EVALUATING A DIGITAL POPULATION HEALTH MANAGEMENT PROJECT:

AUTOMATED SOLUTIONS ASSISTING PRIORITY POPULATIONS (ASAPP)

EVALUATING A DIGITAL POPULATION HEALTH MANAGEMENT PROJECT: AUTOMATED SOLUTIONS ASSISTING PRIORITY POPULATIONS (ASAPP)

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A Thesis Submitted to the School of Graduate Studies in Partial Fulfillment of the Requirements for the Degree Master of Science

McMaster University MASTER OF SCIENCE (2025) Hamilton, Ontario (eHealth)

TITLE: Evaluating a Digital Population Health management Project: Automated Solutions Assisting Priority Populations (ASAPP)

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NUMBER OF PAGES: xii, 128

Lay Abstract

Patients with chronic conditions have a higher risk of hospitalization, which puts a heavy burden on patients and healthcare resources. A software project called Automated Solutions Assisting Priority Populations (ASAPP) ran searches to find complex patients from medical records. The goal of the project was to help people in healthcare to give the best care to these patients and plan resource use. We wanted to see how well the project worked and how it could do better. To do this, we interviewed people like doctors involved in the project and we looked at the data from the project. ASAPP was used in six clinics by 26 doctors caring for over 34,000 patients, and it identified 1,790 complex patients. While ASAPP could help improve care, challenges like low resources limited its potential. Doctors suggested ways to make similar projects better in the future, like involving doctors in the process of developing the project.

Abstract

Population segmentation of complex patients at higher risk of poor outcomes can facilitate improved resource allocation and health outcomes. The Automated Solutions Assisting Priority Populations (ASAPP) project used robotic process automation (RPA) to standardize data in electronic medical records (EMR), and predictive algorithms, as well as neighbourhood-level social determinants of health (SDOH), to identify complex patients at high-risk of hospitalization. The ASAPP data were shared with primary care clinicians and system-level leaders to support the proactive care coordination for complex patients. The purpose of this study was to evaluate the adoption, effectiveness, and value of the pilot ASAPP project to help inform recommendations for future digital population health projects. A summative evaluation with a convergent parallel mixed methods design was conducted, combining data from three semi-structured interviews with four stakeholders, including three clinicians and one system-level leader, and quantitative data on adoption and use. A reflexive thematic analysis was conducted and descriptive statistics and recommendations for improvement were generated. Six sites across three health regions engaged in ASAPP, involving 26 clinicians and 34,710 patients. RPA coded 2,240 additional conditions across five sites; 1,790 complex patients were identified using the predictive algorithms; 220 patients were found to be living in high SDOH complex areas. Four overarching themes were generated: (1) perceived value and unrealized potential of population health management (PHM), (2) effectiveness and limitations, (3) barriers and facilitators, and (4) recommendations. ASAPP demonstrated potential to support PHM, but its value was not fully realized due to technology limitations, and adoption barriers including resource constraints. Stakeholder recommendations included early engagement, clinician champions, and transparent communication. Although the small qualitative sample size limits the transferability of findings to settings beyond early-adopters,

the evaluation highlights the need for more strategic and user-centric development and adoption, prioritizing stakeholder engagement and system-level support.

Acknowledgements

Thank you to my dearest parents – their endless support, sacrifices, and prayers carried me through every step of this journey. This would not have been possible without them.

I would also like to thank my supervisors, Dr. Neil Barr, Dr. Cynthia Lokker, and Ted Alexander for their support, guidance, feedback, and kindness.

I would also like to express my deepest gratitude to the team at the eHealth Centre of Excellence, Lisa Harman, Eric Tian, Justin Wolting, and Lirije Hyseni for their support, leadership, and mentorship. This would not have been possible without you.

Thank you to my dear friends Ayisha Salamath, Lamia Hossain, and Mahrukh Khan, and my dearest sister, Fatima Nazir for their support and encouragement throughout my research.

Finally, I would like to thank the clinicians and OHT leaders who participated in this study and their time and willingness to share their valuable insights.

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List of all Abbreviations and Symbols

ASAPP	Automated Solutions Assisting Priority Populations
eCE	eHealth Centre of Excellence
CCP	Coordinated Care Plan
CPP	Cumulative patient profile
EMR	Electronic medical record
PCP	Primary care physician
PHIPA	Personal Health Information Protection Act
PHM	Population health management
REB	Research ethics board
RISE	Rapid-Improvement Support and Exchange
RPA	Robotic process automation
RTA	Reflexive thematic analysis
OHT	Ontario Health Team
SDOH	Social determinants of health
QI	Quality improvement
VPN	Virtual private network

Declaration of Academic Achievement

The work presented in this thesis was completed by Zainib Nazir. Lisa Harman from the eHealth Centre of Excellence provided guidance and contributed to the study design, data collection, and the initial data analysis of the study. Dr. Neil Barr, Dr. Cynthia Lokker, and Ted Alexander provided guidance, feedback, and contributed to the manuscript revisions.

Introduction

According to the World Health Organization (WHO), chronic diseases account for 89% of all deaths in Ontario, Canada, with heart disease and cancer being the leading causes.[1] Patients who have multiple chronic conditions, mental health conditions, and indications of social determinants of health (SDOH) risks, such as low socioeconomic status, are typically at higher risk for poor health outcomes, emergency department (ED) visits, and hospitalization, leading to high healthcare costs.[2–4] These patients are considered complex as they often have multiple clinical needs and require more specialized care.[4] A recent systematic review revealed that about 27% of hospital readmissions were preventable.[5] Proactive care upstream, in primary care settings, and improved care coordination through patient identification and segmentation can help better manage conditions of complex patients and prevent hospitalizations considered avoidable through timely and coordinated care.[6–8]

Population segmentation refers to the identification of groups of patients with shared needs and similar characteristics related to their health, utilization of health services, sociodemographic factors, and their geographic location.[9] This is one of the three key components of population health management (PHM) described by the Rapid-Improvement Support and Exchange (RISE) initiative, which provides evidence-based support to Ontario Health Teams (OHT), regional health organizations in Ontario, Canada that are responsible for population health.[9,10] PHM aims to improve population health outcomes and reduce health system costs; it includes using data for population segmentation, designing pathways or services to support them, and adopting and allocating health services to the appropriate patient groups.[9,11] In Ontario, these PHM initiatives aim to align with the 'quintuple aim', a framework that emphasizes five elements: "improved patient experience, better patient outcomes, lower costs, improved provider experience, overall health equity".[12,13] The identification and segmentation of complex patients, in particular, allows for health care professions to provide proactive and preventative care they need, thereby enabling PHM, and supporting the quintuple aim. Moreover, social determinants of health (SDOH), defined by WHO as "conditions in which people are born, grow, live, work, and age", play a role in access to care, complexity, and health outcomes.[14,15] SDOH factors may include income, housing insecurity, ethnicity, and employment.[14] Incorporating SDOH data into patient segmentation is critical for identifying complex patients and addressing health disparities in care delivery and advancing health equity. SDOH data is often missing from EMRs but it plays a critical role in patient complexity and health outcomes, and can to be leveraged to direct resources to patients based on their social needs alongside their clinical needs.[16,17]

For patients who have a primary care physician (PCP), the longitudinal health information in the primary care electronic medical record (EMR) curated by the PCP offers a rich data source documenting chronic conditions that develop over time. There is vast opportunity in leveraging primary care data to identify priority patients who are likely to require higher levels of system resources and provide them with the resources and services they need. However, the documentation of primary care data is mostly non-standardized and may not be captured consistently or accurately in the EMR, which has led to the underutilization or the inability to effectively use this data to enhance PHM practices.[18–20] Moreover, there is ample literature that highlights how non-standardized data in the EMR limits the effectiveness of patient identification methods that rely on diagnostic information.[21,22] Primary care EMRs capture patient diagnoses, but PCPs will often not use designated diagnostic codes based on international standards to record these. Instead, they use varying formats, making it difficult to analyze for PHM.[20,23] This poor standardization requires rigorous approaches, which can be laborious and difficult to implement due to resource constraints, to improve the data, including adding the appropriate diagnostic codes.[20,23] Traditional data cleaning initiatives that involve healthcare staff have proven to be difficult to implement due to administrative burden and time or resource constraints, highlighting the need for alternative methods to improve data quality.[18,19] These challenges have led to a lost opportunity for data analysis and sharing data across health systems to support streamlined proactive care of patients and PHM. Overall, improved data quality can enhance data utility and capability of EMR queries to identify patients and thus provide targeted proactive care to patients in need, supporting PHM.[24,25] In addition, enhanced data quality facilitates data sharing between healthcare systems, supporting care teams in care coordination by providing them with a more complete understanding of the patient and the information that they need.[26] Data sharing across systems is especially important for complex patients as they may see multiple specialists across the healthcare continuum. Finally, improved data quality can also support with more meaningful data collection, extraction, and sharing for analytics used for clinical decision support or disease surveillance to enable outreach and proactive care, thereby further supporting PHM of complex patients.[18,24]

Project Overview

The Automated Solutions Assisting Priority Populations (ASAPP) project was a pilot PHM project in Ontario led by the eHealth Centre of Excellence (eCE), a not-for-profit organization that facilitates the adoption of digital health tools for clinicians and organizations across Ontario. The ASAPP project was designed to align with quintuple aim.[12,13] During the 2022-2023 fiscal year, the eCE and 4 OHT partners were awarded funding from Ontario Health to develop and evaluate the ASAPP project. Over the course of the year, the project was developed and adopted in collaboration with the OHTs and with the support of clinician champions, and researchers. All stakeholders contributed feedback throughout the process to develop recommendations for establishing proactive PHM in local health systems.

ASAPP aimed to use a combination of Robotic Process Automation (RPA), predictive algorithms, and artificial intelligence (AI) models to identify patients at high risk of hospitalizations and ED visits to support care coordination. The project leveraged primary care EMR data and publicly available neighbourhood level SDOH information. The RPA involved the use of a software robot ("bot") named Cody that ran validated algorithms in the EMR to identify and code groups of patients with specific characteristics, thereby standardizing data for the diagnoses of patients and improving data quality. The RPA was also used to introduce neighbourhood level SDOH information into the EMR to help inform care and prompt the collection of individual level data for patients (which is currently unavailable and infeasible to collect for all patients). Based on the combined medical and social information, a predictive algorithm identified and generated a list of complex patients to be presented to the participating OHTs. As an extension of the ASAPP project and outside of the scope of this thesis, the project team also explored the development of artificial intelligence (AI) models to increase the accuracy of the Cody bot and the identification of complex patients after the end of the funding period. Although the aim was to support patient outcomes and prevent hospitalizations, this impact was not measurable in the scope and timeline of the project. The different ASAPP components are depicted in Figure 1 and described in Table 1. The project objectives were to:

1. Develop and enhance algorithms for identifying complex patients at high risk of ED visits and hospitalizations.

2. Improve standardization of data or data quality in the EMR by applying standardized approaches to coding data (Cody bot) to support patient segmentation and PHM (complex patient algorithm).
3. Provide lists of complex patients to the appropriate interprofessional team for the purpose of proactive outreach and support.
4. Measure ED and hospitalization rates and determine impact. (Out of scope)

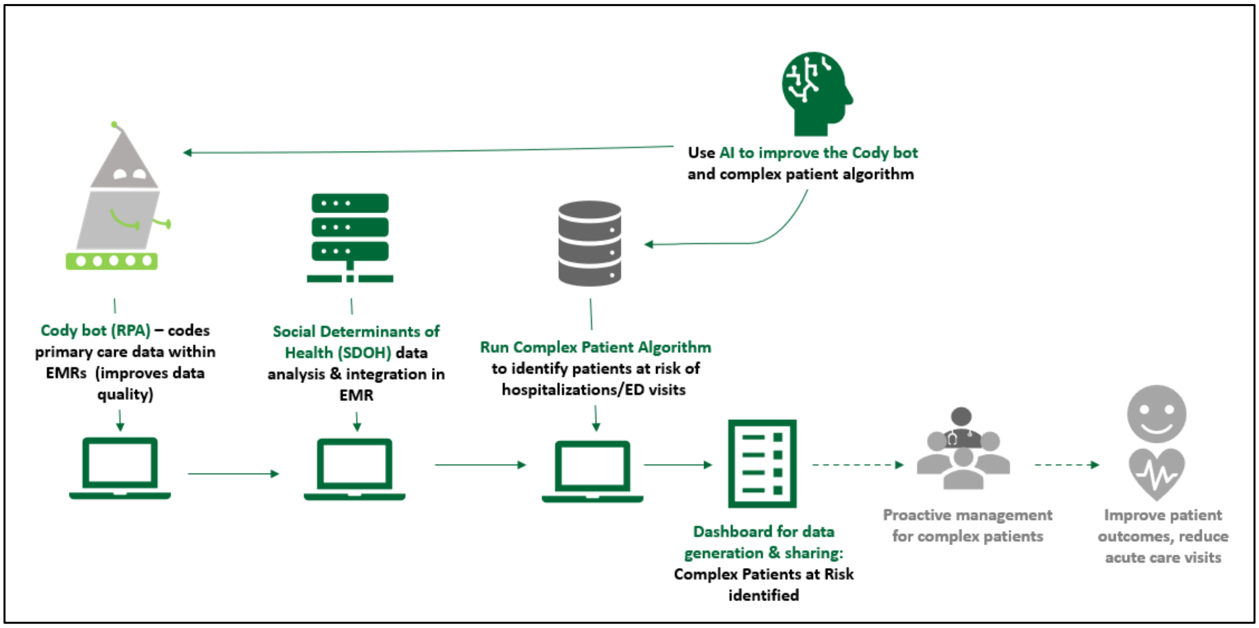

Figure 1. Overview of the ASAPP project components and its goals *(graphic use permitted by eCE)*

Rationale and Purpose

With the digitization of healthcare records, and the high costs and difficulty of managing the care of complex patients, there is a growing trend of digitally-driven PHM projects, like ASAPP, seeking to improve patient outcomes and reduce healthcare costs by improving resource allocation and care coordination.[7,8,27–30] However, the poor standardization of data and lack of available SDOH data have presented obstacles in developing successful digital PHM projects. Upon recognising these challenges, the eCE piloted the ASAPP project to test if a data driven and automation approach could contribute to improving data structure and quality in primary care EMRs. Given that the ASAPP project is unique in its multi-faceted approach, it provided valuable insights into the use of RPA, real-time data in primary care EMRs, and neighbourhood-level SDOH data for PHM purposes.

The purpose of this study was to evaluate the adoption, value, and effectiveness of the ASAPP project components (Cody bot, identification of complex patients, SDOH data use) and inform future digital PHM projects like ASAPP. To do this, four research questions were addressed:

1. Value: What was the perceived value of the ASAPP project?
2. Effectiveness: Did the ASAPP project achieve its intended objectives to improve data standardization and identify complex patients in primary care EMRs using RPA and predictive algorithms?
3. Adoption Facilitators and Barriers: What were the facilitators and barriers of adoption?
4. Future Recommendations: What recommendations can be made for future improvements for ASAPP or other PHM projects?

Table 1. Details on the ASAPP project components

Project Component	Description	Details/ How it functions
1 - Cody Bot (RPA)	The Cody bot implements codes for conditions/ diagnoses in patient EMR charts.	• The bot identifies and assesses non-coded instances of 18 conditions (referred to as "Cody conditions") and codes them if they meet a predefined criteria using rule-based algorithms (EMR searches looking for information across the patient's chart including the Problem List, Medications, History of Past Health, Personal section, Immunizations etc.). The predefined criteria ensure that the patient actually has a condition for the bot to code. • Information can be structured or unstructured depending on the practice. Algorithms to identify these patients take this into account and look for several variations in how information is captured within the EMR. (See *Appendix A* for more details on the functionality of the Cody bot.
2 - a) Predictive Algorithms: Medical Algorithm	An EMR search or query to identify complex patients at risk of hospitalization or ED visits based on clinical factors.	• Developed based on feedback from clinicians and previous experience finding complex patients who were high users of the health system using EMR data. • The general criteria: Patients 25 years or older AND on 5 or more medications AND has 4 or more of a group of 45 conditions. All the information in the criteria was based on the cumulative patient profile (CPP), lab results, or medications.
2 - b) Predictive Algorithms: Hospitalization Algorithm	An EMR search or query to identify patients with a history of hospitalization or ED visits and may be at higher risk for readmission.	• Developed based on clinician feedback and EMR feasibility. • The current criteria: 3 or more encounters with the ED/hospitalization visits, based on eNotifications in the EMR for ED admission, discharge, and inpatient admission & discharge. • The encounters with the ED or hospital were captured from the 'Notifications' or the automated, electronic notifications sent to clinicians within the EMR system from the hospital.
2 - c) Complex Patient Dashboard	An Excel dashboard was developed to provide the complexity data from ASAPP to the stakeholders (includes list of complex patients and their characteristics for complexity understanding).	• This included relevant data for the healthcare professionals to gain more insight into why the patients were selected based on the predictive algorithms (i.e. had information related to age, medications, the different chronic conditions, or the date and time of the eNotification/ hospital encounter. • See *Appendix B* to see what the dashboard generally looked like.
3 - SDOH complexity data analysis	Neighbourhood-level SDOH dimensions from the Marginalization Index were analyzed for the identified complex patients	• Neighbourhood-level SDOH data included the Ontario Marginalization (On-Marg) index data, which included dimensions:[31] material deprivation, residential instability, dependency and ethnic concentration otherwise labeled structural inequity/racism by our equity specialist. • Patient IDs were mapped to their associated neighbourhood level data (i.e. On-Marg) using a process called PCCF+ that maps postal code to an area code used in On-Marg. Patients that did not have postal code were excluded from this analysis. See *Appendix C* for a detailed diagram on this process. • An analysis was conducted on this data and presented to clinicians or healthcare professionals.
4 - SDOH Bot	The SDOH bot was used to bring the data on the neighbourhood-level SDOH for each patient into the EMR using the form.	• The bot followed the workflow outlined in *Appendix D*, to add the neighbourhood level SDOH form into the EMR (*Appendix D*).

Method

Study Design

A summative evaluation of the ASAPP project was conducted using a convergent mixed methods approach, combining quantitative and qualitative data. A summative evaluation involves assessing the development and adoption of project and the experience of participants and stakeholders after its completion.[32] It occurs at the end of a project and aims to support innovative projects, like ASAPP, to understand its impact, capture lessons learned, and gain data-driven recommendations for possible future iterations or similar projects.[32] Although components of ASAPP, such as the bot, continued to be used after the project completion, this was considered a summative evaluation as the PHM component of the project was discontinued. Table 2 provides the framework for the summative evaluation; a high-level overview of the activities of this evaluation starting from the development of the evaluation plan, evaluation questions and goals, understanding the stakeholders, collecting and analysing data, assessing the adoption of the project, and making recommendations.

Table 2. Summative evaluation framework developed for the ASAPP project.

<table>
<tr><th colspan="2">Phase</th><th>Key activities</th></tr>
<tr><td colspan="2">1 - Development of evaluation plan</td><td>• Develop evaluation goals and questions
• Identify data sources and key metrics
• Plan key evaluation deliverables and timelines</td></tr>
<tr><td rowspan="2">2 - Data collection and analysis:</td><td>Qualitative</td><td>• In consultation with project team, understand the roles of the stakeholders and who should be contacted to provide feedback on program activities
• Outline the timeline for data collection and analysis
• Develop interview script with appropriate interview questions to meet evaluation goals
• Consult with project team for review and feedback
• Analyze qualitative data</td></tr>
<tr><td>Quantitative</td><td>• Define metrics with project team
• Determine appropriate timing and procedure to conduct data extractions
• Produce metrics tables determining project reach and patients identified
• Analyze quantitative data</td></tr>
<tr><td colspan="2">3 – Interpretation & discussion</td><td>• Assess the adoption process, effectiveness, use, and value of ASAPP
• Develop lessons learns or recommendations for future improvements</td></tr>
</table>

A convergent parallel mixed methods approach was selected to comprehensively address the evaluation questions (Figure 2). In this approach, quantitative and qualitative data were collected and analysed separately and in parallel, to reduce the influence of the examination of one data type on the other. During the integration phase, the findings from the quantitative and qualitative analyses were related to each other to address the posed evaluation questions.[33] In this way, the results from both data types could inform and enrich one another to more thoroughly address the evaluation questions. Table 3 was created in Phase 1 during the development of the evaluation plan and outlines the qualitative and quantitative data that were collected, as well as how the data were related to the evaluation questions.

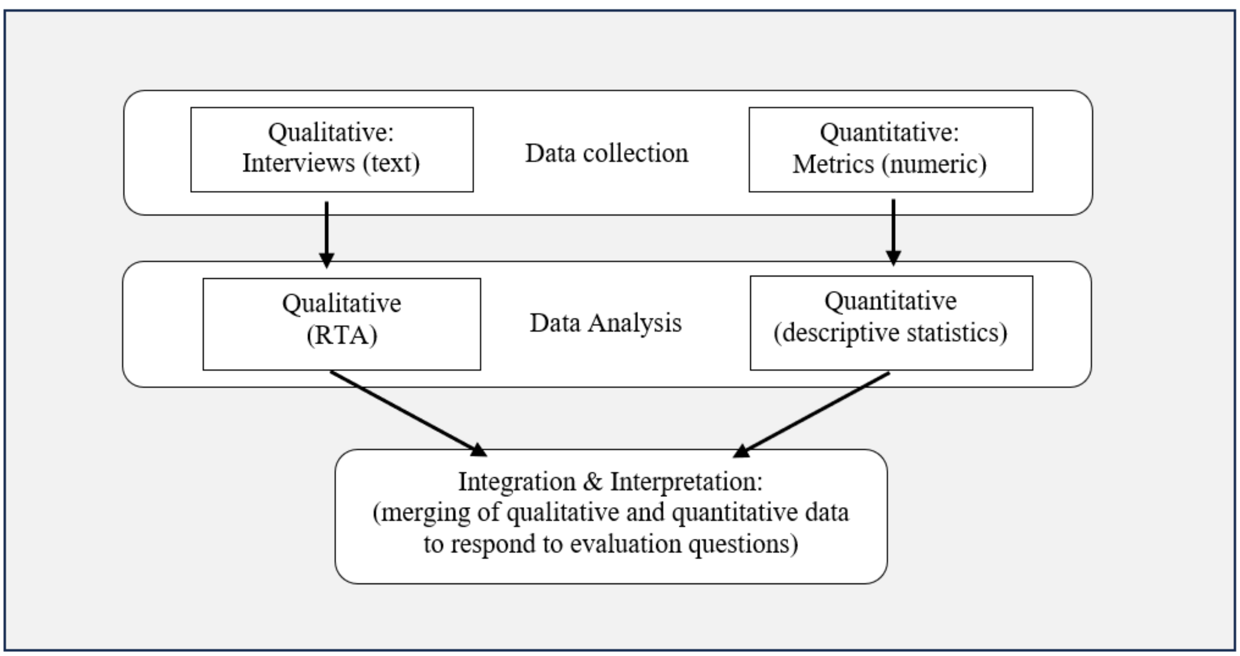

Figure 2. Convergent parallel mixed methods approach for the evaluation of the ASAPP project.
RTA = reflexive thematic analysis.

Table 3. Overview of how the qualitative and quantitative data, data source and analysis plan, were related to the evaluation questions

Topic/ Area	Evaluation Question/Objective	Indicator	Data Source	Analysis Plan
Value	What was the perceived value of the ASAPP project?	Quantitative: Reach/ project component metrics (i.e. number of conditions coded before and after Cody bot implementation, number of complex patients identified) Qualitative: Perceptions and experiences of stakeholders	Quantitative: Reports and excel files for data on the Cody bot and complex patient algorithms Qualitative: Interviews with external stakeholders	Quantitative: Descriptive statistics Qualitative: RTA
Effectiveness in Achieving Intended Objectives	Did the ASAPP project achieve its intended objectives to improve data standardization and identify complex patients in primary care EMRs using RPA and predictive algorithms?	Quantitative: Reach/ project component metrics (i.e. number of conditions coded before and after Cody bot implementation, number of complex patients identified) Qualitative: Perceptions and experiences of stakeholders	Quantitative: Reports and excel files for data on the Cody bot and complex patient algorithms Qualitative: Interviews with external stakeholders	Quantitative: Descriptive quantitative statistics Qualitative: RTA
Adoption Facilitators and Barriers	What were the facilitators and barriers of adoption?	Qualitative: Perceptions and experiences of stakeholders	Qualitative: Interviews with external stakeholders	Qualitative: RTA
Future Recommendations	What recommendations can be made for future improvements for ASAPP or other PHM projects?	Qualitative: Perceptions and experiences of stakeholders	Qualitative: Interviews with external stakeholders	Qualitative: RTA

RTA = reflexive thematic analysis

Context and Setting

The development, outreach, and adoption of the ASAPP project were all conducted by the eCE, located in Kitchener-Waterloo, Ontario, Canada. Much of the work of the organization is done remotely. As such, the data collection and evaluation for this project were conducted remotely.

Researcher Reflexivity and Positionality

In qualitative studies, reflexivity refers to the process by which a researcher recognizes and critically reflects upon the personal, social, and intellectual circumstances that may impact different stages of the research.[34] Positionality, on the other hand, refers to the ‘position’ of the researcher and how it impacts the research process and outcomes.[35] Both concepts are crucial as they acknowledge the researcher's potential influence on the collection, analysis, and interpretation of data. Given the potential implications of the findings of this evaluation for future iterations of the ASAPP project and similar digital PHM initiatives, an overview of the reflexivity and positionality of the researcher proved important.

Reflexivity

As a visible minority, belonging to an equity deserving group, first generation immigrant, student, and someone relatively new to the field of digital health and PHM, my lived experiences and my evolving expertise influenced how I approached this evaluation. My background as a minority and an immigrant affects how I perceive issues related to equity, accessibility, and inclusion within digital PHM initiatives, and has caused me to be acutely aware of inequities that may exist in the digital initiatives in our healthcare system. In addition, as someone new to the field of digital PHM and as a student, I have become attuned to challenges related to usability, access, and stakeholder engagement, which may have subtly impacted my focus during data analysis. Moreover, being a student, I also approached this evaluation with a learning mindset, relying heavily on literature, expert insights, and discussions with experienced colleagues to shape my data collection and analysis methodologies, and contextualize my interpretations. While this perspective helped me to critically question established practices, it also meant that I had to be intentionally aware of gaps in my understanding and my assumptions and how they could potentially impact my analysis.

Positionality

My roles as the report writer, an employee of the eCE, and a member of the ASAPP project team, necessitates a reflexive approach to acknowledge and address biases and assumptions I may have. Being heavily involved in the project's development and adoption, I was uniquely aware of the project's objectives, challenges, and expected outcomes, and had a stake in the project's success. My position in these roles, alongside the feedback I received from colleagues at the eCE could bias the data collection and analysis process and skew the interpretation of the data. To address these concerns, I developed a systematic approach to data collection and analysis and regularly discussed findings with the project team to challenge my interpretations. Lastly, I engaged in continuous self-reflection, documenting my thought processes, assumptions, and decisions to ensure that this evaluation, although impossible to remove bias, was transparent and mitigated bias where possible.

Quantitative Data Collection

A list of possible metrics to assess the ASAPP project was generated in consultation with the ASAPP project team to ensure all relevant and appropriate metrics would be captured. Metrics from the Cody bot runs, the predictive algorithms to identify complex patients, and the neighborhood-level SDOH data were produced at the end of the funding period for the project, as of March 31, 2023. The metrics for the Cody bot and the predictive algorithms were extracted by eCE staff in the form of reports and excel files, respectively. All metrics including the data related to the Cody bot, the algorithm, and the neighbourhood-level SDOH analysis were provided by the project team for this evaluation. All data were de-identified. Below is a summary of the key metrics that were collected:

1. Reach and project adoption: The number of OHTs, sites, and clinicians, that adopted the different components of ASAPP or the number of patients that were identified through ASAPP.
2. Coding: The number of conditions newly coded after adopting the Cody bot.
3. Complex patient identification: The number of complex patients identified using the medically complex and hospitalization algorithms.
4. SDOH integration: The number of patients living in high SDOH complexity areas and the number of complex patients that were living across the different SDOH complex levels.

Qualitative Data Collection

Participants

Purposeful sampling was used to identify key stakeholders of ASAPP, external to eCE, to participate in the interviews. This technique was chosen as it supports the collection of rich and diverse insights from participants that have valuable and relevant knowledge and experience to the study's objectives.[36] A list of stakeholders was developed in consultation with the project team to ensure the list was comprehensive and inclusive of the different people involved. Clinicians and OHT representatives that were directly involved with the project, either having implemented components of ASAPP or having been engaged in the project's development, who could provide informed feedback on the development, implementation, and use of the project were included.

Recruitment

An invitation to participate in semi-structured interviews was sent via email to the identified list of stakeholders, in compliance with the communication policy at the eCE. The email was edited and reviewed by Lisa Harman (LH), a knowledge translation specialist at eCE and Eric Tian (ET), the project manager for ASAPP at eCE, to ensure the objectives of the evaluation were clear. The email introduced the stakeholders to the purpose of the interviews and requested their availability to participate if they were interested (see Appendix E for a copy of the invitation). The invitations were adjusted slightly to each stakeholder based on their familiarity with the researcher, Zainib Nazir (ZN).

Interviews and Consent Process

Semi-structured interviews were conducted in April 2023. An interview script (Appendix F) was developed in collaboration with LH and reviewed by ET, Justin Wolting (JW), Manager of Product Development & Innovation at eCE and one of the leads for the ASAPP project, alongside other members of ASAPP project team at eCE. This ensured that questions aligned with ASAPP objectives, all components of ASAPP were addressed, and all topics of interest for feedback were captured accurately. The semi-structured interview approach was selected to ensure the questions stakeholders were asked were consistent and to allow the flexibility for them to speak on any additional things they wanted to. The interview questions and prompts related to understanding the stakeholders' experiences with the development and implementation of ASAPP, their perspectives on what went well and what did not, alongside their perspective on recommendations for the project moving forward.

Three semi-structured virtual interviews were conducted with four stakeholders over the Microsoft Teams platform. The interviews were each approximately 60 minutes in length, and all participants were given the opportunity to respond to each question. ZN and LH were present in all interviews; ZN led and asked questions based on the interview script, while LH shared their screen showing a PowerPoint slide deck containing the consent statement and the interview questions. Participants were reminded that there were no good or bad answers, and their identity would remain anonymous. Additionally, participants were asked if they were willing to participate in the interview that would be recorded (audio and video) and transcribed automatically from the Microsoft Teams platform. Only the ASAPP project team and evaluation team (ZN and LH) had access to the recording and transcripts. After consent was provided, the interviews were recorded. During the interviews, both ZN and LH took descriptive notes on their initial thoughts, observations, and the participants' responses.

Quantitative Data Analysis

The descriptive statistics related to the Cody bot were generated with support from Disha Desai (DD), a business analyst at eCE working closely with the Cody bot. Descriptive statistics were generated for each component of the project, including the Cody bot, the medically complex and hospitalization algorithms, and SDOH data, and related to one another to respond to the evaluation questions, as in Table 3.

Qualitative Data Analysis

Braun and Clarke's reflexive thematic analysis (RTA) approach was used to analyse and generate themes based on meaningful patterns in the interview data, while ensuring that the unique perspectives of the stakeholders were captured.[37–40] The reflexive approach was selected to support active reflection and consideration of the biases, assumptions, and background of the researchers and investigators.[38,40] In addition, RTA can support the active consideration of the nuances of the participants' experiences and the organizational contexts.[38,39]

Interview transcripts were imported into NVivo 14, software used to aid in conducting thematic analyses. Braun and Clarke's 6 step process for RTA was followed: 1) familiarization with the data, 2) generating initial codes, 3) generating themes, 4) review of potential themes, 5) defining and naming themes, 6) producing the report.[37,39,40] A non-linear and iterative process was followed, and earlier phases were revisited several times during the analysis.[39,40] After interviews were conducted, LH and ZN shared their initial impressions, supporting the familiarization of data (step 1). Due to resource constraints, ZN was the sole coder. In the process of generating initial codes (step 2), ZN referred to LH's notes from the interview and they helped inform the generation of codes and initial themes. ZN engaged in reflexive journalling through memos in NVivo during the analysis phase, reflecting on her reactions, and assumptions based on her roles, professional background, prior experience, and involvement in the ASAPP project team. A combination of an inductive and deductive approach was taken. During the initial coding and generation of themes stages, a largely inductive approach was used to allow the generation of themes to stay as close to the participants' responses as possible. In the review of potential themes (steps 3 and 4) and defining and naming the final themes (step 5), a greater degree of the deductive approach was intentionally taken to ensure the themes related to the evaluation questions and project objectives. The initial themes were shared with the project team members for feedback and any feedback provided was reflected on and used to refine and define the final themes.

Integration and Interpretation

Given the convergent mixed methods approach, the qualitative and quantitative data were integrated by "merging" both for analysis and comparison, after being analyzed separately.[41] For the interpretation and reporting, a narrative and weaving approach was taken, as described by Fetters et al., where the qualitative and quantitative findings were related and compared to each other, on a "concept-by-concept-basis", or, in the case of this study, on a basis of the posed evaluation questions, in a single report.[41]

Ethical Considerations

Ethics Approval

For this study, an ethics waiver was granted by the Hamilton integrated Research Ethics Board (HiREB), acknowledging the study's adherence to quality improvement work and that there was minimal risk for participants.

Data Storage and Confidentiality

All data were stored in a secure SharePoint site, that required multi-factor authentication and could only be accessed by the project and evaluation team. During qualitative data collection, stakeholders provided their verbal consent to participate in the recorded interviews. The quantitative and qualitative data were de-identified and the participating sites, OHTs, and participants were assigned an arbitrary number or letter to ensure their identities remained confidential.

Results

The quantitative results are presented first to introduce the extent to which the different components of the project were implemented across the involved OHTs. The qualitative results are presented second to showcase the perspectives and experiences of stakeholders with the ASAPP project, and the generated themes from the RTA.

Quantitative Results: Key Metrics

Overview of Project Adoption and Reach

Across the four OHTs that engaged in the project, the adoption of ASAPP project components varied. Due to various barriers to adoption (explored in qualitative analysis), one OHT (IV) did not adopt any project components. In OHT II, one site was engaged and adopted all four components of the project, while in OHT I, four sites were engaged—three adopted all components except for the neighbourhood-level SDOH form/bot, and one site only adopted the Cody bot and the predictive algorithms. In the remaining OHT (III) that participated, only one site was engaged and adopted a single component— the predictive algorithms. By the end of the funding period, six sites from three different OHTs with 26 clinicians and 34,710 patients adopted at least one component of ASAPP. Four sites had only one participating clinician and a maximum of 2,018 patients, and two sites had multiple clinicians— one of which had 13 participating clinicians providing care to 16,890 active patients (Table 4).

Table 4. An overview of the sites engaged in the ASAPP project across the three OHTs that adopted one or more project components

OHT	Site	No. of clinicians	No. of patients	Adopted ASAPP project components			
				Cody	Predictive algorithms	SDOH data analysis	SDOH form/bot
I	A	1	1,355	✓	✓	✓	
	B	1	2,018	✓	✓		
	C	9	12,748	✓	✓	✓	
	D	13	16,890	✓	✓	✓	
II	E	1	999	✓	✓	✓	✓
III	F	1	700		✓		
IV	N/A*	N/A	N/A	*No project components adopted*			
Average per clinician (Total No.)		---	1,335				
		(26)	(34,710)				

*OHT IV did not adopt any components of the project due to various barriers to adoption (see qualitative analysis for further insights)

Key Metrics Related to the Cody Bot

The Cody Bot can identify and code 18 medical conditions in EMRs (referred to as "Cody conditions"; see Appendix A and Table 6). Adopters could choose which of these 18 conditions they wanted the bot to identify and code. Of the six sites participating in ASAPP, four fully adopted the bot for all 18 Cody conditions, while one site (D) adopted it for only 8 (Table 5).

The bot scans patient charts to identify potential non-coded instances of the selected Cody conditions. As previously described in Table 1, the bot then assesses these instances and codes them if they meet predefined criteria using rule-based algorithms (see Appendix A for details on Cody's functionality). Over the course of the year, at the four sites that fully adopted Cody, the bot scanned and assessed 6,871 unique patient charts to identify and code Cody conditions across the rosters of the 12 participating PCPs (see Table 5). It is important to note that the bot can scan the same patient chart multiple times, as a single chart may include more than one of the selected 18 Cody conditions.

We compared the total number of Cody conditions coded in patient charts at baseline to the number newly added by the bot. The number of codes added by the Cody bot, and the increase in coded instances of the Cody conditions from baseline to post-bot run, varied significantly across clinicians and sites (see Table 5). For example, site A conditions saw the smallest change, with only a 1.3% increase after the bot run and had just one clinician at the site. In contrast, site B had the largest increase in number of coded conditions post-bot run, with an 863.8% rise. Nine clinicians at site B adopted the bot for all 18 conditions, the highest number among the sites. However, site B also started with the fewest coded conditions, even after adjusting for the number of patients at the site. On average, clinicians at sites that adopted the bot saw a 24.3% increase in the number of coded instances of the selected Cody conditions after the bot ran (see Table 5).

Table 5. A comparison of the number of instances of coded Cody conditions before and after running the Cody bot, for those sites that adopted the bot for all 18 conditions.

OHT	Site	No. of unique patient charts assessed*	No. of coded instances of the Cody conditions** *before* bot run	No. of coded instances of the Cody conditions** *newly added* by the Cody bot	Percent change of coded instances of Cody conditions ** *after* Cody bot run
I	A	503	860	11	↑ 1.3%
	B	762	69	596	↑ 863.8%
	C	5,043	6,873	1,474	↑ 21.4%
II	E	563	924	40	↑ 4.3%
Avg per clinician (total no.)		573 (6,871)	727 (8,726)	177 (2,121)	↑ 24.3%
I	D†	2,065	2,670	315	↑ 11.8%

**Cody conditions: The 18 conditions that the Cody bot has been trained to identify and code. These are outlined in Table 6 and Appendix A.
*Each chart could include more than one of the 18 Cody conditions and thus more than one code before and after coding.
†Site D adopted the bot for only 8 of the 18 conditions.

We also examined the bot's coding activity across the 18 Cody conditions for the four sites that fully adopted the bot. The bot coded the 18 medical conditions at varying rates, with differences in the number of instances of the Cody conditions it successfully coded out of those it identified and assessed (see Table 6). For example, the bot coded 88 instances of atrial fibrillation (Afib) out of the 108 instances that it identified and assessed, thus coding Afib at a rate of 81.5%, which was the highest rate among the 18 Cody conditions. Next, it coded coronary artery disease (CAD) at a rate of 75.8%, followed by cerebrovascular accident (CVA) at 61.3%. On the other hand, the bot coded obesity at the lowest rate (3.9%) among the Cody conditions, despite the bot identifying and assessing the most instances of this condition (3,589). Similarly, the bot identified and assessed 1,497 instances of hyperlipidemia, but the bot coded this condition at a low rate of 13.3%. There were no clear metrics to describe what caused the difference in coding across the conditions for Cody, and its coding rate was presented regardless of the condition prevalence.

Table 6. Details on the coding activity by the Cody bot across sites for the selected 18 Cody conditions.**

Condition	No. of newly coded instances by the bot per site across the selected 18 Cody conditions					No. of instances of the Cody conditions identified and assessed by the bot to potentially code*	No. of newly coded instances of the Cody conditions by the bot*	Percent of assessed instances successfully coded by the bot*δ (Coding rate)
	A	B	C	D†	E			
Atrial fibrillation	0	22	62	N/A	4	108	88	81.5%
CAD	2	44	71	73	1	153	116	75.8%
CVA	0	12	75	71	0	142	87	61.3%
Osteoporosis	0	56	112	N/A	0	359	168	46.8%
Asthma	0	70	85	N/A	0	376	155	41.2%
Hypothyroidism	0	34	164	N/A	0	523	198	37.9%
Depression	1	37	119	N/A	0	421	156	37.1%
COPD	0	11	24	55	24	182	59	32.4%
Diabetes	0	72	39	9	0	356	111	31.2%
Dementia	0	3	32	N/A	3	133	38	28.6%
Hypertension	1	153	74	36	1	831	228	27.4%
Osteoarthritis	5	6	135	N/A	4	838	145	17.3%
Prediabetes	0	32	60	5	2	582	94	16.2%
Hyperlipidemia	1	27	172	N/A	0	1,497	199	13.3%
CKD	0	10	88	39	1	1,018	99	9.7%
CHF	1	6	23	27	0	344	29	8.4%
Obesity	0	1	139	N/A	0	3,589	140	3.9%

CAD = coronary artery disease; CHF = congestive heart failure; CKD = chronic kidney disease; COPD = chronic obstructive pulmonary disease; CVA = Cerebrovascular accident; N/A = not applicable.
†Site D only adopted for the bot for 8 of the 18 conditions.
*Based on only those sites that adopted the Cody bot for all 18 conditions (Site D is not included in these calculations), to enable for a fair comparison across sites.
** Although Diabetes Type I and Type II are coded as separate conditions by the Cody bot, the data received did not distinguish between them. Instead, the counts were provided as a combined total for diabetes. As a result, Table 6 reports 17 distinct conditions rather than 18.
δPercent of assessed instances successfully coded by the bot is calculated as the total instances of the Cody conditions coded by the bot over the total number of instances of the Cody conditions assessed by the bot (i.e. this metric presents the % of newly coded instances per instance assessed for each the Cody conditions).

Key Metrics Related to Identification of Complex Patients from the Predictive Algorithms

The medically complex patient search was performed on all six sites that adopted the ASAPP project components, across three OHTs, for 34,710 patients, with an average of 64 (4.9%) medically complex patients per clinician across the six sites. The clinic with the highest percentage had 12.2% of patients identified as medically complex (see Table 7). Notably, the two sites (D and F) with the lowest percentage of medically complex patients identified (2.3% and 1.0% respectively) did not adopt the Cody bot fully or did not adopt it at all, respectively. The search for patients who met the hospitalization criteria was performed for 34,710 patients across all six sites. The average number of patients to meet the hospitalization criteria per clinician was five and totalled 132 patients. The percentage of patients who met the hospitalization criteria per site ranged from under 0.01% to 3.7%. Across the six sites and 26 physicians, 1,790 unique complex patients were identified (average: 5.2% per clinician; i.e., they met either the hospitalization criteria or the medically complex criteria). Site E had the smallest percent of unique complex patients identified (3.0%), while site E had the most at 13.5%. In addition, an average of 0.1% of patients that met the medically complex criteria also met the hospitalization criteria. Site B had the greatest percent of medically complex patients that had been hospitalized (17.0%), while the clinic with the lowest percentage of medically complex patients that also met the hospitalization criteria had <0.01% of patients identified.

Table 7. Complex patients identified for each site and the percentage of patients that met the hospitalization criteria who were also medically complex.

OHT	Site	Percent of medically complex patients§ (total no.)	Percent of hospitalized patients** (total no.)	Percent of complex patients identified *(patients that were hospitalized OR medically complex)* (total no.)	Percent of medically complex patients who also met the hospitalization criteria (total no.)
I	A	8.6% (117)	2.0% (27)	10.2% (138)	5.1% (6)
	B	2.6% (53)	2.0% (40)	4.2% (84)	17.0% (9)
	C	7.6% (974)	<0.01% (47)	8.0% (1,013)	0.8% (8)
	D†	2.3% (389)	0.9% (14)	2.4% (399)	<0.01% (4)
II	E	12.2% (122)	3.7% (37)	13.5% (135)	11.5% (14)
III	F	1.0% (7)	2.0% (14)	3.0% (21)	-*
Avg percent per clinician		4.9%	0.4%	5.2%	0.1%
Avg no. per clinician (total no.)		64 (1,662)	5 (132)	69 (1,790)	2 (41)

†Site D only adopted the bot for 8 of the 18 conditions.
*Site F data for medically complex patients who were hospitalized data was unavailable.
§Medical complexity criteria: patients over the age of 55 years, taking over 5 medications, and have over 4 medical conditions from a list of 45 medical conditions.

**Hospitalization criteria: patients with over 3 hospital encounters as documented in primary care EMRs through eNotifications for emergency discharge or inpatient discharge or admission.

Key Metrics from Neighbourhood-Level SDOH Data Integration

Social complexity analysis was performed for four out of the six participating sites, across two OHTs. Of the three SDOH complexity levels, 48.4% of patients lived in low SDOH complex areas (n= 20,036). Inversely, the smallest proportion of patients across all sites lived in high SDOH complex areas; 220 patients total (0.5%; see Table 8). Generally, sites had a trend of decreasing patient counts from low, to medium, to high SDOH complexity of the areas; site E had the greatest percentage of patients identified to be living in medium SDOH complexity areas (58.4%). Site D had the largest total number of patients (16,212) and the highest concentration in low SDOH complexity areas, while Site E, with the smallest patient count (978), showed a relatively higher distribution across medium and high SDOH complexity areas.

Moreover, across all four participating sites, medically complex patients tended to live in areas with low or medium SDOH complexity, with 9.2% (795) of medically complex patients living in low SDOH complex areas and 14.1% (801) in medium SDOH complex areas (Table 8). Only 1.1% of medically complex patients lived in high SDOH complex areas across all four sites, and on average, 0.3%. Similarly, more patients meeting the hospitalization criteria lived in low and medium SDOH complex areas as compared to high SDOH complex areas, with 2.8% living in medium SDOH complex areas, 1.7% in low, and only 0.4% in high. The number of medically complex patients who also met the hospitalization criteria was very small across any SDOH area complex level. Of note was site E which had the highest percentage (0.2%) and amount (2) of medically complex patients that met the hospitalization criteria and lived in high SDOH complex areas. No other site had any patients that met these same criteria.

Table 8. The number and percentage of patients living in areas with SDOH complexity levels (low, medium, and high).

Site	Total no. of patients*	Low SDOH Complex Areas	Medium SDOH Complex Areas	High SDOH Complex Areas
		n (%)		
A	11640	922 (7.9%)	345 (3.0%)	33 (0.3%)
C	12579	6,961 (55.3%)	5,462 (43.4%)	74 (0.4%)
D	16212	11,789 (72.7%)	4,345 (26.8%)	85 (0.5%)
E	978	364 (37.2%)	571 (58.4%)	28 (2.9%)
Total	41,409	20,036 (48.4%)	10,723 (25.9%)	220 (0.5%)
Average	10352.3	5,009.0 (43.3%)	2,680.8 (32.9%)	55.0 (1.1%)

*Only some patients per site had a valid postal code or could be processed through PCCF+ to generate their area's associated SDOH data from ON-Marg Index; thus, there was a new number of patients that were involved in generating SDOH data

Table 9. Patients meeting medically complex and hospitalization criteria living in areas with SDOH complexity levels (low, medium, and high).

	Medically complex patients living in areas with SDOH complexity of:			Patients meeting hospitalization criteria living in areas with SDOH complexity of:			Medically complex patients meeting hospitalization criteria living in areas with SDOH complexity of:		
	n (%)								
Site	Low	Med	High	Low	Med	High	Low	Med	High
A	67 (0.6)	42 (0.4)	4 (0.03)	19 (0.2)	8 (0.1)	0 (0)	3 (0.03)	3 (0.03)	0 (0)
C	404 (3.2)	542 (4.3)	5 (0.04)	22 (0.2)	18 (0.1)	2 (0.02)	4 (0.03)	4 (0.03)	0 (0)
D	288 (1.8)	133 (0.8)	2 (0.01)	8 (0.1)	5 (0.03)	1 (0.01)	2 (0.01)	2 (0.01)	0 (0)
E	36 (3.7)	84 (8.6)	10 (1.0)	13 (1.3)	25 (2.6)	4 (0.4)	4 (0.4)	11 (1.1)	2 (0.2)
Total	795 (9.2)	801 (14.1)	21 (1.1)	62 (1.7)	56 (2.8)	7 (0.4)	13 (0.5)	20 (1.2)	2 (0.2)
Avg	198.8 (2.3)	200.3 (3.5)	5.3 (0.3)	15.5 (0.4)	14 (0.7)	1.8 (0.1)	3.3 (0.1)	5 (0.3)	0.5 (0.1)

Qualitative Results: Thematic Analysis of Key External Stakeholder Interviews

Participant Involvement

Three semi-structured, virtual interviews were conducted with 4 stakeholders, including three clinicians and one OHT representative (one interview was with 2 stakeholders together). Participants were from the three OHTs involved in the ASAPP project that adopted at least one component of the project to some degree. Stakeholders from the fourth OHT that participated in the project, but did not adopt any component of the project, declined participation (see Quantitative Results Table 4 for details on adoption per engaged OHT). Each participant was involved with the ASAPP project in different capacities; all supporting the development, adoption, and/or testing of the project, and providing feedback based on their areas of expertise. Detailed demographic information for the participants was not collected. Table 10 provides an overview of the participants, including their primary role, the geographical area of their OHT, and the degree of their involvement with the ASAPP project.

Table 10. Characteristics of participants and involvement with the ASAPP project

Characteristic	Participants' details (at time of interview) (N=4)
Primary role	1 OHT representative (title not mentioned to preserve anonymity) 3 clinicians (primary care physicians)
OHT** geographical area	Urban=3 Rural=1
Time involved with ASAPP*	1 year = 2 <6 months=2
Extent of implementation of ASAPP project components	Adopted at least 1 ASAPP component within their OHT = 3 Non-adopter = 1
Associated Sites (as presented in Quantitative Results)	Participant 1: Site E Participant 2: Site A Participant 3: Site F Participant 4: N/A (non-adopter, stakeholder)

*ASAPP: Automated assisting priority populations (project)
**OHT: Ontario Health Team

The three clinician participants held multiple roles within their OHT outside of being primary care physicians; they were all clinical digital health leads in their OHTs, one was also a clinical lead for privacy and security, two were on the primary care (advisory) council for their OHTs, and one mentioned they were on various planning boards within their OHT. These clinical participants also acted as clinician champions of the project, providing feedback and input from a primary care perspective, choosing to become involved because of their interest in data quality and digital health. No specific details about their interests were requested.

To respect their privacy and ensure confidentiality, as per their request, the specific roles and titles of the participants will not be disclosed in any section of this paper, including when sharing quotes. The participants in the interviews were labelled 1-4 arbitrarily when presenting quotations related to the generated themes.

Overview of Themes

After analysis, four overarching themes were generated from the interview data including: ***perceived value and unrealized potential in PHM, effectiveness and limitations of technology and ASAPP, barriers and facilitators of digital health tool adoption, and recommendations***. Each of these themes shed light on the evaluation questions focused on the value, effectiveness, adoption, and future recommendations for ASAPP (Table 11). The themes relate to one another and are connected; perceived value and unrealized potential is influenced by effectiveness and limitations of technology and the barriers and facilitators of adoption – and recommendations emerge from all 3 of these themes (Figure 3).

Table 11. Overarching themes and sub-themes and relevant evaluation focus for each

Relevant Evaluation Focus	Overarching & Subthemes
Value	***Theme 1: Perceived Value and Unrealized Potential in PHM*** 1.1 Resource Allocation 1.2 Chronic disease management 1.3 Data quality 1.4 SDOH integration in primary care 1.5 Unrealized potential
Effectiveness in Achieving Intended Objectives	***Theme 2: Effectiveness and Limitations of Technology and Project*** 2.1 Limitations of defining and capturing complexity based on EMR data 2.2 Challenges in capturing patient complexity based on tool functionality 2.3 Systemic design concerns limiting usefulness 2.4 Usability and customization of complexity data
Adoption Facilitators and Barriers	***Theme 3: Barriers and Facilitators of Digital Health Tool Adoption*** 3.1 Communication and collaboration as barriers or facilitators 3.2 Technological challenges and iterative troubleshooting as inevitable barriers 3.3 User perceptions and trust in technology as facilitators or barriers 3.4 Privacy & security concerns, and related procedural delays as barriers 3.5 Competing priorities and resource constraints at the clinician and OHT-level
Future Recommendations	***Theme 4: Recommendations*** 4.1 Communication, Collaboration, and Engagement 4.2 Privacy and security compliance assurances. 4.3 Resources and supports for adoption 4.4 Iterative, adaptive development approach and technology enhancements 4.5 Evaluation and lessons learned 4.6 Demonstrating maturity and value for scaling

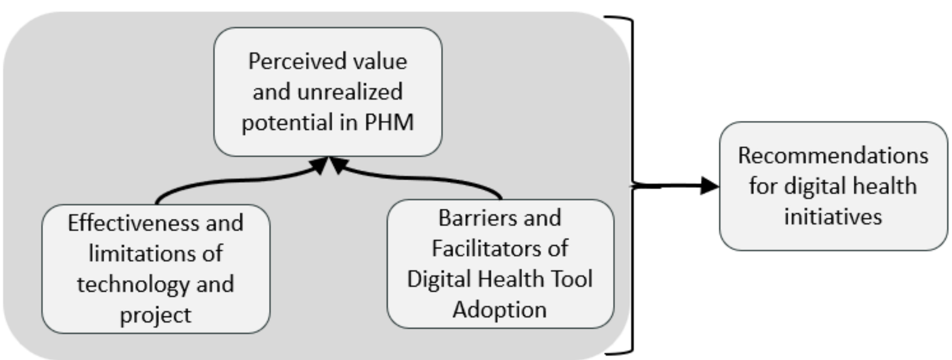

Figure 3. The relationship between the four overarching themes

Theme 1: Perceived Value and Unrealized Potential in Population Health Management

All participants believed that ASAPP could provide value in PHM by supporting **resource allocation, chronic disease management, data quality support, and the integration of SDOH**

data in primary care. However, they also highlighted ASAPP's **unrealized potential**. They commented that by providing complex patient data (i.e. the dashboard) that healthcare professionals need, ASAPP could help them better understand and meet the needs of their populations. The key insights in this theme are summarized in the Table 12.

> *"From a population health perspective, you're right, I totally see the value, [… in having] an aggregate view across the OHT of our population. In terms of the conditions and more importantly, the gaps, right, like where are we worse? Where do we have worse outcomes? Where do we not have any data at all...."* (Participant 4)

Table 12. A summary of key insights on Theme 1.

Perceived Value and Unrealized Potential in PHM (Theme 1) Subthemes	**Summary of Key Insights**
1.1. Resource allocation	• ASAPP's identification of patients that are high-resource users informs better resource allocation to support PHM and thus may: o improve care coordination, ensuring patients in need of care are not missed and directed to the resources they need o support strategic distribution of resources based on complexity ensuring practices with higher complexity patients are adequately supported o support proactive and preventative care of patients, aiming to reduce emergency interventions or hospital admissions o reduce strain/burden on healthcare system and staff, reduce wait times
1.2. Chronic disease management	• Identification of complex patients may support primary care clinicians in chronic disease management and providing preventative care to their patients
1.3 Data quality support	• Many primary care EMRs have poor data quality, particularly for documentation of diagnosis, making it challenging to accurately process patient information • Cody bot helped to improve data quality involving diagnostic codes in the EMR • This improved data quality could: o support patient identification and segmentation capabilities at a clinician and system level, to inform PHM o enable better data sharing capabilities across different systems, supporting OHTs with better care coordination and more PHM initiatives
1.4 Integration of SDOH data in primary care	• Although ASAPP SDOH data was at a neighbourhood level and could not be attributed to an individual patient, it could be valuable in supporting PHM • SDOH are vital in understanding the complexity of patients' needs and support planning and delivery of patient care • SDOH data could support clinicians when referring patients to healthcare services • Minimal individual-level SDOH data available in primary care EMRs to support clinical decision making— ASAPP's SDOH data offered a framework for healthcare professionals to determine which patients to prioritize for individual SDOH data collection, which takes a lot of effort
1.5. Unrealized Potential	• ASAPP had potential to support better healthcare outcomes in the long-run and only at the system-level, but it required further development and improvement to fully realize its potential

	• ASAPP's value relied on data being actionable, but this required more resources (i.e. specialized staff and time)– resource constraints or no practical strategies prevent data from being actionable (Theme 3) • Barriers to adoption (Theme 3), ASAPP's tool limitations, lack of immediacy and certainty in the benefits, and effort it would require from participants, led to hesitation in fully investing in the project and uncertainty in potential benefits being realized

Subtheme 1.1. Resource Allocation. Participants agreed that the data from ASAPP could inform better allocation of resources to support PHM, leading to improved care coordination and patient outcomes. They underscored that the data identified complex patients and could help ensure patients are not underserved within the healthcare system and are directed to the resources they need.

> *"By identifying patients that could be connected with resources that they're not already connected with […and] with the resources that would help them, their care is going to improve in a number of ways. One is they'll be seen, they'll be heard and they won't be falling through cracks. And two is their health will improve because we'll be able to provide them with the resources to get them there."* (Participant 2)

They noted that ASAPP also presented the opportunity to strategically divide resources across their populations based on patient complexity and ensure that practices with higher complexity patients received the necessary support.

> *"…if we start to distribute [name of health services in their OHT] among practices, then knowing the complexity level and the different practices would help. […] The real important part would be patient complexity – [to] divide up your resources based on patient complexity. So, I think that is really helpful."* (Participant 1)

Participants noted that ASAPP identified patients that were complex or high-resource users within the health care system, and this could support clinicians in providing preventative care to these patients, aiming to reduce complications and minimize hospitalization or high-system usage. The data thus supported a resource allocation strategy that was a shared goal across all participants' OHTs.

> *"We're, [in the OHT], trying to identify people that are using up more of the resources [so] that we could maybe help prevent things rather than wait till they need to use those resources."* (Participant 1)

There was also an understanding among participants that enhanced allocation of resources could also result in reducing the burden on the healthcare system and staff, and reduced wait times.

> *"The impact is, and I should say that will take to a certain extent, will take a lot of the burden off physicians and clinics and hospitals and the system in general. By caring for patients in this way more effectively, we're preventing complications, which means more work for the docs, more work for the clinics, more appearances at the emergency room and more admissions. We're preventing that by using this information that way."* (Participant 2)

Subtheme 1.2. Chronic disease management. Participants described ASAPP's value in supporting chronic disease management (CDM) within PHM, emphasizing its contribution in preventative care. They mentioned that many of their patients had ongoing chronic conditions, requiring proactive and long-term management, and ASAPP could support primary care clinicians to provide consistent care for these patients.

> *"I have a huge chronic care practice which I think is actually much more important in the big picture that I manage– like, urgent care is important, but the chronic disease management which this project, I think, focuses on, or part of it does, is hugely important."* (Participant 1)

> *"[ASAPP] is more proactive, preventive chronic disease management. How can I do better–which is very valuable."* (Participant 2)

Subtheme 1.3. Data quality. The need to tackle issues that ASAPP aimed to address, including poor data quality in EMRs to support PHM, was highlighted by participants. They acknowledged that the lack of structure and standardization of data in EMRs, particularly the documentation of diagnoses, could make it challenging to accurately process patient information. However, they also noted that ASAPP's efforts to clean this data at a clinic level could be beneficial at a system level; addressing data quality issues could enable the use of accurate data for PHM. Participants expressed the desire to support improved data quality.

> *"Some physicians, have just listed all the diagnoses for a patient on one line […] that's probably the worst thing I've seen today. But basically, it can be pretty poor [data quality], unfortunately. […] I think just how [the project's] cleaning up data – I think on the organizational level [or] on the systems level, that's important and has value. [...] I would like us to have better quality of data across all EMRs ultimately."* (Participant 1)

Participants that implemented the Cody bot stated that the bot helped to improve data quality involving diagnostic codes in the EMR. Moreover, they discussed that the bot allowed them to better identify a subset of patients with a particular set of diagnoses, which has several benefits, including informing PHM through improved patient segmentation capabilities at a clinician and system level. In addition, participants shared that the Cody bot supports quality improvement as they can be more confident that they have not missed a diagnosis/most have been appropriately coded and added to the diagnosis list in the EMR.

> *"So as a clinician, the Cody bot has allowed me to better identify a subset of patients with a particular set of diagnoses. […] We can then associate that with the care that's being provided for patients with a particular diagnosis and identify patients who may need attention. […] It all hinges on the bot [making] it more accurate when we try to list a set of patients with a particular disease or set of diseases."* (Participant 2)

> *"…if you can search [a medical condition on the EMR] with the ICD code and you can be confident that most of the patients have been appropriately added [to the list] – I think it changes everything because, then, if you do wanna do work that focuses on a diagnosis, then you actually can find a better database to start from. So, I really do think that work is really important. It's really kind of foundation work."* (Participant 1)

One participant noted that improved data quality through Cody enabled better data sharing capabilities across different systems. This was important to their OHT as it allowed them to export EMR data to other systems to support better care coordination and more PHM initiatives.

> *"I'm working with the OHT […] trying to encourage all the offices to use the Cody bot for [ASAPP] and for other projects. So, we're using Cody– we need the diagnostic codes in order to export data to other systems as well like the [database in use by OHT], which is going to be really important for [the] OHT."* (Participant 2)

Subtheme 1.4. SDOH integration in primary care. The ASAPP project included a component that provided clinicians with neighbourhood-level SDOH data about their patients. While participants emphasized that the ASAPP SDOH data was geographical and could not be attributed to, or assumed to be specific to, individual patients, they also expressed that it could be valuable in supporting population level resource allocation.

> *"The SDOH stuff - it's neighbourhood information that's limited to geographic area rather than [being] patient-specific. So, in terms of adoption, with regard to putting notes like that in the charts, that's limited… But I think at a population level information like that is very useful. So as far as adoption at a population level, excellent. I think that's where we're going to see most of the strength in how this actually helps us in our clinic, in a practice, [and] in our OHT."* (Participant 3)

> *"[SDOH data is] not presented by ASAPP on an individual basis. […] So, when we try to use that information at a patient granular level, we have to really limit what we do with that information, understanding that it's not necessarily about that patient in particular. [… But it] does really help inform us specifically about what types of resources we're really going to benefit from in our clinic, or, expanding that to the OHT, […] depending on the social determinant of health."* (Participant 2)

All participants highlighted that SDOH are vital in understanding the complexity of patients' needs when planning and delivering patient care. The one participant that implemented the neighbourhood-level SDOH form into their EMR shared that they hoped to use the form as a clinician to support them when referring patients to healthcare services.

> *"[SDOH data] factors into complexity when we're trying to provide care to patients, part of the decision process should be what's the care that they need, the way they need it. And so it's really helpful to understand their social determinants of health because that does play a role in those decisions."* (Participant 2)

> *"I think people [in my practice] are very mixed in [terms of SDOH-complexity] neighborhoods here, but at least [the data is] there and hopefully it helps me direct people towards seeking like private resources in the community versus me working harder to find them a resource that's covered by OHIP or another social support."* (Participant 1)

Participants noted that there is currently minimal individual-level SDOH information available in primary care EMRs to support clinical decision-making and resource allocation for patients. They suggested that ASAPP could offer a framework for healthcare professionals to determine which patients to start with for the collection of individual SDOH data, which is something that they are hoping to do, but it may be overwhelming and a lot of effort without a starting point.

> *"Right now, [individual SDOH info in EMRs] is almost zero. […Collecting individual SDOH data is] a lot to do for a lot of patients, and because we're basically starting from scratch. So, I see an advantage in the ASAPP SDOH data to provide us with a way to determine who would probably benefit most from [individual SDOH collection] sooner rather than later. […] So yes, it'll help us identify where to start and that's really important."* (Participant 2)

Subtheme 1.5. Unrealized Potential. Despite participants indicating their understanding of ASAPP's overarching goals and potential to support better health outcomes in the long run, they also acknowledged that it had areas of improvements. Some participants expressed cautious optimism and willingness to invest in the project for the benefits it could provide to patient care in the long run.

> *"[ASAPP] does provide us with information that can help us to better care for our patient population and I think that's the success factor. […] I think again that it could be better, but it was good enough and in the sense that there's enough value there that it's worthwhile going through the process to get what you get at the other end."* (Participant 2)

Participants noted that although ASAPP provided useful data, whether the value would be realized or not was contingent upon the data being actioned on, which required additional resources such as time and specialised staff. This reflected a broader issue in healthcare where valuable data may be accessible, such as with ASAPP, but may be unable to be actioned on due to resource constraints or a lack of practical strategies to implement the insights into actionable outcomes (Theme 3).

> *"But I do think it can definitely be applied. So, I think [the dashboard with data on medical complexity and SDOH is] very helpful. It's just, there is always [the fact*

> *that] you can get data but then someone needs to do the work to implement outcomes from the data."* (Participant 1)

Moreover, some participants were less convinced that ASAPP's potential benefits would be realized due to barriers to adoption, including the effort and resources it required (Theme 3) and the limitations of the tools (Theme 2). Participants suggested the potential improvements from ASAPP would likely not be seen in the short-term and they would be seen at the system-level. For some participants, the lack of immediacy and certainty in the benefits, along with the effort it would require from them, led to hesitation in fully investing in the project. The ideal conditions for the project's success had yet to be achieved with the barriers to adoption, leaving much of its potential impact hypothetical and seen as a future possibility rather than a current reality at this stage. Moreover, two participants were less convinced that it would be feasible for this project to realize its value given that it required troubleshooting and effort from clinicians.

> *"It's good for population health management. But it would require a lot of work from me. Would it [realize the value]? It would be hard for me to see just how valuable, if at all, it will end up being. And so, to sink a lot of my time and energy into it, umm, for like a vague promise of better population health, which I'm not convinced it would actually cause – maybe it would. It was a hard thing for me to justify when there's [other things, as a clinician,] I could do for my own clinic to improve the care of my patients right now."* (Participant 3)

> *"Like, I could see in the longer run, this kind of information and the ability to run this especially in multiple EMRs with no input or no need to, you know, do any troubleshooting, I could see this being hugely valuable especially […] looking across our whole population. But the reality of it is that I don't think it's. Something that can be done like that, but the concept of that would be amazing."* (Participant 4)

Finally, participants clearly stated that although patient complexity data from ASAPP could be valuable and they could use it to support PHM, they were unable to get there. They underscored a sense of both hope and frustration, as they recognized the "spirit of the project" alongside the numerous barriers that prevented the adoption of ASAPP in a way that could yield its intended impact.

> *"…If we had a real solid database of patients for a good subset of our population where we can discern reliable information about complexity both medically, socially, I think we would use that. And I think we would try to better the health of our population and I think that's what the spirit of this project came from, but I think… there were several different layers of reasons why we couldn't get there. And maybe we can get there. I don't think we can't, but I don't think we're not there yet."* (Participant 3)

Theme 2: Effectiveness and limitations of project and technology

Participants shared insights on the effectiveness and the limitations of the project in achieving its objectives of identifying complex patients and supporting PHM. They commented on the **limitations of defining and capturing complexity based on EMR data, challenges in capturing and assessing patient complexity based on tool functionality, systemic design concerns limiting usefulness, and usability of complexity data.** The key insights in this theme are summarized in the Table 13.

Subtheme 2.1. Limitations of defining and capturing complexity based on EMR data. The interviews revealed that the ability of ASAPP and other digital health initiatives to identify complex patients was limited by the availability and nature of data in primary care EMRs. They commented that although the ASAPP algorithms were sufficient in identifying complex patients, they were ultimately constrained by the low data quality and lack of completeness in the underlying EMR data the algorithms rely on.

> *"So the predictive algorithm, in my experience, you know, it's pretty good and it's good enough. It's certainly, you know, [the algorithms] are based on data that's not perfect, that's incomplete."* (Participant 2)

Table 13. A summary of key insights on Theme 2.

Effectiveness and Limitations (Theme 2) Subthemes	**Summary of Key Insights**
Subtheme 2.1. Limitations of defining and capturing complexity based on EMR data	• Technology and algorithms to identify complex patients depend on limited, non-coded, and incomplete data in EMR • Key contributors to complexity are psychosocial factors that may only be observed and not be documented in the EMR (with ethical concerns of documenting these) • Primary care EMRs miss unattached patients not connected to PCPs, who may be the most vulnerable or most complex • Limited data availability and capabilities to capture hospitalizations accurately in primary care EMRs
Subtheme 2.2. Challenges in capturing patient complexity based on tool functionality	• Algorithms only leverage a little data in the EMR, missing out on crucial data on complexity • Medically complex algorithm only identifies a limited range of conditions and largely relies on data on conditions that are coded in the EMR to be able to identify complex patients • Medically complex algorithm is constrained by the limitations of the Cody bot – bot codes only 18 of the target 50 conditions and the bot's criteria can be improved for accuracy • Algorithms do not account for patient-specific nuances: variation in severity of medical conditions, reasons for why a patient went to the hospital, and SDOH-complexity level variations across different regions and populations • There were variations across different projects on how SDOH data was handled and measured leading to inconsistencies in the definition of complexity • There were unexpected patterns in the data, related to patient hospitalizations and the SDOH complexity scores of areas where they lived causing uncertainty on data reliability
Subtheme 2.3. Systemic design concerns limiting usefulness	• The design of Cody may not be effective – solutions not integrated into systems/ EMRs seem to be reactive and inefficient ways to address data quality
Subtheme 2.4. Usability and customization of complexity data	• Dashboard was a useful tool with all important information presented in one centralized place, for clinicians to support PHM • Dashboard was flexible, easy to use, and a good tool for data visualization and manipulation to meet the needs of the users • The customizability of the dashboard enabled users to better identify priority complex patients in their OHT

Participants pointed out that defining complexity included psychosocial factors that may not have been easily standardized through coding, including family dynamics and patient behaviours. They highlighted that some factors crucial to understanding patient overall health and complexity may even go beyond what is typically documented or available in the EMR and thus may only be perceived in person by clinicians. Moreover, one participant noted that there may be ethical and practical challenges in documenting some psychosocial factors contributing to patient complexity, such as patient irritability or trauma history, as they may be considered biased or inappropriate to document, further limiting the scope of data that ASAPP had access to in defining and identifying patient complexity.

> *"Complexity, in our world, is based on so many psychosocial factors and family dynamics, probably health literacy, expectations, demands, and difficulty motivating lifestyle changes, […] patient irritability [and] patient history of trauma […]. Our experience of complexity is so much deeper than what the data can find because we can't – you'll never be able to— code that. Like, I can't code that into my EMR because one, it would probably be considered bias. And two, you just can't. So, basically what is complex in primary care? And maybe in the system as a whole, is so different than what we can code, and that's a huge, big discussion."* (Participant 1)

Finally, participants underscored that the complex patients ASAPP aims to identify from the EMR would not capture those people that are not connected to or are unattached to primary care as ASAPP relies on data from primary care clinicians' EMRs**.** They further commented that these are the patients that could however be the most vulnerable and that they were a priority for them.

> *"We [don't cover…] people who are not connected to primary care. […]. Exactly, [the most vulnerable]. So I think that the one part that we miss here is people we don't have data on because they don't see primary care providers and therefore are kind of lost in our system at this point and I would say that we're more and more focusing a lot on that population."* (Participant 4)

In addition, it was added that hospitalization data is limited or incomplete in primary care EMRs and so some hospitalizations that patients may have had may be missed or overstated, thereby limiting the accuracy of the hospitalization algorithm used by ASAPP algorithms to identify complex patients (equal or more than 3 hospital encounters over the last 12 months). Participants stated that although the hospitalization algorithm was sufficient, it was challenging using primary care EMR data to distinguish between one hospital interaction versus multiple interactions triggered by the same acute event. The inability to accurately distinguish between different hospital encounters may lead to misrepresentation of patient complexity.

> *"Based on the limitations with the data that's in the EMRS, it's hard to distinguish the difference between one person showing up in the emergency room and being admitted to the hospital and then discharged. That actually triggers 3 events, the emerge, the admission, and the discharge. […] So, it's not perfect, but it's pretty good to say if they've had more than a certain number of interactions with the hospital that they're likely to be more complex."* (Participant 2)

> *"The hospitalization part— it's not actually hospitalization, it's ER visits [too] and so it's just looking at something different and ideally you would eventually have data that specifically looks […] not at ER visits at all, but just looks at hospitalizations."* (Participant 1)

Subtheme 2.2. Challenges in capturing patient complexity based on tool functionality. Participants noted several limitations in the capability and functionality of the ASAPP medical complexity and hospital algorithms, Cody bot, and SDOH data outputs, to identify, and support the assessment of complexity.

Although the participants acknowledged that the algorithms were "pretty good" (Participant 2), they highlighted that the algorithms may not present a comprehensive view of patient complexity. Moreover, the medical complexity algorithm only leveraged information in the cumulative patient profile (CPP), lab results, or medications, and did not pull information from other places in the chart, thereby possibly missing out on crucial data that could provide more insight into the complexity of a patient. Similarly, another limitation participants mentioned was that the algorithm only identified a limited range of medical conditions or chronic diseases, which may have resulted in some patients being missed.

> *"The algorithms are only looking at quite a limited set of conditions […] The medically complex algorithm to my understanding looks at a certain minimum number of medical conditions that are identified by the algorithm. And like I said, that part of it, it's good, but it's limited in terms of what conditions it's looking to. […] Basically, the algorithms looking straight up at very basic information in the charts like text in the CPP or a lab result or, you know, very basic stuff like that"* (Participant 2)

In addition, participants noted that the medically complex algorithm largely relied on identifying patients based on coded conditions, potentially overlooking many patients as most EMR data was uncoded. In other words, if a diagnosis or condition was coded in the EMR, the medically complex algorithm was able to capture it and if not, it was likely unable to pick it up. Moreover, participants pointed out that the medically complex algorithm was also constrained by the limitations of the Cody bot in identifying complex patients. They highlighted that the Cody only coded for 18 conditions, but the medically complex algorithm searched for over 40 conditions; there was a missed opportunity for the bot to code for all 50 conditions to better enable the algorithm to identify patients and minimize patients that may have been missed. In addition, they commented that the criteria that the bot operated on were limited and needed improvement.

> *"The bot, although it does code quite a few [conditions], it misses quite a few [conditions it could code] [...] So with the Cody bot, there needs to be more work on the algorithms so that they identify diseases more clearly and mostly identify more diseases. It's a very small subset of chronic diseases [in the medically complex algorithm] that are actually being identified by the bot. [...] Some of the conditions required in the [medically complex algorithm] required diagnostic codes, where others use [free-text]."* (Participant 2)

Alongside the limited range of data that the algorithms leveraged in the EMR, a participant highlighted that the medically complex and hospitalization algorithms and the SDOH complexity scores were not nuanced or context driven, which limited the effectiveness in accurately assessing and managing patient complexity based on the ASAPP data. Specifically, they noted that the medically complex algorithm did not capture patient-specific nuances, such as varying severity of diseases, and did not consider the weight of each medical condition in the patient's overall complexity. Moreover, the participant provided clinical insights; highlighting that complexity goes beyond the number of conditions a patient has and needs to consider how well-managed medical conditions are, but this was not captured by the medically complex or the hospitalization algorithms.

> *"[The medically complex algorithm is not] separating the weight of the disease, you know against the weight of another. So, one disease might be a lot more complicated to manage than another, but the [algorithm] just sees them all as just a count […] You might have a lot of complexity and use a lot of resources, whereas other people with the same conditions or even more conditions, might be really stable and well-controlled, and really don't require a lot of other resources."* (Participant 2)

Moreover, participants noted that the hospitalization algorithm did not account for the reason why patients may have visited the hospital, and this may have led to patients inaccurately being flagged as complex. One participant described that more patients may have been flagged by the hospitalization criteria because, in their area, patients frequently used the hospital like a walk-in clinic for non-urgent or non-complex conditions, and simply for convenience or to access services that may not have been available elsewhere. Because the current algorithm may have misclassified patient complexity based on the frequency of hospital visits without considering the underlying reasons, there were limitations to the effectiveness of the algorithms in identifying complex patients.

> *"Our emergency department did an amazing job at having short wait times. […] So basically, we would potentially have more ER visits cause essentially the service is good, so it's a convenience factor. So, I do think that plays significantly into how many ER visits happen […] We don't have an urgent care clinic […] other than the ER. If you have something that needs an X-ray, you really have to go to our emerge. […] If we can find ways to figure out why people are hospitalized – like, what's going on here."* (Participant 1)

Furthermore, one participant highlighted that the SDOH complexity scores and levels were calculated with equal weights to different SDOH dimensions, like dependency and residential instability. However, that may not be accurate depending on the area an individual lives in. They argued that this approach may not reflect the true complexity of patients across different regions or consider the local context of the area, potentially resulting in skewed results that did not align with the actual needs of the patient population. One participant hypothesized that some individuals in an area might have higher vulnerability scores for SDOH dimensions, while others may not, but the higher scores could be used to represent the entire area, which may not be reflective of everyone living there. They continued to suggest that standardized measures used to calculate SDOH complexity levels in ASAPP may not be adaptable enough for regional variations in population characteristics and thus may lead to misclassification of SDOH complexity levels, influencing the effectiveness of using the data to support resource allocation. They were also concerned that the methods were oversimplified or overlooked nuances and contexts needed to assess SDOH factors and patient complexity.

> *"Well, if we have an older population and they live in these, like, apartments and they would potentially show up [to have higher score for] dependency… but other people living in these apartments would then they get classified as that? So maybe dependency is playing too high of a measure in [my city] specifically […] So it's just one of those things. It just brings [up] bigger questions of like, how do you [and] what do you measure? How do you measure? What do you include?"* (Participant 1)

Moreover, the participant also expressed that there was variability in the criteria used to assess neighbourhood-level SDOH data for complexity across different projects, including ASAPP, which may lead to inconsistencies in how patient complexity is identified and addressed. They noted that another database, that different OHTs have used, prioritized one SDOH dimension and used that to define complexity, but it was unclear to them why one was prioritised over the four and if one methodology was more accurate than the other. This caused confusion and made it difficult to create a comprehensive understanding of patient complexity that could be scaled across different health systems, potentially limiting the reliability and applicability of ASAPP data to support patient care.

"[An external network working with SDOH data too] […], involved with the different OHTs – they actually just use the deprivation [SDOH dimension]. So, they just use the five quintiles for the deprivation. They chose not to use the other[s]. […] And so it does bring into that whole discussion of, 'OK, which of those [dimensions] do we include?' […] But I really like the work for sure. It's definitely interesting. It just has to be scaled […] What should we use? Why?" (Participant 1)

Finally, although participants acknowledged that data from the algorithms "work[ed]" in identifying patterns related to patient complexity, one participant observed that the data showed unexpected patterns, particularly regarding hospitalizations among different patient groups based on their area-level SDOH complexity. They noted that patients living in areas of lower SDOH complexity appeared to have higher hospitalization rates compared to patients living in higher SDOH complexity areas. This unexpected "curve" in the data distribution prompted curiosity and uncertainty in the accuracy of the data. Moreover, they suggested that further adjustments to the algorithms could enhance data reliability and alignment with expectations.

"It can always be tweaked in the future with more input, but I think at this time the complex criteria works […] There was definitely some increase in complexity in the ones with the higher [SDOH scores]. And there was some increase in ER visits in that group as well. And then the funny thing was in the middle group, they're the ones with the lowest complexity and much less ER visits. Then you go to the ones with the low [SDOH score]– presumably in less marginalized neighborhoods... they were actually having maybe less complexity but somewhat more ER visits... it was kind of a weird curve […] basically it was curious, and I do think that's informative." (Participant 1)

Subtheme 2.3. Systemic design concerns limiting usefulness. One participant was concerned about whether the design of the Cody bot and the approach ASAPP took to improve data quality was the most effective. They noted that the Cody bot's functionality was reactive, rather than a proactive, and questioned why the EMR itself could not be designed to automatically code conditions as clinicians added them into the system. They noted that they would prefer a more integrated solution at the EMR level, reducing the need for additional tools like Cody. They underscored a broader concern about the utility of introducing separate tools like Cody to address issues that could potentially be resolved through fundamental changes in the existing technology or EMR and implied that although the Cody bot is one solution, it may not be the most optimal or efficient in the larger healthcare system.

> *"Another colleague of mine, when I ran this idea [of the Cody bot] by them, suggested, you know, 'Cool idea, but like, why isn't this just like what the EMR does on its own? Like why did you need a bot? Why isn't it OK? So you go on PS suite and you write asthma by freehand into the thing. Why doesn't it just code it automatically? […] So that seems to me to be a better way to do this type of work. Now [ASAPP team] isn't an EMR company, so that's not what you're doing. Obviously, you're trying to solve a problem within your framework of what you do, but it's not necessarily– […] 'the' solution."* (Participant 3)

Subtheme 2.4. Usability and customization of complexity data. The participants shared insights on the usability of the complexity data ASAPP provided, particularly related to the dashboard of complex patients. Although they noted that they had not yet had a chance to use it extensively, the initial impressions were positive. Specifically, they described it as a useful tool for data visualization and analysis, particularly due to its flexibility and ability to centralize important data in one place. They noted that the dashboard was "incredibly useful" and had a "friendly interface" that allowed them to easily manipulate the data to show them what they wanted to see.

> *"I think [it's] incredibly useful for me because I can program and manipulate a spreadsheet to show me what it is that I want to see. If I've just got the raw data there that the dashboard is a nice tool […] with more of a friendly interface and it looks quite flexible. I think that the dashboard will give people the tools to be able to get what they need out of that data."* (Participant 2)

Moreover, one participant emphasized that the dashboard could support users, including clinicians or OHTs, to customize segmentation of patients based on their specific needs and prioritizes, which could help inform resource allocation and support PHM. The customizability of the dashboard enabled users to better identify priority complex patients in their OHT.

"…Different practices clinics and OHTs will want different criteria for the patients that they're trying to identify for whatever reason they're trying to do it – trying to match the care that they can provide, with the resources that they have to the population that's there. And this tool will help them a lot in actually having a better understanding of exactly that and being able to identify patients based on a set of criteria that's really customizable." (Participant 2)

Theme 3: Barriers and Facilitators of Digital Health Tool Adoption

The interviews revealed several factors that acted as barriers or facilitators for the adoption of the ASAPP project and its components, including **communication and collaboration, technological challenges and iterative troubleshooting, user perceptions and trust in technology, privacy and security concerns and related procedural delays, and competing priorities and resource constraints at the clinician and OHT level** (Figure 4, Table 14). The barriers directly impacted the lack of widespread adoption of ASAPP in clinical practices and across OHTs, and as a result, the potential benefits of the project remained unrealized (Theme 1).

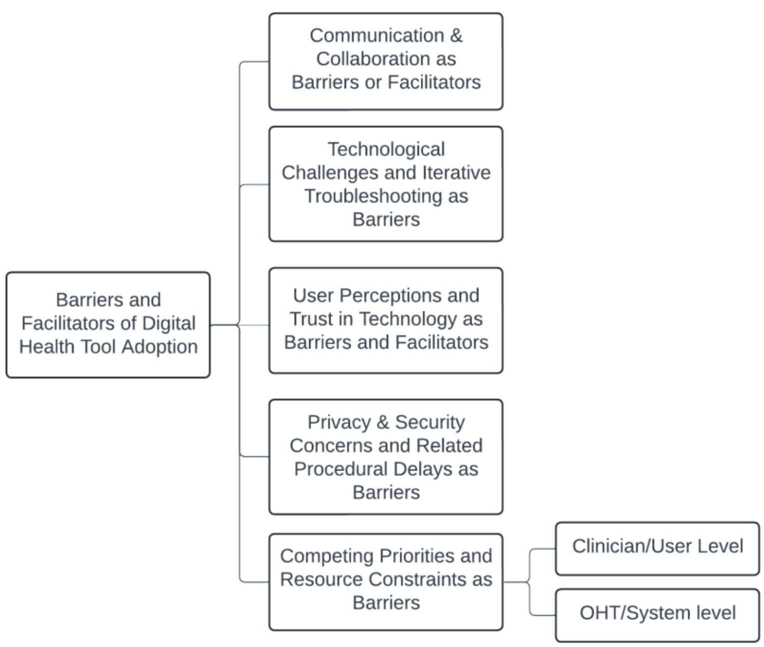

Figure 4. Barriers and Facilitators of Digital Health Tool Adoption (Theme 3)

Subtheme 3.1. Communication and collaboration as facilitators or barriers. The interviews revealed that while effective communication and collaboration were significant facilitators for project adoption for some participants, their absence or inadequacy acted as barriers to successful adoption for others. Participants that adopted the most components of the project highlighted positive experiences with communication and collaboration during the project that supported their understanding of the project objectives and its successful adoption. They noted that the open lines of communication supported the adoption of the project, especially given its iterative nature, as it allowed them to stay informed and understand the different moving parts of the project.

> *"Our communication with the eCE team was fluid. It was seamless, which was excellent. And there was a lot of communication back and forth to establish what was [going to] happen, what the options were when it happened, what happened after it [the bot/predictive algorithm] was run. [...] I think the engagement and support coming from eCE would definitely help facilitate [the use of the project in the clinic or in the OHT]."* (Participant 2)

Table 14. A summary of key insights on Theme 3.

***Barriers and Facilitators of Digital Health Tool Adoption* (Theme 3) Subthemes**	**Summary of Key Insights**
Subtheme 3.1. Communication and collaboration as facilitators or barriers	• Effective communication and collaboration were facilitators, while inadequate communication was a barrier • Open communication includes voicing concerns, asking questions, offering feedback • Lack of clear communication of project timelines, responsibilities result in missed opportunities, confusion, and frustration from users • Mid-project participant turnover and changes are inevitable, and effective communication is especially critical to ensure all participants are brought up to speed to the project
Subtheme 3.2 Technological challenges and iterative troubleshooting as inevitable and necessary barriers.	• Technological challenges (set-up, ongoing errors) and need for iterative troubleshooting were inevitable in early project adoption and act as barriers to project adoption, leading to delays for participants • Proactive project teams in addressing errors and technology challenges were important given the iterative nature of digital health tool development
Subtheme 3.3. User Perceptions and trust in technology as barriers or facilitators	• User perceptions and trust in technology can act as facilitators or barriers to tool adoption • One participant had concerns about the Cody bot accuracy, fears of liability and perceived risk with relying on technology like RPA to do tasks for them in the EMR • Lack of understanding of the technology led to low trust and skepticism

	• Participants expressed optimism about the potential for AI to support future enhancements, with feels of uncertainty in understanding how it worked
Subtheme 3.4. Privacy and security concerns & related procedural delays as barriers.	• Privacy and security concerns, and related procedural delays were barriers to adoption • Privacy and security laws may be outdated, and current regulations were rigid and not well-suited to the environment and needs for digital health projects • Large privacy and security agreements for EMR data access was overwhelming for individual clinicians as they may not have the resources or expertise to manage implications of these agreements • Expressed need for rigorous protocols (e.g. REB) for privacy and security to foster trust in clinicians to adopt digital health tools
Subtheme 3.5. Competing Priorities and Resource Constraints at the Clinician & OHT Level.	• Competing priorities and resource constraints at clinician and OHT level were barriers • Clinician Level: have an existing heavy workload, lack of support/funding hindered adoption; improving data quality and PHM were low priority for clinicians and were only a "theoretical benefit" as they did not provide them direct or immediate benefits to their patient care. • OHT Level: OHTs had competing priorities; some OHTs were not advanced and still trying to address basic priorities over technological innovations; OHTs have limited resources, especially IT resources.

Participants also acknowledged that effective communication in adopting ASAPP was a two-way street and collaborative in nature. They could readily voice concerns or questions and offer feedback, even if it was not directly solicited, and it was received by the project team. Participants also implied that early adopters like themselves may like to be more involved and take the additional initiative to provide feedback and ask questions, implying that others may not take as much initiative with communication.

> *"[The project team members] are very good communicators. And when I had questions or concerns, I was able to send them back. It wasn't always being asked of me to say things or ask things, but I did anyways, so I'm not sure if everyone else would always communicate back, but probably people at this stage of the project are the sorts of people that will. [...] You're a great group and really informative."* (Participant 1)

However, one participant, who only implemented one component of the project, shared instances where communication and collaboration were insufficient, leading to significant barriers to adoption. They expressed confusion, frustration, and uncertainty due to the lack of clear communication regarding project timelines and responsibilities. They were not aware of the project end date and the different needs of the project. The lack of clear communication and not being sufficiently informed resulted in missed opportunities for dissemination, feedback, and engagement with the project, ultimately hindering adoption progress. Moreover, they expressed regret in not being able to test the project completely themselves, and that they would have liked to.

> *"I don't think I was ever given a set defined set of responsibilities. [...] Call it a miscommunication or the lack of understanding from my end. [...] I guess I was given an overview of what the project was, but nobody ever gave me a timeline and so that, I think, significantly impacted how I behaved and unfortunately, I don't think I actually did my job. [...] And when I recognized what was being asked of me, it was a few weeks for the end of the project. [...] I was hoping, in an ideal state, to have a chance to test it out myself and then be able to [support scaling it]."* (Participant 3)

This participant also experienced challenges due to shifts in their team structure in their OHT and joined ASAPP mid-way through the project, with no prior involvement, replacing another member of their OHT who was involved earlier. The lack of continuity and the transfer of responsibilities compounded the communication barriers they faced. They emphasized that mid-project participant changes and turnover is inevitable, and effective communication becomes even more critical to ensure all participants are on the same page.

> *"There's shifting in teams [...] This turnover is gonna always happen for all the projects that we work on going forward. [...] It's more about having an idea going forward of how we can ensure that the project goes ahead as we as we plan. I think the turnover is gonna happen and so we need to make sure there's recognition of what to do when that happens, to make sure that everyone on the same page."* (Participant 3).

Subtheme 3.2 Technological challenges and iterative troubleshooting as inevitable and necessary barriers. The interviews revealed that technological challenges and the need for iterative troubleshooting were barriers to the adoption of ASAPP and other digital health initiatives. Participants encountered various technical issues ranging from the initial setup to ongoing errors that required continuous adjustments in the early adoption of the ASAPP tools. Although this was an identified barrier, participants highlighted that with the iterative nature of digital health projects like ASAPP, troubleshooting and resolving errors was an inevitable part of early adoption. Moreover, these technical challenges led to delays for some participants, hindering the adoption of the project.

> *"The technologies [can be a] barrier. I think that there were definitely iterations that happened with the bot where [the bot] didn't work properly. And either you noticed that there were errors coming up or we noticed that something wasn't reporting out the way it should and so there were iterations that happened and that's still happening. […] It's been an ongoing iterative process to get this working at an effectively sufficiently functioning level that it's not getting stuck with errors and that it's giving us the information that we need. I think that's being a barrier and that's expected when you're developing digital health tools."* (Participant 2)

> *"I didn't do any dissemination. I was busy working out technical challenges on my end."* (Participant 3)

Furthermore, participants appreciated that despite the challenges with technology and errors requiring fixes, the project team was proactive in addressing and fixing these issues as they arose. Furthermore, participants noted that the iterative improvements were clearly moving the project in the right direction, reflecting a positive aspect of the troubleshooting process. They suggested that although the technological errors and troubleshooting could be cumbersome, they were necessary to ensure the products worked smoothly.

> *"What's been impressive is every time we come to barriers like [technology errors, the team said], 'OK, we can fix that, or we can do this'— and I've seen a number of iterations happen that move things clearly in the right direction and I think that'll just be an ongoing process."* (Participant 2)

Subtheme 3.3. User Perceptions and trust in technology as barriers or facilitators. The interviews revealed that user perceptions and trust in technology, particularly in AI and other digital health tools involved in ASAPP, played a vital role in either facilitating or hindering the adoption of ASAPP.

One participant who did not adopt Cody expressed that they definitely had concerns about the accuracy of the bot, for example, in coding diagnoses in their EMR, and how that could impact them legally. They shared some fears of liability and perceived risk associated with relying on technology like RPA to do tasks for them in the EMR, indicating low trust for technology was a barrier to adoption.

> *"The problem is the clinicians are always worried for medical legal purposes of what that can mean, so it thought this patient has asthma, this patient doesn't have asthma, but now it says they have asthma. […] I think a lot of clinicians said the same thing when I would sort of chat with people about this project in passing."* (Participant 3)

Participants also revealed they were skeptical about the practically of the technology, expressed that they had a lot of questions regarding the technology, and asked why certain functions of the bot, such as coding diagnoses automatically, were not already integrated into existing EMR systems. This skepticism, coupled with the lack of understanding of some of the technology, suggested a concern that the ASAPP technology may not be the optimal solution and hindered adoption of ASAPP.

> *"I didn't actually do any dissemination [of Cody]. […] Another colleague of mine […] suggested, you know cool idea, but like, why isn't this just like what the EMR does on its own? Like why did you need a bot? […] It is a solution but not 'the' solution."* (Participant 2)

On the other hand, participants also conveyed optimism about the potential of AI to support future enhancements of the project with its broader capabilities, including its ability to process uncoded data. They recognized AI could uncover insights beyond what the current technology could do and believed it could help make them interpret, make use of, and action on the data. Participants expressed this hopefulness and curiosity at AI's potential to add realized value to ASAPP, while also articulating that they were uncertain about how exactly AI worked.

> *"We [will] start to factor in what the AI can do to inform the algorithms – that it will pull in a lot of valuable information that's otherwise just hidden in the charts right now. So, I'm looking forward to seeing that improve the algorithms as well. […] That's something we're really looking forward to."* (Participant 2)

"Maybe AI will figure out a nice way to [capture uncoded data]. Or maybe if AI codes it and I don't code it, people be OK with it. I'm not sure, but we'll see... I think AI will be probably really good at [interpreting the data to support decision making], I imagine. But you know, if we can find patterns and then target things more based on the patterns we have, instead of, […] assumptions, we can actually use data. Or maybe if AI codes it and I don't code it […]– I'm not sure, but we'll see." (Participant 1)

Subtheme 3.4. Privacy and security concerns & related procedural delays as barriers.

The participants shared that privacy and security concerns, coupled with related procedural delays were significant barriers to the adoption of ASAPP. They noted that complexities surrounding privacy and security compliance working with patient health information (PHI), as well as procedural delays in implementing the necessary technological safeguards, such as the set-up of a virtual private network (VPN), and the relevant regulations, either hindered their ability to fully engage in the project or delayed it. One participant shared that initially there was an extensive delay in setting up VPN access effectively for the Cody Bot to operate in their clinic's EMR system. Thie delay, which involved coordination with their IT team and the eCE team, was a procedure barrier that slowed the project's progress.

"Basically, I think there was a long period of time initially where basically it was just trying to find how to [set-up the] VPN into our EMR effectively so that the Cody bot could operate." (Participant 1)

Participants shared that the current privacy and security laws were outdated and there was a lot that still needed to be understood to ensure compliance with the health privacy legislation, Personal Health Information Protection Act (PHIPA). They suggested that current regulations were rigid and complex and were not well-suited to the environment and needs for digital health projects, hindering the adoption of new technologies in healthcare.

"So privacy and security [are a] huge barrier— there's a lot to be understood. The privacy and security laws are all outdated. […] So, we're trying to make a PEG fit into a square hole as far as trying to make sure that we're compliant from PHIPA point of view." (Participant 2)

"Our privacy laws are really making this work extremely difficult." (Participant 1)

Moreover, participants highlighted that concerns about privacy and security whenever taking on projects like ASAPP may prevent clinicians from moving forward with digital health initiatives. They also expressed that signing large agreements to allow for technologies involved in ASAPP to access their EMR data, often designed for larger organizations like hospitals, was overwhelming as they did not have the same resources or expertise to manage implications of these agreements at smaller community practices. This led to feelings of uncertainty and vulnerability and an understanding that they would be put at risk if the agreements were not in compliance with PHIPA. They emphasized that the reality of individual clinicians working independent of large organizations could contribute to the hesitancy and resistance in adopting new digital health tools and signing large agreements.

> *"Like I saw more recently, I got to sign that huge document, [the agreement to run the Cody bot on my EMR]. […Unlike hospitals with the resources to review this contract, we are a group of providers at a community clinic and] it is very difficult to expect us to have the same abilities and to sign a document like that, but I signed it because I guess at some point in time you just have to cross your fingers and so I hope you're bot and the management behind it doesn't do anything nefarious in my EMR. […] I do have concerns, but I think at some point in time you have to move forward. […] And yes, there will be clinicians that have too many concerns to move forward with this work."* (Participant 1)

On the other hand, one participant who worked in a setting associated with a hospital, a larger organization, expressed another frustration when working with larger organizations on digital health projects; they had lengthy processes in place for reviewing privacy and security aspects of projects and often had other priorities which acted as barriers to technology adoption. This participant shared they were unable to adopt the Cody bot in part because they were waiting for their privacy and security team to provide approval, further emphasizing the procedural delays accompanied by privacy and security measures.

> *"I'm not based in an office outside of the hospital [as a primary care clinician]. As a result, there are very specific technical guidelines to anything digital that we're implementing and we have an entire security team who reviews these things. So instead of me sitting in my office and saying, OK, I'll look at this with my office staff and my few other physician colleagues and say, hey, are we OK with this? I had to go through our hospital security and privacy team to make sure this met their privacy standards. And there were several questions and they did start looking into it. And then as hospitals do, they had other priorities, and this became a back burner issue for them."* (Participant 3)

Moreover, participants expressed concerns about the broader privacy and security implications of sharing patient data, even when it was de-identified. They questioned whether safeguards were in place and whether research ethics board (REB) approval was necessary for the data sharing aspect of the project. These concerns were pronounced for one participant, for projects like ASAPP, when data sharing was for purposes outside of quality improvement (QI) activities within their own practices and involved external organizations. They also noted that there would be legal issues with a bot dealing directly with patient data. In addition, they shared that they did not feel comfortable sharing their data at the time of the project, as they required more communication of the ethics procedures completed by the ASAPP project team to feel comfortable to continue with the data sharing process within the project timeline.

> *"I personally found it very hard to justify calling this QI. [...] This is still a QI project, but QI that then requires massive amounts of data to be shared with an outside organization [...] requires REB approval. And so I felt extremely uncomfortable sharing my data. [...] I didn't find I had what I needed to comfortably share [my data]."* (Participant 3)

Subtheme 3.5. Part 1. Competing Priorities and Resource Constraints at the Clinician Level. Participants stated that clinicians faced challenges in adoption due to competing priorities and limited resources. They shared that the project involved additional time and effort on their end on top of their already heavy workload, which was a challenge that hindered clinician engagement and thus project adoption. Moreover, they needed to spend time understanding the technology, learning how it worked before adopting it, and providing feedback to support its development.

> *"The things that we try to push on primary care— [they] usually require the primary care side to do a heck of a lot of the actual work."* (Participant 4)

> *"[The Cody bot] still requires a fair bit of input from the doctors when it comes to what the bot is going to do – especially in terms of messaging. […And so, the project's] challenges were engagement, especially when it added to work that needed to be done by either physicians at the clinic or other people at the clinic that would be reviewing the results of the bot."* (Participant 2)

> *"Physicians are really pretty against any more work at this time. […] Physicians will push back against anything that requires significant amounts of their time."* (Participant 1)

Participants described that they could not delegate the work out, even if they had available staff to support it, as their expertise and familiarity with their patient rosters was needed to review the ASAPP data and provide feedback to ensure the tools were functioning properly. They emphasized that the project relied on their time and effort for successful adoption.

> *"I did go through and review [the ASAPP data]. So, I guess an administrator could have done that part, but I don't know if they could have done it well. […I could] delegate it to one of my staff, but that wasn't really the point of this. The point of this was to make sure it was working properly, and they would have had zero ability to do that. […] At this point in time, I really just was focusing on understanding the social determinant of health part, how and how that plays in to complexity and ER visits. [...] but I haven't gotten far enough to. Other than talk to a colleague about it at this point in time."* (Participant 2)

Participants underscored that while clinicians and healthcare professionals may have a desire to engage with innovative digital health projects like ASAPP, they often lacked the necessary resources, time, and support to do so. They have a limited amount of time, and they needed to prioritize the daily demands of their clinical practice, which takes precedence over supporting additional projects. They also highlighted that although the project enabled improved data quality in their EMRs (in their CPP for example), this was considered lower priority compared to the immediate patient care responsibilities in their practice.

> *"But there's gonna be lots of like clinicians and groups of healthcare providers elsewhere that are not going to have that ability [to get the resources they need to support projects], even if they have all the wonderful intentions, even if they could do it, if they had enough time to do it. But there may be like just too busy with their other work. […] It would be nice to have all of my diagnosis and CPP coded as a clinician. […But,] I would say it's far lower a priority for me than many other things right now. We're just worried about the day-to-day struggles of being a family doctor and this one wouldn't solve that."* (Participant 3)

Participants noted that ASAPP focused on population-level benefits rather than immediate, patient-specific benefits, which was not their priority. They went on to say that because of this, ASAPP was seen to create only a "theoretical benefit" to physicians, and did not directly tie into their "one-on-one patient care". This disconnect made it difficult for clinicians, who are focused on managing immediate patient needs, to see the value in adopting new tools that do not immediately help them in their primary role of patient care. Participants also highlighted that the timing of the project exasperated this challenge as it was introduced after the pandemic, while clinicians were experiencing higher stress levels and workloads in their daily clinical workflows.

> *"It's a theoretical benefit to the physicians. So, it doesn't actually help get help them specifically with a specific patient. […] It's additional care, it's not one-on-one patient care as much as get a list of patients who have a particular diagnosis and do something about it. So, it's a bit of a hard sell, especially [given] the timing is challenging because through the pandemic and other things, [clinicians are] all, you know, overworked and stressed out and not looking for new solutions to help improve the care at a population level. We're just trying to fight fires at a patient specific level. So, it's difficult to get engagement when there's no immediate benefit."* (Participant 2)

Despite this, participants expressed they still believed the objectives of ASAPP were important, but they had limited resources, including funding, to support the work, which was yet another barrier to adoption.

> *"[The Cody bot improving data quality] is really kind of foundation work, but, like, the problem is, is that no one wants to pay for that work."* (Participant 1)

Subtheme 3.5. Part 2. Competing Priorities and Resource Constraints at the OHT Level. Participants shared that when adopting a project such as ASAPP, including the Cody bot, into an OHT, it can be a "massive" challenge as there are other issues and aspects of healthcare that the OHT needs to prioritize. Two participants shared that their OHT had more basic priorities at that time, and they were not yet advanced enough for projects like ASAPP. They suggested that the clinicians and the healthcare system may need help with simpler tasks.

> *"I think we probably have other initiatives, you know, both aligned to and near the OHT that are probably more useful for our primary care providers right now. […] The digital work – it is really hard to really find the right balance and OHTs, we're in a place right now we're just trying to cover the basics. And we're not even doing that yet. […] It has been a huge challenge to implement this bot."* (Participant 4)

Two participants expressed that the ASAPP project did not align with their OHT's priorities, leading to the OHT not endorsing or pushing the project to be adopted by their clinicians. The participants implied that OHTs sometimes need to make difficult decisions about where to allocate their limited resources and focus on initiatives that align more closely with their priorities and goals. Moreover, the adoption of projects like ASAPP relies on OHT support to encourage adoption and engagement with their clinicians. Although the OHTs would not push the project or similar digital health initiatives to their clinicians, they would encourage those that were already interested and willing to take part, without providing additional resources to support its adoption.

> *"This would not something, to be totally honest, that [the OHT] pushed a lot because [they] didn't feel like it was a very high priority for [the OHT] at this time. Whereas if there were a handful of clinicians who came forward and said, 'we really want to try this, we think it's so cool'. Great – that would be great, but we would really take the people who are willing and not try to push it."* (Participant 4)

In addition, participants highlighted that resource constraints were a significant barrier to the adoption of projects like ASAPP. One participant revealed that their OHT's participation in

ASAPP was limited primarily to one individual largely due to a lack of sufficient IT or project management resources. When these resources are scarce, OHTs may struggle to fully engage with new initiatives, leading to limited participation in projects like ASAPP. They further emphasized that OHTs sometimes need to make difficult decisions about where to allocate their resources, time, and efforts when deciding which projects they can actively participate in.

> *"It's not like [our OHT hasn't] participated in other projects, but I would say this was mainly myself and that's mostly just probably because of a lack of resources. Probably we don't have great IT resources here. Or project management to be honest. […] It's just, we don't have a lot of [resources]. So, they basically have to decide where they're putting their time."* (Participant 1)

> *"We don't have enough money [to support these projects]."* (Participant 4)

Meanwhile, only one participant (Participant 2) mentioned that their OHT had access to recently available systems and resources that could help utilize and action on the data from ASAPP, facilitating the project's adoption in their OHT. This demonstrated that valuable data may be accessible (Theme 1), such as with ASAPP, but it may be unable to be actioned on due to resource constraints or a lack of practical strategies to implement the insights into actionable outcomes.

> *"We will take that information [… and] give it to our [system newly implemented in the OHT] and [OHT-specific dedicated care teams] – a list of patients that match the resources that they know are available. So that they can use that list to make sure that those patients get access and actually to inform us about what resources need to be available, but ultimately to make sure that the patients identified are connected with the resources to provide care to them. […] We have care coordinators."* (Participant 2)

Theme 4: Recommendations

The interviews revealed several recommendations for technology, and adopting and scaling ASAPP and other digital health initiatives. Many of these recommendations directly addressed the limitations of the project (Theme 2), and barriers and facilitators to adoption (Theme 3) previously discussed. Several subthemes emerged including **communication, collaboration and**

engagement, privacy and security compliance assurances, resources and supports for adoption, technology enhancements and iterative development, evaluation and lessons learned, and demonstrating maturity and value for scaling. Table 15 summarizes the recommendations from this theme.

Subtheme 4.1. Communication, Collaboration, and Engagement. Participants made several suggestions to support the adoption and scaling of ASAPP related to enhancing communication, collaboration, and engagement with stakeholders, including clinicians and OHTs. The recommendations included: maintain comprehensive communication and keep stakeholders informed, take a co-designed approach and address stakeholder needs and interests, collaborate with OHTs to strategically integrate the use of PHM data into planning and operations, tailor supports and resources to the local context and the community's needs, understand and align with the landscape of the system or OHT, and garner support from clinician champions.

Table 15. A summary of recommendations (Theme 4).

Recommendations (Theme 4) Subthemes	Summarized recommendations to support adoption and scaling of ASAPP and other PHM digital health tools
Subtheme 4.1. Communication, Collaboration, and Engagement	1. Comprehensively communicate all project details and how the project and tools work, ensuring stakeholders are informed. 2. Collaborate with OHTs or systems in early phases to integrate project into system workflows and ensure processes are in place to use and action on PHM data. Take a co-designed, collaborative approach, engaging with clinicians as well as OHTs, and ensure project aligns with their unique priorities, needs, resources, and capacities. 3. Understand the community's needs and tailor supports and resources to the local context and the community's needs. 4. Understand the landscape of the system or OHT and align with existing initiatives with similar objectives and explore the use of existing databases used by the OHT. 5. Have clinician champions to advocate for the project and support its adoption and scaling to other clinicians and organizations.
Subtheme 4.2. Privacy and security compliance assurances.	6. Provide assurance regarding privacy and security compliance to users for transparency and building trust and ensure adherence to best practices for privacy and security standards and procedures.
Subtheme 4.3. Resources and supports for adoption	7. Provide dedicated non-PCP staff and move PHM work to team structures to reduce downstream workload on PCPs. 8. Garner government policies and financial supports to support and sustain data quality initiatives.
Subtheme 4.4. Iterative, adaptive development approach and technology enhancements	9. Take an adaptive, iterative approach to technology development. 10. Make tool enhancements to optimize technological capabilities and accuracy in identifying complex patients. a. Explore the identification of complex patients with the use of AI to enable the use of more available data in the EMR and to account for nuances in patient characteristics b. Enhance medically complex algorithm for broader disease identification and ensure that algorithms account for nuances across patients. c. Leverage AI to support more accurate segmentation of complex patients and identify actions from data to support PHM. d. Leverage additional datasets outside of primary care EMRs to gain access to more data contributing to complexity and potentially capture unattached patients. e. Enhance the Cody bot to be more comprehensive and accurate. f. Offer flexibility and customization of features to support different users with the technology based on their preferences.
Subtheme 4.5. Evaluation and lessons learned	11. Conduct evaluations and extract lessons learned to inform enhancements and future initiatives.
Subtheme 4.6. Demonstrating maturity and value for scaling	12. Establish maturity and demonstrate the project's value to scale the project.

First, participants recommended that all details about the project and technology should be communicated comprehensively so every stakeholder feels informed. One participant recommended that any external parties coming on to join the project, especially when joining after it has already begun, should receive clear communication on the project timelines, their role on the project, and any details on the project that they need to agree to adopt the project.

> *"I don't think I was ever given a set defined set of responsibility. […] Going forward, […] if a clinician comes on late [to the project], make sure that clinician is really, really clear on anything obviously [related to] the project, but [also] on the timelines. […] Make sure that every clinician is on board and again if a new clinician joins late – from the get-go, [let them know,] 'OK here's what we're doing. Here's how we're doing it'."* (Participant 3)

Next, they suggested that the project team should communicate how the technology works so participants feel reassured and informed. Participants mentioned that they did not understand in detail how the Cody bot was operating at first and that they would want to know how it was, to better understand what it was doing and gauge if they agreed with the process. Moreover, participants shared that explanations of Cody bot processes could help foster trust with the technology and support adoption.

> *"I didn't understand all of the things [like] how exactly the Cody Bot was operating, but then you sent me some of [the algorithms used by Cody]. I think that's really helpful just as an informative point, [for] really any physician using the platform. They don't need to look at it if they don't wish to look at it. But for people that are thinking to themselves, how is this operating like, do I agree with it or not? Like when [the bot is] making that decision [to code in the EMR]? […] It's good to know what it's doing so that you can be like, 'Oh, that's what it's doing and this is why I don't agree with it.'"* (Participant 1)

Moreover, when tools like the predictive algorithms help identify complex patients or the SDOH complexity scores for supporting patient care, participants suggested that it would be important for them as clinicians to understand the criteria used to identify the complex patients.

> *"I think we need to know, like, why we choose things, when we make these kind of algorithms."* (Participant 1)

Participants also emphasized the importance of actively engaging with clinicians or end-users, especially in the planning and development stages, to ensure the project aligned with their needs, available resources, and priorities. Participants recommended a co-designed and collaborative approach; involving clinicians in the planning and development phases to ensure their needs are understood and so that a project that aligns with their priorities and needs is created. To improve patient outcomes, which was one of the ultimate goals of ASAPP, participants noted that it was important to engage primary care clinicians and develop tools that would meet their needs and address their struggles. They also suggested that the OHT's digital health initiative priorities would be tied to the needs of its primary care clinicians.

> *"[We want to] provide better care for their patients. Perhaps we can start with that co-design process with the primary care providers to say, 'hey, what do you need help with?' […] I think until we get our primary care providers to a place where they're able to do just the basic stuff— [in a way that is] a little bit easier than they already do it. […] You know, how do we work together? Who [is the OHT made of]? Who are all the primary care providers that we're trying to reach out to?"* (Participant 4)

Participants emphasized that collaboration and active feedback collection from end-users or clinicians during advisory group meetings for example, was essential for the project success, necessary to keep the project team informed about end-user needs, and vital for clinician adoption into daily practice.

> *"I've tried to provide some feedback and the goal of that was that ultimately if we can create something that works for physicians, then they'll consider using it..."* (Participant 1)

> *"I [provided] my own insight when we had our group meetings to provide some insight from primary care and I wasn't the only clinician there. [… We provided] the project and the team with views from primary care views from the ground."* (Participant 3)

In the same vein, two participants went on to suggest that clinicians in their OHTs needed support with simpler tasks and that perhaps ASAPP was too complex and did not meet their needs. They expressed that the project team should consider making simpler tools and increase available support for more basic workflows like appointment booking.

> *"Things like […] being able to refer and being able to have their patients book appointments online and they're very, very sort of rudimentary and nowhere near the sort of AI [or] bot stuff [used in ASAPP]. […] I know eCE has a huge portfolio of opportunities that perhaps would have been, you know, great for our primary care providers and perhaps other things. I don't know if they're bundled with them or if we, you know, provide some other digital enablers that perhaps would have been more of interest to certain primary care providers in our OHT."* (Participant 4)

Participants highlighted that projects should have pre-existing interest from clinicians or their primary target users and ensure the users have the capacity or ability to participate and adopt the technology.

> *"There needs to be a certain level of ability and interest… [ASAPP] is a very physician-centered project and so really it's about getting your physicians interested."* (Participant 1)

In highlighting that stakeholder needs and priorities should be met, participants emphasized that clinicians were already overworked and had limited time and capacity to support projects, as previously discussed in the theme describing the barriers to adoption (Theme 3). Thus, they recommended that future projects should not increase the workload of clinicians and implied that alternative ways or supports should be established in the project to help mitigate efforts required by clinicians.

> *"I think there is a way to [adopt and use] the bot so it has less work involvement where it automatically does do the coding without a clinician having [to review the results] report."* (Participant 3)

> *"We have to create something that doesn't increase workload significantly and works the way you expect it to work – for people to not be turned away."* (Participant 1)

The interviews also revealed the importance of engaging and collaborating with leaders in OHTs and their working groups to identify ways to make use of PHM data from projects like

ASAPP. This would ensure processes were in place that could action PHM data and be utilized in existing OHT operations and planning processes.

> *"So, I've been working with the [OHT-level working group] to determine how this information [on complex patients from ASAPP] can be absorbed by the OHT to benefit the care that we're providing. [I've been also been] working with individual executive directors […]* so *that each of the clinics that are associated with [OHT-specific care teams] can best absorb this information into our planning, other resources, technical resources."* (Participant 2)

Notably, participants acknowledged that while the availability of PHM data (dashboard of complex patients) was a significant first step accomplished by ASAPP, it was equally important to develop strategies for utilizing this data. Participants expressed that there is a growing need for OHTs to consider how best to integrate these insights into their broader system and plans. This approach will ensure that the data not only informs decision-making but also drives meaningful improvements in patient outcomes.

> *"It would be super helpful, but people do have to be creative and thoughtful in how they use data. But I think first you need the data and I think this project is already helpful for me [for that]. […] I feel like our OHT is just starting to have data presented to it and it's going to need to start to think about how to use that data."* (Participant 1)

In the same vein, the interviews uncovered that adopting and scaling digital health initiatives like ASAPP needs to involve addressing the unique challenges each OHT or community faces, particularly in smaller or less-resourced communities, as there are diverse populations across the province. To maximize impact of digital health initiatives, participants recommended that the project team should understand the local context and provide targeted supports such as dedicated resources that align with the local context and capabilities of each OHT or community the project is being deployed into. One participant shared that their OHT had the infrastructure, existing resources, and care teams needed to adopt ASAPP and make use of the PHM data it provided, while others shared that their OHT lacked the same supports. Thus, the interviews revealed the importance of moving away from a one-size fits all approach, and considering the varying resource levels, capacities and specific needs of the different OHTs or communities when designing, adopting, and scaling PHM digital health projects.

> *"Though [some communities or OHTs that adopt digital health tools] are not communities that represent the majority of communities in Ontario, and so creating a product that works for those communities, is lovely for those communities, but won't scale because we don't have the supports [they do]. [...] And so basically, they're gonna need less resources to manage their complex patients [... as] compared to [a smaller city]. But just as a percentage of their population and as a percentage of their workforce like yeah, you can probably implement things because you have less people to target as a percentage."* (Participant 1)

> *"The use case scenario for the [OHT] is we will take that information [... and] give it to our [system newly implemented in the OHT] and [OHT-specific dedicated care teams] – a list of patients that match the resources that they know are available. So that they can use that list to make sure that those patients get access and actually to inform us about what resources need to be available, but ultimately to make sure that the patients identified are connected with the resources that we then have to provide care to them."* (Participant 2)

Moreover, participants emphasized that the project could have had a greater impact if they had the resources and supports they needed to adopt and scale the project in their area. Thus, the project team should understand the resource and support constraints in OHTs and root their planning in realistic, local contexts of the diverse communities in the province.

> *"I'm reflecting on the data that [ASAPP has] given me and obviously I'm just one practice, but, I don't know, I think if this can be scaled, if there's support to do it, it could have impacts. Of course you need the resources, but I think this is a good place, in my opinion, to start."* (Participant 1)

The participants also recommended that ASAPP or PHM projects should understand the landscape of relevant organizations or OHTs in planning and development, by learning about and aligning with other existing initiatives with similar objectives and leverage existing databases OHTs intend to use and adopt. More OHT other existing initiatives with similar objectives and leverage existing databases, and learn how OHTs, or their organizations, intend to adopt and use them respectively. One participant shared that their OHT was in the process of integrating databases and systems with another initiative with similar objectives to ASAPP. This participant took initiative and interest in ASAPP, so they took the time to recognize how ASAPP was relevant to their OHT objectives and how it could work together with the other initiative to enhance its utility in the broader healthcare system. They made specific recommendations to ensure alignment between the two projects and ensure that ASAPP was still relevant to the OHT and could still have an impact. (Note: specific recommendations and details involving the other project are omitted to preserve anonymity). Although the other existing initiative in their OHT was a competitor to ASAPP, the participant shared insights on how ASAPP could complement the other initiative. The interviews thus revealed the importance of understanding OHT objectives and other existing projects and systems for the successful adoption and scaling of ASAPP and other initiatives.

> *"[Our OHT is] specifically talking about the [similar initiative to ASAPP…] and that moving forward, there really would be [a] benefit in matching to standards [with ASAPP and the similar initiative…] as much as possible. […] That's a work in progress. But from an OHT point of view, we are going to be using [similar initiative to ASAPP] through [an existing database system]. […] The ASAP project has access to far more information in the EMRs than we have in the [existing database system] […] so, [ASAPP] really can complement the information that we're getting."* (Participant 2)

Finally, to scale and facilitate the adoption of ASAPP or other digital health initiatives, participants recommended having clinician champions to "champion" the project or advocate for the project within their clinics and OHTs by sharing their positive experiences and sharing the benefits of innovations. Clinician champions play an important role in encouraging their peers or other healthcare professionals to try and adopt new technologies. One participant shared their perspective on the value of clinician champions, noting that their role is to validate the project by personally testing it and then recommending it to colleagues. They implied that word-of-mouth support for projects from clinician champions held credibility and trust, could help bridge the gap between projects and healthcare professionals and could enhance the scaling and adoption of initiatives.

> *"I think having champions really helps with [facilitate the use of the project in the clinic or in the OHT]. So, you know, in my clinic I'm the champion. I can really help move things along and fortunately in our OHT, we've had several other physicians and non-physicians in our OHT take the lead with these projects and I think that really helps too."* (Participant 2)
>
> *"I was hoping [that in an ideal state…] I'd them be able to tell colleagues by word of mouth, 'Hey, I've tried this out. Here's why it's great.' That's one of the roles of the primary care clinician for any project is to say, 'I've tried it. You should too.' That's why it works to have primary care champions."* (Participant 3)

Subtheme 4.2. Privacy and security compliance assurances. To address privacy and security concerns, participants indicated that the steps involved in privacy and security standards should be thoroughly completed and clearly communicated to the clinicians to increase feelings of reassurance and foster trust. They also suggested that when taking on digital health projects involving large data sharing from primary care offices to external organization(s) like the eCE, REB processes should be considered. This is especially important given that they may not have expertise in this area, which can lead to discomfort and concerns, as highlighted in Theme 3.

> *"If you're doing any major data sharing from a primary care office to an external organization […] it's really, really clear to clarify what requires and what does not require REB. And if it doesn't require REB – fine, but then to make sure that every clinician is on board. […We need] some reassurance that that those, you know, those processes have been gone through and if there's something to ask, […it] could be really helpful for the next time around.[…] And this is not the only project where this sort of lesson has come up."* (Participant 3)

Subtheme 4.3. Resources and supports for adoption support. Participants recommended that the PHM work in ASAPP or other similar projects should have dedicated non-physician staff or team members who can process the information and match it to available services. This may be helpful in reducing downstream work expected from ASAPP and may also better enable action on the PHM data that ASAPP provides to "then route patients to those services [they need…] so that they can get the care that they need." Participants suggested that because clinicians are unable to support projects that require lots of time or efficiently action on the ASAPP data, it would be valuable to have their systems provide support in analysing the data and putting it into action to support PHM.

> *"I think there's a lot of value in delegating this away from the physicians to practices that are fortunate enough to be part of a team, whether it's a family health team or an Ontario Health Team where this kind of information can be absorbed by non-physicians in those teams that can then process the information and match that to the services that are available and then route patients to those services [they need…] so that they can get the care that they need."* (Participant 2)

> *"I just know that in the big picture, physicians will push back against anything that requires significant amounts of their time and […so] unless someone is gonna analyze the [medical complexity] data and make it meaningful and apply it, it's not going to help [population health management]. So that's where like our systems are maybe able to participate."* (Participant 1)

In sharing that supports are needed to enable digital health initiatives, especially those related to data quality, participants emphasized that government policies endorsing and providing funds within their system are needed.

> *"I think at some point in time there also has to be some government policy that says – you know, how do we improve the quality of data within our system and how do we provide, essentially, financial support, so that that can be done– but you have a good product to help that."* (Participant 1)

Subtheme 4.4. Iterative development approach and technology enhancements. Due to the iterative nature of the project and the inevitable technological errors (Theme 3) and limitations with developing technology (Theme 2), recommendations emerged regarding ASAPP tool enhancements and maintaining an adaptive approach when developing technology.

Participants stated that projects should "go with the flow" or adapt to the different technological errors and challenges encountered when developing technology (Theme 3), by taking participants' feedback and iteratively adjusting the tools or approaches appropriately. All participants that implemented the project described that they provided iterative feedback to the project team; after they reviewed the results of the different project components, they evaluated them and shared feedback with the project team, who then made adjustments and provided the project components back to the participants, who then reviewed the components and repeated that cycle.

> *"You go with the flow, you see what's available, you develop tools as you can, and you try to do the best with the data that you can. […] What's been impressive is every time we come to barriers, [like technology errors, the project team said,] 'OK, we can fix that or we can do this' […] As time goes by and we learn more, these were things that [helped to] facilitate the use of the project in the clinic or in the OHT."* (Participant 2)

> *"[There was] a second round of back and forth [with the Cody bot] […] I was able to go through [the bot results] and evaluate what was coded and the ones that [could be] potentially coded, and then [provided] feedback."* (Participant 1)

Similar to the feedback provided during the project, in the interviews, participants provided further feedback to enhance the technology used in ASAPP and address its limitations (Theme 2). These enhancement recommendations from the participants are summarized below and all revolved around improving the ASAPP's capabilities and accuracy of identifying complex patients.

a. Explore the use of AI to optimize the capabilities of the technology and more accurately identify complex patients. Participants highlighted that AI would enable the use of more available data in the EMR, which may contain crucial information that contributes to patient complexity that is otherwise unaccounted for by the ASAPP algorithms, and thus help to account for nuances in the data. Participants noted that AI has the ability to process free text in the EMR that the currently ASAPP algorithms are not able to process and capture. Finally, they noted that AI could be used to help standardize or code for intangible factors that impact complexity that the current algorithms cannot capture – which was a limitation previously discussed in Theme 2.

> *"AI can [be used] to inform the algorithms [and] it will pull in a lot of valuable information that's otherwise just hidden in the charts [...] I'd say most of the information that's in a chart is not accessible with standard [algorithms like the ones used in ASAPP] that we're provided with in the EMR. So even customized searches are limited in what they can search for. And the AI can do two things to my understanding to really improve that and get the data that's in there out that we wouldn't otherwise be able to see. [...It could use] natural language processing where we can understand chart notes and extract data from text that otherwise, [for] the algorithms would be hidden."* (Participant 2)

> *"And I can see how [the ASAPP data] can be used knowing that there's all these other like more intangible factors [impacting complexity] that's just hard to code at this point in time. Maybe AI will figure out a nice way to do it."* (Participant 1)

b. Enhance medically complex algorithm for broader disease identification and ensure that algorithms account for nuances across patients, such as differences in how well-managed conditions are. This recommendation stems from the identified limitation that the algorithm only included a limited range of conditions and did not differentiate complexity based upon the severity of a condition or the affect it was having.

> *"The algorithms are only looking at quite a limited set of conditions [...] The algorithms are limited in what they're looking for – so, [the medically complex algorithm captures] X number of chronic diseases and they're not separating the weight of the disease, you know against the weight of another."* (Participant 2)

c. Leverage AI to support the analysis of the ASAPP data, more accurate segmentation of complex patients, and identify actions from data to support improved PHM and resource allocation. Participants highlighted that AI could identify patterns in the ASAPP data that may not otherwise be recognized, and this can facilitate the use of the complex patient data for PHM and resource allocation.

> *"And then secondly, that the AI can start to see patterns to identify subgroups of patients, like complex patients that [the algorithms] would otherwise not be able to*

(a), recognize the patterns or know the patterns, and (b) create an algorithm to identify them. So, the AI can really help look at the patterns that can help inform when patients are categorized like that." (Participant 2)

"I think AI will be really good at [identifying patterns in data], I imagine. But you know, if we can find patterns and then target things. More based on the patterns we have instead of like kind of assumptions like we can actually use data." (Participant 1)

d. Leverage additional datasets outside of primary care EMRs to gain access to more data that could be used to identify complexity and aim to support more unattached patients that do not have a primary care clinician and may not be captured in primary care EMRs. Participants expressed a desire to utilize the ASAPP project to support vulnerable patients or those that are not connected to primary care EMR, but may have accessed other healthcare services. They were unsure however, even outside of the ASAPP project, how this could be done and if it was possible.

"So the next level would be, well, what if we didn't just focus only on primary care? What if there was a way and I don't know, maybe to something the eCE can look into, to pull together data from physiotherapy clinic EMRs and from home care data systems and from… I think anything and everything if we can pull together data and try to find everybody… I'm like I'm thinking ideal state […] but it's I don't know how to get it there." (Participant 3)

e. Enhance the Cody Bot to be more comprehensive in the number of conditions it codes for, and more accurate in coding conditions. Participants noted that clarity and completeness in coding directly affected the project's ability to accurately identify complex patients, which was central to ASAPP's objectives.

"So, with the Cody bot, there needs to be more work on the algorithms [used by Cody to code operate], so that they identify diseases more clearly and mostly identify more diseases. You know there's a very small subset of chronic diseases that are actually being identified by the bot." (Participant 1)

f. Offer flexibility and customization of features to support different users with the technology based on their preferences. For example, with the Cody bot, users could be offered the option to opt-out of coding some conditions, provided the opportunity to review the criteria the bot uses to code conditions, and adjust what it looks for. Participants recognized that planning for site-specific customization needs were essential.

> *"Just [make] sure the product works the way you expect it to work and maybe there's some user adjustments. [Ask,] – 'Are there any of these conditions you don't want us to code?'[…So,] people should [be able to] opt out of conditions […] And basically, [eCE should] able to say for these conditions, this is the criteria [Cody uses…,] 'do you agree with that criteria? [… The] criteria [for these conditions] can be modified."* (Participant 1)

Subtheme 4.5. Evaluation and lessons learned. Participants shared insights regarding the importance of evaluating digital health initiatives for future improvement. They suggested that regular evaluation of technologies or projects like ASAPP should be conducted to ensure the project is in optimal operational status. Participants highlighted that by conducting an evaluation, lessons learned from one project could be applied to the ASAPP moving forward or to future projects.

> *"I think we keep doing these sorts of projects and then keep doing this evaluation piece. […] That's where we're going to be able to take those lessons forward to the next project and to the same project."* (Participant 3).

Subtheme 4.6. Demonstrating maturity and value for scaling. Participants stated the project would need to reach a level of maturity and demonstrate its value before it could be scaled to other OHTs. They highlighted that maturity for ASAPP would be defined as addressing all its known technical issues, operating smoothly and reliably, and having minimal administrative burden. Moreover, participants recommended that the project should first be fully adopted by one OHT such that its benefits and effectiveness could be realized and demonstrated. Showcasing use and realized value could encourage others to participant, lead to more buy-in, and scaling.

> *"I think that a certain level of maturity needs to be established with the ASAPP project to get it into a state that's almost [easy for clinicians to adopt, so] there's not a ton of paperwork and there's not going to be a bunch of errors and there's going to be basically a smooth running of the program.[…] It's not quite at that point right now [to scale to other OHTs], but it's close and once it gets past the last few issues that we've run into.[…] Once that's done I think that [ASAPP] is something that would benefit all OHTs across the province."* (Participant 1)

> *"I think to encourage people to participate, you would have to scale it in certain OHT and then do a demonstration of how those OHT's are implementing the use of the data […] But I think the real value, the real ability to scale will be when it's showing to have value at that level."* (Participant 1)

Integration and Interpretation

The quantitative and qualitative findings were merged, related and compared to each other to address the posed evaluation questions of this study. This section presents the integrated findings as they relate to the four evaluation questions on perceived value, effectiveness in achieving intended objectives, adoption facilitators and barriers, and future recommendations. Additionally, any qualitative and quantitative findings that were not directly comparable but provided valuable insight into the evaluation questions were also presented. Notably, the qualitative findings were coherent with the quantitative findings and confirmed or expanded on one another across the four evaluation topics. Table 16. provides a high-level summary of the integration and how the quantitative and qualitative findings were merged and interpreted to address the study's evaluation questions.

Table 16. High-level summary of the integration of quantitative and qualitative findings, in relation to the evaluation question topics. Note: for some evaluation topics, the same quantitative metrics were relevant and merged with the relevant themes with emphasis on different insights.

Evaluation Topic / Question	***Effectiveness in Achieving Intended Objectives****: Did the ASAPP project achieve its intended objectives to improve data standardization and identify complex patients in primary care EMRs?*	***Value:*** *What was the perceived value of the project?*	***Adoption Facilitators and Barriers:*** *What were the facilitators and barriers of adoption?*	***Future Recommendations:*** *What recommendations can be made for future improvements for ASAPP or other PHM projects?*
Quantitative metric(s)*	Bot metrics Identification of complex patients' metrics	Neighbourhood-level SDOH metrics Reach metrics	Adoption metrics	*All metrics (not directly related)*
Qualitative data/ theme(s)	Theme 2: Effectiveness and limitations Subtheme 1.3: Data quality	Theme 1: Perceived value and unrealized potential in PHM	Theme 3: Barriers and Facilitators of Adoption, Theme 2.4: Usability and customization of complexity data	Theme 4: Recommendations
Integration Summary	Confirmation and Expansion: Qualitative data expanded on the effectiveness/limitations of the achieved objectives reflected by metrics.	Confirmation and expansion: Qualitative data aligned with and elaborated on the potential value implied by the quantitative metrics.	Expansion: Qualitative data identified barriers and facilitators that influenced the quantitative metrics on adoption.	Expansion: Qualitative data outlined targeted recommendations to support future adoption or scaling of ASAPP or other similar PHM digital initiatives, aligned with quantitative metrics.
Interpretation summary	Coding for improved data standardization and identification of complex patients were achieved but were limited by constraints in the EMR data and by tool design limitations.	ASAPP's perceived value was in PHM, and it was not fully realized due to insufficient support to action on complex patient data and barriers to adoption preventing full and broad adoption of all project components.	The facilitators and barriers for adoption may have contributed to the low and selective adoption of the ASAPP project components across the engaged sites and OHTs.	Specific strategies to address barriers or facilitators to adoption and effectiveness or limitations of the project were generated and may support with broader adoption, scaling, and realizing value.

**Metrics are presented in general in this table. For details on each metric, review the interpretation text, or the Quantitative Results section.*

Effectiveness in Achieving Intended Objectives

Quantitative Findings. *Data standardization:* The Cody bot newly coded 2,121 conditions, achieving an average increase of 24.3% of coded conditions per clinician. However, the bot's coding varied greatly across clinicians and sites as one site only saw a 1.3% increase in coding by the bot, while another saw an 863.8% increase. The Cody bot also had varying coding rates across the 18 different medical conditions, with it coding atrial fibrillation at the highest rate of 81.5% (for 108 charts reviewed), and obesity at the lowest rate of 3.9%, despite the bot reviewing the most charts for this condition (3,589). There were no clear metrics to describe what caused the difference in coding across the conditions for Cody. *Identification of complex patients:* The predictive algorithm identified 1,790 unique complex patients from 34,710 patients reviewed (average of 69 or 5.2% per clinician), where 1,662 patients were identified by the medically complex algorithm, 132 by the hospitalization criteria, and 2 patients were identified to meet both criteria. Notably, there was variation and inconsistencies in the percent of complex patients identified across the adopter sites, ranging from 3.0% at one site to 13.5% at another. On average, only 0.1% of patients that met the medically complex criteria also met the hospitalization criteria, with variation across sites, where the highest percent of medically complex patients that had been hospitalized at a site was 17.0%. Finally, 220 patients (0.5%) were identified to be living in high SDOH complex areas.

Qualitative Findings. *Data standardization:* Participants recognized the Cody bot's potential to enhance data quality in EMRs (subtheme 1.3), but they also noted that the bot needed improvements (subtheme 2.2) and the solution design itself may not be an effective way of improving data quality as it was not integrated in the system and took a reactive and inefficient approach to addressing data quality (subtheme 2.3). *Identification of complex patients:* Participants highlighted that although the predictive algorithms identified complex patients, they were restricted (subtheme 2.1, 2.2) by the limitations of the data in the EMR, which may be incomplete, unstructured, missing psychosocial data contributing to complexity, and does not contain data on unattached patients who could be the most vulnerable or complex. They also noted that the algorithms were reliant on a narrow set of coded conditions, overlooked patient-specific nuances, such as condition severity or reasons for hospitalizations, and were constrained by limitations of the Cody bot that only coded 18 of the target 45 conditions. In addition, there were unexpected patterns in the data, related to patient hospitalizations and the SDOH complexity scores, causing uncertainty on data accuracy, impacting perceptions of ASAPP data effectiveness. On the other hand, participants shared that the usability and customization of the dashboard of complex patients provided within ASAPP enabled them to better identify priority complex patients in their OHT based on their needs (subtheme 2.4).

Integration. The qualitative findings confirmed and expanded on the quantitative metrics. While coding improvements and patient identification metrics demonstrated that project objectives were achieved, their variations and inconsistencies across sites and the qualitative findings revealed limitations of the RPA and predictive algorithms, including systemic design errors, relying on incomplete data in the EMR, capturing a limited number of conditions, and missing nuances in complexity. Despite these challenges, the participants did mention that the presentation of the complex patient list was easy to use and customizable to support OHTs in better identifying complex patients based on their priorities. Although ASAPP did achieve its objectives, it could benefit from making improvements to the tools to address their limitations, more efficiently improve EMR data standardization, and better capture patient complexity.

Perceived Value

Quantitative Findings. Reach metrics demonstrated population engagement; ASAPP's different components were adopted for 26 physicians, and 34,710 patients. However, there was low or selective adoption, where only three of the four engaged OHTs adopted ASAPP across six sites, and only one site adopted all four ASAPP components, while others selectively adopted fewer components. Moreover, only four sites adopted the Cody bot fully across 18 conditions, and one site adopted it only for eight conditions. In terms of coding, the Cody bot was run for 6,871 unique patient charts, achieving an average increase of 24.3% in coded conditions. 1,790 complex patients (4.9% of total patients reviewed) were identified, and 220 patients (0.5%) were identified to be living in high SDOH complex areas. Finally, there was a lack of impact metrics given that the project was just adopted at the time, and metrics measuring what, if any, care coordination, or preventative interventions or steps were taken after the bot and predictive algorithms were run.

Qualitative Findings. Participants expressed that by equipping healthcare professionals with data about their complex patients, ASAPP could support PHM through resource allocation, CDM, data quality, and with SDOH data integration in primary care EMRs (theme 1). They noted that the identification of complex patients, if acted upon, could support care coordination and directing resources to support proactive care, thereby aiding in reducing complications and hospital admissions. Moreover, participants mentioned that the Cody bot could improve data quality to enable better patient identification and segmentation capabilities in the EMR and support data sharing across systems. Although individual level SDOH data would be more beneficial, neighbourhood level SDOH data could provide help understand patient needs and prioritize individuals for detailed SDOH data collection. Despite the identified potential, participants expressed that much of its value was not fully realized largely due to barriers to adoption and resource constrains making the data unactionable. Some participants noted that the value of the project would be realized in the long term and be seen at a system-level rather than at a clinician level, not benefiting clinicians directly at the point of care with their patients.

Integration. The qualitative findings confirmed and expanded on the quantitative metrics. The reach, coding, and patient identification metrics highlighted ASAPP's potential value in PHM and participants' insights elaborated on the potential and how it could be achieved through resource allocation, CDM, data quality, and SDOH data integration. In addition, the low and selective adoption data aligned with the participant feedback on unrealized value due to barriers of adoption and resource constraints against taking action on the data. Thus, the findings suggested that ASAPP's perceived value was in PHM, and it was not fully realized due to insufficient support to action on patient complexity data and barriers to adoption, including clinician perception that its value would be seen more at the system-level, not at the clinician-level, and in the long-term.

Adoption Barriers and Facilitators

Quantitative Findings. There was low uptake and selective adoption for ASAPP. Of the four OHTs that were engaged in the project, one OHT did not adopt any project components due to barriers to adoption, and only one site in one OHT adopted all four components of the project. Moreover, one site within another OHT only adopted the predictive algorithm, which was the least intensive component, and did not adopt the Cody bot at all. In addition, one site using the Cody bot only adopted it for 8 of the 18 conditions it codes for.

Qualitative Findings. Participants revealed that several factors acted as barriers or facilitators for the adoption of the ASAPP project and its components (theme 3), including communication and collaboration, technological challenges and iterative troubleshooting, user perceptions and trust in technology, privacy and security concerns and related procedural delays, and competing priorities and resource constraints at the clinician and OHT level. Clinicians noted that an existing heavy workload and a lack of support or funding both hindered project adoption. For many clinicians improving data quality and PHM were low priorities, presenting only a "theoretical benefit", without any direct or immediate benefits to their patient care or clinical workflow. Notably, the participants who described adoption facilitators tended to adopt more ASAPP project components, while those who did not adopt many project components described several barriers to adoption, limiting potential value realization (subtheme 1.4). For example, one participant who adopted three of four project components described that their OHT had existing supports and systems that enabled them to action on the complex patient data from ASAPP, facilitating the project's adoption in their OHT.

Integration. The qualitative findings confirmed and expanded on the quantitative metrics, describing the barriers for adoption that may have played a role in the low uptake and adoption of the ASAPP project components across the engaged sites. Participants' insights on project communication, technological challenges, user perceptions and trust in technology, privacy concerns, competing priorities, and resource constraints at both the clinician and system levels aligned with the selective adoption observed. These findings highlight the need to address these barriers to support broader adoption.

Future Recommendations

Quantitative Findings: There were no direct quantitative findings related to future recommendations. However, the low and selective adoption metrics, where project components were not uniformly or broadly adopted, the coding variations, and the variation in the identification of complex patients across adopter sites, as summarized above, highlighted the need for targeted recommendations.

Qualitative Findings: Interviews revealed several recommendations for technology, and adopting and scaling ASAPP and other digital health initiatives (theme 4). Many of these recommendations directly addressed the effectiveness or limitations of the project (theme 2), and barriers and facilitators to adoption (theme 3) previously discussed. Recommendations emphasized early collaboration with OHTs and users to ensure the project integrates with their existing workflows and systems, privacy and security compliance assurances, adequate resources, funding, stagging, or supports for adoption, iterative development of technology, tool enhancements to optimize capabilities and accuracy of identifying complex patients, conducting evaluations to inform future iterations, and demonstrating maturity and value to support project scaling.

Integration: The qualitative findings outlined targeted recommendations to support future adoption or scaling of ASAPP or other similar PHM digital initiatives, aligned with quantitative adoption and performance metrics. They described specific strategies to address barriers for adoption and limitations of the project.

Discussion

Project Overview

Proactive management and care coordination for complex patients, particularly those with increased risk for more frequent and hospitalizations and ED visits, is critical to support patient outcomes and alleviate strain on the healthcare system.[7,42] The ASAPP project used a combination of RPA (Cody bot) and predictive algorithms in primary care EMRs, alongside neighbourhood-level SDOH data to identify these complex patients, to support their care management and reduce their risk for hospitalizations. This summative evaluation revealed that although ASAPP achieved its objectives in improving data standardization and identifying complex patients, there were several technological limitations and adoption barriers that hindered the project from fulfilling its potential to support PHM. Alongside the barriers, stakeholders described facilitators of adoption and shared strategic recommendations for future iterations and for the scaling of ASAPP or similar digital PHM projects.

Unrealized Potential Value in PHM

Although not fully realized, the interviews revealed that the data on complex patients provided to healthcare professionals by ASAPP had the potential to support PHM. This aligns with literature suggesting that predictive algorithms and digital tools can enhance the care coordination and PHM of complex patients, leading to improved quality of care, outcomes, and reduced associated costs to the healthcare system.[7,21,43] Furthermore, as ASAPP stakeholders highlighted, automating the process of flagging complex patients at risk of hospitalization allows healthcare professionals to allocate resources more efficiently and focus on patients who would benefit most from proactive and preventative care.[43] In addition, ASAPP leveraged real-time EMR data as opposed to static data repositories that do not update patient information regularly, which could enable more timely and accurate identification of complex patients.[44] Many complex patients tend to have poor adherence to their treatments and low attendance for their primary care appointments, and directing resources more effectively to them may also help reduce clinician income loss caused by frequent missed appointments.[21] Given that manually reviewing each patient chart to identify complex patients is time-consuming and impractical for widespread adoption, tools like ASAPP may offer a practical solution for complex patient management. This approach warrants further study to fully realize its potential and better integration with clinical workflows to support meaningful uptake in primary care.

Stakeholders emphasized the need for better systems and infrastructure to help clinicians act on the complex patient data to unlock ASAPP's value for PHM. Unlike ASAPP's complex patient data, which was displayed outside the EMR in a separate dashboard, one study, in an acute care setting, developed a predictive model to identify patients at risk of hospital readmission, and embedded these risk assessments directly into the EMR and clinical workflows.[44] This integration allowed clinicians to easily view and act on the risk indicators during a patient visit and in their clinical workflows, improving usability of the data.[44] Although conducted in acute care, the study demonstrates the potential value of embedding similar "complexity flags"—indicators of patient complexity—directly within primary care EMRs to facilitate real-time actions by clinicians.[44] Unlike ASAPP's external dashboard, which exists outside clinician workflows, this embedded approach of integrating complexity flags into primary care EMRs could ensure the information is more accessible to clinicians during routine care, supporting proactive care, and may be represent a future direction for similar PHM initiatives.

Several prediction models have been developed to identify complex patients or patients at risk of hospitalizations in both primary care and acute care settings, that demonstrate the importance of population identification and segmentation for enhanced PHM, in line with the findings of this study.[45–49] However, like ASAPP, the practical value of these tools is often limited by clinician capacity and available resources needed to facilitate action or support intervention for the identified patients.[45,50] In addition, predictive models and algorithms like those used in ASAPP, often do not account for the 'perceived impactability' — whether the identified complex patients would benefit from additional proactive or preventative care.[45,51] For example, a complex patient may be at risk for hospitalization but their care may already be well managed or alternatively, the deterioration of their condition may not be preventable.[45,51] Flaks-Manov et al. found that about two thirds of patients that were identified as high risk for hospitalization were also perceived as 'impactible', suggesting that the 1,790 patients identified by ASAPP may not all fall in this actionable category.[45] This highlights a key insight from this evaluation: predictive tools must not only identify patients at risk but also help prioritize patients most likely to benefit from intervention. Without a mechanism to distinguish impactable patients or guide referral pathways, the clinical utility of these tools is limited, even if their predictive performance is strong. Flaks-Manov et al.'s study also involved specific readmission prevention programs that patients that could be referred to, enabling a pathway for the identified patients to gain proactive or preventative care.[45] In contrast, ASAPP lacked designated pathways and relied on OHTs or clinicians to operationalize follow-up care, resulting in the data remaining largely unacted upon. Only one ASAPP stakeholder reported their OHT having a designated clinical team in place to support follow-up for the identified complex patients, while others described the absence of systems as burdensome and prevented them from being able to action on the complex patient data. This aligns with the findings from prior literature on PCP perspectives on caring for complex patients.[6] PCPs reported facing barriers when caring for complex patients including insufficient support or resources, complexity of the care of the patients themselves, lack of training in managing certain complex conditions, high workload, and clinical burnout.[6] These factors highlight the importance of developing predictive tools not only based on technical capacity but also based on the PCP perspective and clinician realities. In line with the findings of this evaluation, the value of predictive PHM tools like ASAPP lies not simply in identifying complex patients but also in ensuring the identified patients are 'impactible' and the necessary infrastructure, pathways, and resources exist to translate data into meaningful care interventions and preventative care, supporting PHM.

Integration of SDOH Data in Primary Care

The ASAPP project also considered social complexity by integrating neighbourhood level SDOH with primary care EMR data. Stakeholders expressed the value of considering SDOH for complexity prediction to support PHM. However, one systematic review that studied the impact of the integration of SDOH in EMRs on risk prediction models found that integrating individual-level SDOH into EMRs led to enhanced prediction of risk for poor outcomes including risk for hospitalization compared to geographical SDOH.[15] This aligns with the hesitation from ASAPP stakeholders expressed in relying on neighbourhood-level SDOH data to inform individualized care. However, another study, that refers to neighbourhood-level SDOH data as ‘community vital signs’, suggests that its impact may be limited because of the need for more research and best practices on how to leverage this data at an individual patient level, better integrate it into clinical workflows for data utility, and identification of which neighbourhood-level SDOH data elements best predict complexity or health outcomes.[17] Moreover, clinicians currently do not have training or education on how to use SDOH data for clinical decision making or PHM, which may have influenced the concern and hesitation from ASAPP stakeholders in integrating the neighbourhood-level SDOH data directly into their EMRs through the ASAPP bot.[17,52] Clinicians could apply ASAPP’s framework in practice by using it to prioritize patients for targeted individual-level SDOH data collection, streamlining data capture to address social risk factors. Future iterations of ASAPP or similar PHM projects could explore expanding SDOH data integration, as individualized SDOH data could enhance patient segmentation and care personalization in clinical settings.

Limitations of Technologies

Interviews also revealed several limitations with ASAPP's technologies impacting their effectiveness in identifying complex patients. Stakeholders consistently noted that the predictive algorithms lacked accuracy as they did not account for nuances such as disease severity and psychosocial factors, which may be missing or inconsistently captured in the EMR. This concern aligns with studies outlining that PCPs define patient complexity using more than the number of comorbidities a patient has; instead, they consider psychosocial issues and individualized measures of disease severity.[21,46] Their findings revealed that there was a difference between the complex patients identified by traditional comorbidity scales or complexity algorithms, like the ASAPP algorithm, which did not adequately capture these considerations, compared to those identified by PCPs.[46] In fact, a model developed by physicians was found to be more effective in predicting patients at risk of future ED visits compared to other predictive models for complexity, illustrating the importance of contextual clinical insight.[21] Although limited, literature demonstrates that considering outpatient utilization data and psychosocial factors such as poor adherence to treatment, poverty, lack of insurance, low attendance to primary care appointments, and living in lower socioeconomic neighbourhoods can improve complexity predictive algorithms.[21,46,53–55] ASAPP did provide information on the neighbourhood level SDOH complexity levels of the identified complex patients, but this was not directly included into the predictive algorithms, and it was up to the clinicians how they wanted to consider the information. As such, the potential influence of SDOH data on complexity identification was left underutilized.

Another gap with the ASAPP project was the absence of a formal clinical validation step; studies suggest that a clinical validation process may be critical in accurately identifying complex patients for PCPs to support their proactive care, even though clinician assessment for complexity can be subjective.[46,56] While clinicians contributed to the ASAPP predictive algorithm development, there was no explicit or structured process for clinicians to refine or validate the list of identified complex patients, which may have contributed to the feelings of uncertainty and skepticism among the stakeholders for ASAPP outputs. In addition, they suggest that ASAPP's current predictive algorithms may not fully align with the real-world needs of PCPs for accurate identification of complex patients, leading to underutilization of ASAPP for proactive care. The variation and inconsistencies in the identified complex patients across ASAPP adopter sites may also be partially attributed to the lack of post-algorithm validation, low accuracy of the predictive algorithm, compounded by differences in EMR data completeness, patient demographics, and PCP experience levels, as PCPs with more experience tend to have the most complex patients.[46,56]

Notably, stakeholders also raised concerns about structural exclusion: individuals who do not have a regular PCP or are "unattached" from the primary care system may not be captured by ASAPP.[57] Because the ASAPP tools entirely rely on data available in primary care EMRs, these individuals may not be in the system and may be missed despite being among the most vulnerable. This limitation has significant implications on health equity, suggesting that PHM efforts must intentionally design strategies to identify and support unattached populations in the planning stages. Doing so would be essential in addressing systemic inequities and ensuring PHM efforts do not exacerbate existing disparities.

Moreover, given ASAPP's limited reach and adoption, more research is needed to draw definitive conclusions and better understand the best way to identify complex patients and support their care coordination. One study conducted a review and found that there were 90 unique complex population definitions and criteria used for stratification, segmentation, and targeting complex patients, demonstrating the ambiguity and variation in the process and the need for further studies to evaluate and determine best practices in complexity predictive models.[48] Overall, although ASAPP's tools represent a meaningful step forward toward automating complexity identification in primary care, the limitations outlined above reveal opportunities for refinement. A hybrid model that integrates structured EMR data with outpatient utilization, SDOH indicators, disease severity considerations, and clinician validation may offer a more robust and actionable approach for future iterations or similar PHM projects.

Barriers and Facilitators of Adoption

To realize the value of digital tools like ASAPP, it is essential to consider not only their technical effectiveness but the conditions that support or hinder their adoption in real-world clinical settings. This evaluation revealed several barriers to ASAPP's adoption, including competing priorities, resource constraints, limited capacity to act on the data, user perceived lack of value or trust, privacy concerns, and procedural delays. Facilitators included effective communication and stakeholder engagement during development, user trust in technology, and alignment with broader PHM or OHT-level goals. These findings are consistent by broader literature on eHealth adoption; for example, the issue of resource constraints and competing priorities observed by ASAPP stakeholders is confirmed by Schreiweis et al., in their systematic literature analysis of 38 articles and expert opinion analysis.[58] They found that lack of necessary devices, problems with financing, and workload were of the most frequently cited barriers to adoption of ehealth tools.[58] Similarly, Granja et al., in a systematic review of 221 studies, found that added financial burden, workload and workflow disruption were common barriers to adoption, emphasizing that clinicians valued tools that create time for them to provide care, rather than add to their burden.[59] The lack of perceived value reported by ASAPP stakeholders aligns with literature citing unclear benefits to clinical care as a common barrier to adoption.[58] Granja at al. further outlined that "quality of healthcare" was one of the greatest contributing factors to the success of eHealth tools, implying that when healthcare professionals do not see clear benefits for their patients or their own workflows, and the tool does not demonstratively improve diagnoses, communication, or patient care, adoption is less likely.[59] Conversely, if tools are perceived as beneficial, they are more likely to be embraced by users in healthcare and more likely to be integrated into practice.[59] Notably, some frequently cited barriers in the literature, such as poor digital literacy or general resistance to change did not prominently emerge in this evaluation.[58,59] This may be because the ASAPP stakeholders were primarily clinician champions, digital health leads, or clinicians with an interest in digital tools, and were already predisposed toward adopting new technologies.

Although this evaluation identified fewer facilitators than barriers, the facilitators that did emerge— such as stakeholder engagement, communication, and alignment with broader system goals— were consistent with those reported in the literature.[58,59] This imbalance may reflect the early-stage of ASAPP adoption, where adoption barriers were more immediately visible to stakeholders and potential benefits from the project would likely not be immediate or patient-specific but rather would be seen over time at the system-level, as revealed in the findings. Furthermore, ASAPP, as a PHM tool, may have been better suited for care coordinators or PHM teams rather than PCPs focused on direct patient care and already overextended in their priorities in primary care. McGough et al. emphasize that it is unrealistic and unsustainable to expect individual PCPs to manage both direct patient care and population health responsibilities as current demands of preventative care exceed capacity of individual PCPs, advocating for team-based approaches and distributing PHM responsibilities across multidisciplinary team to enable more coordinated, comprehensive, and scalable care delivery.[60] These findings reinforce that digital health adoption is as much a social and organizational challenge as a technological one, and without addressing these challenges, even highly accurate tools may remain underused.

Broader Implications for ASAPP and the Digital PHM Landscape

There is a lack of evaluative studies on digital PHM initiatives for complex patients, particularly in primary care, limiting understanding of best practices for their design, development, and adoption. This study thus contributes to the growing body of knowledge seeking to understand and enhance the value, effectiveness, and adoption of PHM projects with similar objectives to enhance how digital tools can support complex patient identification, care coordination, and proactive management in primary care.

There are several widely used risk stratification and predictive models and PHM initiatives designed to identify complex patients at a system and planning level; these models typically rely on hospitalization and administrative data from a variety of sources to predict future healthcare use and cost, providing insights for health system design, resource allocation, and supporting PHM efforts at a system level rather than at the point of care.[61,62] Given the existence of these models, there may have been an opportunity for ASAPP to leverage an existing framework to identify complex patients rather than develop a standalone predictive tool from the ground up. This could have facilitated integration with broader PHM strategies and improved accuracy of the patient identification. Furthermore, most of the similar projects to ASAPP in the literature that aim to go beyond identification to support care coordination are positioned in acute care or hospital settings, where centralized data and measurable short-term outcomes, such as re-admission, make predictive capabilities more straightforward; few initiatives have been specifically designed for identifying and managing complex patients at risk of hospitalizations in primary care or community settings.[44,45,49] A comparable project to ASAPP was the Ontario Health Links project which aimed to improve care coordination for identified complex patients by “linking” them to a designated care coordinator or interdisciplinary care team to connect services and a personalized coordinated care plan (CCP).[63] For patient identification, the Health Links project relied on a combination of processes and tools including the LACE index, which is a widely used tool to predict risk of hospital readmission or death, hospital utilization data, clinician referrals, and manual flagging, in contrast to ASAPP which relied solely on primary care EMR data and automated extraction.[63] While Health Links emphasized individual care planning and cross-sector collaboration, it lacked the technical infrastructure, automation capabilities, and data-driven capabilities that ASAPP introduced.[63] However, Health Links had infrastructure, pathways, and resources in place to support PHM efforts and act on the identified patients, unlike ASAPP that focused on the first step of patient identification and did not have embedded follow-up systems.[63] While the Health Links project was ultimately phased out and integrated into broader OHT plans, due to inconsistent system-level outcomes, failure to meet cost control expectations, and limited scalability and digital integration, it highlighted the importance of interdisciplinary collaboration, care planning, and embedding coordination infrastructure.[63] Thus, for PHM projects like ASAPP, this reinforces that accurate patient identification alone is insufficient; predictive tools should be paired with tangible follow-up pathways, infrastructure, and system level capacity to ensure that insights translate into meaningful impact.

Moreover, ASAPP and this evaluation could support improved development and adoption of complexity predictive models in primary care, and it may encourage the exploration of the use of RPA technology to better leverage EMR data for PHM efforts. There is also limited literature on similar PHM projects that seek to integrate neighbourhood level SDOH factors into the identification of complex patients. Although ASAPP did not directly include SDOH factors into its predictive algorithms, it will add to the literature of how these neighbourhood level SDOH factors may add value in identifying complex patients. The ASAPP project laid the foundation for PHM projects to further explore connections between primary care data and future acute care usage and improve the performance of the Cody bot. The project's successes and limitations offer valuable insights into the complexities of adopting digital health interventions in real-world settings, contributing to the ongoing work to understand how best to leverage technology to improve care and patient outcomes.

Recommendations

Through this evaluation, several recommendations to improve the design and adoption of future iterations of ASAPP and other similar PHM initiatives have emerged, highlighting the importance of a collaborative, iterative, and user-centric approach that aligns with the clinical, contextual, and organizational realities of primary care. First, the value proposition for all target users should be clearly articulated, alongside how the project plans to enhance patient care and clinical workflows, aligning with prior literature that emphasizes that improving quality of care can be the greatest success factor for adoption of digital tools.[54] These priorities also align with the quintuple aim, which digital tools like ASAPP are often designed to support, emphasizing improving patient experience, provider well-being, population health, cost efficiency, and health equity. As such, it is recommended to ensure the initiative's goals and design aligns with the current clinical and operational priorities, ensuring its perceived value is evident from the outset. To do this, as per the stakeholder's feedback in this evaluation, a co-design design thinking approach is recommended to ensure the initiative can be tailored to a clearly defined local need and to facilitate better understanding of and integration with clinical workflows and organizational structures in the site and OHT. With this iterative and user-centric approach, stakeholders like clinicians and system-level users can be involved throughout the entire development cycle, not just as advisors, but as active participants in shaping the solution. Furthermore, as outlined in this evaluation, ongoing feedback loops should be built in to iteratively refine the solution, increase its usability, and embed it more meaningfully into practice. Moreover, to guide future evaluations, theoretical frameworks designed to assess and identify factors influencing the successes and failures of digital health projects should be leveraged. For example, the Non-adoption, Abandonment, Scale-up, Spread, Sustainability framework can be utilized to identify challenges and facilitators associated with the technology itself, the perceived value proposition for different stakeholders, adopter readiness, and organizational or broader system-level influences, including sociocultural or policy factors.[64] Applying these frameworks can support a more structured and holistic approach towards evaluation and ensure both user and system-level factors are sufficiently considered and comprehensive recommendations can be generated.

When it comes to adoption, a structured framework should be used to support with planning and help ensure known barriers are anticipated and addressed,. For example, the Technology Acceptance Model and Diffusion of Innovations Theory can be used to understand how the project would be perceived and adopted across different stakeholder groups; they would also offer structured guidance on how to improve usefulness, ease of use, and the likelihood of sustained adoption.[65,66] Leveraging established frameworks will enable an evidence-based and systematic approach for adoption.

Moreover, to support meaningful action on and use of patient identification data, tools should be embedded directly into existing workflows. For example, complexity flags or tools should be embedded within the EMR or clinical environment, rather than outside of the EMR, for easy access for clinicians at point of care. In addition, automated patient outreach or referral to appropriate care pathways or services can help ensure proactive follow-up for the identified patients without creating additional workload for the clinicians. These pathways should be co-defined with the OHT or site to align with their priorities such as mental health or frailty. Where there are existing resources and care coordination teams in place, identified complex patients could be referred to those teams to support proactive management and to ensure value for both clinicians and health system and enable actionality in the initiative. When possible, funding and human resources to provide follow-up proactive care should be advocated for. Given the early-stage nature of initiatives like ASAPP, and resource constraints, it is recommended to pilot and refine the tool within one OHT before attempting to scale it across regions or multiple OHTs.

If feasible, when taking a partnership approach at the system level, other relevant organizations can also be engaged to support care coordination and identification; for example, unattached complex patients could be identified with the support of ED referrals, as previously leveraged in the Ontario Health Links initiative. Finally, as teams gain an understanding of the organizational realities by engaging closely with the clinicians and OHTs, a market and landscape analysis should be conducted to identify similar, competing, or complimentary existing tools and models. This will enable the initiative to build on prior learnings, and ensure the tools complement rather than complete with existing efforts already in use at the site or region.

Moreover, to improve the accuracy of ASAPP's predictive algorithm for identifying complex patients, future iterations or similar projects should consider incorporating hospitalization data where feasible or leverage existing risk stratification frameworks that are well established and widely used. A structured validation process should also be implemented, using clinical review or supplemental data sources to refine the identified patient lists. Additionally, prioritization based on impactability should be built into the tool, where scoring mechanisms can support clinicians or care coordinators identify which complex patients are most likely to benefit from proactive care or available follow-up pathways.

Furthermore, the use of neighbourhood-level SDOH data could be piloted as a tool to help prioritize individuals for targeted collection of individual-level SDOH information. This data could then be used to update their social complexity profiles and assess whether such integration improves care planning or outcomes. To support this, clinicians should be provided with training and clear clinical guidance on how to interpret and apply SDOH data within care planning workflows, ensuring it can be meaningfully used to inform decisions and prioritize care.

Limitations and Future Research Directions

The evaluation did have several limitations that may impact the applicability or transferability of the findings. First, the evaluation of the project included a small sample size of four key external participants, with limited diversity in their roles, only one non-clinician participant in OHT leadership, and all clinicians having active roles in their OHT. This sample size can limit the extent to which the findings can be applied to other primary care settings or organizational contexts, and may reduce the transferability of the insights to broader system-level, non-pilot adoption efforts. However, it is important to note that even with a small sample, the participants provided rich insights based on their experience in primary care and involvement in the project. Given that this was a pilot project, and participants were early adopters or advisors, their perspectives reflect frontline adoption insights and lessons learned that are particularly valuable for informing any future iterations of ASAPP or similar PHM projects. Still, future evaluations should aim to include a boarder and more diverse group of participants, including additional OHT leadership and system-level voices to better capture the full range of adoption conditions and contextual variations across primary care settings. Expanding the sample can strengthen the applicability of the findings to a wider range of care models and enhance the transferability of lessons to other digital health initiatives. Furthermore, considering that PCPs and OHT or system-level leads have limited time, high clinical demands, and competing responsibilities, the engagement of the small sample size in the ASAPP evaluation was still valuable. This limitation alongside the fact that multiple recruitment efforts were employed, including outreach through different contacts, email invites, and follow-up reminders, the sample size remained small, highlights a broader challenge in digital health research. This highlights the need for further exploration on effective strategies to improve recruitment and sustained engagement with PCPs and health system leaders, especially in the context of early-stage adoption of pilot digital health projects.

With only six sites participating, and four participants, the ability to compare clinical and geographical contexts was restricted. While one PCP was located at a rural OHT, the small sample size and distribution of sites did not support a focused or systematic analysis of the role of geographical location may have influenced adoption or the effectiveness of the predictive algorithms in ASAPP to identify complex patients. Future evaluations should consider explicitly examining the influence of geography—such as rural versus urban settings, regional infrastructure, and access to digital supports—on the adoption and impact of PHM tools to inform context-sensitive implementation strategies.

Similarly, due to the barriers in the project itself, associated with privacy and security, only some sites implemented the Cody bot while some sites chose not to participate in the SDOH complexity analysis. This variation limited the evaluation’s ability to assess the full user experience, particularly in sites that did not have the full range of features or outputs, potentially underestimating the potential value of the ASAPP data. Moreover, the evaluation was also limited by its short timeline, as it did not follow sites longitudinally to assess how adoption patterns or perceived value may have evolved over time. In addition, this evaluation for the ASAPP project was designed to identify the perceived value, effectiveness, facilitators and barriers of adoption, and recommendations for future iterations or similar PHM projects. As a result, we were unable to assess ASAPP's impact or how the data generated by ASAPP influenced clinical decision-making, care coordination, or patient outcomes. Without follow-up on how clinicians or care teams acted upon the identified complex patient lists, the long-term effectiveness and impact of ASAPP remains unknown. Future evaluations on ASAPP could focus on outcome assessment, examining the clinical or operational impact of ASAPP use. Similar digital PHM projects should thus also embed plans for outcome measurement into their design from the outset. This assessment could include measuring the frequency of interactions or interventions provided to the identified complex patients and assessing if these actions resulted in enhanced care, patient experience, or reduced acute care usage. In addition, gathering direct feedback from patients, alongside clinicians, could provide insights into how the interventions influenced care delivery and quality, and overall patient outcomes. This evaluation could provide more insight into the value of the project.

Conclusion

The ASAPP project demonstrates the promise, complexity, and challenges of adopting digital PHM tools in primary care. By leveraging automation and predictive algorithms, ASAPP aimed to improve patient identification, data standardization, and proactive care coordination through automation and predictive analytics. While the project met its technical objectives and successfully identified complex patients and improved data quality, limitations in the technology, barriers to adoption, including resource constraints and limited follow-up infrastructure, prevented full realization of its potential and intended value to support PHM. This evaluation highlights an important insight that there can be a discrepancy between what an innovative digital health solution is designed to achieve in theory and the actual value it delivers in practice. For digital tools to meaningfully enhance PHM and patient outcomes, they must not just generate data on priority patients but also enable action within the clinical and organizational realities. This requires designing tools to integrate into existing systems, accounting for clinical and organizational structures and workflows. It is essential to clearly define the value proposition for end-users, through a co-designed and iterative approach with early and sustained engagement with end-users such as clinicians and system leaders, to facilitate adoption and use. Stakeholder insights highlighted the importance of developing digital PHM initiatives in partnership with those who will use them to ensure they integrate within systems that support care coordination and targeted interventions. Moreover, it is essential that digital solutions are designed to anticipate and address adoption barriers to facilitate use and uptake, especially in primary care contexts where clinicians have competing priorities and are overworked. Data-driven digital PHM projects like ASAPPP may need to be positioned outside of primary care or require dedicated staff or teams and infrastructure to facilitate action on data on priority populations to support PHM efforts. The lessons from this evaluation offer guidance for future iterations of ASAPP and contribute to the broader conversation on how to design effective digital PHM projects that serve those who need them most. To support the development, adoption, and realization of the potential value of PHM initiatives like ASAPP, policymakers and system leaders should prioritize and advocate for sustained funding, incentive, and infrastructure, such as dedicated care coordination teams, to build capacity for more proactive and targeted care for complex patients in primary care. In addition, to prioritize health equity, policymakers should mandate the capturing of SDOH data in EMRs and fund system-level strategies that proactively connect underserved and unattached patients to care, ensuring reach the most vulnerable, not just those that are the easiest to identify with the currently available EMR data.

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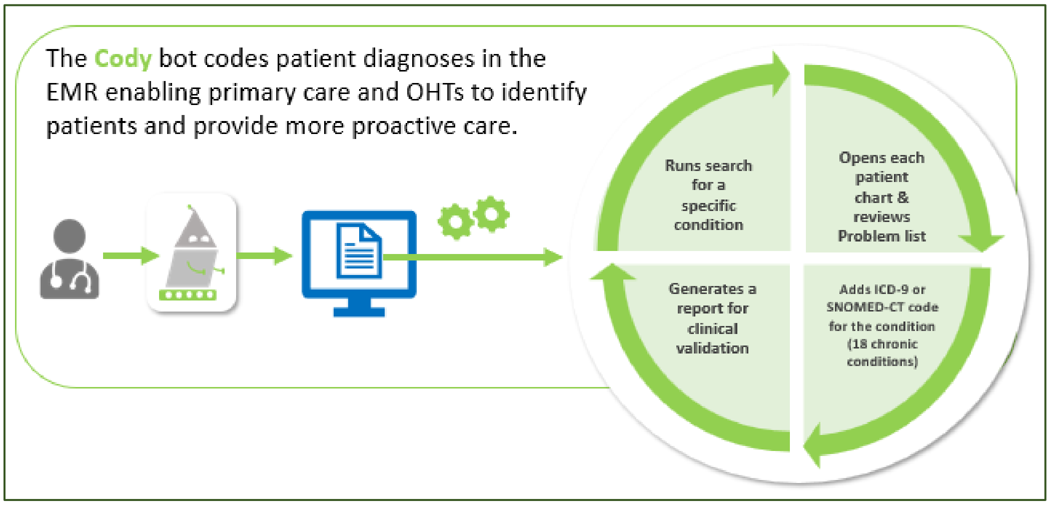
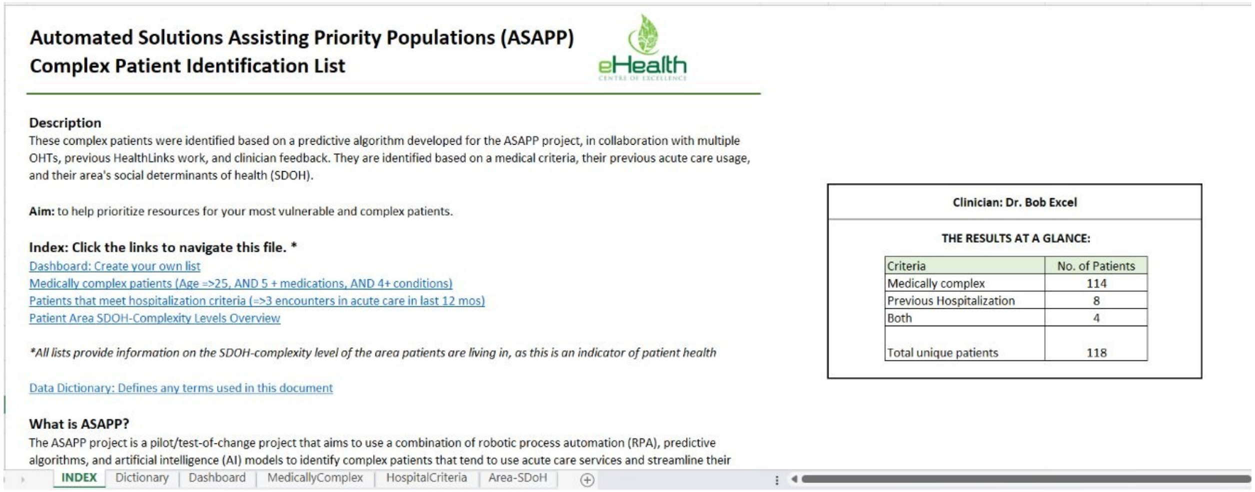
Appendices

Appendix A: Cody Bot Functionality



Cody bot functionality diagram. eCE permitted for use.

Appendix B: Complex Patient Dashboard Screenshot



Automated Solutions Assisting Priority Populations (ASAPP)
Complex Patient Identification List

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Description
These complex patients were identified based on a predictive algorithm developed for the ASAPP project, in collaboration with multiple OHTs, previous HealthLinks work, and clinician feedback. They are identified based on a medical criteria, their previous acute care usage, and their area's social determinants of health (SDOH).

Aim: to help prioritize resources for your most vulnerable and complex patients.

Index: Click the links to navigate this file. *
Dashboard: Create your own list
Medically complex patients (Age =>25, AND 5 + medications, AND 4+ conditions)
Patients that meet hospitalization criteria (=>3 encounters in acute care in last 12 mos)
Patient Area SDOH-Complexity Levels Overview

All lists provide information on the SDOH-complexity level of the area patients are living in, as this is an indicator of patient health

Data Dictionary: Defines any terms used in this document

What is ASAPP?
The ASAPP project is a pilot/test-of-change project that aims to use a combination of robotic process automation (RPA), predictive algorithms, and artificial intelligence (AI) models to identify complex patients that tend to use acute care services and streamline their

Clinician: Dr. Bob Excel

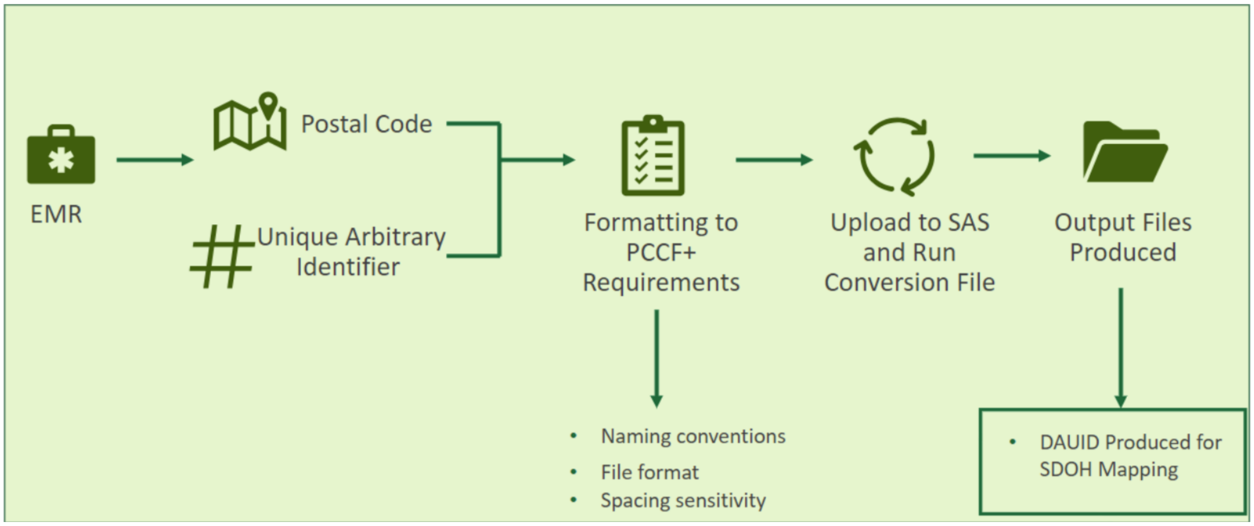
THE RESULTS AT A GLANCE:

Criteria	No. of Patients
Medically complex	114
Previous Hospitalization	8
Both	4
Total unique patients	118

INDEX | Dictionary | Dashboard | MedicallyComplex | HospitalCriteria | Area-SDoH

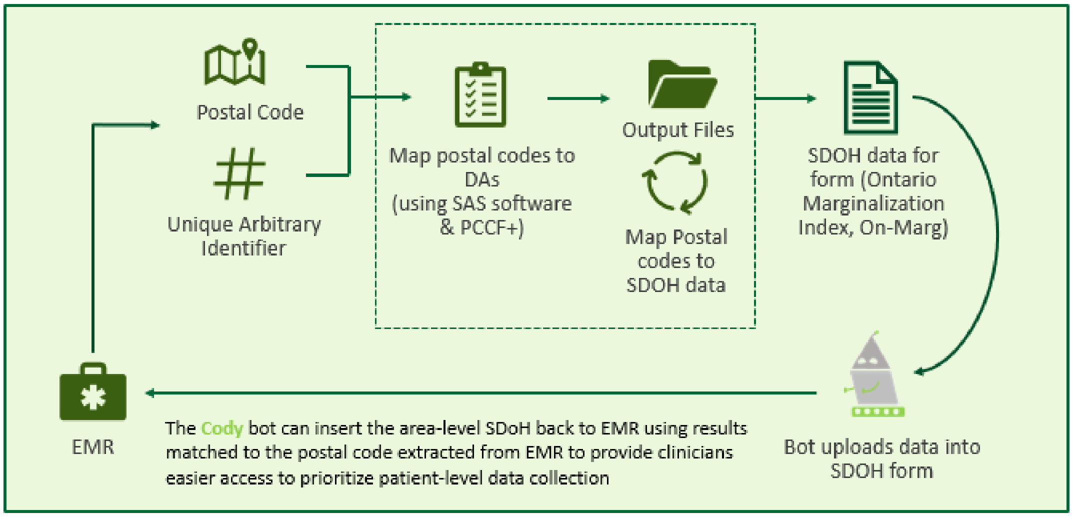
Complex patient dashboard screenshot. Note: arbitrary data is shown on the screenshot

Appendix C: Process to map patients to their neighbourhood level SDOH data

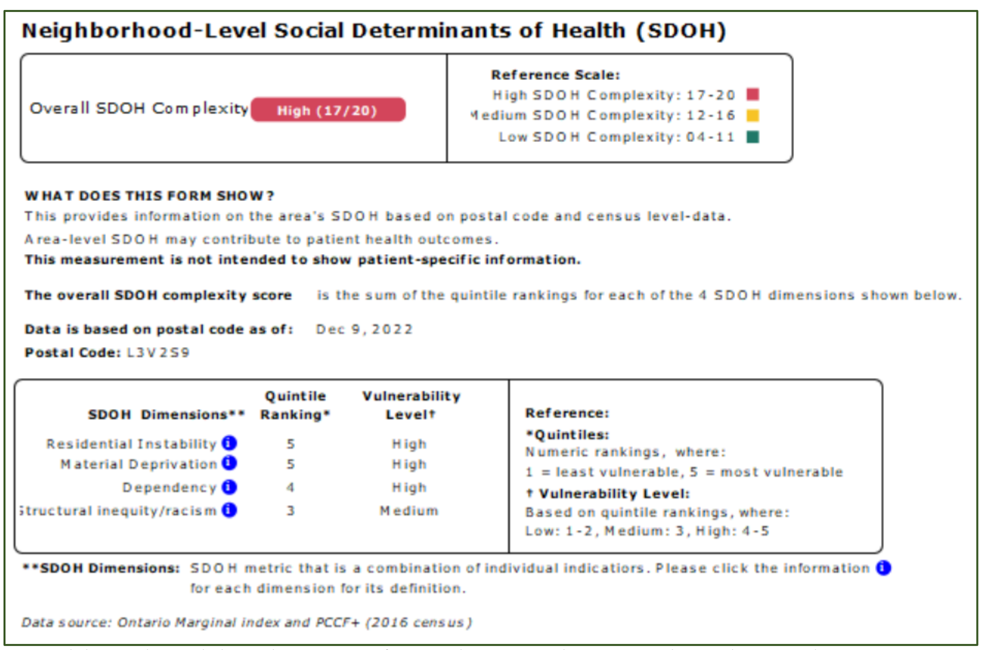


Process to map patients to their associated neighbourhood-level SDOH data. eCE permitted for use.

Appendix D: SDOH Bot Process to Integrate neighbourhood level SDOH data into the EMR



RPA process to introduce neighbourhood-level SDOH data into the EMR. eCE permitted for use.



Neighborhood-Level Social Determinants of Health (SDOH)

Overall SDOH Complexity High (17/20)	**Reference Scale:** High SDOH Complexity: 17-20 Medium SDOH Complexity: 12-16 Low SDOH Complexity: 04-11

WHAT DOES THIS FORM SHOW?
This provides information on the area's SDOH based on postal code and census level-data.
Area-level SDOH may contribute to patient health outcomes.
This measurement is not intended to show patient-specific information.

The overall SDOH complexity score is the sum of the quintile rankings for each of the 4 SDOH dimensions shown below.

Data is based on postal code as of: Dec 9, 2022
Postal Code: L3V 2S9

SDOH Dimensions**	Quintile Ranking*	Vulnerability Level†
Residential Instability	5	High
Material Deprivation	5	High
Dependency	4	High
Structural inequity/racism	3	Medium

Reference:
***Quintiles:**
Numeric rankings, where:
1 = least vulnerable, 5 = most vulnerable
† Vulnerability Level:
Based on quintile rankings, where:
Low: 1-2, Medium: 3, High: 4-5

****SDOH Dimensions:** SDOH metric that is a combination of individual indicators. Please click the information for each dimension for its definition.

Data source: Ontario Marginal index and PCCF+ (2016 census)

Neighbourhood-level SDOH form that can be introduced into the EMR. eCE permitted for use.

Appendix E: Email Invitation for Interview Recruitment

Subject: Request for follow up engagement for ASAPP project: [Clinician/OHT] Perspective

Hi [Stakeholder Name],

I hope you are well! Thank you for your ongoing support for Automated Solutions Assisting Priority Populations (ASAPP) project and thank you for your interest and willingness to share your thoughts for the evaluation of ASAPP. We are hoping to wrap up the project in the next 2 weeks and will follow up about this soon. As you are a clinician champion for ASAPP, you have been identified as a key informant that would provide valuable insights for the evaluation of ASAPP. We are hoping to connect with you in the form of a virtual interview to capture your individual perspective as a clinician.

The goal of these engagements is to gain an in-depth understanding of the perceptions of key stakeholders, regarding the different components of the ASAPP project, including the Cody bot and the predictive algorithm to identify complex patients, as well as the project implementation and value in your OHT. Your participation in this evaluation is important to identify strengths and areas for improvement in the ASAPP project and contribute to continuous quality improvement and help pave the way for future population segmentation projects. The engagements will be conducted by the eCE evaluation team and will be semi-structured. They will last approximately 60 minutes (time permitting) and will be conducted on a virtual platform suitable for all parties. We understand that your time is valuable, so we will work with your schedule to find a convenient time for the interview.

If possible, could you please let us know what days/times work best for you between XX – XX, 2023 for the interview to capture your individual perspective as a clinician? If you only have availability at a later date, please let us know and we are happy to adjust to what works best for you all.

Thank you for your time and consideration, and we look forward to hearing from you soon. If you need any information from us, please let us know.

Warmly,

Zainib Nazir

MSc. eHealth Intern Analyst

eHealth Centre of Excellence

[phone number]

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Act. If you receive this transmission in error, please notify me immediately at the telephone number listed above, and do not print, copy, distribute or disclose it further. Thank you for your co-operation and assistance.

Appendix F: Interview Guide

ASAPP Evaluation

Key External Partner Informant Engagement Guide & Script

The interviews will be conducted virtually, on Teams. Using Teams, we can create a live transcript which alongside the audio recording of the interview will serve as a record of the conversation and remove the need to take detailed notes. It's good practice to inform the interviewee of the purpose of the interview as well as the purpose of the interview being recorded.

In addition, a PowerPoint slide deck will be shared, containing the consent statement and the interview questions. The aim of this is to help ground the conversation back to the main questions and evaluation goals to allow the respondents to re-read the question, while contributing positively to accessibility.

Preamble

Thank you for agreeing to take part in this interview. The goal of this interview is to gain an in-depth understanding of the perceptions of key stakeholders in the ASAPP project regarding the Cody bot and the predictive algorithm to identify complex patients at risk for hospitalizations, with the broader goal to evaluate the overall effectiveness of the implementation of the ASAPP project in the involved Ontario Health Teams (OHT). The information gathered will inform the project components, including the Cody bot, integration of area-level social determinants of health data into the EMR, and the predictive algorithm to support future enhancements to the ASAPP work to better meet the needs of the target audience/OHTs.

There are no good or bad answers. We're interested in your opinion and experiences. We have prepared a few questions for this interview, but I may address other issues to get a better understanding of the comments you share.

I will share my screen with a slide deck now. It will highlight what we will talk about. Once we start the interview, each question will be shown on a slide, and I will read them out loud.

Before we begin this interview, I want to remind you that your identity will be kept confidential and any information you share will remain anonymous in any reports or publications. We will be recording the interview. The interview recording and transcript will only be accessible to the internal ASAPP project and evaluation teams. The expected duration of the interview is 60 minutes.

- Do you consent to take part in this interview, which will be recorded?
- Do you consent to the use of anonymous quotations in any presentation, publication, or research that results from this conversation?

You may decline to answer any questions and you can stop the interview at any time.

Before we begin, would I be able to obtain your verbal consent that you'd still like to take part?

[Confirm consent]

Before we get started, do you have any questions about this process?

Then, the interviewer would start the Teams recording and proceed through the interview guide. After the interview, the audio recording and transcript should be saved in a password protected folder, and any quotes used directly from interviews (i.e., beyond aggregate summaries) should be anonymized.

Questions:

1. To start, please describe your role in the OHT and your involvement with the project.

[Prompts – Only asked if needed to guide the conversation]

- Specifically, the implementation of the bot in the EMR, data extraction of the SDoH work or AI work and the predictive algorithm to identify complex patients. [explanation may be adjusted for clarification].
    i. OHT Rep: the implementation for the overall and/or specific components of the project by clinicians in your OHT.

2. Can you describe the adoption process of or the efforts to implement the ASAPP project, such as the Cody bot, within your [organization: clinic/OHT]?

[Prompts – Only asked if needed to guide the conversation]

Process:

- Can you describe the steps of the adoption process for [your organization]?
    i. What are the key activities that were required or will be required down the line to implement the project?
- What resources were required in the process?
    i. How were they used?

Experience:

- What was your perceived experience of the adoption process?
    i. For instance, this may include communication with the eCE team, integration of the ASAPP project in your clinical workflows, and provision of the list of patients.
    ii. Was the project implemented as you thought it would be?

iii. What went well?

iv. What did not go well?

v. What would you recommend for improvement?

3. Next, we want to discuss how this project could impact your work, your OHT, or others.

- The components of the project included: the Cody bot to help improve standardization of data, data extraction (postal codes, the medically complex patient lists or data for the future AI work), the area-level social determinants of health analysis of patients and the associated optional form(s), the complex patient algorithm including the medically complex and previous hospitalization algorithms, and the final output to present the list of complex patients.

To start, could you describe how the components of this project have or could impact your work or [your organization], if at all?

[Prompts – Only asked if needed to guide the conversation]

- Who is/are the target population(s) of the complex patient algorithm?
    i. From your perspective, did the ASAPP algorithm identify the target complex patients?

- Were there barriers created by the ASAPP project or for the adoption of the project that impacted your organization's workflow?
- What facilitated the use of the project for you and/or in your organization?
- Can you explain, or from your perspective, what was the overall experience and/or perspectives of those involved (e.g., clinicians, program coordinators) and those impacted (e.g., patients, complex patient care teams) for [each of the project components as applicable]?

- Has or could the project add value for you, or within [your organization]?
  i. If yes, what is or was the value?
- What are some changes you would suggest for the overall project?
  i. What recommendations may you have for this project moving forward?

4. Are you aware of any current or proposed uses of the information produced from the ASAPP project, such as the list of complex patients or the area-level SDOH distribution analysis or RPA form?

[Prompts – Only asked if needed to guide the conversation]

Current:

- What has been done so far [with regard to how the information created by ASAPP is being used in your clinic/practice/OHT]?

- What is your or [the organization's] current plan?

Future changes/feedback for future work:

- What are some changes you would suggest for the overall project?
- Could you describe any future impact you foresee as a result of this program to you or [your organization], or your target population?
- What recommendations may you have for this project moving forward?
    i. What recommendations may you have for expanding this project in other OHTs?

5. Those are all the questions we have. Is there anything you would like to discuss or share about the project?