional faces		Helps to improve monitoring communication skills	
Zhou Y. et al., 2014	Autism Spectrum Disorder			Helps to better monitor its related biomarkers	Helps prognosis using its related biomarkers
Chen H. et al., 2016	Autism Spectrum Disorder	Helps with diagnosis and disease-related biomarkers			
Hart H. et al., 2014	Attention Deficit Hyperactivity Disorder	Helps to improve the diagnostic accuracy and optimally clinical outcomes			
Khaleghi A. et al., 2015	Bipolar disorders type 1 and 2	Helps to differentiate between two subtypes			
Ang RP. et al., 2013	Adolescents' offending and delinquency	Helps with diagnosis		Helps to improve the follow-ups	
Strigo IA. et al., 2017	Eating disorder	Helps with diagnosis and disease classification			
Zhang Z. et al., 2017	Generalized Anxiety Disorder	1) Helps with diagnosis and disease-related biomarkers 2) Increase the knowledge about disease pathogenesis			
Reid JC. et al., 1994	Hopelessness		Helps to improve treatment	Helps to better monitor	
Kashani JH. et al., 1996	Hopelessness	Helps to improve diagnosis	Helps to improve treatment		
Barzman D. et al., 2018	School violence	Helps with disease assessment			
Velupillai S. et al., 2019	Suicidality	Helps to identify disease			
DiGuiseppi GT. et al., 2020	Homelessness (following substance use treatment)	Helps with diagnosis			
Fitzgerald A. et al., 2018	Substance use disorder/behavior	Helps to identify associated risk factors			
Garcia E.G. et al., 2010	Substance use disorder/behavior	Helps to identify associated risk factors			
Gervilla E. et al., 2011	Cannabis use disorder	Helps with diagnosis			
Ruan H. et al., 2019	Alcohol binge drinking	Helps with diagnosis	Helps with targeted interventions		
Squeglia L. et al., 2017	Alcohol use disorder (underaged drinking)	Helps with diagnosis			
Thakur S. et al., 2016	Alcohol consumption traits	Helps to identify the alcoholic vs non-alcoholic			
Foland-Ross L. C. et al., 2015	Depression	Helps understand patterns of brain structure			
Geraci J. et al., 2017	Depressive/Dysthymic disorder	Helps with diagnosis			
Downs J. et al., 2019	Early onset psychosis			Helps in better monitoring antipsychotic-treated adolescents	
Liu, Y. et al., 2018	Acute onset schizophrenia	Helps with diagnosis			
Lenhard F. et al., 2018	Obsessive-compulsive disorder			Helps with better monitoring	
Fujisawa T. X. et al., 2018	Reactive attachment disorder	Helps to improve diagnosis accuracy	Helps to improve treatment accuracy	Helps with better monitoring	
Xue Y. et al., 2014	Unspecified outcomes of other psychological stress/pressure level (mild-moderate level)		Helps with treatment		
Jin L. et al., 2016	Unspecified outcomes of other psychological stress/pressure level	Helps with diagnosis			
Li Y. et al., 2015	Unspecified outcomes of other psychological stress/pressure level	Helps with diagnosis			
Tyulyupo S. V. et al., 2018	Psychological well-being estimation			Helps with better monitoring in rural schools	
Gan Y , 2012	Left behind adolescents' life satisfaction				Helps with better evaluation

Table 2.4. Types of data used to develop AI interventions (N=30)

Clinical data 12/30 (40%)	**Image and computer vision data** 11/30 (37%)	**Text Data** 7/30 (23%)
1-Mental Health questionnaire: 11/12	1-Magnetic Resonance Imaging of Brain: 10/11	1-Electronic Health Records using NLP: 3/7
2-Electroencephalogram: 1/12	2-Virtual Reality-based eye-tracking system: 1/11	2-Mental health survey on school safety and child aggression using NLP: 1/7
		3-Social Media: 1/7
		4-Tweets: 1/7
		5-Social Media and Tweets: 1/7

2.7 Figures

Figure 2.1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart of the selection procedure. AI: Artificial Intelligence

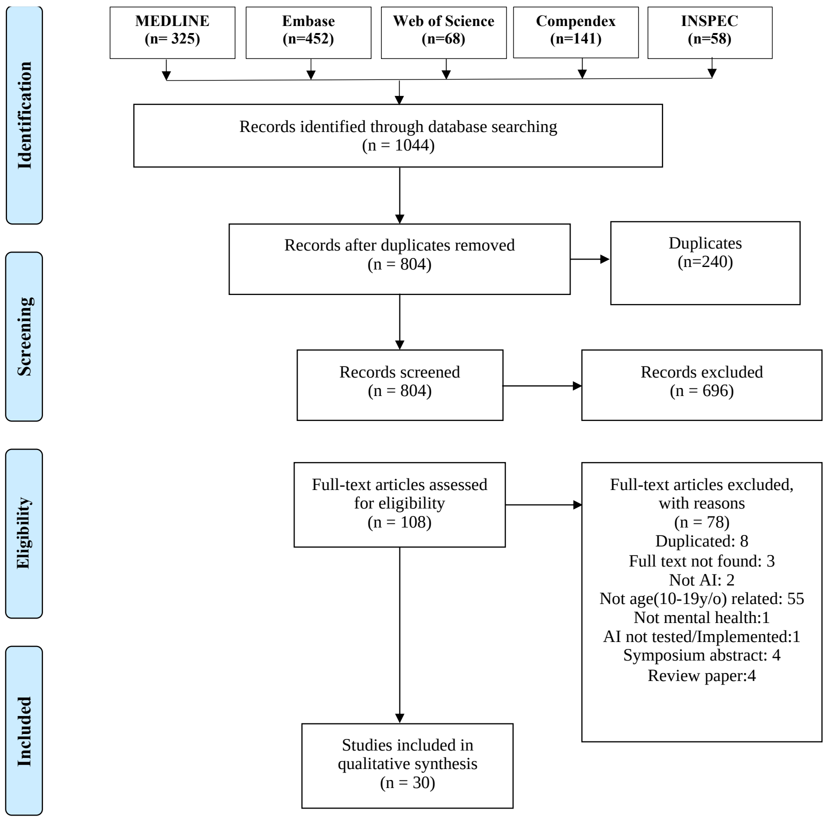


Figure 2.2. Frequency and timeline of Artificial Intelligence research studies by year of publication

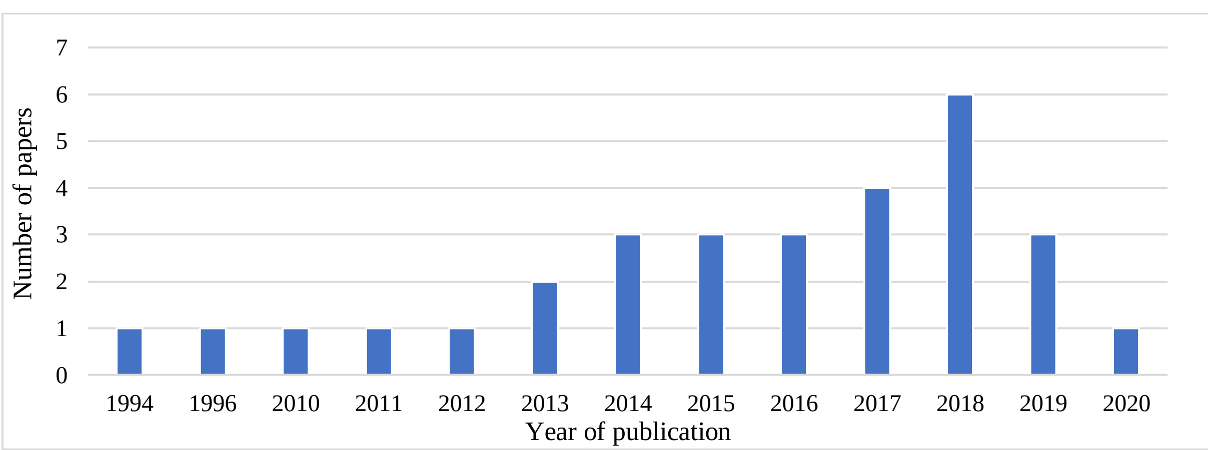
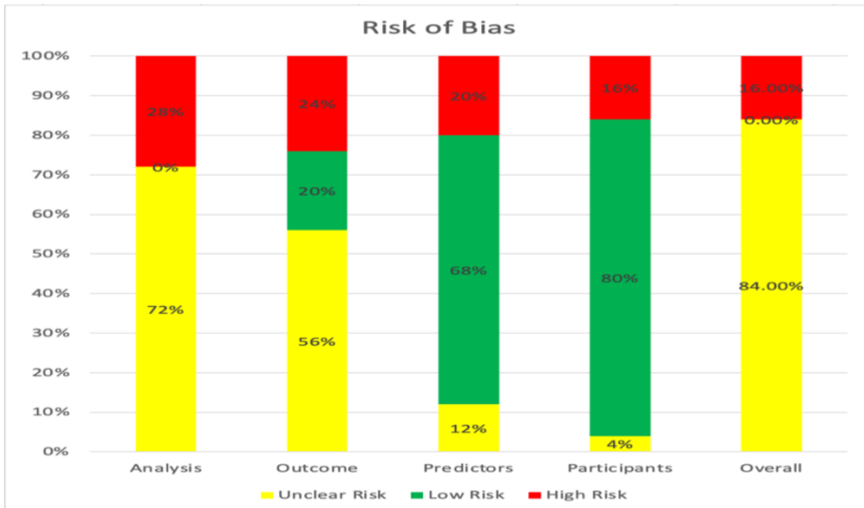


Figure 2.3. Risk of bias graph: assessing the risk of bias in five categories namely overall, participants, predictors, analysis, and outcome (presented as percentages)



2.8 Appendix

2.8.1 Appendix 1. Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
TITLE			
Title	1	Identify the report as a scoping review.	28
ABSTRACT			
Structured summary	2	Provide a structured summary that includes (as applicable): background, objectives, eligibility criteria, sources of evidence, charting methods, results, and conclusions that relate to the review questions and objectives.	29-31
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known. Explain why the review questions/objectives lend themselves to a scoping review approach.	32-35
Objectives	4	Provide an explicit statement of the questions and objectives being addressed with reference to their key elements (e.g., population or participants, concepts, and context) or other relevant key elements used to conceptualize the review questions and/or objectives.	35
METHODS			
Protocol and registration	5	Indicate whether a review protocol exists; state if and where it can be accessed (e.g., a Web address); and if available, provide registration information, including the registration number.	36
Eligibility criteria	6	Specify characteristics of the sources of evidence used as eligibility criteria (e.g., years considered, language, and publication status), and provide a rationale.	36
Information sources*	7	Describe all information sources in the search (e.g., databases with dates of coverage and contact with authors to identify additional sources), as well as the date the most recent search was executed.	37
Search	8	Present the full electronic search strategy for at least 1 database, including any limits used, such that it could be repeated.	37
Selection of sources of evidence†	9	State the process for selecting sources of evidence (i.e., screening and eligibility) included in the scoping review.	37-38
Data charting process‡	10	Describe the methods of charting data from the included sources of evidence (e.g., calibrated forms or forms that have been tested by the team before their use, and whether data charting was done independently or in duplicate) and any processes for obtaining and confirming data from investigators.	38
Data items	11	List and define all variables for which data were sought and any assumptions and simplifications made.	39

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
Critical appraisal of individual sources of evidence§	12	If done, provide a rationale for conducting a critical appraisal of included sources of evidence; describe the methods used and how this information was used in any data synthesis (if appropriate).	N/A
Synthesis of results	13	Describe the methods of handling and summarizing the data that were charted.	39
RESULTS			
Selection of sources of evidence	14	Give numbers of sources of evidence screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally using a flow diagram.	39
Characteristics of sources of evidence	15	For each source of evidence, present characteristics for which data were charted and provide the citations.	39-41
Critical appraisal within sources of evidence	16	If done, present data on critical appraisal of included sources of evidence (see item 12).	N/A
Results of individual sources of evidence	17	For each included source of evidence, present the relevant data that were charted that relate to the review questions and objectives.	42-44
Synthesis of results	18	Summarize and/or present the charting results as they relate to the review questions and objectives.	64-67
DISCUSSION			
Summary of evidence	19	Summarize the main results (including an overview of concepts, themes, and types of evidence available), link to the review questions and objectives, and consider the relevance to key groups.	44-54
Limitations	20	Discuss the limitations of the scoping review process.	55
Conclusions	21	Provide a general interpretation of the results with respect to the review questions and objectives, as well as potential implications and/or next steps.	55-56
FUNDING			
Funding	22	Describe sources of funding for the included sources of evidence, as well as sources of funding for the scoping review. Describe the role of the funders of the scoping review.	N/A

JBI = Joanna Briggs Institute; PRISMA-ScR = Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews.
* Where *sources of evidence* (see second footnote) are compiled from, such as bibliographic databases, social media platforms, and Web sites.
† A more inclusive/heterogeneous term used to account for the different types of evidence or data sources (e.g., quantitative and/or qualitative research, expert opinion, and policy documents) that may be eligible in a scoping review as opposed to only studies. This is not to be confused with *information sources* (see first footnote).
‡ The frameworks by Arksey and O'Malley (6) and Levac and colleagues (7) and the JBI guidance (4, 5) refer to the process of data extraction in a scoping review as data charting.
§ The process of systematically examining research evidence to assess its validity, results, and relevance before using it to inform a decision. This term is used for items 12 and 19 instead of "risk of bias" (which is more applicable to systematic reviews of interventions) to include and acknowledge the various sources of evidence that may be used in a scoping review (e.g., quantitative and/or qualitative research, expert opinion, and policy document).
From: Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMAScR): Checklist and Explanation. Ann Intern Med.

2.8.2 Appendix 2. Some of the extracted data from the included studies

Author	Title	Objective	Input information	Details about the AI system	Performance	AI Methods	Compared with other methods? (Yes/No)	Eligible for PROBAST (Yes/No)
1. Khaleghi A. et al., 2015	EEG classification of adolescents with type I and type II of bipolar disorder	To classify the EEG signal of BD I from BD II adolescents using different analysis including NN	Electroencephalogram signal (EEG)	After preprocessing, state-of-the-art algorithms from different fields are implemented to categorise the two groups. Four feature selection strategies are used to increase classification accuracy: mutual information maximisation (MIM), conditional mutual information maximisation (CMIM), fast correlation-based filter (FCBF), and double input symmetrical relevance (DISR). With and without feature selection, a Multilayer Perceptron (MLP) neural network with a hidden layer of five neurons is utilised for classification.	Best average accuracy rate for testing data set was for DISR: 91.83 ± 0.41 %	Multilayer Perceptron Neural Networks (MIM, CMIM, FCBF and DISR)	Yes	Yes
2. Bekele E. et al., 2013	Virtual reality-based facial expressions understanding for teenagers with autism	To analyse physiological and eye tracking data from a usability study to evaluate a new VR-based face expression detection system.	Physiological signals	VR-based facial emotion recognition mechanism in the presence of contextual storytelling.	94% for GM and 91% for k-means	Gaussian mixture and k-means clustering methods (machine learning algorithm)	No	Yes
3. Jin L. et al., 2016	Integrating human mobility and social media for adolescent psychological stress detection	Unclear. However, it seems to be proposing a co-training-based stress detection model based on teens' daily Global Positioning System (GPS) trajectories and microblog data	Positional and temporal outlier features from teens' daily trajec-tories to facilitate stress detection.	One classifier is conditional random field (CRF), which takes out- lier features from GPS trajectories as input to model the daily moving behavior correlation of stress. The other classifier is deep neural network (DNN) involving tweet features to model the social media behavior correlation of stress.	Best accuracy: 88.92% Best F1-measure: 91.02%	Compared different frameworks and come up with a new result (Co-training framework) =>One classifier is conditional random field (CRF), The other classifier is deep neural network (DNN), RF, SVM, NB (Naive Bayes), GBDT (Gradient Boosted Decision Tree), Co Training (considering all methods together)	Yes	Yes
4. Gan Y , 2012	Evaluation on life satisfaction of left-behind junior high school children based on LVQ network	Unclear. However, the intuitional objective seems to evaluate the life satisfaction of left-behind children using NN and classify them with less labor and time.	Data obtained from Chinese adolescent students' life satisfaction scale	The LVQ used to evaluate of left-behind junior high school children's life satisfaction consists of three layers, with 6 and 3 neurons in the input and output layers for the assessment index and life satisfaction grades.	The absolute and relative correct rate of prediction were 97.8% and 100%, and the trained network exhibited high performance.	LVQ NN	No	Yes
5. Tyulyupo S. V. et al., 2018	Adolescents psychological well-being estimation based on a data mining algorithm	Unclear- However, it sems to be 1) Creating a software that can measure 12-17-year-olds' psychological well-being based on a questionnaire without a psychologist's help. 2) Using machine learning, reduce, correct, and expand the number/kind of questions used to assess adolescents' psychological well-being.	Responses of about 200 adolescents aged 12-17 years from 11 rural schools.	The algorithm of twice-multilayered modified polynomial neural network with active neurons used to construct classifiers for 4 classes of well-being of schoolchildren.	Accuracy of determining psychological well-being is already at the level of 72-91%	Group method of data handling (GMDH) which is called twice-multilayered modified polynomial neural networks	No	No
6. Xue Y. et al., 2014	Detecting Adolescent Psychological Pressures from Micro-Blog	To propose a pressure detection strategy on micro-blog to timely and effective detect teenagers' psychological pressures status and changes	Teenagers' tweets on micro blog platform	Investigate some features that may reveal teenagers' pressures from their tweets, and then test five classifiers (Naive Bayes, Support Vector Machines, Artificial Neural Network, Random Forest, and Gaussian Process Classifier) for pressure detection.	Gaussian Process: Showed best accuracy (highest precision and recall rates) between 0.826-0.820-0.823	Tested five classifiers (Naive Bayes, Support Vector Machines, Artificial Neural Network, Random Forest, and Gaussian Process Classifier)	Yes	No
7. Strigo IA. et al., 2017	The clinical application of fMRI data in a single-patient diagnostic conundrum: Classifying brain response to experimental pain to distinguish between gastrointestinal, depressive and eating disorder symptoms	Used a novel machine learning to classify (i) the patient's functional brain imaging during an experimental pain paradigm, and (ii) patient self-report psychological measures, to categorize the patient's diagnostic phenotype.	Using age as a covariate, created pain-related brain activation masks in the 23 healthy control women who previously performed the same task, anticipating and characterizing brain response to high vs low pain.	The SVM classifier was created on the GIP, MDD, and RAN groups, and Anna was classified according to her responses on psychological measures. An additional SVM was performed using subjects' responses on behavioral measures.	1)Accuracy of SVM for 'brain activation/brain-based classifications: 84% 2) Accuracy of SVM for 'psychological (behavioural) variables/based classifications: 54%	SVM	No	Yes
8. Zhang Z. et al., 2017	Frequency-specific functional connectivity density as an effective biomarker for adolescent generalized anxiety disorder	1) To investigate how Generalized Anxiety Disorder (GAD) affects the brain's short- and long-range functional connectivity density (S-FCD and L-FCD) in adolescents across different frequency bands 2) To examine whether the frequency specific FCD could help to discriminate patients with GAD from Healthy Controls	Data from 31 adolescent patients with GAD and 28 matched healthy controls	SVM classifier was further used to examine the discriminative ability of the frequency- specific FCD values.	Best SVM classification performance was derived from combining both S-FCD and L-FCD in which the AUC value of 0.9414 and the corresponding sensitivity, specificity, and accuracy of 87.15, 92.92, and 89.83%, respectively	SVM	No	Yes
9. Chen H. et al., 2016	Multivariate classification of autism spectrum disorder (ASD)using frequency-specific resting-state functional connectivity-A multi-center study	Unclear. However, Multivariate pattern analysis (MVPA) appears to be used by the virtue of multi-centre datasets to find a robust objective neuroimage biomarker to diagnose ASD.	Data of adolescents with ASD	Used a linear kernel SVM as it can reduce the risk of overfitting and allows direct extraction of the feature weights	A relatively high classification accuracy of 79.17% (AUC: 0.7917) (77.78% for sensitivity, 80.47% for specificity, permutation test p b 0.001, 1000 times)	SVM	No	Yes
10. Thakur S. et al., 2016	Identification of chief characteristics of alcohol consumption traits in schools using rough set and formal concept analysis	Unclear. However, it seems to be to extract the major attributes that correlates most to a teenager's drinking habits from the Portuguese high school alcohol consumption dataset.	Questionnaire-based school reports	Make use of rough set theory as well as formal concept analysis over traditional probabilistic and fuzzy models as rough set exclude the various assumptions made in the later models.	1) For Alcoholic trait: 100% accuracy 2) For non-alcoholic trait: 90-100%	Fuzzy sets, Data mining	No	Yes

Author	Title	Objective	Input information	Details about the AI system	Performance	AI Methods	Compared with other methods? (Yes/No)	Eligible for PROBAST (Yes/No)
11. Foland-Ross L. C. et al., 2015	Cortical thickness predicts the first onset of major depression in adolescence	Unclear. It appears to elucidate machine learning methods by which brain anomalies in grey matter structure increase depression risk in adolescents over time.	MRI Data	Used SVMs to test whether baseline cortical thickness could reliably distinguish adolescents who develop depression from adolescents who remained free of any Axis I disorder.	Performance measure: Overall accuracy of 69.7% (69.3 % sensitivity, 70% specificity; p = 0.021)	SVM	No	Yes
12. Hart H. et al., 2014	Pattern classification of response inhibition in ADHD: Toward the development of neurobiological markers for ADHD	1) Gaussian Process Classifiers (GPCs) of task-based fMRI data during the tracking Stop task in 30 boys with and 30 healthy boys can identify distributed neurofunctional patterns that will provide accurate diagnostic predictors of ADHD. 2) To use traditional univariate analyses to replicate previous findings of reduced function in inhibitory regions of ventrolateral prefrontal cortex (VLPFC) and the basal ganglia in a relatively large cohort of 30 ADHD patients	fMRI data	fMRI data were analyzed with Gaussian process classifiers (GPC), a machine learning approach, to predict individual ADHD diagnosis based on task-based activation patterns.	Performance measures: Overall classification accuracy of 77% (sensitivity of 90% and specificity of 63%, (P < 0.001, positive predictive value (PPV) was 71.05% and the negative predictive value (NPP) was 86.36%)	Gaussian process classifiers (GPC)	Yes	Yes
13. Zhou Y. et al., 2014	Multiparametric MRI characterization and prediction in autism spectrum disorder (ASD) using graph theory and machine learning	1) To evaluate multi-parametric functional and structural MRI of the brain in ASD versus typically developed (TD) children using small-world network analysis based on graph theory to derive local and global efficiency, 2) To use machine-learning algorithms to evaluate the ability of these multiparametric MRI matrices to classify ASD versus TD groups, 3) To employ machine-learning algorithms of these multiparametric MRI matrices to predict ASD clinical phenotypic outcomes, such as the revised autism diagnostic interview (ADI-R), autism diagnostic observation schedule (ADOS), and intelligence quotient (IQ) scores reflecting different aspects of social and learning abilities of subjects	MRI data	An integrative model of 22 quantitative imaging features was used for classification and prediction of phenotypic features that included the ASD diagnostic observation schedule, the revised ASD diagnostic interview, and intelligence quotient scores.	The 'random tree classifier' had the highest classification accuracy (100%), (close to 100% sensitivity and specificity for correctly identifying ASD patients with the full dataset, and 70% accuracy for differentiating ASD patients from TD children using 80% percentage split cross validation. Based on the 4 imaging features, the random tree classifier also had the highest accuracy (98%) for the full dataset for two-group classification, with 68% accuracy for 10-fold cross validation	A total of 67 available classifiers, including SVM, Bayes network (BayesNet), radial basis function (RBF), and sequential minimal optimization (SMO) algorithms, were tested with batch-mode scripts developed in WEKA software. The 'random tree classifier' was another AI technique used among 67 classifiers.	Yes	Yes
14. Ang RP. et al., 2013	Predicting juvenile offending: a comparison of data mining methods	To predict juvenile offending with reasonable accuracy and to identify common risk factor correlates, using data mining methods on a large Asian youth sample	Data from Behavior assessment system for children–self report of personality, Teacher–student relationship inventory (TSRI), Reactive-Proactive Aggression Questionnaire (RPQ), State-trait anxiety inventory for children (STAIC), Narcissistic Personality Questionnaire for Children–Revised (NPQC-R)	The DT, ANN, and SVM classifiers were generated using the training data set to predict if an adolescent would be charged with criminal offense. The validation and testing data sets were used to evaluate the performance (accuracy rates) of the classifier.	1) ANN accuracy: 97.22% 2) Decision Tree accuracy: 96.64% 3) SVM accuracy: 94.16% 4) Logistic regression accuracy: 94.50%,) ANN area under the curve ROC: 0.973, Confidence Interval [.962, .984]. Decision Tree area under ROC: 0.968, Confidence Interval [.956, .979]. SVM area under ROC 0.946, Confidence Interval [.929, .960]. Logistic regression area under ROC: 0.950, Confidence Interval [.935, .965]	Logistic regression, predictive data mining techniques such as decision trees (DTs), artificial neural networks (ANNs), and support vector machines (SVMs)	No	Yes
15. Gervilla E. et al., 2011	Quantification of the influence of friends and antisocial behaviour in adolescent consumption of cannabis using the ZINB model and data mining	To analyze and quantify the predictive value of different personal, family and environmental variables on adolescents' cannabis use.	Number of joints used each week, peer group consumption, weeknights out, gender, forbidden behaviour production, and other substances use.	Association rules highlight the relationship between cannabis and tobacco consumption, ease of access, production of forbidden behaviour. Decision trees used to predict cannabis consumption and the number of joints an adolescent will consume per week based on the production of forbidden behaviour, other substances use and number of friends who consume cannabis.	Not reported	Poisson regression model (PRM) and a data mining using a decision tree (DT)	No	Yes
16. Garcia E.G. et al., 2010	Study of the factors associated with substance use in adolescence using Association Rules	To analyse adolescent substance use using Data Mining's association rules and descriptive tools.	Adolescents answered an anonymous questionnaire on personal, family, and environmental substance use risk factors.	The association rules indicate the link between perceived parental action, deviant behaviours from norms, peer consumption, and legal and illegal drug abuse in adolescence..	1) confidence = 0.8528, confidence = 0.8032, 0.8718 and 1.0000, respectively), and the use of ecstasy to peer consumption (confidence = 1.0000)	Data Mining	No	Yes
17. Kashani JH. et al., 1996	Relationship of personality, environmental, and DICA variables to adolescent hopelessness: A neural network sensitivity approach	To identify psychiatric diagnoses, personality traits, and familial and social support variables related to adolescent hopelessness	Data from Millon Adolescent Personality Inventory, the Parental Bonding Questionnaire, the Social Support Questionnaire, the Hopelessness Scale for Children and were interviewed by trained clinicians on the Diagnostic Interview for Children and Adolescents.	Developed a multilayer back-propagation neural network model and trained it using adolescent responses, and then performed a sensitivity analysis. The training process was validated to ensure that the network mapped the relationships well.	More than 80%, The neural network model was able to obtain a good fit for the data (R2 = .9908), whereas the linear regression did not (R2 = .3316).	Neural Network	Yes	Yes

Author	Title	Objective	Input information	Details about the AI system	Performance	AI Methods	Compared with other methods? (Yes/No)	Eligible for PROBAST (Yes/No)
18. Reid JC. et al., 1994	Detecting dysfunctional behavior in adolescents: the examination of relationships using neural networks	To identify the most important mental health variables from a set of personality, family, and social support variables related to hopelessness using a neural network model.	Data collected from Million Adolescent Personality Inventory (MAPI) the Diagnostic Interview or Children and Adolescents (DICA); the Parental Bonding Questionnaire; the Social Support Questionnaire, and the Hopelessness Scale for children.	After training a multi-layer back propagation neural network using adolescent responses, a sensitivity analysis was undertaken.	Accuracy within 25% for 79% of the adolescents and within 50% for 93% of the adolescents.	Artificial Neural Networks	No	No
19. Li Y. et al., 2015	Predicting Teenager's Future Stress Level from Micro-Blog	To predict teenagers' future adolescent stress level from micro-blog	Data from micro-blog	Investigate some stress level prediction features and the use of multi-variant seasonal stochastic time series prediction techniques.	Nearest mean approach=> Error: 0.7161- 0.7501 2) Linear interpolation => Error: 0.7755- 0.8036 3) Exponential smoothing=> 4) Gaussian Process Regression(GPR)=> Error: 0.4794-0.4973 5) Supported Vector Regression (SVR)=> Error: 0.5429- 0.5656 Gaussian Process Regression (GPR) showed the lowest possible error compared to other methods! (GPR error: 0.4794-0.4973). Error for the rest of the ML methods used were more than 50%.	Nearest mean approach, Linear interpolatio,Exponential smoothing, Gaussian Process Regression (GPR), Supported Vector Regression (SVR)	No	Yes
20. DiGuiseppi GT. et al., 2020	Predictors of adolescents' first episode of homelessness following substance use treatment	To identify predictors of youths' first episode of homelessness during the 12 months after substance use treatment entry	Data from survey on children using receiving substance use treatment	Logistic regression and Lasso machine learning regression were used to predict participants' first episode of homelessness in the 12 months after treatment intake.	Not reported	LASSO machine learning regression	No	Yes
21. Ruan H. et al., 2019	Adolescent binge drinking disrupts normal trajectories of brain functional organization and personality maturation	To identify how adolescent binge drinking affects brain and personality development.	Information about 19-year-olds' brain function architecture, personality traits, and genetic variants	Used multivariate approaches to explore discriminative features in brain functional architecture, personality traits, and genetic variants in 19-year-old individuals. Multivariate approaches explored 19-year-olds' brain functional architecture, personality traits, and genetic variants. Using a longitudinal design, researchers identified features that were more altered in early binge drinkers. With these features, they trained a hierarchical SVMs model.	Accuracy: 71.2%, AUC: 0.900	SVM	No	Yes
22. Velupillai S. et al., 2019	Identifying Suicidal Adolescents from Mental Health Records Using Natural Language Processing	1) Generate a manually annotated reference standard of adolescent mental health conditions. 2) Apply and modify an existing NLP approach for specified clinical construct mention-level extraction.	Electronic Health Record (EHR) documentation related to suicide risk	Adapted and evaluated a simple lexicon- and rule-based NLP approach to identify suicidal adolescents from a large EHR database.	1) Inter-annotator agreement on the subset of 100 documents was very high: 0.96, 98% accuracy, >80% f1 score at both document and patient level 2) Accuracy on a patient level was not reported, Recall results: ranged from 74% to 90%	NLP	No	Yes
23. Downs J. et al., 2019	Negative symptoms in early-onset psychosis and their association with antipsychotic treatment failure	1) identify the prevalence of Negative Symptoms (NS) at first presentation to mental health services 2) If NS predicted multiple treatment failure (MTF) before 18 y/o	Data extracted from the electronic health records having Marder Factor, NS and antipsychotic use.	The association between presenting with ≥2 NS and the development of MTF over a 5-year period was modeled using Cox regression.	PPV 0.91, recall 0.73	NLP	No	No
24. Fitzgerald A. et al., 2018	Dissociable psychosocial profiles of adolescent substance users	To examine the role of the Individual, Family, School, Peer, and Social Environment on alcohol (lifetime and risky), tobacco (risky only), and cannabis use (lifetime and riskiness).	Substance use behavior alongside risk and protective factors across Individual, Family, School, Peer and Social domains were used.	Used logistic regression with Elastic Net regularization, which allows relevant but correlated coefficients to co-exist in a sparse model fit.	Accuracy more than 88%, Model A: Precision: 0.8106 Recall: 0.8326 AROC: 0.8924 F1 Score: 0.8101, Model B: Precision: 0.6816 Recall: 0.8810 AROC: 0.9051 F1 Score: 0.7688 , Model C: Precision:0.5437 Recall: 0.8979 AROC: 0.8814 F1 Score: 0.6723 , Model D: Precision: 0.4484 Recall: 0.9314 AROC: 0.9156 F1 Score: 0.6039, Model Precision: 0.3100 Recall: 0.9606 AROC: 0.9247 F1 Score: 0.4687	Logistic regression with Elastic Net regularization (LASSO, ridge regression)	No	Yes
25. Fujisawa T. X. et al., 2018	Type and timing of childhood maltreatment and reduced visual cortex volume in children and adolescents with reactive attachment disorder (RAD)	To investigate the effects of type and timing of childhood adversities on structural alterations in regional grey matter (GM) volume in maltreated RAD children.	High-resolution MRI datasets	Structural images were analyzed using a whole-brain voxel-based morphometry approach and the type and timing of maltreatment, which may be more strongly associated with structural alterations, was assessed using random forest regression with conditional inference trees.	Accuracy related reported information: Reasonable accuracy based on type and number of types of maltreatment ($r = 0.650$, $p < 0.05$)	Random forest regression with conditional inference trees	No	Yes
26. Barzman D. et al., 2018	Automated risk assessment for school violence: a pilot study	To describe manual annotation findings to show feasibility of developing an automated system (e.g., machine learning) for preventing school violence.	Interview transcripts of students	Not reported	AUC: 91.02%	Novel ML framework	No	Yes
27. Liu, Y. et al., 2018	Decreased Resting-State Interhemispheric Functional Connectivity Correlated with Neurocognitive Deficits in Drug-Naive First-Episode Adolescent-Onset Schizophrenia	To examine functional connectivity between homotopic brain regions in drug-naïve, first-episode patients with Adolescent onset schizophrenia (AOS)	Data from MRI scans	Data were subjected to voxel-mirrored homotopic connectivity and support vector machine analyses.	Sensitivity of 100%, specificity of 87.09%, and accuracy of 94.93%	SVM	No	Yes

Author	Title	Objective	Input information	Details about the AI system	Performance	AI Methods	Compared with other methods? (Yes/No)	Eligible for PROBAST (Yes/No)
28. Lenhard F. et al., 2018	Prediction of outcome in internet-delivered cognitive behaviour therapy for paediatric obsessive-compulsive disorder: A machine learning approach	To test four machine learning methods for predicting treatment response in pediatric obsessive-compulsive disorder (OCD) patients receiving Internet-delivered cognitive behaviour therapy (ICBT).	Clinical baseline variables were used to predict three-month ICBT response.	Used a linear model with best subset predictor selection and three flexible models, L1 Elastic Net (Lasso), Random Forests, and SVMs. The four chosen models have different statistical characteristics and are a trade-off between flexibility and interpretability.	1) A linear model: 83% % [95% confidence interval (CI) (52–98%)]- 2) L1 Elastic Net (Lasso): Accuracy in the test sample was 75% [95% CI (43–95%)]- 3) Random Forests: Accuracy was 75% [95% CI (43–95%)]- 4) Support Vector Machines: Accuracy was 75% [95% CI (43–95%)]- . All Accuracies between 75 to 83%	1) A linear model 2) L1 Elastic Net (Lasso), 3) Random Forests 4) Support Vector Machines	Yes	No
29. Geraci J. et al., 2017	Applying deep neural networks to unstructured text notes in electronic medical records for phenotyping youth depression	To use NLP and ML to identify phenotype: 12–18-year-olds with DSM-IV criteria of Major Depressive Disorder or Dysthymic Disorder	Electronic Medical Record (EMR) documents	Used an R language implementation of the H2O.ai package, which includes a multilayer, feedforward deep neural network for the purpose of prediction under a supervised protocol.	1) A Brute Force search method using NLP package: sensitivity=80%, specificity=88%, Accuracy: Not reported 2) sensitivity 93.5%; specificity 68%; positive predictive value (precision) 77%) DL0_2: 87% accurate	1) A Brute force search method using NLP package 2) Deep Neural Network using NLP package	No	Yes
30. Squeglia L. et al., 2017	Neural Predictors of Initiating Alcohol Use During Adolescence	To identify variables that predict adolescents' alcohol use by age 18 (underaged drinking)	Mix of demographic, behavioral, neuropsychological, and neuroimaging data	Random forest classification models identified the most important predictors of alcohol use from a large set of demographics, neuropsychological, sMRI, and fMRI variables.	Not reported	Random forest classification model	No	Yes

2.8.3 Appendix 3. Risk of Bias (ROB) table: based on authors' judgements about each risk of bias item. (Low ROB , High ROB , Unclear ROB)

Author	Participants		Predictors			Outcome						Analysis								
	Were appropriate data sources used, e.g.: cohort, RCT, or nested case–control study data?	Were all inclusions and exclusions of participants appropriate?	Were predictors defined and assessed in a similar way for all participants ?	Were predictor assessments made without knowledge of outcome data?	Are all predictors available at the time the model is intended to be used?	Was the outcome determined appropriately?	Was a prespecified or standard outcome definition used?	Were predictors excluded from the outcome definition?	Was the outcome defined and determined in a similar way for all participants?	Was the outcome determined without knowledge of predictor information?	Was the time interval between predictor assessment and outcome determination appropriate?	Were there a reasonable number of participants with the	Were continuous and categorical predictors handled appropriately?	Were all enrolled participants included in the analysis?	Were participants with missing data handled appropriately?	Was selection of predictors based on univariable analysis avoided? (For developmental studies only)	Were complexities in the data (e.g., censoring, competing risks, sampling of control participants) accounted for appropriately?	Were relevant model performance measures evaluated appropriately?	Were model overfitting, underfitting, and optimism in model performance accounted for? (For developmental studies only)	Do predictors and their assigned weights in the final model correspond to the results from the reported multivariable analysis? (For developmental studies only)
Khaleghi A. et al., 2015	+	+	+	+	+	+	-	-	+	-	?	-	+	+	?	+	+	-	-	+
Bekele E. et al., 2013	+	+	?	?	+	?	-	-	+	+	?	-	?	+	?	+	-	-	?	+
Jin L. et al., 2016	+	+	-	-	+	-	+	+	+	+	-	-	?	+	-	?	?	+	?	?
Gan Y, 2012	+	+	+	-	-	-	-	+	+	+	?	-	?	+	?	-	-	+	-	+
Strigo IA. et al., 2017	-	+	+	+	+	+	-	-	+	-	+	-	+	+	+	NA	?	-	NA	NA
Zhang Z. et al., 2017	+	+	+	+	+	+	+	?	+	+	+	-	-	+	?	?	-	+	-	+
Chen H. et al., 2016	+	+	+	+	+	+	+	+	+	+	+	-	+	+	-	-	+	+	-	+
Thakur S. et al., 2016	+	-	+	-	?	-	+	+	-	-	?	+	-	-	?	-	-	-	-	+
Foland-Ross L. C. et al., 2015	+	+	+	+	+	+	+	+	+	+	+	-	+	+	?	+	+	+	+	+
Hart H. et al., 2014	+	-	+	-	+	-	+	-	?	-	+	-	-	+	?	-	-	+	-	+
Zhou Y. et al., 2014	+	+	+	+	+	+	+	-	+	+	+	+	-	+	-	?	+	+	-	+
Ang RP. et al., 2013	+	+	+	-	+	+	+	+	+	+	+	+	+	+	-	+	+	+	+	+
Gervilla E. et al., 2011	+	+	+	+	+	+	+	+	+	+	?	+	-	+	?	-	+	+	+	+
Garcia E.G. et al., 2010	+	+	+	+	+	-	+	-	+	?	?	+	+	+	?	?	+	+	?	+
Kashani JH. et al., 1996	+	+	+	+	+	+	+	+	+	+	-	-	-	+	-	NA	-	+	NA	NA
Li Y. et al., 2015	?	+	+	+	+	+	+	+	+	+	+	?	+	?	?	+	-	+	+	+
DiGuiseppi GT. et al., 2020	+	+	+	+	+	+	+	+	?	+	+	-	+	+	?	?	+	+	+	+
Ruan H. et al., 2019	+	+	+	+	+	+	?	?	-	+	+	-	+	+	+	+	-	+	+	+
Velupillai S. et al., 2019	+	+	+	+	+	+	+	+	+	+	+	+	+	+	?	?	?	+	-	?
Fitzgerald A. et al., 2018	+	+	+	+	+	+	+	+	+	+	?	+	+	+	?	+	?	+	+	+
Fujisawa T. X. et al., 2018	+	-	-	+	+	+	?	+	-	?	+	-	-	+	?	+	?	+	-	+
Barzman D. et al., 2018	+	+	+	+	+	+	+	+	+	+	-	+	-	+	-	NA	-	+	NA	NA
Liu, Y. et al., 2018	+	+	+	?	+	+	+	-	+	+	+	-	+	+	?	+	+	+	+	+
Geraci J. et al., 2017	+	+	+	+	+	+	+	?	+	+	+	+	+	+	+	+	-	+	+	+
Squeglia L. et al., 2017	+	+	+	+	+	+	+	+	+	-	?	-	-	+	-	+	-	+	+	+

2.9 References

1. Age limits and adolescents. Paediatr Child Health. 2003;8(9):577-8.
2. Murphy M, Fonagy P. Mental health problems in children and young people. 2012:1-13.
3. Aoki C, Romeo RD, Smith SS. Adolescence as a Critical Period for Developmental Plasticity. Brain Res. 2017;1654(Pt B):85-6.
4. Macdonald W, Bradley S, Bower P, Kramer T, Sibbald B, Garralda E, et al. Primary mental health workers in child and adolescent mental health services. J Adv Nurs. 2004;46(1):78-87.
5. Fuhrmann D, Knoll LJ, Blakemore SJ. Adolescence as a Sensitive Period of Brain Development. Trends Cogn Sci. 2015;19(10):558-66.
6. Trotman HD, Holtzman CW, Ryan AT, Shapiro DI, MacDonald AN, Goulding SM, et al. The development of psychotic disorders in adolescence: a potential role for hormones. Hormones and behavior. 2013;64(2):411-9.
7. Organization WH. Adolescent mental health-Institute of health Metrics and Evaluation. Global Health Data Exchange (GHDx). 2022.
8. Waddell C, Shepherd C, Schwartz C, Barican J. Child and youth mental disorders: prevalence and evidence-based interventions. 2014.
9. Polanczyk GV, Salum GA, Sugaya LS, Caye A, Rohde LA. Annual research review: A meta-analysis of the worldwide prevalence of mental disorders in children and adolescents. J Child Psychol Psychiatry. 2015;56(3):345-65.
10. Globah Health Data Exchange. Global Burden of Disease, . 2022.
11. Micali N, De Stavola B, Ploubidis G, Simonoff E, Treasure J, Field AE. Adolescent eating disorder behaviours and cognitions: gender-specific effects of child, maternal and family risk factors. Br J Psychiatry. 2015;207(4):320-7.
12. Organization WH. Global Health Estimates. 2022.
13. Wasserman D, Cheng Q, Jiang G-X. Global suicide rates among young people aged 15-19. World psychiatry. 2005;4(2):114.
14. Organization WH. Global status report on alcohol and health 2018: World Health Organization; 2019.
15. Malla A, Shah J, Iyer S, Boksa P, Joober R, Andersson N, et al. Youth Mental Health Should Be a Top Priority for Health Care in Canada. Can J Psychiatry. 2018;63(4):216-22.
16. Wyman PA. Developmental approach to prevent adolescent suicides: research pathways to effective upstream preventive interventions. Am J Prev Med. 2014;47(3 Suppl 2):S251-6.
17. Wells KB, Kataoka SH, Asarnow JR. Affective disorders in children and adolescents: addressing unmet need in primary care settings. Biol Psychiatry. 2001;49(12):1111-20.
18. Cockburn IM, Henderson R, Stern S. The impact of artificial intelligence on innovation. National bureau of economic research; 2018.
19. D'Alfonso S, Santesteban-Echarri O, Rice S, Wadley G, Lederman R, Miles C, et al. Artificial Intelligence-Assisted Online Social Therapy for Youth Mental Health. Front Psychol. 2017;8:796.

20. Bohr A, Memarzadeh K. The rise of artificial intelligence in healthcare applications. Artificial Intelligence in Healthcare: Elsevier; 2020. p. 25-60.
21. Fatima S, Desouza KC, Dawson GS. National strategic artificial intelligence plans: A multi-dimensional analysis. Economic Analysis and Policy. 2020;67:178-94.
22. Garbuio M, Lin N. Artificial intelligence as a growth engine for health care startups: Emerging business models. California Management Review. 2019;61(2):59-83.
23. Rowe JP, Lester JC. Artificial intelligence for personalized preventive adolescent healthcare. J Adolesc Health. 2020;67(2):S52-S8.
24. Kar A, Wreesmann VB, Shwetha V, Thakur S, Rao VU, Arakeri G, et al. Improvement of oral cancer screening quality and reach: The promise of artificial intelligence. Journal of Oral Pathology & Medicine. 2020;49(8):727-30.
25. Van Hartskamp M, Consoli S, Verhaegh W, Petkovic M, Van de Stolpe A. Artificial intelligence in clinical health care applications. Interactive journal of medical research. 2019;8(2):e12100.
26. Noorbakhsh-Sabet N, Zand R, Zhang Y, Abedi V. Artificial intelligence transforms the future of health care. The American journal of medicine. 2019;132(7):795-801.
27. Liyanage H, Liaw S-T, Jonnagaddala J, Schreiber R, Kuziemsky C, Terry AL, et al. Artificial Intelligence in Primary Health Care: Perceptions, Issues, and Challenges. Yearb Med Inform. 2019;28(1):41-6.
28. Shimizu H, Nakayama KI. Artificial intelligence in oncology. Cancer Sci. 2020;111(5):1452-60.
29. Chang HY, Jung CK, Woo JI, Lee S, Cho J, Kim SW, et al. Artificial Intelligence in Pathology. J Pathol Transl Med. 2019;53(1):1-12.
30. Lopez-Jimenez F, Attia Z, Arruda-Olson AM, Carter R, Chareonthaitawee P, Jouni H, et al., editors. Artificial intelligence in cardiology: present and future. Mayo Clinic Proceedings; 2020: Elsevier.
31. D'Alfonso S, Santesteban-Echarri O, Rice S, Wadley G, Lederman R, Miles C, et al. Artificial Intelligence-Assisted Online Social Therapy for Youth Mental Health. Front Psychol. 2017;8:796-.
32. D'Alfonso S, Santesteban-Echarri O, Rice S, Wadley G, Lederman R, Miles C, et al. Artificial intelligence-assisted online social therapy for youth mental health. Front Psychol. 2017;8:796.
33. Dhelim S, Chen L, Ning H, Nugent C. Artificial Intelligence for Suicide Assessment using Audiovisual Cues: A Review. arXiv preprint arXiv:220109130. 2022.
34. Voss C, Schwartz J, Daniels J, Kline A, Haber N, Washington P, et al. Effect of Wearable Digital Intervention for Improving Socialization in Children With Autism Spectrum Disorder: A Randomized Clinical Trial. JAMA pediatrics. 2019;173(5):446-54.
35. Nordin JD, Solberg LI, Parker ED. Adolescent primary care visit patterns. The Annals of Family Medicine. 2010;8(6):511-6.
36. Adams SH, Park MJ, Twietmeyer L, Brindis CD, Irwin CE. Association between adolescent preventive care and the role of the Affordable Care Act. JAMA pediatrics. 2018;172(1):43-8.

37. Colizzi M, Lasalvia A, Ruggeri M. Prevention and early intervention in youth mental health: is it time for a multidisciplinary and trans-diagnostic model for care? International Journal of Mental Health Systems. 2020;14(1):1-14.
38. Le Glaz A, Haralambous Y, Kim-Dufor D-H, Lenca P, Billot R, Ryan TC, et al. Machine learning and natural language processing in mental health: Systematic review. J Med Internet Res. 2021;23(5):e15708.
39. Lovejoy CA. Technology and mental health: the role of artificial intelligence. European Psychiatry. 2019;55:1-3.
40. Dominitz JA. ADVANCES IN ENDOSCOPY. Gastroenterology & Hepatology. 2021;17(11):551.
41. Research CIfA. Building a Learning Health System for Canadians; Report of the Artificial Intelligence for Health Task Force,. 2020.
42. Levac D, Colquhoun H, O'Brien KK. Scoping studies: advancing the methodology. Implementation science. 2010;5(1):1-9.
43. Peters M, Godfrey C, McInerney P, Soares C, Khalil H, Parker D. The Joanna Briggs Institute reviewers' manual 2015: methodology for JBI scoping reviews. 2015.
44. Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation. Annals of internal medicine. 2018;169(7):467-73.
45. Wolff RF, Moons KG, Riley RD, Whiting PF, Westwood M, Collins GS, et al. PROBAST: a tool to assess the risk of bias and applicability of prediction model studies. Annals of internal medicine. 2019;170(1):51-8.
46. Wolff RF, Moons KG, Riley RD, Whiting PF, Westwood M, Collins GS, et al. PROBAST: a tool to assess the risk of bias and applicability of prediction model studies. Annals of internal medicine. 2019;170(1):51-8.
47. Stone P. Popping the (PICO) question in research and evidence-based practice. Nurs Res. 2002;15(3):197-8.
48. Amisha, Malik P, Pathania M, Rathaur VK. Overview of artificial intelligence in medicine. J Family Med Prim Care. 2019;8(7):2328-31.
49. Beaujean AA. Simulating data for clinical research: A tutorial. Journal of Psychoeducational Assessment. 2018;36(1):7-20.
50. Cochrane Effective Practice and Organisation of Care Group (EPOC). Data Collection Checklist. https://methods.cochrane.org/sites/methods.cochrane.org.bias/files/public/uploads/EPOC%20Data%20Collection%20Checklist.pdf [accessed 2021-07-28]
51. Alpaydin E. Introduction to machine learning: MIT press; 2020.
52. Popay J, Roberts H, Sowden A, Petticrew M, Arai L, Rodgers M, et al. Guidance on the conduct of narrative synthesis in systematic reviews. A product from the ESRC methods programme Version. 2006;1:b92.
53. Pooria Ghadiri MJY, Laura Pinkham, Gauri Sharma, Perry Samuel John Adler, Genevieve Gore, Samira Abbasgholizadeh Rahimi, editor AI in Mental Healthcare for

Adolescents: Scoping Review. Family Medicien Forum; 2021 November 2021; Toronto, Canada.
54. Pooria Ghadiri LP, Gauri Sharma, Perry Samuel John Adler, Genevieve Gore, Mark J. Yaffe, Samira Abbasgholizadeh Rahimi, editor AI Interventions in the Care of Adolescents' Mental Health: A systematic scoping review. the Advancement of Artificial Intelligence (AAAI) 2021 Spring Symposium Series, Applied AI in Healthcare Symposia; 2021 March 2021; Palo Alto, USA
55. Oakden-Rayner L, Palmer L. Docs are ROCs: a simple off-the-shelf approach for estimating average human performance in diagnostic studies. arXiv preprint arXiv:200911060. 2020.
56. Schrouff J, Rosa MJ, Rondina JM, Marquand AF, Chu C, Ashburner J, et al. PRoNTo: pattern recognition for neuroimaging toolbox. Neuroinformatics. 2013;11(3):319-37.
57. Bekele E, Zheng Z, Swanson A, Davidson J, Warren Z, Sarkar N, editors. Virtual reality-based facial expressions understanding for teenagers with autism. 7th International Conference on Universal Access in Human-Computer Interaction: Design Methods, Tools, and Interaction Techniques for eInclusion, UAHCI 2013, Held as Part of 15th International Conference on Human-Computer Interaction, HCI 2013, July 21, 2013 - July 26, 2013; 2013; Las Vegas, NV, United states: Springer Verlag.
58. Duan X, Liu F, Lu F, Ma X, Zhang Y, Uddin LQ, et al. Multivariate classification of autism spectrum disorder using frequency-specific resting-state functional connectivity-A multi-center study. Progress in Neuro-Psychopharmacology and Biological Psychiatry. 2016;64:1-9.
59. Zhou Y, Yu F, Duong T. Multiparametric MRI characterization and prediction in autism spectrum disorder using graph theory and machine learning. PLoS ONE. 2014;9(6):e90405.
60. Xue YY, Li Q, Jin L, Feng L, Clifton DA, Clifford GD. Detecting Adolescent Psychological Pressures from Micro-Blog. In: Zhang Y, Yao G, He J, Wang L, Smalheiser NR, Yin X, editors. Health Information Science, His 2014. Lecture Notes in Computer Science. 8423. Berlin: Springer-Verlag Berlin; 2014. p. 83-94.
61. Yiping L, Jing H, Hao W, Ling F, editors. Predicting Teenager's Future Stress Level from Micro-Blog. 2015 IEEE 28th International Symposium on Computer-Based Medical Systems (CBMS), 22-25 June 2015; 2015; Los Alamitos, CA, USA: IEEE Computer Society.
62. Li J, Yuanyuan X, Qi L, Ling F, editors. Integrating human mobility and social media for adolescent psychological stress detection. Database Systems for Advanced Applications 21st International Conference, DASFAA 2016, 16-19 April 2016; 2016; Cham, Switzerland: Springer International Publishing.
63. Garcia EG, Blasco BC, Lopez RJ, Pol AP. Study of the factors associated with substance use in adolescence using Association Rules. Adicciones. 2010;22(4):293-9.
64. Fitzgerald A, Mac Giollabhui N, Dolphin L, Whelan R, Dooley B. Dissociable psychosocial profiles of adolescent substance users. PLoS ONE. 2018;13(8):e0202498.
65. Kashani JH, Nair SS, Rao VG, Nair J, Reid JC. Relationship of personality, environmental, and DICA variables to adolescent hopelessness: a neural network sensitivity approach. J Am Acad Child Adolesc Psychiatry. 1996;35(5):640-5.

66. Reid JC, Nair SS, Kashani JH, Rao VG. Detecting dysfunctional behavior in adolescents: the examination of relationships using neural networks. Proceedings / the 1994;Annual Symposium on Computer Application [sic] in Medical Care. Symposium on Computer Applications in Medical Care.:743-6.
67. Cavaller-Bellaubi M, Faulkner SD, Teixeira B, Boudes M, Molero E, Brooke N, et al. Sustaining meaningful patient engagement across the lifecycle of medicines: a roadmap for action. Therapeutic innovation & regulatory science. 2021;55(5):936-53.
68. Taati B, Zhao S, Ashraf AB, Asgarian A, Browne ME, Prkachin KM, et al. Algorithmic bias in clinical populations—evaluating and improving facial analysis technology in older adults with dementia. IEEE Access. 2019;7:25527-34.
69. Graham S, Depp C, Lee EE, Nebeker C, Tu X, Kim HC, et al. Artificial Intelligence for Mental Health and Mental Illnesses: an Overview. Curr Psychiatry Rep. 2019;21(11):116.
70. Collins GS, Moons KG. Reporting of artificial intelligence prediction models. The Lancet. 2019;393(10181):1577-9.
71. Stevens LM, Mortazavi BJ, Deo RC, Curtis L, Kao DP. Recommendations for reporting machine learning analyses in clinical research. Circulation: Cardiovascular Quality and Outcomes. 2020;13(10):e006556.
72. Collins GS, Reitsma JB, Altman DG, Moons KG. Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): the TRIPOD statement. Journal of British Surgery. 2015;102(3):148-58.
73. Rajkomar A, Dean J, Kohane I. Machine learning in medicine. New England Journal of Medicine. 2019;380(14):1347-58.
74. Lee EE, Torous J, De Choudhury M, Depp CA, Graham SA, Kim H-C, et al. Artificial intelligence for mental health care: clinical applications, barriers, facilitators, and artificial wisdom. Biological Psychiatry: Cognitive Neuroscience and Neuroimaging. 2021;6(9):856-64.
75. Marmar CR, Brown AD, Qian M, Laska E, Siegel C, Li M, et al. Speech-based markers for posttraumatic stress disorder in US veterans. Depression and anxiety. 2019;36(7):607-16.
76. Corcoran CM, Carrillo F, Fernández-Slezak D, Bedi G, Klim C, Javitt DC, et al. Prediction of psychosis across protocols and risk cohorts using automated language analysis. World Psychiatry. 2018;17(1):67-75.
77. Arnedo J, Svrakic DM, Del Val C, Romero-Zaliz R, Hernández-Cuervo H, Fanous AH, et al. Uncovering the hidden risk architecture of the schizophrenias: confirmation in three independent genome-wide association studies. Am J Psychiatry. 2015.
78. Drydakis N. Mobile Applications Aiming to Facilitate Immigrants&Apos; Societal Integration and Overall Level of Integration, Health and Mental Health: Does Artificial Intelligence Enhance Outcomes? Available at SSRN 3747451. 2020.
79. Schmaal L, Marquand AF, Rhebergen D, van Tol M-J, Ruhé HG, van der Wee NJ, et al. Predicting the naturalistic course of major depressive disorder using clinical and multimodal neuroimaging information: a multivariate pattern recognition study. Biol Psychiatry. 2015;78(4):278-86.

80. Bernert RA, Hilberg AM, Melia R, Kim JP, Shah NH, Abnousi F. Artificial intelligence and suicide prevention: a systematic review of machine learning investigations. International journal of environmental research and public health. 2020;17(16):5929.
81. Whelan R, Watts R, Orr CA, Althoff RR, Artiges E, Banaschewski T, et al. Neuropsychosocial profiles of current and future adolescent alcohol misusers. Nature. 2014;512(7513):185-9.
82. Etkin A, Patenaude B, Song YJC, Usherwood T, Rekshan W, Schatzberg AF, et al. A cognitive–emotional biomarker for predicting remission with antidepressant medications: a report from the iSPOT-D trial. Neuropsychopharmacology. 2015;40(6):1332-42.
83. Dwyer DB, Falkai P, Koutsouleris N. Machine learning approaches for clinical psychology and psychiatry. Annu Rev Clin Psychol. 2018;14:91-118.
84. Garcia-Ceja E, Riegler M, Nordgreen T, Jakobsen P, Oedegaard KJ, Tørresen J. Mental health monitoring with multimodal sensing and machine learning: A survey. Pervasive and Mobile Computing. 2018;51:1-26.
85. American Psychiatric Association D, Association AP. Diagnostic and statistical manual of mental disorders: DSM-5: American psychiatric association Washington, DC; 2013.
86. Luxton DD. An introduction to artificial intelligence in behavioral and mental health care. Artificial intelligence in behavioral and mental health care: Elsevier; 2016. p. 1-26.
87. Silva SA, Silva SU, Ronca DB, Gonçalves VSS, Dutra ES, Carvalho KMB. Common mental disorders prevalence in adolescents: A systematic review and meta-analyses. PLoS ONE. 2020;15(4):e0232007.
88. Yang SJ. Guest Editorial: Precision Education-A New Challenge for AI in Education. Journal of Educational Technology & Society. 2021;24(1).
89. Yang S, editor Precision education: New challenges for AI in education [conference keynote]. Proceedings of the 27th International Conference on Computers in Education (ICCE)(pp XXVII-XXVIII) Kenting, Taiwan: Asia-Pacific Society for Computers in Education (APSCE); 2019.
90. Shneiderman B. Human-centered artificial intelligence: Reliable, safe & trustworthy. International Journal of Human–Computer Interaction. 2020;36(6):495-504.
91. Horvatić D, Lipic T. Human-Centric AI: The Symbiosis of Human and Artificial Intelligence. Multidisciplinary Digital Publishing Institute; 2021. p. 332.
92. Chen J, Lim CP, Tan KH, Govindan K, Kumar A. Artificial intelligence-based human-centric decision support framework: an application to predictive maintenance in asset management under pandemic environments. Annals of Operations Research. 2021:1-24.
93. Jorritsma W, Cnossen F, van Ooijen PM. Improving the radiologist–CAD interaction: designing for appropriate trust. Clinical radiology. 2015;70(2):115-22.
94. Martinez-Martin N. Minding the AI: Ethical Challenges and Practice for AI Mental Health Care Tools. Artificial Intelligence in Brain and Mental Health: Philosophical, Ethical & Policy Issues: Springer; 2021. p. 111-25.
95. Gerke S, Minssen T, Cohen G. Ethical and legal challenges of artificial intelligence-driven healthcare. Artificial Intelligence in Healthcare: Elsevier; 2020. p. 295-336.

96. Velupillai S, Epstein S, Bittar A, Stephenson T, Dutta R, Downs J. Identifying Suicidal Adolescents from Mental Health Records Using Natural Language Processing. Stud Health Technol Inform. 2019;264:413-7.
97. Luxton DD, Anderson SL, Anderson M. Ethical issues and artificial intelligence technologies in behavioral and mental health care. Artificial intelligence in behavioral and mental health care: Elsevier; 2016. p. 255-76.
98. Shatte AB, Hutchinson DM, Teague SJ. Machine learning in mental health: a scoping review of methods and applications. Psychol Med. 2019;49(9):1426-48.
99. Otten D, Tibubos AN, Schomerus G, Brähler E, Binder H, Kruse J, et al. Similarities and differences of mental health in women and men: A systematic review of findings in three large German cohorts. Frontiers in Public Health. 2021;9:40.
100. Zhao Q, Huang Y, Li C. Does adolescents' Internet addiction trigger depressive symptoms and aggressive behavior, or vice versa? The moderating roles of peer relationships and gender. Computers in Human Behavior. 2022;129:107143.
101. Möller-Leimkühler AM. The gender gap in suicide and premature death or: why are men so vulnerable? European archives of psychiatry and clinical neuroscience. 2003;253(1):1-8.
102. De Choudhury M, Sharma SS, Logar T, Eekhout W, Nielsen RC, editors. Gender and cross-cultural differences in social media disclosures of mental illness. Proceedings of the 2017 ACM conference on computer supported cooperative work and social computing; 2017.
103. Mauvais-Jarvis F, Merz NB, Barnes PJ, Brinton RD, Carrero J-J, DeMeo DL, et al. Sex and gender: modifiers of health, disease, and medicine. The Lancet. 2020;396(10250):565-82.
104. Kim S, Kimber M, Boyle MH, Georgiades K. Sex differences in the association between cyberbullying victimization and mental health, substance use, and suicidal ideation in adolescents. The Canadian Journal of Psychiatry. 2019;64(2):126-35.
105. Martin J, Hadwin JA. The roles of sex and gender in child and adolescent mental health. Wiley Online Library; 2022. p. e12059.
106. Straw I, Callison-Burch C. Artificial Intelligence in mental health and the biases of language based models. PLoS ONE. 2020;15(12):e0240376.
107. Cirillo D, Catuara-Solarz S, Morey C, Guney E, Subirats L, Mellino S, et al. Sex and gender differences and biases in artificial intelligence for biomedicine and healthcare. NPJ digital medicine. 2020;3(1):1-11.
108. Blease C, Locher C, Leon-Carlyle M, Doraiswamy M. Artificial intelligence and the future of psychiatry: qualitative findings from a global physician survey. Digital health. 2020;6:2055207620968355.
109. Wies B, Landers C, Ienca M. Digital Mental Health for Young People: A Scoping Review of Ethical Promises and Challenges. Frontiers in digital health. 2021:91.
110. Daneshjou R, Smith MP, Sun MD, Rotemberg V, Zou J. Lack of Transparency and Potential Bias in Artificial Intelligence Data Sets and Algorithms: A Scoping Review. JAMA Dermatol. 2021;157(11):1362-9.
111. Coley RY, Johnson E, Simon GE, Cruz M, Shortreed SM. Racial/ethnic disparities in the performance of prediction models for death by suicide after mental health visits. JAMA Psychiatry. 2021;78(7):726-34.

112. Han SS, Kim MS, Lim W, Park GH, Park I, Chang SE. Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm. Journal of Investigative Dermatology. 2018;138(7):1529-38.
113. Adamson AS, Smith A. Machine learning and health care disparities in dermatology. JAMA Dermatol. 2018;154(11):1247-8.
114. Parikh RB, Teeple S, Navathe AS. Addressing bias in artificial intelligence in health care. Jama. 2019;322(24):2377-8.
115. Pham Q, Gamble A, Hearn J, Cafazzo JA. The Need for Ethnoracial Equity in Artificial Intelligence for Diabetes Management: Review and Recommendations. J Med Internet Res. 2021;23(2):e22320.
116. Assembly UG. Convention on the Rights of the Child. United Nations, Treaty Series. 1989;1577(3):1-23.
117. Rosen JE. Adolescent health and development (AHD): a resource guide for World Bank operations staff and government counterparts. 2004.
118. Sawyer SM, Afifi RA, Bearinger LH, Blakemore S-J, Dick B, Ezeh AC, et al. Adolescence: a foundation for future health. The lancet. 2012;379(9826):1630-40.
119. Pham MT, Rajić A, Greig JD, Sargeant JM, Papadopoulos A, McEwen SA. A scoping review of scoping reviews: advancing the approach and enhancing the consistency. Research synthesis methods. 2014;5(4):371-85.

CHAPTER 3 - BRIDGING

In previous chapter, the study was conducted with the aim of identifying AI interventions tested and/or implemented in adolescents' mental health care. Our review established that AI interventions were most frequently reported for Autism Spectrum Disorder, Outcomes of Psychological Stress/Pressure Level, Substance Use Disorder and Dysfunctional Behavior. These interventions were used for the mediation of diagnostic processes, monitoring and evaluation, treatment, and prognosis of adolescents' mental health problems. Adolescents and/or health care professionals (HCPs) were rarely found to be involved in testing AI interventions, and no study was found describing their engagement in validating these interventions. User-center design in partnership with HCPs and patients may maximize the usefulness of AI interventions in adolescent mental health care.

We did a scoping review to get a broader view of current work in the field and identify the knowledge gaps in the literature concerning tested and/or implemented AI interventions in adolescents' mental health care. In this review, we found a knowledge gap in identifying primary care physicians' (PCPs') perceived needs and challenges for AI interventions supporting adolescents' mental health. PCPs are increasingly recognized for their critical roles in identifying and managing adolescent mental health problems, with the majority of such issues being addressed in primary care settings. We, therefore, aimed to conduct a more detailed exploratory qualitative study on PCPs' perceived needs and challenges in providing mental health care to adolescents, using AI interventions to fill the current knowledge gap and shed light on future studies.

CHAPTER 4

MANUSCRIPT 2: PRIMARY CARE PHYSICIANS' PERCEPTIONS OF ARTIFICIAL INTELLIGENCE INTERVENTIONS IN THE CARE OF ADOLESCENTS' MENTAL HEALTH

Pooria Ghadiri [1,3,4], Mark J. Yaffe [1,2]
Alayne Mary Adams [1], Perry SJ. Adler [1], Samira A. Rahimi [1,3,4]

Affiliations:

[1] Department of Family Medicine, McGill University, Montreal QC, Canada
[2] St. Mary's Hospital Center, Montreal, QC, Canada
[3] Mila-Quebec AI Institute, Montreal, QC, Canada
[4] Lady Davis Institute for Medical Research (LDI), Jewish General Hospital, Montreal, QC, Canada

ABSTRACT

Background and objectives: Adolescence is a critical stage in the human life span during which the onset of some behaviors and conditions can negatively impact physical and mental health over the lifespan. These include functional and behavioural impairments, increase in healthcare costs and heightened risk for premature death. Primary care physicians (PCPs) can potentially play important roles in the identification and management of mental health problems in this population but face many challenges. Artificial Intelligence (AI) interventions may offer solutions, but such interventions often need to be adapted for primary care. We therefore sought to identify the perceived challenges to PCPs in providing adolescents' mental healthcare, along with their attitudes towards AI interventions in delivering such care.

Methods: For this qualitative study we used purposeful sampling to recruit participants for a Focus Group Discussion (FDG) that explored these issues. The FDG was audio-visually recorded through Zoom software and lasted 1 ¼ hours. It was later reproduced verbatim for thematic analysis using a combination of A-priori and inductive coding. Two facilitators moderated the Focus Group (FG), with one cleaning the raw data. It was then reproduced verbatim through Zoom software. Later, three research team members used A-priori and inductive coding to thematically analyze the verbatim.

Results: Out of 35 PCPs in Montreal, Canada, identified with a specific interest in adolescent mental health and AI, we reached four who agreed to participate, and we conducted an FG of four participants. Participants highlighted structural and systematic challenges faced while giving care to adolescents, including parental involvement and teen-age psychosocial influences such as sex and gender, family, culture, peers, and habits. PCPs saw AI interventions as potentially cost-effective (time, money, and resources), able to handle large amounts of data, and relatively credible. They envisioned AI to assist in collecting patients' data, suggesting a diagnosis, and establishing a treatment plan. However, they were concerned about these interventions' performances and outcomes and feared losing clinical competency. PCPs desired AI interventions that were user-friendly (simple to use, easily operational, seamless, and supported by "just in time" technical support). They were willing to assist in designing and developing AI interventions if it was within their scope of practice, and they were compensated through external incentives (financial or professional development study credits). They indicated a need for regulatory bodies to deal with medicolegal and ethical aspects of AI intervention usage (e.g., confidentiality, privacy, liability) for creation of clear guidelines/frameworks to reduce/eliminate harm to patients as a result of using such interventions.

Conclusion: This study provides the groundwork for assessing AI interventions' practical utility, applicability, and effectiveness in adolescents' mental health care practice in primary care. A larger scale study is necessary to offer more in-depth understanding of the acceptability and use of AI by PCPs. Parallel study of adolescents' perspectives on integrating AI into mental healthcare might contribute a fuller understanding of the potential of AI for this population.

Keywords: Adolescent health; Mental health; Artificial Intelligence; Innovative Technologies; Primary Care Physicians; Family physicians

4.1 Introduction

4.1.1 Adolescents' mental health importance and trends

Adolescence is a formative developmental stage for health, skills, and ability, rather than just a transitory time between childhood and maturity (1). The World Health Organization defines it as the period between ages 10 and 19 (2, 3). The greater independence and self-reliance during these years may be challenging for those who already have emotional or social concerns, resulting in higher interpersonal, emotional, and mental health problems, leading to significant psychosocial and economic ramifications for adolescents, families, and communities (4-6). Anxiety, depression, and substance abuse disorders may all substantially influence development and represent some of the most debilitating conditions for adolescents, causing them to struggle with self-regulation and impulse control (7). It is estimated that half of those who satisfy the criteria for a mental health disorder throughout their lifespans begin experiencing related symptoms before the age of 14 (8).

An estimated one in five in Canada (9) have a mental health problem. One in four, between the ages of 17 and 19 suffers from severe depression or anxiety, with half having attempted suicide or engaged in self-harm (10). The number of non-suicidal self-harming behaviours has almost quadrupled in the UK over the last decade, while suicide has nearly doubled for every 100,000 adolescents (11, 12). Annually, approximately 140 000 people aged 10 to 24 succumb to suicide worldwide (13). In several nations, including Canada, suicide is the second leading cause of mortality in this age bracket (14, 15).

Adolescents' depression is the main contributor to disability-adjusted life years lost, imposing a high social and economic cost over their lifetime (16). The Canadian Institute for Health Information reported that adolescents' emergency department visits for mental health problems climbed by 61% between 2008–2009 and 2018–2019 (9). The alarming increasing prevalence of the mental health problems among adolescents leads to serious consequences both during the adolescent period and later in life (17). Therefore, this is an essential research priority in promoting prevention and early intervention, extending access to care, and suggesting need to alter mental healthcare systems (18). While the significance of early detection and intervention has become clearer, the method by which this aim should be achieved remains complicated. Optimizing gateways into mental healthcare and incorporating early interventions into primary care for adolescents with mental health problems is critical in ensuring prompt and adequate care for many of these difficulties.

4.1.2 Adolescents and primary care

Primary care (PC) is "the provision of integrated, accessible healthcare services by clinicians who are accountable for addressing a large majority of personal healthcare needs, developing a sustained partnership with patients, and practicing in the context of family and community" (19). The portrayal of PC in the research literature incorporates various types of formal and casual investigations. These include the identification of physical or mental illnesses, strategies to manage troubled patients and referral to specialized services, and research that assists in tracing patients' profiles in a retrospective or longitudinal fashion (20). The necessity for ongoing PC by primary care physicians (PCPs) for adolescents have been highlighted in best practice standards (21, 22). During visits, PCPs may do physical exams, screen for risky behaviors, and attempt to build trusting relationships with adolescents (23). It is also known that adolescents visit their PCPs much less often than the general population (23, 24).

Given the benefits and importance of PC, various issues may jeopardize PCPs' capacity to manage adolescent patients with mental health problems properly, such as 1) adolescents may be reluctant historians (25) and might not trust the medical services of the people who deliver them (26), 2) the reality where few healthcare workers are comfortable with adolescents or their mental health problems (26), and 3) medical services may not easily be accessible geographically or temporally when the adolescent wants to be seen (26).

4.1.3 Potential for Artificial Intelligence in adolescents' mental healthcare in a primary care

During the past two decades, numerous approaches have been proposed and/or put in place to alleviate the difficulties that PCPs face in delivering mental healthcare. Several interventions have sought to enhance integration and cooperation with mental health experts (27, 28); others have advocated for increased continuous medical education (29) or monetary incentives (30). Furthermore, recent years have witnessed the emergence and development of novel technologies such as artificial intelligence (AI) interventions, which have created opportunity for improving and even transforming interventions for assisting PCPs in taking charge of adolescents' mental healthcare (31). AI is a discipline of engineering and computer science dedicated to developing intelligent machines (32). In 1956, John McCarthy introduced the phrase "artificial intelligence," which he defined as "the science and engineering of making intelligent machines" (32). AI is seen as a method for facilitating, augmenting, and/or enhancing human work (33, 34). AI has the potential to make significant improvements in a variety of fields and levels of healthcare services (34), including automating medical devices (33), administrative planning (35), and resource management (36) to support prevention, screening, diagnostics, management, and treatment (33).

Although healthcare has been slow to adopt/implement AI compared to other service sectors, interest in AI interventions have steadily grown in prominence in PC for physical health applications although at a compared slower rate for mental health (37). It may be critical for PCPs to consider AI adoption to recognize its distinctiveness and uniqueness (38). However, since careful navigation will be necessary to ensure the proper application of this modern technology, it is time to rethink our approaches to mental problems and the need for early interventions to serve adolescents' unique needs using AI.

4.1.4 Objectives and research questions

The overall objective of this study was to explore the perceived needs of PCPs about AI interventions in the care of adolescents' mental health. Specific objectives of this study were to gain knowledge/better understanding on:1) What are the perceived challenges of PCPs in providing adolescents' mental health care? and 2) What are PCPs' perceived needs for AI interventions that might support the adolescents' mental health?

4.2 Methodology

4.2.1 Design:

We conducted a qualitative descriptive study to understand PCPs' perceptions of AI interventions in the care of adolescents' mental health. This methodology is suitable for obtaining "straight and essentially unadorned (i.e., minimally theorized or otherwise changed or spun) responses to topics of particular interest to practitioners and policymakers (39). It also aims to capture the many components of "truth" about the phenomena and present a thorough summary by considering the meanings that participants attributed to it (39). In general, while studying a new phenomenon which is not clearly identified, and around which little work has been performed, qualitative inquiry is a reasonable beginning point for the research (40). Based on a scoping review we conducted on the use of AI in adolescents' mental health care, we are not aware of prior research that has explored PCPs' perceived needs for and challenges with AI interventions that support adolescents' mental health (Ghadiri P, MSc, McGill University, 2022).

4.2.2 Eligibility criteria and participant recruitment

For this study, we purposefully selected (identified by colleagues) Montreal-based family physicians and primary care pediatricians who speak English and are known to routinely provide adolescent (age 10-19) healthcare. Purposeful sampling is a widely used qualitative research approach. In this type of sampling, participants are intentionally selected based on the objectives or information needs of a study (41).

We obtained the contact information (emails) of potential participants from physician leaders known to our team. An initial list of 35 names was generated, with the aim of recruiting 12-18 people for 2-3 focus groups. An initial email was sent out giving an overview to the study - to explore perceived needs of PCPs about AI interventions in the care of adolescents' mental health. There was telephone follow up 10-14 days later, using office numbers located on the website of the College des Médecins du Québec. Those interested in the study were sent an electronic consent, while those not reachable were sent a second email reviewing the study and directing interested individuals to the electronic consent. An online 'Doodle poll' was then used to establish a common date and time for the focus groups (FG).

4.2.3 Consent

FG participants underwent informed consent. They were told the discussion would be on-line, lasting between 60-90 minutes through Zoom software, with 256-bit End-to-end encryption, making it impossible for anyone but the interviewer and interviewee to understand the contents (42). They were advised that all data generated remained confidential as allowed by law, would be kept anonymously, used for descriptive purposes, and discussed only by the research team; that they had the right to ask questions or choose not to answer a question; that they were identified by code number to protect their privacy; could withdraw any time from the FG without consequence or reasons, but information already gathered would be retained; all recordings of FG, written notes, and transcripts were transferred to a password-protected computer hard drive secured in a safety cabinet and stored on the McGill OneDrive server (developed by Microsoft) and will be destroyed after seven years, according to the University's policy (43). There was no compensation for participating in this study.

4.2.4 Data Collection:

Since the COVID-19 pandemic forced social distancing and discouraged indoor meetings, in-person FG was not a possibility, and an on-line meeting platform was adopted for the FG. We conducted a single FG virtually using Zoom software in a session that took approximately 75 minutes. A one-page instruction sheet was supplied to participants for log-in to the ZOOM software to join the FG. At outset, participants filled out a short on-line questionnaire enquiring into their demographics. The consent and demographic personalized forms were created using Google Form, a free software which allows collecting information from users through surveys (44).

To ensure that participants began with some common knowledge, the FG started with a brief PowerPoint presentation (Appendix A) of AI, given by facilitator #1 (PG). FG discussion was directed by a semi-structured interview guide (Appendix B) created by the research team for exploring PCPs' perceived needs from AI interventions and challenges in providing adolescents' mental healthcare. Using open-ended questions, participants were invited to share their perspectives on AI, and adjusted them depending on the content and dynamics of the discussion. This facilitated conversation and also allowed us to increase the depth and breadth of the data through probes and requests for elaboration (45).

Facilitator #2 (MJY) primarily participated in the FG as an observer and supported PG as needed. The two facilitators had a 36-minute debriefing session immediately after the FG, based on literature that suggests debriefings prompt quick thoughts on emerging results and compel data collectors to think through the data that has just emerged (46). Zoom software was used to record and transcribe the discussions into Word documents for later thematic analysis.

4.2.5 Data Analysis

We transcribed the Zoom FG recordings verbatim into a Microsoft Word document, using precise punctuation marks and symbols indicating pauses, and reflections on participant tone and engagement. This facilitated the future reading of the data and helped us transfer the participants' feelings and purposes through text (Table 4.1). The transcription process enabled us to listen to different portions of the discussion several times to become familiar with the data.

We analyzed the data using conventional thematic analysis approach. "Thematic Analysis" is a method for identifying, analyzing and reporting patterns (themes) within data (47). It minimally organizes and describes the data set in detail (47). This method was used because our focus was to provide a detailed description of a phenomenon, namely the perceived needs and challenges of PCPs in adolescents' mental healthcare using AI interventions. We (SR, MJY, AA, PG) manually analyzed the data in the Word document over the course of twelve two-hour sessions. During these meetings, assumptions and interpretations of the codes/themes categories and subcategories were analyzed, questioned, and occasionally modified.

We performed our thematic analysis in the six phases recommended by Braun and Clarke (48, 49). The first phase focused on data familiarization, internalization, and immersion through reading and re-reading the transcriptions. The viewpoints of the participants were conveyed in vernacular conversation. This approach enabled reflection on the comments of participants to reduce the volume of data, identify recurring concepts, identify areas where participants agreed or disagreed, leading to more accurate coding and theme development. We next initiated the coding process, which involved utilizing "tags or labels" to provide units of meaning to the descriptive or inferential information gathered throughout the research." Typically, codes are associated with "chunks" of varied sizes of words, phrases, sentences, or whole paragraphs and are used to locate, retrieve, fetch, and sort the chunks of data (50). Initial codes were thus created, and specifically defined to capture the perceived challenges and needs of PCPs about the use of AI interventions in adolescents' mental healthcare.

We utilized both inductive and *apriori* coding approaches. We derived the *apriori* codes, particularly from ideas presented in the main questions asked during the FG. We also developed additional codes based on our personal interpretation of the data (inductive coding). This was accomplished through "close examination of the data without attempting to fit the information to pre-existing conceptions or ideas from theory (45)."

The third stage was theme development, with themes defined as "recurrent notions that may be utilized to summaries and organize the variety of subjects, opinions, experiences, or beliefs expressed by participants (56)". Categories were grouped into themes, and each theme represented a different dimension related to the perceived needs and challenges of PCPs in adolescents' mental healthcare using AI interventions. Over a number of iterations, the categories were organized into themes that progressed from being broad concrete reflections of what the participants stated to more abstract concepts. Possible links or correlations between themes were sought.

In the fourth phase, each theme was iteratively reviewed, evaluated, and validated for meaningful coherence. A thematic map evolved for describing PCPs' perceived needs and challenges in adolescents' mental healthcare using AI interventions.

The fifth phase involved the definition of themes and the generation of sub-themes, along with ongoing analysis to justify theme generation. In the final or sixth phase we created a logical and cohesive report by grouping the results into five themes.

4.2.6 Trustworthiness

To ensure rigour, the five criteria for trustworthiness in research proposed by Lincoln and Guba (credibility, transferability, dependability, confirmability, and authenticity) were followed (51). The research team brought strong credentials in primary healthcare, AI, qualitative analysis, in-depth research experience, and knowledge translation and transfer. We performed an "Audit Trail," detailing the process of data collection, analysis, and interpretation. We recorded the FG discussions for later analysis and wrote down our thoughts about coding, provided a rationale for merging codes, and explained what the themes and codes meant. To make sure that our work may be replicated, the Appendices provide supplementary information and explanations. We also provide raw quotes and actual words said during the FG to ensure authenticity.

4.3 Results:

The recruitment process generated 11 enrolled participants and 7 later withdrew due to unanticipated commitments derived from the COVID-19 pandemic. This resulted in a single FG comprised of 3 females and 1 male participant. Years in medical practice ranged from 6 to 40, spending an estimated 5 to 20% of their clinical time caring for adolescents in an ambulatory setting (Figure 4.1 and Table 4.2). Table 4.3 summarizes the outcome of our analysis of the verbatim text in which we identified 5 themes, 17 sub-themes, and 38 sub-sub themes. Numbers in parenthesis are identifiers to attribute remarks made by specific participants. Considering the care of adolescents' mental health, identified themes were: 1) General challenges; 2) Perceived features and characteristics of AI interventions; 3) Potential applications of AI interventions; 4) Possible negative aspects of using AI intervention; and 5) Perceived requirements for the application of AI interventions. These themes will be discussed in detail below.

4.3.1 Theme 1: Challenges of adolescents' care in ambulatory setting

This theme represents the difficulties that PCPs face in providing outpatient care to adolescents and was separated into two subthemes: 1) Fostering and maintaining a relationship; and 2) The time-consuming nature of adolescent care.

4.3.1.1 Fostering and maintaining a relationship

PCPs noted challenges related to establishing relationship with adolescent patients. Among these were problems building the necessary trust to initiate a relationship due to adolescent stage of development, personal characteristics, peers, parents, as well as technological barriers. An example of the latter relates adolescent to particularities in cell phone use that impedes good communication:

A lot of times because of confidentiality, you'll have their [adolescents] *numbers like their cell phone on file, but they're in school and they won't pick up the phone and they don't call back.* (P1)

Despite the difficulties of establishing a longitudinal connection with adolescents, a number of PCPs emphasized their desire for mutual understanding, continuity of care, and better health outcomes over time.

If you follow your patient longitudinally, as a child, and then having that foundation, so that when they have a problem, you had a relationship already; [but] *that's a challenge!* (P2)

At the same time, participants proposed pragmatic strategies to maintain the doctor-patient relationship. For example, "normalizing certain behaviors" was important in every meeting with adolescents, including clearly defining issues such as "confidentiality" in order for adolescents to express themselves more freely, resulting in a more stable and trusting relationship.

Having data on your patient beforehand is important and there's a lot of data that we could ask [however, adolescents aren't] *forthright with their answers when you do it in person; but a questionnaire that's done objectively can allow them to feel like they're not being judged when answering those questions.* (P2)

Participants reported a paradigm shift in today's adolescents' preference for computers and tablets over human doctors, giving them more space to open up and lead to better care.

They don't have a person in front of them asking the question. Kids today like to have the computers so they can be comfortable. These are their comfort zone. (P2)

Some PCPs identified the positive and negative impacts of parental involvement in dealing with adolescents' noncompliance in providing accurate information to the doctor.

Various challenges included legal issues, and struggles around parental control, including their reluctance/inability to give their child autonomy. Some parents are "overprotective" and "too present," making adolescents uncomfortable/hesitant to express themselves at appointments.

[If] *the parent sees the questionnaire* [history intake questionnaire]*, either before or after it's filled out, they may discourage the teenager from filling it out truthfully.* (P2)

PCPs also highlighted adolescent's' sex and gender, family background, culture, peers, and habits as important influences in doctor-patient encounters that need to be managed. Some of these require PCPs to use a new lexicon.

Something I find very challenging in dealing with adolescents is the complexity of the social environment: [for example] *different family backgrounds…and we don't talk on the same level as we talk with adults. We have to use another vocabulary.* (P3)

4.3.1.2 Adolescents' take time:

PCPs indicated that more time is required to care for adolescents due to the complexity of their life cycle issues, noting the utility of self-administered questionnaires and multiple visits before the bigger picture becomes clear. One sub-theme that arose related to time management in the context of adolescent mental health care.

"I will have to see this person, maybe a second or third time, before I start to get the picture…That's why we use questionnaires is for adolescent patients that they fill out before they come in ... But we have to invest a lot more time into these patients [Adolescents]" (P3)

A solo private practitioner expressed frustration about time spent linking adolescents to supportive community services, adding that those working in public practice centers may have fewer problems accessing multidisciplinary programs. PCPs also noted their job is to "identify the problem" and "provide care" rather than coordinate and organize access to supporting resources, as they are commonly not compensated for these time-consuming tasks.

My job is to figure out what the problem is and what I should do, but then to go and find out where the fax number is and who might know what resources might be available…that's challenging, time consuming and below our pay grade. (P2)

4.3.2 Theme 2: Perceived features and characteristics of AI interventions

A variety of benefits were suggested by PCPs related to creating efficiencies in accessing mental health resources, and collecting, storing and handling large volumes of data (e.g., patients' demographic information or lab results); time and costs efficiencies related to patient history and questioning, and treatment planning, and support with facilitating relationships with patients, promoting medical adherence and organizing interactive patient questionnaires.

Participants felt that AI interventions might increase access to resources and primary care more conveniently and perhaps optimize resource utilization.

It [have robots to do the Cognitive Behavioral Therapy] *is more cost effective, and maybe even more easy access than then having a real a real person as the bot has zero bias … and it's free!* (P2)

Cost and time efficiencies and more efficient questioning were also noted as potential benefits of AI interventions for patients and PCPs, especially in the context of referrals to specialists, which prolong patient treatment and are a "cost-drain" on the system.

I'm not sure that patients benefit so much from a full psychiatrist evaluation just to answer one question it's a cost-drain on the system. (P2)

AI's capacity to handle enormous amounts of data was another benefit, with one participant reflecting that easier access to information may allow PCPs to better address adolescents' mental health and other primary care concerns.

Family Medicine is a very challenging task, and we need to know a little bit about everything…and we are exposed to many different things, and AI it's just hungry for data, it will just never tire! (P2)

One respondent expressed that AI might facilitate collaboration between the PCP and multidisciplinary healthcare system (including specialists and social workers), saving time and making adolescent visits more efficient. Another PCP suggested using AI to take histories that involve sensitive questions to help doctors who feel uncomfortable asking certain issues to adolescents.

Having some tools [AI] *that there's some multi or interdisciplinary things going on, can be extremely useful and lead to efficient visits!* (P2)

Several PCPs further noted that AI interventions have the potential to tailor the application of available therapeutic resources to the adolescents' specific objectives and requirements, resulting in a personalized treatment strategy for each patient.

AI could be useful to more specific treatment plan, [and] *give us real concrete targets.* (P2)

Another type of benefit related to AI's potential contribution to enhancing patient-provider relationship. PCPs felt that since adolescents are comfortable engaging with technology and computer savvy, supporting the doctor-patient relationship with AI interventions (e.g., self-administered questionnaires on a laptop rather than face-to-face inquiry) would make it less threatening.

Adolescents are more comfortable answering to a computer than a doctor. (P4) … Can the machine [AI intervention] *persuade* [instead of compelling patients by a human doctor], *a patient to take a treatment?!maybe! (P3)*

However, uncertainty was also expressed. Several participants struggled with whether AI interventions would be accepted by patients---based on whether the AI intervention seemed to possess credibility. An example of negative or low credibility was voiced:

We can still talk and try to persuade the patient … I think that if the patient has confidence in us, they may agree to the treatment. Now, would they have the same reaction to a machine [AI intervention]*?!* (P3)

Offsetting this viewpoint was the potential for AI interventions to learn and direct patients more positively than doctors and hence might exhibit positive credibility:

AI can learn one day to do that [treatment adherence]*, and to do it better than the best doctor*. (P2)

As one participant aptly noted, however, the so-called "potential" of AI ultimately rests with the PCP. Individual doctors perceive the role of such interventions differently and cannot project roles that have not yet been recognized.

I'm not sure that my type of practice, would be able to replace or be close to that [specialized adolescent clinics where each patient receives a long visit] *in terms of time and resources that I can devote to it. Certainly, having tools would help.* (P2)

4.3.3 Theme 3: Potential applications of AI interventions

Several applications of AI interventions were identified by PCPs in the areas of clinical care, obtaining and analyzing data, and medical education and research.

In terms of clinical care, several PCPs discussed how AI interventions might be useful in facilitating administrative tasks (e.g., appointments, paperwork for in-office and out-of-office care, patient discharge) and case management (which may involve collaboration with interdisciplinary services).

I'm at a severe disadvantage working alone, compared to those who work at the clinic Y [public clinic]. [it's] *now maybe hard to access certain services. I'm sure you all have challenges in terms of bookings, whether it's* [for] *social workers, nutritionist, psychologist, and AI can help here.* (P2)

PCPs also noted AI interventions might aid decision-making by providing PCPs, adolescents, or other individuals with knowledge and person-specific information filtered or presented at appropriate times to enhance mental health diagnosis and treatment planning.

Machine learning can be used as to for a decision support system, for example, where it may pick up on some computable data [to] *make recommendations helping diagnosis and treatment planning and that could be more specific than we might think in adolescents.* (P2)

Given the complexity of accurately diagnosing adolescents' mental health problems, PCPs viewed AI interventions favourably to assist with diagnosis and its validation.

It [AI], *really helps in terms of diagnosis. We don't want to miss something that serious when you have to make critical decision. Should I send this patient home or to ER* [Emergency Room] *because the stakes are quite high in terms of self-harm?!* (P3)

Participants further identified the utility of AI with the complex and time-consuming act of patient referral, including consultation with a medical colleague, home care, organizing a visiting nurse, or finding community resources including CBT services. Indeed, one participant suggested how CBT provided by an AI robot outfitted with forms, characters, and faces to replicate human interaction with patients would be more cost-friendly, bias-free, and engaging for adolescents.

AI could be useful, give us real concrete targets in terms of what's out there in our community, particular to every area and it would know, for example, that there's five places left on this support group starting next week. There are chatbots for this purpose [CBT], *work* [based] *on 3D avatars, facial expressions and interacting with a virtual person.* (P2)

A second application of AI relates to data collection and analysis to facilitate adolescent mental health assessment and support. PCPs believed that AI-assisted medical robots could generate and analyze patient information to generate answers to clinical questions efficiently and cost-effectively and help them have a more focused practice. As one participant remarked:

It's not cost effective [PCPs' managing patients intake tasks, trashing out the patients, spending an hour to get personalized data] *… but I dream of having that as an AI bot or system to tailor the questions we need more detail and skip over things you don't need a detail to really concentrate more on certain aspects of the patient* (P2 and P3).

Distillation helps PCPs discover hidden or missing data. A PCP (P2) with higher AI knowledge noted that Natural Language Processing might automatically summarise patients' information during/after a visit. He suggested that AI models may evaluate patients' cardiovascular risk factors instead of a doctor doing it manually in the office.

Like for Framingham risk calculator [Cardiovascular risk assessor]. *The actual meat of the conversation automatically gets summarized for me succinctly* [by AI]. *This would be extremely useful.* (P2)

PCPs also recognized AI's potential to identify red flags and abnormalities in patients' data.

Machine learning can be used for a decision support system, where it may pick up on some of the computable data that comes out of an interaction or questionnaire… it may raise some flags, and say: "*have you considered this diagnosis or that?"* (P2)

A final area of application was in the area of medical education. PCPs noted the potential use of AI interventions in continuing medical education (CME) to suggest courses and training based on practitioners' interests and practice composition. Also, they saw potential in such interventions to handle and compare trials of varied sizes, diverse sample populations, overlapping research topics, and store previously collected data.

- [AI may] have *a role in recommending* [CME] *courses that you might find interesting. A recommendation like a Netflix for CME, … based on your history of CME or the configuration of* *practice.* (P2) - [Using AI] *for research, if we can have this* [collected data] *piled somewhere, and somebody would like to have research done,* [it] *would be so easier.* (P4)

4.3.4 Theme 4: Possible negative aspects of using AI interventions

Despite perceived benefits and applications of AI, several negative aspects were noted. One area of concern was the implications of AI for professional practice whereby AI might compete with or replace highly skilled clinicians given potential capacity to perform more sophisticated tasks.

I said to one of the ICU docs: "how do you feel that in 2028 your job will be replaced by computer?" … I shouldn't have said it, but I believe this to be somewhat true. (P2)

The issue of trust in AI was also raised. PCPs referred to the risk of lack of confidence in the truth, validity, accountability, or effectiveness of using such interventions; impressions based either on an individual's intuitive/gut response (mistrust) or real experience (distrust) are illustrated in doctors' comments as follows. Concerns with performance accountability were noted in particular:

For 'diagnostics' I think the fear was always it [using AI] *was wrong! I don't want to act on something that just calculated things wrong! … it* [AI intervention] *can tunnel vision you even though you try to use your clinical judgment.* (P1)

Given the widespread presence of misinformation (incorrect material) and disinformation (intentional spreading of misinformation) found in social media, one participant worried about what controls there would be on AI interventions used in healthcare. One worried PCP projected into the future:

What I'm hearing is AI is gonna replace everything? How can it replace us eventually one day?!

A further worry was the fact that AI interventions, as artificial beings, lack passion, enthusiasm, worry, empathy, and face-to-face emotion, all of which are critical dimensions of good clinical practice:

The human aspect of medicine is very important. We don't want the patient to feel they treated by a robot. That is the disadvantage [of AI interventions]! *That's very important that patients feel empathy…*[Hence] *patients feel a lot better*. (P3)

Concerns about the potential for diminished clinical competency of were also expressed. PCPs worried that using AI interventions might undermine their medical and patient communication skills. An example are the potential negative impacts of AI on knowledge, attitudes, and skills.

I mean in surgery, if someone talks about robotic surgery versus laparotomy! just when you don't use it [using the clinical skill in the related subject], *you're not going to know how*. (P1)

4.3.5 Theme 5: PCP's perceived requirements for the application of AI interventions

PCPs were asked to discuss how they envisioned their needs using AI interventions in adolescents' mental healthcare.

Education on AI was identified as a priority for their own continued professional development as well as for those in training e.g., medical residents and students. While PCPs felt the need for CME training on AI to learn about new and developing areas in their fields, concern was expressed about how demanding, time-consuming, or relevant such courses might be.

I guess it's a new technology! I'd be interested in doing it [CME on AI], *but hopefully we will spend the minimal time on this, and we can use it!* (P3)

For residents and medical students, training on AI was deemed vital, part of the mandatory curriculum, and perhaps as a new discipline.

I think this [training in AI] should start in medical school! There should be even a specialty such as "medical informatics." (P2)

At the same time, PCPs stressed the importance of governance and regulation to ensure AI interventions were used ethically and effectively.

Definitely I think it makes a lot of sense to have some kind of regulation, when that we're using [AI intervention] *therapeutically!*

Particularly vital was preventing potential ethical or physical harms arising from the use of AI interventions in the adolescent age group. Because today's adolescents are more tech-savvy, they might express themselves better via computers, resulting in a more confidential visit. PCPs were therefore concerned about AI-driven privacy breaches and acknowledged the importance of protecting patients' data and anonymity. However, they struggled with the nuances of perceived responsibility (doctors vs AI) when utilizing such interventions.

- *There are all kinds of privacy issues. All it takes is one breach and people will lose confidence* [on AI] *… a doctor making a decision that was supported by AI; who's responsible?! It's clear that we are! So, can you use that as a defense in front of a judge?! I don't think that'll hold up very much, but it'll probably be used as a defense at some point!* (P2)

For this reason, several PCPs emphasized that they should be held accountable for possible erroneous AI-assisted care, and suggested that frameworks/guidelines and human supervision be put in place to ensure that AI interventions “do not harm”:

Once that technology [AI] *is mature,* [and] we *can have the right framework in place to make it safe for patients. I certainly don't want to be responsible for people committing suicide because of my chatbot! We're going to be supervising these systems and making sure that are working.* (P2)

PCPs also noted the importance of ensuring that AI interventions employ a friendly user interface, so non-technical users with limited AI understanding might rapidly attain mastery, sync it with their practices, and get on-demand, “just in time” technical support.

Technical support is very important… have a good instruction manual that I can understand … [being] *user friendly if I run into difficulties … can call someone* [for] *help*. (P3)

They also expressed a desire to contribute to AI interventions' design and development if deemed helpful to patients. Three important features were deemed essential in AI intervention roll-out; that AI interventions be easily operational and seamless; relevant and meaningful to practice; and that uptake be incentivized through credited CMEs, as well financial and professional opportunities. On the issue of incentivization, PCPs felt it necessary to offer external incentives and opportunities including to engage in AI intervention design and development.

I don't think that you'll get a lot of capture with volunteering. It has to be incentivized, either through credits [CME credits], *interest research or being paid for a time.* (P2)

The financial implications of adopting AI interventions were stressed in particular, with PCP participants noting that PCPs were unlikely to use AI interventions if initial and operating expenses were too costly:

If you [AI intervention] *are too expensive, we just don't look at you!* (P1)

4.4 Discussion

This qualitative research yielded valuable insight into how PCPs see AI interventions influencing mental healthcare for the adolescent population. Drawing on their own practice experience, participants reflected on how AI interventions might help overcome challenges in serving this population and better meet their mental health needs. At the same time, they identified many complexities limiting the adoption of AI interventions by practitioners that would need to be addressed. This study opens the door for future research on AI-based assessment interventions that offer promise in enhancing adolescents' access to better mental healthcare.

The study raised four key issues warranting attention and action in relation to AI adoption: 1) the particular challenges of ambulatory care for adolescents; 2) the features and potential applications of AI interventions; 3) risks associated with their adoption, and 4) requirements for their ethical and effective application in adolescent mental health care.

4.4.1 Ambulatory adolescent care challenges

Adolescent care offers unique challenges in the primary care context, owing to their unique biological and psychosocial characteristics (52). Our findings highlighted the challenges that PCPs face as a result of a range of psychosocial, cultural, peer and familial influences on which adolescents are susceptible. This is consistent with a broader literature that has demonstrated the impact of peer influence, family cultures, and personal characteristics and views on adolescent health and adherence to care (53, 54). For example, research indicates that the stigmatisation of adolescents with allergies by peers may affect compliance with follow-up (55).

Parents are gatekeepers in adolescent care, but they may be a barrier to adolescents' visits (56). Our results similarly suggest that that giving adolescents autonomy to make their own care choices may be hard for parents (56) and impact adolescent behaviour (57). Patient-centred care methods recognize the importance of both adolescents' and parents' opinions during a visit, although balancing them is difficult (56). Therefore, most professional organizations recommend adolescents have one-on-one time with their doctor for a private discussion (21). Adolescents' concerns about healthcare confidentiality also affects their interactions with the system (58). A previous study found that creating and sustaining solid connections between doctors and adolescent patients is crucial for developing favourable lifelong attitudes (59). Similarly, our results highlighted the importance of clarifying confidentiality during each session to build rapport, trust, and effective therapeutic relationships between adolescents and PCPs.

Literature shows the many barriers faced by adolescents and their PCPs throughout the adolescent transition (60), which impact continuity of care ranging from individual and interpersonal factors and well as those connected to family, service delivery (56). These context-dependent aspects suggest that the challenges of caring for adolescents in an ambulatory setting are multifaceted, and future studies should take this complexity into account when investigating the introduction of new approaches and interventions. Future work should also focus on understanding adolescents' attitudes, and preferences for care to encourage needed follow-up visits and compliance with care.

4.4.2 Features and potential applications of AI interventions

Our findings indicate that AI interventions have the benefit of easing activities, providing efficiencies, and facilitating PCPs' and healthcare systems' work. This was similar to previous studies, suggesting that AI interventions may have clinical use for more accurate differential diagnoses, especially when evaluations are costly or time-consuming (61), potentially reducing human labour, freeing up PCPs' time, and enhancing their productivity, accuracy and efficacy (32).

Some PCPs believed AI might help collect patients' data more efficiently, given that clinical practice relies on accurate patient data (62). These results support the idea that AI in laboratory medicine improves access to data to provide better insights for physicians, helps make real-time interpretations of health risks and test results, and increases patients' quality of care (63, 64).

Contrary to our findings, a recent study in Japan found that did not improve data collection due to the time required to process the data and patients' characteristics, especially in low-complexity situations, where patients' medical data is readily obtained (65).

Our findings showed AI might benefit in collecting handling large volumes of data. The rapid development and production of massive and complex datasets from various sources, including electronic medical records, are creating opportunities for the mental health sector (66, 67). AI also enables analysis and interpretation of digital information in mental health, which offers tremendous potential for tailored and targeted therapy, prognosis, monitoring relapse, and identifying and preventing mental problems (66, 68).

There are conflicting studies in the literature with regard to creditability and safety of AI interventions (69). For instance, wrong label in AI training data (data samples used to fit the AI method (70)) may cause unfair suggestions and interpretations by AI interventions due to bias, and maybe causing patient harm and undermining their credibility among patients and clinicians

(71, 72). On the other hand, previous research has demonstrated that these interventions have an unlimited capacity to learn and the potential to lead patients more favourably than physicians, supporting credibility (73). In this study, we found similar concerns about the “credibility” of potential AI usage, with certain participants questioning whether they were credible enough to suggest a treatment plan to patients.

A critical feature of determining the adoption and acceptability of emerging technologies like AI is their dependence on the perceptions of prospective users' (PCPs) in addition to systems standards (74). Impartial recognition of new technology (e.g., AI) is determined by how relevant an individual evaluates technology innovation characteristics while acknowledging that primary influence variables such as financial implications, cost-benefit evaluations, training, or job facilitation may elicit different responses in different individuals (75). Therefore, future works should meaningfully and explicitly consider physicians' perceived features for AI interventions to increase the potential of using AI in adolescents' mental healthcare.

Our results showed AI's potential in establishing diagnoses and identifying community resources. Similar to our findings, studies have also shown that AI-assisted online behavioural therapy and conversational chatbots may be a cost-effective and engaging treatment planning alternative (76). Chatbots are artificial, virtual, and interactive entities that can simulate human communication and engage users (77). The creation of CBT online chatbots, e.g., Sara (78) and Woebot (79), replicating common communication methods was shown to reduce depression and anxiety in college adolescents, boost adherence to treatment and psychological management.

Our results further highlight the potential of AI in managing the operational aspects of care, such as administrative support and patient case management, allowing doctors to focus on individualized care rather than transactional tasks. Recent research has revealed that AI might also automate repetitive, time-consuming tasks like paperwork and administrative information processing, which often contribute to physician burnout (80, 81). For instance, AI interventions might assist clinicians in monitoring their patients' health between visits and facilitate discharge processes, increase work efficiency and reduce fatigue by optimizing patients' seat usage, level-loading appointments, and patient congestion, thus freeing them to provide more focused care (82, 83).

Participants also discussed how AI interventions may be used to facilitate clinical decision-making. These findings, which is in line with earlier research, illustrate the feasibility of using AI-enabled decision support interventions in various clinical contexts, e.g., aid in choosing antidepressant medications (84-86) or medical triage (87). Triaging is also vital to patient care workflow. Medical staff, such as nurses and doctors, must routinely make triage choices, particularly in high-risk and expensive settings, to prioritize patients and maximize healthcare resources and personnel (88). AI shows potential in automating patient triage, reducing expert work, and improving classification reliability (88). Our findings echoed this literature. A promising example of the application of AI to support adolescent mental health is Kids' Help, an online AI platform, to triage users (children and adolescents) who contact the crisis text line (89) or acting as a patient intake coordinator that performs screening tests before linking them to a physician (90). Similar approaches may be implemented into triaging-based healthcare processes to improve quality, save costs, and satisfy a larger number of patients.

Given that AI applications for mental health are often limited to clinical settings, most are still in the research and development stage and have not been scaled up for clinical or patient use (91). If responsively developed, the implications of integrated AI in mental healthcare is exciting, with the potential to support both operational and clinical functions (92). As AI interventions advance, they might help populations needing mental health services and improve life opportunities for vulnerable groups like adolescents. There remains, however, a substantial gap between AI's potential contribution to mental health breakthroughs and its practical usage by physicians and adolescent patients.

4.4.3 Risks of using AI interventions

Our results showed that AI interventions might compromise PCPs' professions and skills. We found that most participants were equally optimistic and fearful about AI's role in their disciplines, which a lack of AI knowledge might explain, as voiced in previous literature (93, 94). Concerns regarding AI in healthcare may stem from de-skilling and/or replacing health professionals and increased knowledge needs in their respective professions (93, 95). Incorporating AI into mental health might be used to justify replacing traditional services, resulting in fewer AI-driven health resources, decreasing practitioners' competency and eventually worsening health inequities (96). Therefore, before integrating AI into clinical practice, it is necessary to determine what tasks can be shifted without jeopardizing the quality of care and PCPs' ability to practice, which is advised to be a focus of future work.

Study participants stressed the importance of face-to-face human interaction, noting that AI can't replace humans in delivering empathetic care. While AI interventions in healthcare aim to replicate or improve physicians' efficiency (97), replacing doctors' tasks with technology risks reducing emotional touch as mirrored in our findings (64, 98, 99). Due to persistent legal concerns in medical practice, there is growing concern about using AI interventions in mental and physical healthcare (69, 97). Therefore, it is critical to create AI architecture that supports a patient-centred model of care that is compassionate and competent in responding to patient needs. Ultimately, AI uptake will only occur if trust is present; the development depends on proof of its effectiveness and credibility in supporting quality care.

4.4.4 Requirements and conditions for using AI interventions

Our FG participants highlighted the importance of AI education for the general population. AI has expanded in many sectors, e.g., business and science, to enhance user experience, work efficiency, and job opportunities (100). However, public perceptions of AI and how to determine AI literacy are relatively unexplored (101). The development of an equitable, knowledge-based society requires every individual to be "digitally literate". This underscores the importance of public education for AI literacy, learning, and education (101, 102). This should be a central component of any initiative to scale-up AI deployment in healthcare.

Study participants indicated the need for AI education for physicians, residents, and students. Earlier research stressed the importance of introducing AI into medical school and residency curricula (103); although few such initiatives have been made (104, 105). Physicians must be trained on the use and limitations of AI to ensure its safe application in clinical practice and, as appropriate, how to communicate AI results to patients. Only when physicians feel comfortable using AI interventions will their potential to enhance patients' mental and physical health outcomes be realized (106). Therefore, as AI becomes common in healthcare, investments in training are essential.

FG respondents required user-friendly AI interventions, co-developed with clinicians, and offered with timely support. A previous study reached a similar conclusion, emphasizing that adequate technical support is essential when introducing innovative technologies to healthcare inclusive of assistance with technology configuration and staff training (107). The literature also reflects participants' concerns about convenience, usefulness, usability, and technical dependability, which may might encourage or discourage clinicians from adopting AI interventions (107, 108). Previous studies have demonstrated how clinicians' needs influence AI use, and that leveraging these needs are necessary to maintain health innovation technologies in primary care (107). Developing and deploying AI interventions and strategies that respond to PCP needs is therefore essential.

Medical-ethical-legal standards regulate the doctor-patient-family relationship (109). Ethics and law intersect frequently; acting ethically is often synonymous with acting lawfully, although ethically correct reactions aren't always backed up by the law (109). FG participants emphasized that trust and privacy are critical ethical and medico-legal issues surrounding AI that might impede or facilitate the doctor-patient relationship. A growing literature also underlines the significance of trust and privacy, urging that AI intervention developers disclose what type of data is gathered, who has access to it, how the information will be used, and what measures are in place to prevent harmful use of the data (110).

AI interventions should be understandable to the physicians employing them (111). While clinicians may be liable if they do not properly examine an AI intervention before using it on patients, some question whether AI should be held responsible for medical malpractice (112). This is consistent with the views of participants in our study. While they agree that PCPs should be held accountable for employing AI interventions in their practice, their liability is viewed as only one piece of a larger ecosystem, opening the door for such interventions to be viewed as "individuals" and thus potential defendants in legal proceedings.

Hacked, malfunctioning, damaged, or dishonest AI may harm patients (113). The need for regulatory bodies may increase in direct proportion to the capabilities and accessibility of AI in mental healthcare to minimize breaches caused by either the AI or physicians (113). This too was reflected in our findings, emphasizing the importance of governing authorities to ensure that AI interventions are medico-legally safe. For instance, the Canadian Protocol checklist (an ethical framework for AI applications in mental health) and the Canadian AI Algorithmic Impact Assessment (an open-source platform) help AI decision-making intervention developers mitigate privacy, transparency, health, and bias risks. That said, there are several future research avenues for a better understanding of AI interventions in mental health, and this chapter is just the beginning. We need more general guidelines, structural incentives, appropriate methodologies, and well-designed trials to aid in developing future AI interventions for mental health.

4.4.5 Strengths and Limitations:

This study's strength is use of exploratory qualitative inquiry to investigate PCPs' perceived challenges and needs for AI interventions that may support adolescents' mental health. A limitation however was the small number of participants. Enrollment coincided with the COVID-19 pandemic, and the increasing burden on PCPs to meet the needs of Montreal health care institutions had implications for our work. Despite using a purposeful sampling strategy, we were unable to recruit a larger number of PCPs able to adjust their pandemic-altered schedules to take part in a focus group, even though it was scheduled to take place at the end of a workday. However, we did have a group of participants who were clearly interested in the study topic and were highly vocal and opinionated. Since qualitative research is focused on the quality and depth of information rather than on the number of participants, the four PCPs in this study provided a reasonable amount of rich data. We believe that our findings are transferrable to other contexts, depending on their degrees of resemblance to ours.

Conducting a qualitative study using Zoom software presented its own challenges. We audio-visually recorded the FG on personal computers rather than utilizing cloud-based online storage to maintain data confidentiality. While this presented occasional inconsistent internet connection or voice cuts, the overall virtual environment was not felt to compromise our data collection. Further, as prior research has argued, we believe that participants felt more comfortable and confident in their familiar environments and as typically busy clinicians, had more time to discuss their views and experiences (114, 115).

4.4.6 Conclusion:

This descriptive research provides insight into PCPs perceptions of AI interventions and their application with a focus on adolescent mental healthcare. The needs, limits, and benefits of these interventions and PCPs' challenges regarding adolescents' mental health have been highlighted. While a range of attitudes were expressed, both convergent and divergent, most participants were enthusiastic about the potential for AI interventions in improving quality and scope of their roles as primary care providers. However, to integrate and utilize AI appropriately, it is critical to understand all parties' opinions, including patients, as such interventions might affect their experiences favourably or adversely.

This study provides the groundwork for assessing the utility, applicability, and effectiveness of AI interventions in adolescents' mental health care practice in primary care. Nevertheless, larger-scale surveys may be necessary to offer greater clarity on the diverse viewpoints and experiences of PCPs, as are clinical trials of particular AI interventions. We also suggest that further study should be done to explore adolescents' perspectives on integrating AI into mental healthcare, as patient experience is crucial in providing patient-centered care. The COVID-19 pandemic has demonstrated how unexpected events can overstretch primary care infrastructure and how it may benefit from technological solutions to ease challenges related to overstretched primary healthcare systems. However, priority must be given to the design and implementation of regulatory frameworks to ensure ethical standards are met, evaluations are performed, and generalizable and fair AI interventions are developed to assist adolescents' mental health care.

4.5 Tables

Table 4.1. Symbols used in transcription verbatim

Punctuation mark / symbol	Indication
(? time)	The exact timing of a phrase or sentence couldn't comprehend owing to low audio quality
…	A long pause or a sudden shift in sentence
Bolding and underlining words/phrases	Words/phrases expressed loaded with emphasis and significantly louder volume
[]	Added term to the statement to better express the idea of the participant
2.1.1 " "	A direct verbatim quote from the participant

Table 4.2. Demographic characteristics of the participants

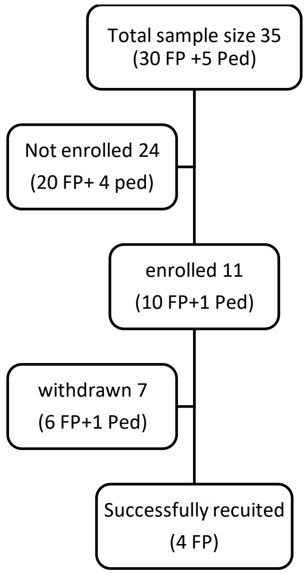
Participants	Gender (Male/Female)	Clinical experience in medical practice (Years)	Participants' ambulatory care time spent on adolescents (%)
P1	Female	6	10-15
P2	Male	13	12
P3	Female	40	5
P4	Female	22	20

Table 4.3. Themes, subthemes, and sub-sub themes in adolescents' mental healthcare in the primary care setting.

Themes	Subthemes	Sub-Sub themes
1. Challenges of adolescents' care in ambulatory setting	1.1 Fostering and maintaining a relationship	1.1.1 Difficult due to level stage, characteristics, peers, parents, and technology
	1.2 Adolescent care is time-consuming	1.2.1 Physicians' time management
2. Perceived features and characteristics of AI interventions	2.1 Perceived benefits to PCPs and healthcare system by easing activities, and providing efficiencies and facilitation	2.1.1 Easing access to the resources 2.1.2 Easing data collection and storage (e.g., patients' demographic information or lab results) 2.1.3 Handling large volume of data 2.1.4 Cost efficiency 2.1.5 Time efficiency 2.1.6 Taking patients' history 2.1.7 Treatment planning 2.1.8 Facilitating relationship with patients 2.1.9 Efficient questioning 2.1.10 Interactive patients' questionnaires 2.1.11 Promoting medication adherence
	2.2 Credibility	2.2.1 Negative Credibility 2.2.2 Positive Credibility
	2.3 Potentiality for benefit varies by user	
3.Potential applications of AI interventions	3.1 Clinical care	3.1.1 Administrative support 3.1.2 Patients' triage 3.1.3 Decision support 3.1.4 Establishing/helping to validate diagnosis 3.1.5 Tracking patients' progress and improve patients' adherence to treatment 3.1.6 Identifying community resources to which patients may be referred i.e., psychological management through CBT
	3.2 Obtaining and analyzing data	3.2.1 Algorithm-generated questionnaires 3.2.2 Questioning based on high yield queries suggested by AI 3.2.3 Identifying patients' possible associated conditions 3.2.4 Distilling patients' information for use in a particular clinical context 3.2.5 Finding and Interpreting variables that might suggest red flags
	3.3 Medical education and research	
4. Possible negative aspects of using AI interventions	4.1 Profession threatening	
	4.2 Trust issues (Mistrust or Distrust)	4.2.1 Performance Accountability
	4.3 Misinformation or disinformation	
	4.4 Lack of human connection	
	4.5 Diminished clinical competency	4.5.1 Negative impacts on knowledge, attitudes, and skills
5. Perceived requirements for the application of AI interventions	5.1 Need for education on AI	5.1.1 Population in general 5.1.2 Continued professional development 5.1.3 Medical residents and students
	5.2 Need for user-friendly AI interventions co-developed with clinicians, supported by "just in time" technical support	5.2.1 Easily operational and seamless 5.2.2 Relevance and meaningfulness to practice 5.2.3 External incentives (credited CMEs, financial) or personal reward and interest in research and topic
	5.3 Need for AI regulatory bodies	5.3.1 Issues of confidentiality, privacy, trust, and liability 5.3.2 Need for having a framework/guideline to increase safety of AI interventions 5.3.3 Need for research into AI interventions' validation and its applications
	5.4 Financial implications of AI use	

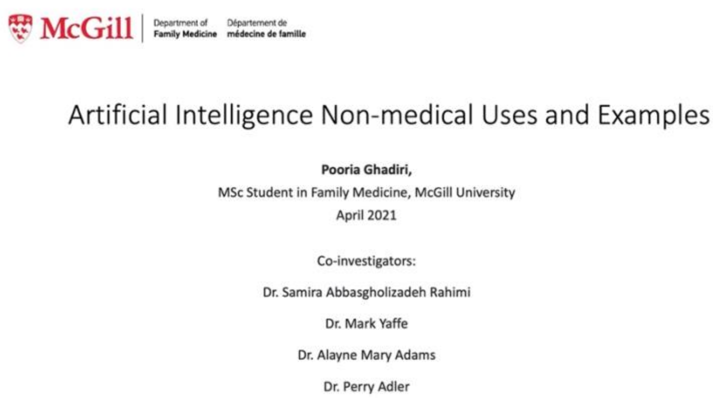
4.6 Figures

Figure 4.1. Participant recruitment process and results. (FP: Family Physician; Ped: Pediatrician)

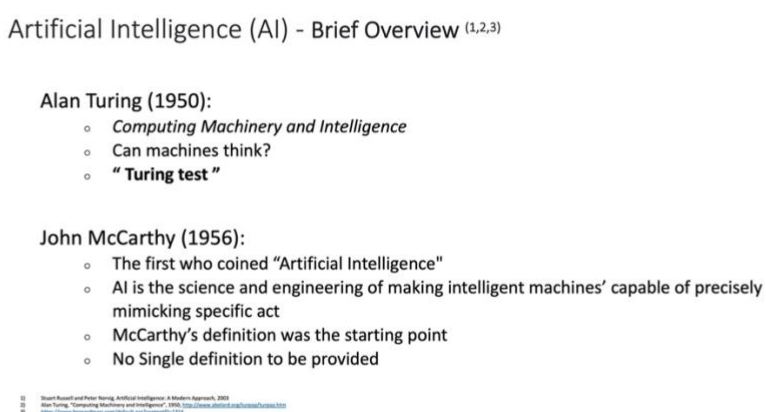


4.7 Appendices

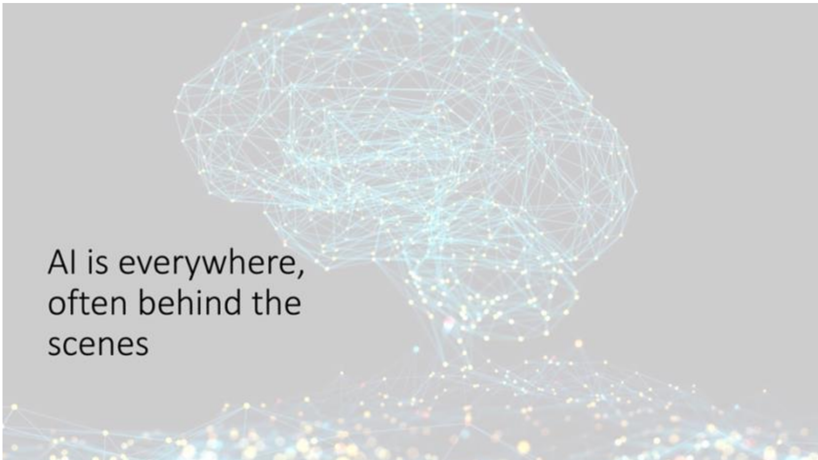
4.7.1 Appendix A: Artificial Intelligence Non-medical Uses and Examples- Presented as PowerPoint slide slides to the participants
(Narratives related to every slide is written following each slide)



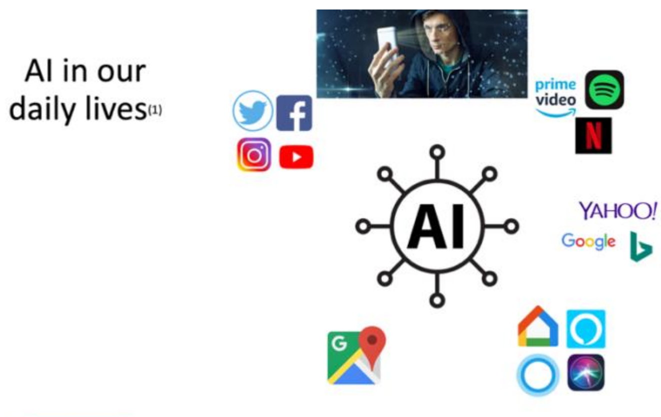
Now, on behalf of all team, today I am going to present to you some examples about “Artificial Intelligence Non-medical Uses” in 7-8 minutes in order that everyone in the focus group has the same understanding of what AI is, so that we can then discuss your ideas about AI in the care of adolescents' mental health.



In 1950 English Mathematician Alan Turing, one of the very first AI pioneers, published a paper entitled “Computing Machinery and Intelligence” which opened the doors to the field that would be called AI. The paper itself began by posing the simple question, “Can machines think?” Turing proposed a method for evaluating whether machines can think, which came to be known as the ‘Turing test’. The ‘Turing test’ takes a simple pragmatic approach, assuming that a computer that is indistinguishable from an intelligent human actually has shown that machines can think. Years later, the term Artificial Intelligence was first coined by Dr. John McCarthy at Dartmouth conference, Hanover, New Hampshire, USA in 1956. He defined AI as ‘the science and engineering of making intelligent machines’ capable of precisely mimicking specific act! It is necessary to mention that the given definition was just a starting point and there is not really a single definition to be provided.

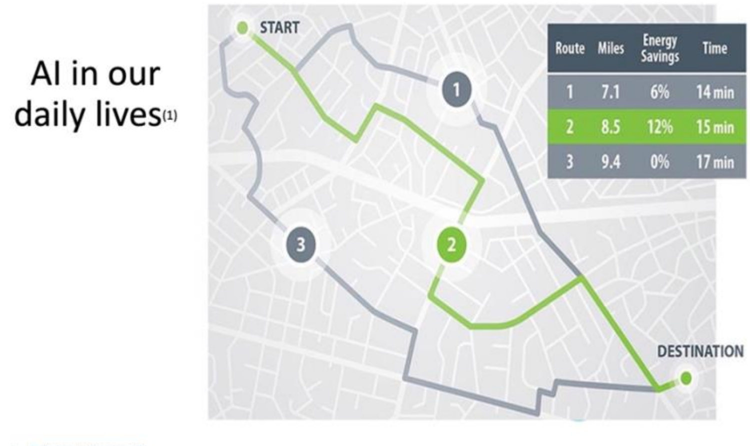


Sometimes, when we hear the word AI, we might think that this has nothing to do with us or something we don't encounter within our day to day lives! However, the truth is quite the opposite. Every single one of us meets AI multiple times each day. Even if we aren't aware of it, AI is at work, often behind the scenes, as we go about our everyday lives. For instance:



Face Recognition: When people wake up in the morning, picking up their iPhone, and it opens up automatically by recognizing their face, this is basically AI in practice which scans the face and grants a subsequent access to the phone content. **Recommender Systems:** When users check on social media feeds such as Facebook, Twitter, Instagram, AI is used to supply users with information close to their history and interests. Such companies also use AI to further protect their users by screening fake news, fighting to cyberbully running in the background without people necessarily knowing. Similarly, companies such as Netflix, Spotify, and Amazon use AI to recommend content related to their users' tastes by learning their interests and behaviors. Google search engine serves users based on what it knows about them and what are the themes in which the users are interested. This is all driven by AI. Every search result is now personalized to the users, thanks to the AI working in the Google background.

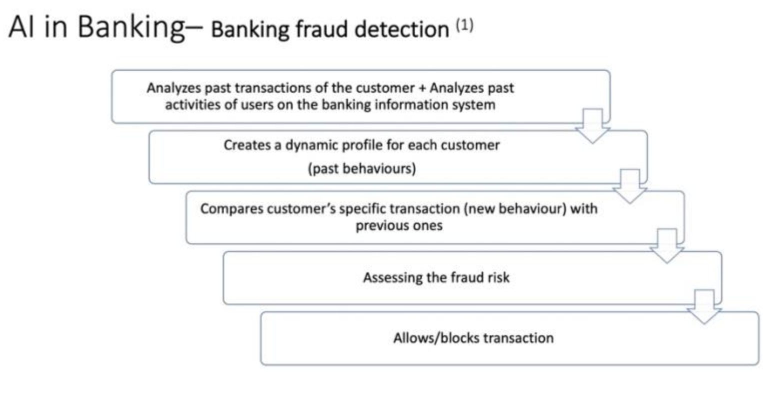
Speech Recognition: Apple Siri, Amazon Alexa, Google Home, Microsoft Cortana use AI to understand what the users are actually saying to them and generating reasonable answers. **Natural language processing and natural language understanding:** Chatbots use Natural Language Processing to understand and communicate with humans. Known as a NLP, this AI technology focusses on understanding on how humans communicate with each other and how we can get a computer to understand and replicate that behaviour. In business setting, for instance, chatbots are quickly finding their place in customer services. It is expected that in a few years, chatbots will power 85% of all customer service interactions.



Optimization and Scheduling: While driving to work, people might use Google Maps, which uses AI to monitor live traffic conditions, compare them to previous traffic conditions, use weather information to recommend the best route to drive to the destination. In another collaborative work between Google and US National Renewable Energy Laboratory, Google is trying to find more echo-friendly routing in Google maps which allows users to co-optimize travel time and energy consumption for individual vehicles, fleets, or entire transportation networks. As you can see in the picture, the green route indicates the best energy saving level (12%) with average reasonable time (15 min) to get to the destination

AI in Weather forecast: The chaotic nature of climate makes it almost impossible to make real-time predictions. For decades, weather forecast, in best scenario, had been 6 to 12 hours behind the real data. The good news is that now big companies such as Microsoft or Google are feeding all weather signals of the past from the satellites into Artificially Intelligent networks, memories to better model a weather prediction in advance. This have had huge impacts on agriculture businesses and supply chain management. Results also indicates that these computational models are cheaper, faster and more accurate compared to the more conventional approaches of weather forecasts. The weather forecasting and how AI is helping in forming a physics free understanding of weather is quite noticeable nowadays, helping to turn forecasting into nowcasting!

AI in Banking: AI has the potential to modify today's banking. Large Canadian Banks such as TD, for instance, are using AI to analyse data which it uses to learn more about customers and anticipate their needs.



Banking fraud detection: When it comes to the Fraud detection, AI can be used to monitor financial transactions and user behaviour every time to detect suspicious activities or financial transactions. AI is capable of analysing the past transactions of the customer to learn their transactional behaviour as well as past activities of users on the banking information system and create a dynamic profile for each customer. Therefore, AI would be able to compare the customer's specific transaction against the customer profile and compute a risk score out of it. If the risk score is sufficiently high, the AI machine will decide to block the transaction and qualify it for further investigation by the bank.

4.7.2 Appendix B: Focus Group Discussion Interview Guide

Introduction

Hello. Welcome everyone. My name is Pooria Ghadiri. I am an MSc student at the department of Family Medicine, McGill University. I would like to start off by thanking each of you for taking time to participate today. We will be here for about 60 to 90 minutes. The purpose of this gathering is to gather your input on 'Exploring the perceived needs of Primary Care Physicians (PCPs) about Artificial Intelligence (AI) interventions in the care of adolescents' mental health**.'** I'm going to lead our discussion today. I will be asking you questions and then encouraging and moderating our discussion. Dr, Mark Yaffe, professor in the Department of Family Medicine, McGill University and St. Mary's Hospital Center, is participating in this FG session predominantly as an observer, as well as to provide support for me should it be required. I will guide the conversation by asking questions that each of you can respond to. There are no right or wrong answers to these questions. We want you to share your thoughts with us so that we can get a broad range of ideas and opinions. If you wish, you can also respond to each other's comments, hopefully in friendly, non-judgemental fashion, like you would in an ordinary conversation. It is my job to make sure that everyone here gets to participate and that we stay on track. I also would like you to know this focus group will be audio-visually recorded both through Zoom or WebEx software and an external digital audio recorder. The identities of all participants will remain confidential. The recording allows the research team to revisit our discussion for the purpose of consolidating the ideas and opinions expressed.

Ground Rules

To allow our conversation to flow more freely, I'd like to go over some ground rules:

1) First, before the focus group discussion begins, we want to ensure that all the members who agreed to participate today have received and signed off the consent form through an email.
2) We want you to do the talking. We hope everyone will participate according to their level of comfort.
3) Only one person speaks at a time. This is doubly important as our goal is to make a written transcript of our conversation today. It is difficult to capture everyone's experience and perspective on our audio-visual recording if there are multiple voices at once.
4) There are no right or wrong answers. Every person's opinions and experiences are important. Speak up whether you agree or disagree. We expect and want to hear a wide range of opinions and we do not anticipate consensus, just sharing.
5) Please avoid side conversations or virtual chatting through the Zoom or WebEx platform while the discussion is on.

6) We emphasize that what is said in this virtual room should remain here. You should be able to share anything if sensitive issues come up. Please do not disparage other participants' remarks.
7) You may use each other names in the discussions, but I will not report your names or who said what. You may, however, later discuss with others what was addressed here, as long as you do not disclose who said what. Audio-visual recordings will be secured by the Principal Investigator, Dr. Samira Rahimi at McGill University's One-Drive network. We may provide summary details of the study in oral or written reports once the study is complete.
8) I understand that I should keep both the audio and video on to ensure the discussion flow during the focus group. However, while I will plan to have no personal interruptions during the focus group, should that unexpectedly occur, I will click off the audio and video and re-open them as soon as possible afterwards.
9) In the end, I am happy to take questions if there are any.

Introduction of the Participants

May I ask if you could please introduce yourself and tell us a little about your practice. Let's start from Dr …

Demographic Questions

Thank you so much for your attendance and sharing your valuable inputs. We would like to know a little about your demographic backgrounds. I will launch a very brief questionnaire through a link provided in a chat box. You should be able to see it running on your screen and be able to answer the question accordingly. Your answers will be anonymous and confidential.
https://forms.gle/4WTGp6HL6t6BvALfA

Study title: Primary Care Physicians' Perceptions of Artificial Intelligence interventions in The Care of Adolescents' Mental Health.

Please answer the following questions:

1. What is your gender? Female☐; Male☐; Non-binary ☐
2. How many years have you been working in medical practice? (Please write down)
3. What percent of your patient care time is devoted to the care of adolescents in the ambulatory setting? (Please write down)

FG Opening Question

1. **Have you faced any challenges in the care of adolescents in the ambulatory setting? Tips to initiate: Would anyone like to start the discussion to the following?**
    - If yes, what are they?
    - Note: Now they have given me general responses. I need to break it down by asking: **"**Is the difficulty that you experience one that occurs only when you are treating a physical problem? Or when you are treating a mental health problem? Or is it all the time?"
    - More specifically, what about their mental healthcare---how do you approach it? Are you comfortable with it? What might make it better? What might make it easier?

Key Questions

1. **Can you think of any way AI technology that could help in adolescents' mental healthcare? (For example, in diagnosis, treatment, management or any other related fields?)**
    - What made you think of that approach?
    - Does anyone agree or disagree with that suggestion? Why?
2. **What might be some of the possible benefits of using AI in adolescents' mental healthcare?** Note: (Be ready to break down the question in the three probing aspects below)
    - Benefits: to patients? to a care provider? To the healthcare system?
3. **What might be some of the possible risks or down-sides of using AI in adolescents' mental healthcare?**
4. **How comfortable would you feel in using AI in your practice?**
    - Impact on workload
    - Positive and negative reactions from patients, uncertainty about how to interpret the AI data,
    - Questions about how their colleagues might react to using AI (How your colleagues might react to using AI?)
5. **If you thought you'd like to try AI in your practice, what would be needed to give it a go? (What would you need to get started?)**
6. **Are there any financial implications (positive or negative) to you using AI in your practice?**
7. **Are you interested to be involved in the design and development stage of AI interventions for your practice?** Break this question into two parts:
    - If YES, who would be interested and why?
    - If NO, who would not be interested and why?
8. **Do you think there is a need for more continuing professional development such as courses, seminars, workshops for doctors on the theme of AI as we have discussed it here today?**

Closing: We have gotten to the end of our session. Thanks for coming today and talking about these issues. Your comments have given us lots of different ways to see this issue. But before doing so, are there any additional comments that people would like to make?

4.8 References

1. Shlafer R, Hergenroeder AC, Jean Emans S, Rickert VI, Adger H, Spear B, et al. Adolescence as a critical stage in the MCH Life Course Model: commentary for the Leadership Education in Adolescent Health (LEAH) interdisciplinary training program projects. Maternal and child health journal. 2014;18(2):462-6.
2. Age limits and adolescents. Paediatr Child Health. 2003;8(9):577-8.
3. World Health Organization, Adolescent health; Access date: April 4th, 2022 2022 [Available from: https://www.who.int/health-topics/adolescent-health#tab=tab_1.
4. Walker JS, Gowen LK. Community-based approaches for supporting positive development in youth and young adults with serious mental health conditions. 2011.
5. Lynch FL, Clarke GN. Estimating the economic burden of depression in children and adolescents. Am J Prev Med. 2006;31(6):143-51.
6. Saraceno B. Caring for children and adolescents with mental disorders: Setting WHO directions. Geneva, Switzerland: World Health Organization. 2003.
7. Wissow LS, Van Ginneken N, Chandna J, Rahman A. Integrating children's mental health into primary care. Pediatric Clinics. 2016;63(1):97-113.
8. Kessler RC, Berglund P, Demler O, Jin R, Merikangas KR, Walters EE. Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the National Comorbidity Survey Replication. Arch Gen Psychiatry. 2005;62(6):593-602.
9. Information CIfH. Child and youth mental health in Canada — Infographic. 2022.
10. Sadler K, Vizard T, Ford T, Marchesell F, Pearce N, Mandalia D, et al. Mental health of children and young people in England, 2017. Richmond, Surrey, UK: NHS Digital, Part of the Government Statistical Service; 2018. p. 35.
11. McManus S, Gunnell D, Cooper C, Bebbington PE, Howard LM, Brugha T, et al. Prevalence of non-suicidal self-harm and service contact in England, 2000–14: repeated cross-sectional surveys of the general population. The Lancet Psychiatry. 2019;6(7):573-81.
12. Bould H, Mars B, Moran P, Biddle L, Gunnell D. Rising suicide rates among adolescents in England and Wales. The Lancet. 2019;394(10193):116-7.
13. Perquier F, Hetrick S, Rodak T, Jing X, Wang W, Cost KT, et al. Association of parenting with suicidal ideation and attempts in children and youth: protocol for a systematic review and meta-analysis of observational studies. Syst. 2021;10(1):1-10.
14. Hawton K, Saunders KE, O'Connor RC. Self-harm and suicide in adolescents. The Lancet. 2012;379(9834):2373-82.
15. Skinner R, McFaull S. Suicide among children and adolescents in Canada: trends and sex differences, 1980–2008. Cmaj. 2012;184(9):1029-34.
16. Mojtabai R, Olfson M, Han B. National trends in the prevalence and treatment of depression in adolescents and young adults. Pediatrics. 2016;138(6).
17. Wyman PA. Developmental approach to prevent adolescent suicides: research pathways to effective upstream preventive interventions. Am J Prev Med. 2014;47(3 Suppl 2):S251-6.
18. Collins PY, Patel V, Joestl SS, March D, Insel TR, Daar AS, et al. Grand challenges in global mental health. Nature. 2011;475(7354):27-30.

19. Vanselow NA, Donaldson MS, Yordy KD. A new definition of primary care. Jama. 1995;273(3):192-.
20. Amaral CE, Onocko-Campos R, de Oliveira PRS, Pereira MB, Ricci ÉC, Pequeno ML, et al. Systematic review of pathways to mental health care in Brazil: narrative synthesis of quantitative and qualitative studies. International journal of mental health systems. 2018;12(1):1-14.
21. Cooley WC, Sagerman PJ, Pediatrics AAo, Physicians AAoF. Supporting the health care transition from adolescence to adulthood in the medical home. Pediatrics. 2011;128(1):182-200.
22. Singh SP, Anderson B, Liabo K, Ganeshamoorthy T. Supporting young people in their transition to adults' services: summary of NICE guidance. bmj. 2016;353.
23. Klein D, Wild TC, Cave A. Understanding why adolescents decide to visit family physicians: qualitative study. Canadian Family Physician. 2005;51(12):1660-1.
24. Nordin JD, Solberg LI, Parker ED. Adolescent primary care visit patterns. The Annals of Family Medicine. 2010;8(6):511-6.
25. Zanus C, Battistutta S, Aliverti R, Montico M, Cremaschi S, Ronfani L, et al. Adolescent admissions to emergency departments for self-injurious thoughts and behaviors. PLoS ONE. 2017;12(1):e0170979.
26. Kim B, White K. How can health professionals enhance interpersonal communication with adolescents and young adults to improve health care outcomes?: systematic literature review. International Journal of Adolescence and Youth. 2018;23(2):198-218.
27. Sarvet B, Gold J, Straus JH. Bridging the divide between child psychiatry and primary care: the use of telephone consultation within a population-based collaborative system. Child and Adolescent Psychiatric Clinics. 2011;20(1):41-53.
28. Kates N, Mazowita G, Lemire F, Jayabarathan A, Bland R, Selby P, et al. The evolution of collaborative mental health care in Canada: A shared vision for the future. Canadian Journal of Psychiatry. 2011;56(5):I1.
29. Gotovac S, Espinet S, Naqvi R, Lingard L, Steele M. Evaluating training programs for primary care providers in child/adolescent mental health in Canada: a systematic review. Journal of the Canadian Academy of Child and Adolescent Psychiatry. 2018;27(2):99.
30. Child AAo, Access APCoHC, Health ETFoM. Improving mental health services in primary care: reducing administrative and financial barriers to access and collaboration. Pediatrics. 2009;123(4):1248-51.
31. D'Alfonso S, Santesteban-Echarri O, Rice S, Wadley G, Lederman R, Miles C, et al. Artificial intelligence-assisted online social therapy for youth mental health. Front Psychol. 2017;8:796.
32. Amisha PM, Pathania M, Rathaur VK. Overview of artificial intelligence in medicine. J Family Med Prim Care. 2019;8(7):2328.
33. Bohr A, Memarzadeh K. The rise of artificial intelligence in healthcare applications. Artificial Intelligence in Healthcare: Elsevier; 2020. p. 25-60.
34. Liyanage H, Liaw S-T, Jonnagaddala J, Schreiber R, Kuziemsky C, Terry AL, et al. Artificial Intelligence in Primary Health Care: Perceptions, Issues, and Challenges. Yearb Med Inform. 2019;28(1):41-6.

35. Ghosh S, Mukherjee A, Ghosh SK, Buyya R. STOPPAGE: Spatio-temporal data driven cloud-fog-edge computing framework for pandemic monitoring and management. arXiv preprint arXiv:210401600. 2021.
36. Yabanci O. From human resource management to intelligent human resource management: a conceptual perspective. Human-Intelligent Systems Integration. 2019;1(2):101-9.
37. Graham S, Depp C, Lee EE, Nebeker C, Tu X, Kim HC, et al. Artificial Intelligence for Mental Health and Mental Illnesses: an Overview. Curr Psychiatry Rep. 2019;21(11):116.
38. Sun TQ. Adopting Artificial Intelligence in Public Healthcare: The Effect of Social Power and Learning Algorithms. International Journal of Environmental Research and Public Health. 2021;18(23):12682.
39. Sandelowski M. Whatever happened to qualitative description? Research in nursing & health. 2000;23(4):334-40.
40. Knafl KA. Patton, M.Q. (1990). Qualitative evaluation and research methods (2nd ed.). Newbury Park, CA: Sage, 532 pp.,. Research in Nursing & Health. 1991;14(1):73-4.
41. Patton MQ. Qualitative research & evaluation methods: Integrating theory and practice: Sage publications; 2014.
42. Blum J, Booth S, Gal O, Krohn M, Lyons K, Marcedone A, et al. E2e encryption for zoom meetings. Zoom Video Commun, Inc, San Jose, CA, Tech Rep Version. 2020;2(1).
43. McGill University Faculty of Medicine and Health Sciences, Institutional Research Ethics Board; Access date: Feb 11, 2022 [Available from: https://www.mcgill.ca/medhealthsci-researchethics/.
44. Simanjuntak B, Limbong T. Using Google form for student worksheet as learning media. International Journal of Engineering & Technology. 2018;7(3.4):321-4.
45. Green J, Thorogood N. Qualitative methods for health research: sage; 2018.
46. McMahon SA, Winch PJ. Systematic debriefing after qualitative encounters: an essential analysis step in applied qualitative research. BMJ global health. 2018;3(5):e000837.
47. Morse JM. The significance of saturation. Sage publications Sage CA: Thousand Oaks, CA; 1995.
48. Braun V, Clarke V. Using thematic analysis in psychology. Qualitative research in psychology. 2006;3(2):77-101.
49. Terry G, Hayfield N, Clarke V, Braun V. Thematic analysis. The SAGE handbook of qualitative research in psychology. 2017;2:17-37.
50. Rubin HJ, Rubin IS. Qualitative interviewing: The art of hearing data. 3rd ed: Sage ; 2011. 288 p.
51. Lincoln YS, Guba EG. Naturalistic inquiry. Beverly Hills, Calif.: Sage Publications; 1985. 416 p.
52. Albon L, Vaughan L. Adolescents and young adults on the acute medical unit: how might we do it better? Clinical medicine. 2014;14(6):618.
53. Conn KM, Halterman JS, Fisher SG, Yoos HL, Chin NP, Szilagyi PG. Parental beliefs about medications and medication adherence among urban children with asthma. Ambulatory Pediatrics. 2005;5(5):306-10.

54. Rhee H, Wyatt TH, Wenzel JA. Adolescents with asthma: Learning needs and internet use assessment. Respiratory care. 2006;51(12):1441-9.
55. Chen E, Chim LS, Strunk RC, Miller GE. The role of the social environment in children and adolescents with asthma. American journal of respiratory and critical care medicine. 2007;176(7):644-9.
56. Hendrickx G, De Roeck V, Maras A, Dieleman G, Gerritsen S, Purper-Ouakil D, et al. Challenges during the transition from child and adolescent mental health services to adult mental health services. BJPsych Bulletin. 2020;44(4):163-8.
57. Kassem NO, Lee JW. Understanding soft drink consumption among male adolescents using the theory of planned behavior. Journal of Behavioral Medicine. 2004;27(3):273-96.
58. Zucker NA, Schmitt C, DeJonckheere MJ, Nichols LP, Plegue MA, Chang T. Confidentiality in the doctor-patient relationship: Perspectives of youth ages 14-24 years. The Journal of pediatrics. 2019;213:196-202.
59. Claire Roden R, Berlan ED. How Can We Best Communicate with Adolescents?: Springer Cham, Gewerbestrasse, Switzerland; 2018 24 May 2018. 246 p.
60. Schraeder K, Dimitropoulos G, McBrien K, Li JY, Samuel S. Perspectives from primary health care providers on their roles for supporting adolescents and young adults transitioning from pediatric services. BMC family practice. 2020;21(1):1-12.
61. Kalmady SV, Greiner R, Agrawal R, Shivakumar V, Narayanaswamy JC, Brown MR, et al. Towards artificial intelligence in mental health by improving schizophrenia prediction with multiple brain parcellation ensemble-learning. npj Schizophrenia. 2019;5(1):1-11.
62. Spinazze P, Aardoom J, Chavannes N, Kasteleyn M. The Computer Will See You Now: Overcoming Barriers to Adoption of Computer-Assisted History Taking (CAHT) in Primary Care. J Med Internet Res. 2021;23(2):e19306.
63. Paranjape K, Schinkel M, Hammer RD, Schouten B, Nannan Panday R, Elbers PW, et al. The value of artificial intelligence in laboratory medicine: current opinions and barriers to implementation. American Journal of Clinical Pathology. 2021;155(6):823-31.
64. Jiang F, Jiang Y, Zhi H, Dong Y, Li H, Ma S, et al. Artificial intelligence in healthcare: past, present and future. Stroke and vascular neurology. 2017;2(4):230-43.
65. Harada Y, Shimizu T. Impact of a Commercial Artificial Intelligence–Driven Patient Self-Assessment Solution on Waiting Times at General Internal Medicine Outpatient Departments: Retrospective Study. JMIR Medical Informatics. 2020;8(8):e21056.
66. Beam AL, Kohane IS. Big data and machine learning in health care. Jama. 2018;319(13):1317-8.
67. Mesko B. The role of artificial intelligence in precision medicine. Taylor & Francis; 2017. p. 239-41.
68. Liang Y, Zheng X, Zeng DD. A survey on big data-driven digital phenotyping of mental health. Inf Fusion. 2019;52:290-307.
69. Gerke S, Minssen T, Cohen G. Ethical and legal challenges of artificial intelligence-driven healthcare. Artificial Intelligence in Healthcare: Elsevier; 2020. p. 295-336.
70. Alpaydin E. Introduction to machine learning: MIT press; 2020.

71. Price WN, II, Gerke S, Cohen IG. Potential Liability for Physicians Using Artificial Intelligence. JAMA. 2019;322(18):1765-6.
72. D'Amour A, Heller K, Moldovan D, Adlam B, Alipanahi B, Beutel A, et al. Underspecification Presents Challenges for Credibility in Modern Machine Learning2020.
73. Ryan M. In AI we trust: ethics, artificial intelligence, and reliability. Science and Engineering Ethics. 2020;26(5):2749-67.
74. Schäfer M, Keppler D. Modelle der technikorientierten Akzeptanzforschung. Zentrum Technik und Gesellschaft. TU Berlin, Discussion paper 34/2013; 2013.
75. Safi S, Thiessen T, Schmailzl KJ. Acceptance and resistance of new digital technologies in medicine: qualitative study. JMIR research protocols. 2018;7(12):e11072.
76. Chow JCL. Artificial Intelligence in Radiotherapy and Patient Care. Artif Intell Med: Springer; 2022. p. 1275-86.
77. Adamopoulou E, Moussiades L, editors. An overview of chatbot technology. IFIP International Conference on Artificial Intelligence Applications and Innovations; 2020: Springer.
78. Almurayh A. The Challenges of Using Arabic Chatbot in Saudi Universities. IAENG International Journal of Computer Science. 2021;48(1).
79. Fulmer R, Joerin A, Gentile B, Lakerink L, Rauws M. Using psychological artificial intelligence (Tess) to relieve symptoms of depression and anxiety: randomized controlled trial. JMIR Ment Health. 2018;5(4):e9782.
80. Reuben DB, Sinsky CA. From transactional tasks to personalized care: a new vision of physicians' roles. The Annals of Family Medicine. 2018;16(2):168-9.
81. Marr B. How is AI used in healthcare-5 powerful real-world examples that show the latest advances. Forbes, July. 2018;27.
82. Meskó B, Görög M. A short guide for medical professionals in the era of artificial intelligence. NPJ digital medicine. 2020;3(1):1-8.
83. Glover WJ, Li Z, Pachamanova D. The AI-Enhanced Future of Health Care Administrative Task Management. NEJM Catalyst Innovations in Care Delivery. 2022;3(2).
84. Chekroud AM, Krystal JH. Personalised pharmacotherapy: an interim solution for antidepressant treatment? BMJ: British Medical Journal (Online). 2015;350.
85. Chekroud AM, Zotti RJ, Shehzad Z, Gueorguieva R, Johnson MK, Trivedi MH, et al. Cross-trial prediction of treatment outcome in depression: a machine learning approach. The Lancet Psychiatry. 2016;3(3):243-50.
86. Chekroud AM, Gueorguieva R, Krumholz HM, Trivedi MH, Krystal JH, McCarthy G. Reevaluating the efficacy and predictability of antidepressant treatments: a symptom clustering approach. JAMA Psychiatry. 2017;74(4):370-8.
87. Marchiori C, Dykeman D, Girardi I, Ivankay A, Thandiackal K, Zusag M, et al., editors. Artificial Intelligence Decision Support for Medical Triage. AMIA Annual Symposium Proceedings; 2020: American Medical Informatics Association.
88. Singh VK, Shrivastava U, Bouayad L, Padmanabhan B, Ialynytchev A, Schultz SK. Machine learning for psychiatric patient triaging: an investigation of cascading classifiers. J Am Med Inform Assoc. 2018;25(11):1481-7.

89. Haner D, Pepler D. “Live Chat” clients at kids help phone: Individual characteristics and problem topics. Journal of the Canadian Academy of Child and Adolescent Psychiatry. 2016;25(3):138.
90. Baumel A, Tinkelman A, Mathur N, Kane JM. Digital peer-support platform (7Cups) as an adjunct treatment for women with postpartum depression: feasibility, acceptability, and preliminary efficacy study. JMIR mHealth and uHealth. 2018;6(2):e9482.
91. Wells C, Hill S, Argaez C. Artificial intelligence and machine learning in mental health services: an environmental scan. CADTH health technology review.2021-06.
92. Cresswell K, Cunningham-Burley S, Sheikh A. Health care robotics: qualitative exploration of key challenges and future directions. J Med Internet Res. 2018;20(7):e10410.
93. Laï M-C, Brian M, Mamzer M-F. Perceptions of artificial intelligence in healthcare: findings from a qualitative survey study among actors in France. Journal of translational medicine. 2020;18(1):1-13.
94. Desai AN. Artificial intelligence: promise, pitfalls, and perspective. JAMA. 2020;323(24):2448-9.
95. Gong B, Nugent JP, Guest W, Parker W, Chang PJ, Khosa F, et al. Influence of artificial intelligence on Canadian medical students' preference for radiology specialty: ANational survey study. Academic radiology. 2019;26(4):566-77.
96. Fiske A, Henningsen P, Buyx A. Your robot therapist will see you now: ethical implications of embodied artificial intelligence in psychiatry, psychology, and psychotherapy. J Med Internet Res. 2019;21(5):e13216.
97. Loh E. Medicine and the rise of the robots: a qualitative review of recent advances of artificial intelligence in health. BMJ leader. 2018:leader-2018-000071.
98. Gilvary C, Madhukar N, Elkhader J, Elemento O. The missing pieces of artificial intelligence in medicine. Trends in pharmacological sciences. 2019;40(8):555-64.
99. Inkster B, Sarda S, Subramanian V. An empathy-driven, conversational artificial intelligence agent (Wysa) for digital mental well-being: real-world data evaluation mixed-methods study. JMIR mHealth and uHealth. 2018;6(11):e12106.
100. Steinbauer G, Kandlhofer M, Chklovski T, Heintz F, Koenig S. A differentiated discussion about AI education K-12. KI-Künstliche Intelligenz. 2021;35(2):131-7.
101. Ng DTK, Leung JKL, Chu SKW, Qiao MS. Conceptualizing AI literacy: An exploratory review. Computers and Education: Artificial Intelligence. 2021;2:100041.
102. Bawden D. Origins and concepts of digital literacy. Digital literacies: Concepts, policies and practices. 2008;30(2008):17-32.
103. Setrakian J, Gauthier G, Bergeron L, Chamberland M, St-Onge C, Magagna W, et al. JMIR Medical Education. JMIR. 2020;6(1).
104. James CA, Wheelock KM, Woolliscroft JO. Machine learning: the next paradigm shift in medical education. Academic Medicine. 2021;96(7):954-7.
105. Fogel AL, Kvedar JC. Artificial intelligence powers digital medicine. NPJ digital medicine. 2018;1(1):1-4.

106. Association AM. AMA passes first policy recommendations on augmented intelligence. 2018. Accessed at www ama-assn org/ama-passes-first-policy-recommendations-augmented-intelligence on. 2018;6.
107. Kuzel A, Feng L, DeShazo J, Love L. EHRs in primary care practices: benefits, challenges, and successful strategies. The American journal of managed care. 2012;18(2):e48-54.
108. Shachak A, Hadas-Dayagi M, Ziv A, Reis S. Primary care physicians' use of an electronic medical record system: a cognitive task analysis. Journal of general internal medicine. 2009;24(3):341-8.
109. Olick RS. It's ethical, but is it legal? Teaching ethics and law in the medical school curriculum. The Anatomical Record: An Official Publication of the American Association of Anatomists. 2001;265(1):5-9.
110. Carr S. 'AI gone mental': engagement and ethics in data-driven technology for mental health. Journal of Mental Health. 2020;29(2):125-30.
111. Carr S. 'AI gone mental': engagement and ethics in data-driven technology for mental health. Taylor & Francis; 2020. p. 125-30.
112. Jovanovic I. AI in endoscopy and medicolegal issues: the computer is guilty in case of missed cancer? Endoscopy International Open. 2020;8(10):E1385-E6.
113. Calo R, Evtimov I, Fernandes E, Kohno T, O'Hair D. Is Tricking a Robot Hacking? University of Washington School of Law Research Paper. 2018(2018-05).
114. Creswell JW, Poth CN. Qualitative inquiry and research design: Choosing among five approaches. Thousand Oaks, CA: Sage publications; 2016.
115. Tremblay S, Castiglione S, Audet L-A, Desmarais M, Horace M, Peláez S. Conducting qualitative research to respond to COVID-19 challenges: Reflections for the present and beyond. International Journal of Qualitative Methods. 2021;20:16094069211009679.

CHAPTER 5 - DISCUSSION

5.1 General thesis Discussion:

Adolescence is one of the most critical and formative stages of life (70). It is a time of personal, social, educational, and vocational exploration and experimentation. It is challenged by vulnerabilities presented by physical changes, mental health issues, and an increasing prevalence of risky health-related behaviors, including smoking, substance abuse, varied sexual practices, poor diet, and lack of exercise, many of which may affect subsequent health outcomes (71, 72).

Primary care physicians (PCPs) are increasingly acknowledged for their essential roles in recognizing and managing adolescent mental health problems, with an estimated 75% of such issues being addressed in primary care settings (73). PCPs, on the other hand, encounter numerous difficulties when delivering mental healthcare to this demographic, e.g., time restrictions and problems accessing specialized collaboration for help with complex patients (29). Under such conditions PCPs may value the innovative mental health care technologies such as Artificial Intelligence (AI) interventions that might be used in the assessment and care of adolescents' mental health problems.

This thesis reviewed the literature on tested and/or implemented AI interventions in adolescents' mental health care (Manuscript 1/Chapter 2). Informed by this review, the third chapter reports results of the conducted exploratory qualitative research on Montreal's PCPs' perceived needs and challenges in providing mental health care in this population, and then more specifically, using AI interventions (Manuscript 2/Chapter 4).

Our review results indicated that AI interventions were most commonly reported for Autism Spectrum Disorder, Outcomes of Psychological Stress/Pressure Level, Substance Use Disorder and Dysfunctional Behavior. AI interventions were used for the mediation of diagnostic processes, monitoring and evaluation, treatment, and prognosis. We also identified ML methods as commonly reported AI methods. Adolescents and/or health care professionals (HCPs) were rarely found to be involved in testing AI interventions, and no research was found describing their engagement in validating these interventions.

We used this literature review to help inform the creation of our qualitative exploratory study in which we identified five themes pertinent to the use of AI in the care of adolescents' mental health: Theme 1) General challenges of adolescents' care in an ambulatory primary care setting ; 2) Perceived features and characteristics of AI interventions; 3) Potential applications of AI interventions; 4) Possible negative repercussions of using AI interventions; and 5) Perceived requirements for the application of AI interventions. Our findings demonstrated structural and systematic challenges in delivering care to adolescents, including parental involvement and adolescent psychosocial influences such as sex, gender, family, culture, peers, and habits (Theme 1). PCPs perceived AI interventions as potentially cost-effective (time, money, and resources), able to handle large amounts of data, and relatively credible (Theme2). They proposed the following potential use case of AI in assisting with collecting patients' data, suggesting a diagnosis, and establishing a treatment plan (Theme 3). However, some were worried about the performance and outcomes of these interventions and feared losing clinical competency (Theme 4). PCPs needed user-friendly interventions with "just in time" technical support. They were keen to help design and develop AI interventions if it was within their scope of practice and were compensated with external incentives (financial or professional development study credits). They identified a need for regulatory bodies to deal with the medicolegal and ethical issues of AI intervention use (e.g., confidentiality, privacy, liability) to provide clear guidelines/frameworks to reduce/eliminate harm to patients caused by the use of such interventions (Theme 5).

5.2 Strengths and limitations

Strengths and limitations of the studies were thoroughly discussed in the corresponding manuscripts. Our literature review effectively mapped the relevant scientific exploration of the topic, and was found to be low in volume, and sometimes not comparable in methodology or issues evaluated. Because only English language papers were included in the scoping review, there may have been publication bias. As well we may not have captured all relevant studies because we limited ourselves to the World Health Organization definition of adolescence to determine our inclusion criteria, while the definition of adolescence can vary by country and charter. Nonetheless our outcome was a valuable synthesis for researchers and HCPs to possibly better understand the potential of AI in adolescent mental health care.

Using exploratory qualitative inquiry, we explored PCPs' perceived challenges and needs for AI interventions in supporting adolescents' mental health care. While we had an initial, adequately large sample of PCPs to approach for Focus Groups, and indeed an adequate number actually consented to participate, our study occurred during the COVID-19 pandemic. This was associated with an increased burden on PCPs to satisfy the needs of Montreal health care institutions and their office practices, and to work in various atypical ways. As a consequence, the size of the final group was smaller than planned for. Nonetheless these PCPs were interested in the topic, and animated in discussion and ideas, and our analysis has generated clearly important themes for consideration by AI innovators, health care policy planners, and clinicians.

5.3 Perspectives for the future

HCPs, patients, and AI developers might benefit from further exploration of the potential role that AI may play in the mental healthcare of adolescents, along with an open review of possible concerns or drawbacks. This would optimally involve discussion, participation of all stakeholders, along with possible co-design and ongoing opportunity for feedback. Standards for AI intervention development are fundamental to such exchange, as well as transparent guidelines for creating and using AI interventions in the interests of quality assurance, minimizing bias, and keeping them patient-centred and accurate.

This thesis lays a foundation for AI interventions' usability, applicability, and effectiveness in adolescents' mental health care practice in primary care. Nonetheless, larger-scale surveys with more participants are required to provide a more comprehensive understanding of PCPs and their needs. The COVID-19 pandemic has shown how unexpected situations may strain primary care infrastructure and how it might benefit from technology solutions such as AI interventions to address problems more effectively.

5.4 Conclusion

This thesis has, through a scoping review, identified a lack of knowledge concerning tested and/or implemented AI interventions in adolescents' mental health care. Through exploratory qualitative inquiry it has opened the door to an issue absent in the literature, namely PCPs' perceived needs and challenges for AI interventions supporting adolescents' mental health care. Both works contribute to the evidence-based potential use of AI interventions in adolescents’ mental healthcare, identify PCPs' requirements and challenges for AI interventions, and provide the basis for future studies on AI's practical usability, applicability, and effectiveness in adolescents’ mental healthcare.

5.5 References

1. Age limits and adolescents. Paediatr Child Health. 2003;8(9):577-8.
2. Orben A, Tomova L, Blakemore S-J. The effects of social deprivation on adolescent development and mental health. The Lancet Child & Adolescent Health. 2020;4(8):634-40.
3. Kessler RC, Petukhova M, Sampson NA, Zaslavsky AM, Wittchen HU. Twelve-month and lifetime prevalence and lifetime morbid risk of anxiety and mood disorders in the United States. Int J Methods Psychiatr Res. 2012;21(3):169-84.
4. Aoki C, Romeo RD, Smith SS. Adolescence as a Critical Period for Developmental Plasticity. Brain Res. 2017;1654(Pt B):85-6.
5. Rudolph MD, Miranda-Domínguez O, Cohen AO, Breiner K, Steinberg L, Bonnie RJ, et al. " At risk of being risky: The relationship between “brain age” under emotional states and risk preference": Erratum. 2020.
6. Dahl RE, Allen NB, Wilbrecht L, Suleiman AB. Importance of investing in adolescence from a developmental science perspective. Nature. 2018;554(7693):441-50.
7. National Academies of Sciences E, Medicine. The promise of adolescence: Realizing opportunity for all youth: National Academies Press; 2019.
8. Organization WH. Promoting mental health: Concepts, emerging evidence, practice: Summary report: World Health Organization; 2004.
9. Galderisi S, Heinz A, Kastrup M, Beezhold J, Sartorius N. Toward a new definition of mental health. World Psychiatry. 2015;14(2):231.
10. Keyes CL. Mental health as a complete state: How the salutogenic perspective completes the picture. Bridging occupational, organizational and public health. 2014:179-92.
11. Fuchs T, Schlimme JE. Embodiment and psychopathology: a phenomenological perspective. Current opinion in psychiatry. 2009;22(6):570-5.
12. Organization WH. Comprehensive mental health action plan 2013–2020 (WHA66. 8). Retrieved May. 2013;12:2016.
13. Slade M. Mental illness and well-being: the central importance of positive psychology and recovery approaches. BMC health services research. 2010;10(1):1-14.
14. Murphy M, Fonagy P. Mental health problems in children and young people. 2012:1-13.
15. Waddell C, Shepherd C, Schwartz C, Barican J. Child and youth mental disorders: prevalence and evidence-based interventions. 2014.
16. Wiens K, Bhattarai A, Pedram P, Dores A, Williams J, Bulloch A, et al. A growing need for youth mental health services in Canada: examining trends in youth mental health from 2011 to 2018. Epidemiology and psychiatric sciences. 2020;29.
17. Das JK, Salam RA, Lassi ZS, Khan MN, Mahmood W, Patel V, et al. Interventions for Adolescent Mental Health: An Overview of Systematic Reviews. J Adolesc Health. 2016;59(4S):S49-S60.

18. Kutcher S, Venn D. Why youth mental health is so important. The Medscape Journal of Medicine. 2008;10(12):275.
19. Shain B, Braverman PK, Adelman WP, Alderman EM, Breuner CC, Levine DA, et al. Suicide and suicide attempts in adolescents. Pediatrics. 2016;138(1).
20. Organization WH. Global status report on alcohol and health 2018: World Health Organization; 2019.
21. Twenge JM, Martin GN, Campbell WK. Decreases in psychological well-being among American adolescents after 2012 and links to screen time during the rise of smartphone technology. Emotion. 2018;18(6):765.
22. Duffy ME, Twenge JM, Joiner TE. Trends in mood and anxiety symptoms and suicide-related outcomes among US undergraduates, 2007–2018: Evidence from two national surveys. J Adolesc Health. 2019;65(5):590-8.
23. Twenge JM. Increases in depression, self-harm, and suicide among US adolescents after 2012 and links to technology use: Possible mechanisms. Psychiatric Research and Clinical Practice. 2020;2(1):19-25.
24. Malla A, Shah J, Iyer S, Boksa P, Joober R, Andersson N, et al. Youth Mental Health Should Be a Top Priority for Health Care in Canada. Can J Psychiatry. 2018;63(4):216-22.
25. Wells KB, Kataoka SH, Asarnow JR. Affective disorders in children and adolescents: addressing unmet need in primary care settings. Biol Psychiatry. 2001;49(12):1111-20.
26. Lund C, Petersen I, Kleintjes S, Bhana A. Mental health services in South Africa: Taking stock. African Journal of Psychiatry. 2012;15(6):402-5.
27. The Free Medical Dictionary. 2022.
28. Thomas-MacLean R, Tarlier D, Ackroyd-Stolarz S, Fortin M, Stewart M. TUTOR-PHC 2003/2004 research trainees."No cookie-cutter response" conceptualizing primary health care. London, ON: Western University; 2008.
29. Ferrari M, Suzanne A. Youth Mental Health, Family Practice, and Knowledge Translation Video Games about Psychosis: Family Physicians' Perspectives. J Can Acad Child Adolesc Psychiatry. 2017;26(3):184-9.
30. Romer D, McIntosh M. The role of primary care physicians in detection and treatment of adolescent mental health problems. Treating and preventing adolescent mental health disorders: What we know and what we don't know New York: Oxford. 2005:579-96.
31. Radez J, Reardon T, Creswell C, Lawrence PJ, Evdoka-Burton G, Waite P. Why do children and adolescents (not) seek and access professional help for their mental health problems? A systematic review of quantitative and qualitative studies. Eur Child Adolesc Psychiatry. 2021;30(2):183-211.
32. Zwaanswijk M, van Dijk CE, Verheij RA. Child and adolescent mental health care in Dutch general practice: time trend analyses. BMC Family Practice. 2011;12(1):1-11.
33. Golding KS. Multi-agency and specialist working to meet the mental health needs of children in care and adopted. Clinical Child Psychology and Psychiatry. 2010;15(4):573-87.
34. Schneider SJ, Grilli SF, Schneider JR. Evidence-based treatments for traumatized children and adolescents. Current Psychiatry Reports. 2013;15(1):332.

35. Eadie K, Douch M, Zahir SF. Outcomes for Indigenous children in care presenting at a specialist child and youth mental health service. Australian Social Work. 2022;75(1):48-61.
36. Arvidson J, Kinniburgh K, Howard K, Spinazzola J, Strothers H, Evans M, et al. Treatment of complex trauma in young children: Developmental and cultural considerations in application of the ARC intervention model. Journal of Child & Adolescent Trauma. 2011;4(1):34-51.
37. Cantos AL, Gries LT. Therapy outcome with children in foster care: A longitudinal study. Child and Adolescent Social Work Journal. 2010;27(2):133-49.
38. Institute of Medicine . Committee on Child Maltreatment Research P, II PftNDP. New directions in child abuse and neglect research: National Academies Press; 2014.
39. Handbook S. Rashtriya Kishor Swasthya Karyakram. Adolescent Health Division Ministry of Health and Family Welfare Government of India. 2014.
40. Care P. America’s Health in a New Era. Primary Care: America’s Health in a New Era National Academy Press, Washington, DC. 1996.
41. Servili C. Organizing and delivering services for child and adolescent mental health. IACAPAP e-textbook of child and adolescent mental health. 2012.
42. Archie S, Akhtar-Danesh N, Norman R, Malla A, Roy P, Zipursky RB. Ethnic diversity and pathways to care for a first episode of psychosis in Ontario. Schizophr Bull. 2010;36(4):688-701.
43. Schraeder KE, Brown JB, Reid GJ. Perspectives on monitoring youth with ongoing mental health problems in primary health care: family physicians are “out of the Loop”. The journal of behavioral health services & research. 2018;45(2):219-36.
44. Gray BP, Dihigo SK. Suicide risk assessment in high-risk adolescents. Nurse Pract. 2015;40(9):30-7; quiz 7-8.
45. McPherson A. Adolescents in primary care. Bmj. 2005;330(7489):465-7.
46. Erikson EH. Identity: Youth and crisis: WW Norton & company; 1968.
47. Koepke S, Denissen JJ. Dynamics of identity development and separation–individuation in parent–child relationships during adolescence and emerging adulthood–A conceptual integration. Developmental review. 2012;32(1):67-88.
48. Adams GR, Marshall SK. A developmental social psychology of identity: Understanding the person-in-context. Journal of adolescence. 1996;19(5):429-42.
49. Erikson EH. Identity and the life cycle: WW Norton & Company; 1994.
50. Kim B, White K. How can health professionals enhance interpersonal communication with adolescents and young adults to improve health care outcomes?: systematic literature review. International Journal of Adolescence and Youth. 2018;23(2):198-218.
51. Lim SW, Chhabra R, Rosen A, Racine AD, Alderman EM. Adolescents’ views on barriers to health care: a pilot study. Journal of primary care & community health. 2012;3(2):99-103.
52. Douthit N, Kiv S, Dwolatzky T, Biswas S. Exposing some important barriers to health care access in the rural USA. Public health. 2015;129(6):611-20.
53. Bodenheimer T, Pham HH. Primary care: current problems and proposed solutions. Health affairs. 2010;29(5):799-805.

54. D'Alfonso S, Santesteban-Echarri O, Rice S, Wadley G, Lederman R, Miles C, et al. Artificial Intelligence-Assisted Online Social Therapy for Youth Mental Health. Front Psychol. 2017;8:796.
55. Bohr A, Memarzadeh K. The rise of artificial intelligence in healthcare applications. Artificial Intelligence in Healthcare. 2020:25-60.
56. Liyanage H, Liaw S-T, Jonnagaddala J, Schreiber R, Kuziemsky C, Terry AL, et al. Artificial Intelligence in Primary Health Care: Perceptions, Issues, and Challenges. Yearb Med Inform. 2019;28(1):41-6.
57. Lovejoy CA, Buch V, Maruthappu M. Technology and mental health: The role of artificial intelligence. Eur Psychiatry. 2019;55:1-3.
58. Graham S, Depp C, Lee EE, Nebeker C, Tu X, Kim HC, et al. Artificial Intelligence for Mental Health and Mental Illnesses: an Overview. Curr Psychiatry Rep. 2019;21(11):116.
59. Khalifa M. Clinical decision support: Strategies for success. Procedia Computer Science. 2014;37:422-7.
60. Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. Future healthcare journal. 2019;6(2):94.
61. Kundu M, Nasipuri M, Basu DK. Knowledge-based ECG interpretation: a critical review. Pattern Recognition. 2000;33(3):351-73.
62. De Dombal F, Leaper D, Staniland JR, McCann A, Horrocks JC. Computer-aided diagnosis of acute abdominal pain. Br Med J. 1972;2(5804):9-13.
63. Shortliffe EH, Davis R, Axline SG, Buchanan BG, Green CC, Cohen SN. Computer-based consultations in clinical therapeutics: explanation and rule acquisition capabilities of the MYCIN system. Computers and biomedical research. 1975;8(4):303-20.
64. Barnett GO, Cimino JJ, Hupp JA, Hoffer EP. DXplain: an evolving diagnostic decision-support system. Jama. 1987;258(1):67-74.
65. Manak MS, Varsanik JS, Hogan BJ, Whitfield MJ, Su WR, Joshi N, et al. Live-cell phenotypic-biomarker microfluidic assay for the risk stratification of cancer patients via machine learning. Nature biomedical engineering. 2018;2(10):761-72.
66. Rahimi SA, Légaré F, Sharma G, Archambault P, Zomahoun HTV, Chandavong S, et al. Application of Artificial Intelligence in Community-Based Primary Health Care: Systematic Scoping Review and Critical Appraisal. J Med Internet Res. 2021;23(9):e29839.
67. Young AT, Xiong M, Pfau J, Keiser MJ, Wei ML. Artificial intelligence in dermatology: a primer. Journal of Investigative Dermatology. 2020;140(8):1504-12.
68. Taddeo D, Egedy M, Frappier JY. Adherence to treatment in adolescents. Paediatr Child Health. 2008;13(1):19-24.
69. World Health Organization. Global strategy on human resources for health: workforce 2030. 2016.
70. van Sluijs EM, Ekelund U, Crochemore-Silva I, Guthold R, Ha A, Lubans D, et al. Physical activity behaviours in adolescence: current evidence and opportunities for intervention. The Lancet. 2021;398(10298):429-42.

71. Patton GC, Coffey C, Romaniuk H, Mackinnon A, Carlin JB, Degenhardt L, et al. The prognosis of common mental disorders in adolescents: a 14-year prospective cohort study. The Lancet. 2014;383(9926):1404-11.
72. Erskine H, Moffitt TE, Copeland W, Costello E, Ferrari A, Patton G, et al. A heavy burden on young minds: the global burden of mental and substance use disorders in children and youth. Psychol Med. 2015;45(7):1551-63.
73. Gotovac S, Espinet S, Naqvi R, Lingard L, Steele M. Evaluating training programs for primary care providers in child/adolescent mental health in Canada: a systematic review. Journal of the Canadian Academy of Child and Adolescent Psychiatry. 2018;27(2):99.