The Use of Artificially Intelligent Symptom checkers by University Students – An Exploratory Sequential Mixed Methods Study

by

Stephanie Aboueid

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Examining Committee Membership

External Examiner	Dr. Farah Magrabi Associate Professor Australian Institute of Health Innovation Macquarie University
Internal/External Examiner	Dr. Jesse Hoey Associate Professor David R. Cheriton School of Computer Science University of Waterloo
Supervisor	Dr. Ashok Chaurasia Assistant Professor School of Public Health and Health Systems University of Waterloo
Internal Member(s)	Dr. Samantha Meyer Associate Professor School of Public Health and Health Systems University of Waterloo
	Dr. Jim Wallace Associate Professor School of Public Health and Health Systems University of Waterloo

Author’s Declaration

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

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

Statement of Contributions

This thesis, in part, informed the publication and submission of four articles. A statement of contributions has been included in each of these articles.

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Contributions: SA conceived and designed the review. RHL, BND, AC, and SE participated in the conception of the study. SA, RHL, and BND carried out the review. All authors read and improved the final manuscript.

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As lead author of these articles and the thesis, I was responsible for conceptualizing the studies, developing the research questions, conducting literature reviews, leading the study designs, conducting the statistical analyses, interpreting the results, and writing the initial drafts of the manuscripts. My co-authors provided guidance throughout the research process and provided feedback on draft manuscripts. Specifically, AC, SBM, and JW assisted in the conception of the study. AC contributed to the quantitative data analysis and coding. SBM provided editorial comments and direction for the qualitative data analysis. JW supported in the theoretical framework. AC, SBM, and JW reviewed and provided editorial comments on the thesis. SA self-funded the survey but was supported by the President Graduate Scholarship and the Ontario Graduate Scholarship throughout her doctoral training as well as the CIHR HSI Fellowship award.

Abstract

Rising healthcare costs, wait times, unnecessary care, and lack of access to a primary care provider, are pressing issues encountered by various health systems and in part, are a result of misinformed patient demand. The literature suggests that one way to economize the healthcare system is to provide patients with reliable tools to inform better decisions on when to seek care. The Internet is often used as a source of health information. University students, a population group considered to be technology savvy, often browse the Internet for health topics and self-diagnosis; however, the information is abundant and may not be reliable which can have negative consequences on health. Relatively new artificially intelligent (AI)-enabled symptom checkers seek to address this limitation by enabling self-triage and self-diagnosis based on data inputted by users. Given the direct-to-consumer nature of this technology and availability, little to none is known about the factors associated with the behavioural intention to use this technology. This thesis focuses on university students between the ages of 18 and 34 – a demographic that is technology savvy and undergoing a critical transition period as they start making individual decisions regarding their health. Inspired by the Technology Acceptance Model (TAM), the overarching aim of this dissertation was to understand university students' use of AI-enabled symptom checkers for self-triage and self-diagnosis.

A scoping review conducted as part of this work helped inform the following research questions: (i) What are university students' perspectives towards the use of AI-enabled symptom checkers for self-triage and self-diagnosis? (ii) What are university students' perspectives on the platform's influence on the use of health services? (iii) What are the population profiles (latent classes) associated with the intent to use AI-enabled symptom checkers? This study received ethics clearance from the Research Ethics Board (#41366) and approval from the Institute of Analysis and Planning at the University of Waterloo.

A two-phased mixed methods sequential exploratory research design was used for objectives (i) and (ii) using qualitative research methods and procedures (i.e., semi-structured interviews and a think-aloud exercise). A total of 24 participants were recruited across faculties at the university to address research question 1 of which 22 were included in the sample to address the second research question. Using NVivo software, inductive thematic analysis, informed by the factors identified in the UTAUT, was used to analyze qualitative data.

Findings from the qualitative phase suggests that more than half of participants (n=13) were unaware about the existence of symptom checkers prior to the study. Most participants had a positive outlook on the use of AI in healthcare due to the use of big data and pattern recognition; however, skepticism regarding the quality of data used and biases against minority groups emerged. Based on participants' experience using a symptom checker during the interview, the platform was perceived to be more personalized and interactive in nature as compared to using the Internet search engine for seeking health information. Symptom checkers, however, were believed to be unreliable if it limits a user's input of data and were thus more accepted for self-triage rather than self-diagnosis. Many barriers and enablers – related to the individual, disease, healthcare system, or the symptom checker itself – for using symptom checkers were identified. Some enablers included trust, curiosity, having pre-existing or "embarrassing" health conditions, being uncertain about the care required, experiencing symptoms that can be easily described, endorsement by doctors and health organizations, and increased awareness regarding their existence. Identified barriers included the use of medical jargon, lack of explanation as to why certain questions are being asked, disclaimer undermining the credibility of the platform, skepticism from the media regarding the use of AI and lack of human interaction. Following the use of a symptom checker, participants mentioned various areas of improvement that would enhance the user experience – these included having the ability of entering symptoms as free text, the use of visuals to pinpoint affected areas, tailoring the experience based on a user's health literacy, providing an option to speak to a health provider following the initial assessment, providing information related to other users who reported similar symptoms, providing information on the conditions listed, and recommending nearby locations for accessing health services.

Symptom checkers were perceived to have a positive effect on health of university students through the integration of health reminders, enablement of proactive care seeking, and mental health. A few participants believed that it may have a negative influence on health due to a suboptimal understanding of the user's contextual factors, overall health status, and the reactive

nature of the platform (i.e., focus on symptoms). As for the platform's influence on health services, symptom checkers were perceived to affect three main areas that include the reduction in unnecessary medical visits, increasing patient engagement and improving access to care. To have any influence on the use of health services, symptom checkers must be adopted by the general public with the top five factors identified by participants to be important for adopting a symptom checker for self-triage being trust towards the platform, perceived credibility, demonstrability, perceived accessibility (for self-triage), and output quality (for self-diagnosis). Given its centrality, trust was explored further – participants believed that symptom checkers could be trusted for minor conditions. Moreover, various factors related to the input, process, and output were considered to influence a user's level of trust in the platform.

To address the third objective, findings from the first phase and input from the Survey Research Center, were used to develop a survey. University students were notified of the survey through an email invitation sent by the Registrar's office and an announcement made in a newsletter. A total of 1,547 students opened the survey link of which some were screened out due to ineligibility (n=14) and others were removed due to their prior use of symptom checkers (n=180). The remaining sample who had not used the platform in the past year were identified as "non-users" and were the focus of this thesis. Quantitative analyses were conducted on complete cases (n=1,305) with the sample being approximately evenly split between men and women, healthy, non-white, enrolled in an undergraduate program, and often have access to the Internet. Latent Class Analysis (LCA) was used to understand response patterns and define the population profiles (latent classes) which were identified based on attitudes towards symptom checker functionality and AI – these five classes were labeled as *tech acceptors*, *tech rejectors*, *skeptics*, *unsure acceptors*, and *tech seekers*. Using a General Linear Model (GLM), these latent classes were regressed on the intent to use symptom checkers (the outcome had three categories with the category of interest being the use of symptom checkers as compared to the neutral referent group) while controlling for confounders (i.e., gender, self-perceived health, race, healthcare use, wait time, health literacy). Results suggest a significant effect of latent classes on the intent to use symptom checkers, even when controlling for other variables (p-value <.0001). As compared to *tech rejectors*, the odds of future symptom checker use are 7.6, 5.6, 2.6, and 2 times higher in *tech seekers*, *tech acceptors*, *skeptics*, and *unsure acceptors*, respectively. Interestingly, *tech seekers* –

categorized as a latent class that has positive attitudes about functionality and AI but do not perceive to have accessibility to symptom checkers – was the class with the highest odds of intending to use a symptom checker. This may suggest that the perception of not having access to symptom checkers increases the odds of intending to use a symptom checker. Moreover, addressing the variables that categorize "*skeptics*" and "*unsure acceptors*" will be important to understand which aspects should be addressed to increase symptom checker use. For example, *skeptics* were defined as the group that perceive symptom checkers to be easy to use but have negative attitudes towards the output of the platform whereas *unsure acceptors* show negative attitudes towards the output but perceive the platform difficult to use.

Findings from this work have theoretical, methodological, and practical implications that will inform the use of an understudied technology. This thesis contributes to the technology acceptance literature by focusing on a relatively new technology that has not been studied in this population all the while employing a sophisticated statistical technique (i.e., LCA) that provides valuable insights about the population profiles among subjects. Methodological implications include the interview protocol, survey development, and survey data analysis, which could be employed in future studies to assess symptom checker acceptance and use among other population groups. Moreover, policymakers, health professionals, health institutions, technology companies, and the general public may be interested in understanding the perceptions of AI-enabled health diagnostics, as well as the factors and profiles associated with its intended use. Importantly, understanding end-user reception of this technology will inform the integration of AI-enabled symptom checkers by healthcare systems as a potential approach to economize and reduce the burden on these systems.

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List of Abbreviations

AIC	Akaike’s information criterion
AI	Artificial intelligence
BIC	Bayes information criteria
CDSS	Clinical decision support systems
CHIT	Consumer-oriented health information technology
CIHI	Canadian Institute for Health Information
CMA	Canadian Medical Association
COVID-19	Coronavirus Disease 2019
CSR	Case study research
DTC	Direct-to-consumer
EDA	Exploratory data analysis
FDA	Food and Drug Administration
HIPAA	Health Insurance Portability and Accountability Act
IS	Information systems
IT	Information technology
LCA	Latent class analysis
MMR	Mixed methods research
NHS	National Health Service
PAS	Privacy and security
PCP	Primary care provider
PEOU	Perceived ease of use
PU	Perceived usefulness
QR	Quick Response
TA	Technology acceptance
TAM	Technology acceptance model
TRI	Technology readiness index
UK	United Kingdom
UX	User experience
UNESCO	United Nations Educational, Scientific and Cultural Organization
UTAUT	Unified theory of acceptance and use of technology
WHO	World Health Organization

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Chapter 1: Introduction

Rising healthcare costs, wait times, unnecessary care, and lack of access to a primary care provider, are all pressing issues in healthcare systems around the world (Marchildon, 2013; Dieleman et al., 2017a; Canadian Institute for Health Information, 2017; Statistics Canada 2017; Statistics Canada, 2016). It is of increasing importance to ensure that those who seek care actually need it. At the same time, individuals are becoming more engaged in their health and most will seek health information on the Internet (Case & Given, 2016; Anderson-Lewis et al., 2018). Researching health information as a means of assessing one's health can have both positive and negative effects on individuals. Positive effects include being more knowledgeable (Iverson et al., 2008; Tonsaker et al., 2014), more involved in health decision-making (Edwards et al., 2009; Chen et al., 2018), and more empowered (Fox et al., 2005; Oh et al., 2012). It is important to acknowledge, however, that health information/advice on the Internet can be unreliable and subjective. Importantly, those seeking health information may not have the health literacy to assess relevance of the information to their individual context (White & Horvitz, 2010; Karnam & Raghavendra, 2017).

Given the challenges associated with health information in an open/free space such as the Internet and shortage of the health workforce globally (World Health Organization, 2019), companies have leveraged advances in technology and information systems to develop consumer-oriented health information technology (CHIT) (Tao et al., 2019). Examples of these technologies include artificially intelligent symptom checkers – their two main functions (among many) include assistance with triage and providing a list of potential diagnoses to users based on self-reported symptoms (Semigran et al., 2015). Despite the pervasiveness of these platforms and the substantial investments in AI, both nationally and internationally, little is known about the use of this technology (Aboueid et al., 2019; Chambers et al., 2019; Tsai et al., 2021). More importantly, user perception and acceptance of such technology remains unstudied along with their influencing/associated factors. This is worrisome because the benefits of these platforms will be lost or not seen to its full potential if its target audience is less than accepting of this technology (Davis, 1989).

Gattiker (1984) defined Technology Acceptance (TA) as “an individual’s psychological state with regard to their voluntary or intended use of a particular technology”. To identify measures and constructs associated with technology acceptance, Davis (1989) introduced the Technology Acceptance Model (TAM) which has been applied in various contexts and has been extended to include additional constructs depending on the context and relevance (Venkatesh, 2013). Examples of these extensions include the Unified Theory of Acceptance and Use of Technology (UTAUT) and UTAUT 2 (Venkatesh et al., 2003). While most of these models were intended to assess technology acceptance in an organizational context, some have been adapted to non-organizational contexts in which the end user is a consumer rather than an employee (Bagozzi, 2007; Benbasat & Barki, 2007; Venkatesh et al., 2007). Given the importance of assessing the acceptance of innovative technologies, the stream of research related to individual acceptance and use of information technology (IT) is one of the most established in information systems (IS) (Venkatesh et al., 2007).

This study drew from the aforementioned TA literature and applied the framework to a non-organizational context in which the end-users are consumers. To limit the scope of this work, the target population were university students – this population was purposely selected because typically, university students are young adults (between the ages of 18 and 34) – a demographic that is technology savvy, regularly engages in risky health behaviours, and are in a critical transition period as they have to make more decisions on their own, including decisions about their health (Escoffery et al., 2005; Heller & Sarmiento, 2016; Hopper & Moninger, 2017; Basch et al., 2018; Canadian Medical Association, 2018a). Given that this target population is thought to be technology savvy and eagers adopters of technology (CMA, 2018a); they are considered to be the ideal target for optimizing symptom checker use.

The overarching aim of this dissertation was to assess university students’ use of AI-enabled self-diagnosing digital platforms for self-triage and self-diagnosis. Due to the limited literature available on this topic, this work employed an exploratory sequential mixed methods study as well as a theoretical framework that has been widely used to understand technology acceptance and use. The first phase used a qualitative research design and aimed to (i) gauge university students’ general attitudes regarding the use of online symptom checkers, and (ii) identify constructs that could be important in assessing use of symptom checkers. Findings from the qualitative phase informed the development of a survey which was employed in the latter phase of this work to identify latent classes associated with the intent to use symptom checkers in the future. This thesis highlights the importance of including key stakeholders (e.g., end-users, symptom checker developers, Governmental entities, and health professionals) in the conception, roll-out, and refinement of such platforms. The rest of the thesis is organized as follows.

Chapter 2 is a published scoping review which sought to identify the existing literature on AI-enabled symptom checkers. The objectives of the scoping review were to: 1) systematically map the extent and nature of the literature and topic areas pertaining to digital platforms that use computerized algorithms to provide users with a list of potential diagnoses, and 2) identify key knowledge gaps. Results indicate that literature surrounding the topic is scarce thus serving as an impetus for this thesis.

Chapter 3 provides a background on pressing issues in healthcare – including access to care, wait times, unnecessary care, and self-assessment tools available to the public – and why they should be addressed. This chapter investigates factors associated with health query and the use of the Internet among the general public, specifically university students. Additionally, an overview on the rise of AI-enabled symptom checkers and their adoption by various organizations (national and global) is discussed. The chapter concludes with an overview on technology acceptance models, their applications in the healthcare context, and an overview of LCA applications.

Chapter 4 summarizes key takeaways from the background section and provides a rationale for the scope and aim of this thesis. It also outlines the main research questions and their respective objectives, with their significance tied-in to the overarching aim of this work. The methods that were used for the outlined objectives, with a rationale for choosing an exploratory mixed-methods research design are also outlined in this chapter.

Chapters 5 provides a description of the first and second research questions which employ a qualitative research design and methods (i.e., semi-structured interviews and a think-aloud exercise). This chapter provides information on methods, sampling and participant recruitment, data collection and analyses, results, and significance of the findings from the first phase to inform the second phase of the work.

Chapter 6 discusses the quantitative component of the thesis and addresses the third research question of identifying latent classes and their association with the use of symptom checkers. This section discusses the quantitative research design that was employed, as well as information on survey development, sample size requirement, participant recruitment, data collection, and statistical models which were utilized in identifying profiles associated with the use of symptom checkers and their association with intention of using symptom checkers in he future. Results for the third research question are also included within this chapter.

Chapter 7 provides a discussion of the key findings of all research questions explored in this thesis and their respective implications for key stakeholders. This discussion includes an overview of the strengths and limitations, and directions for future research. Lastly, chapter 8 concludes with a brief overview of key implications that should be considered in this research area as well as the potential and significance of this work from theoretical and practical perspectives.

Chapter 2: Scoping Review

2.1 Overview

The content of this chapter is a scoping review which was published in JMIR Medical Informatics (Aboueid et al., 2019). It provides an overview on why the scoping review was conducted as well as key findings and gaps in the literature. The scarcity of research in the area of AI-enabled symptom checkers and its use in healthcare systems informed/motivated this thesis.

2.2 Introduction

Researching health information on the Internet has become common practice by the general public (Statistics Canada, 2009; Beck et al., 2014; Pew Research Center, 2013). Those who do not have access to health care services are more likely to use the Internet for health information (Amante et al., 2015). In some cases, browsing the Internet for health information can have certain benefits such as improving health outcomes by increasing the availability of information, providing social support, and improving self-efficacy (Ybarra & Suman, 2006; Tonsaker et al., 2014). However, potential negative consequences still exist; the information may not be reliable, and the individual seeking information may have low health literacy (Tonsaker et al., 2014). For example, an individual may not be able to critically analyze the health information and assess the applicability of the information to their case, which could result in detrimental effects on their health (Tonsaker et al., 2014). Therefore, health information widely circulated on the Internet should be interpreted with caution (Mosa et al., 2012).

Significant technological advances have resulted in the rise of more sophisticated digital health platforms, which could potentially mitigate this issue, especially those involving artificial intelligence (AI). Interest in AI appears to be relatively recent; however, the term dates back to the 1950s and is described as the theory and development of computer systems that can perform tasks that would normally require human intelligence (Turing, 1950; Senate Canada 2017). Notably, AI has become incorporated in computerized diagnostic decision support systems, which were initially developed for health professionals. These platforms have now become readily available to the general public and are known as self-diagnosing apps or symptom checkers, which include the Mayo Clinic symptom checker, Babylon Health, the Ada health app, and the K Health app. On the basis of the medical information and symptoms provided by an individual, these digital platforms perform 2 main functions: (1) provide individuals with a list of potential diagnoses and (2) assist with triage (Semigran et al., 2015). While the accuracy of symptom checkers is still under question (Millenson et al., 2018; Business Insider, 2018), this technology has been gaining traction globally (Business Insider, 2018; Digital Health, 2018) owing to its potential in addressing the lack of access to primary care providers (PCPs) and unnecessary medical visits—prominent issues in Canada and most parts of the world (Brownlee et al., 2017; Morgan et al., 2016; Canadian Institute for Health Information, 2017; Organization for Economic Co-operation and Development, 2019).

Although accuracy is important to consider, it is of equal importance to understand the overall body of knowledge that surrounds this technology, including legal and ethical implications and user experiences. In light of this, it is imperative to systematically map the literature available on artificially intelligent self-diagnosing digital platforms to identify the areas of research pertaining to this topic and to outline the key gaps in knowledge. This information can support the growing interest in leveraging AI technology in health care systems. As such, this scoping review aimed to answer the following question: What is known about the use of artificially intelligent self-diagnosing digital platforms by the general public and what are the main knowledge gaps in the literature?

2.3 Methods

In this review, self-diagnosing digital platforms were defined as platforms that utilize algorithms to provide a list of potential diagnoses to the user based on the medical information and symptoms provided. Although this scoping review does not entail quality assessment, it follows a sound methodological approach to map out the results in a concise manner for knowledge users. This scoping review follows the 2018 checklist developed by Tricco et al. for reporting scoping reviews. Ethics approval was not required.

The 3 main overarching concepts that guided this search were (1) self-diagnosis; (2) digital platforms; and (3) public or patients. Given the relatively new emergence of this technology and its use by the general public, the search was not limited by a publication date. Articles that were included in the review were those that (1) pertained to the use of self-diagnosing digital platforms by the lay public or patients and (2) were written in English or French. Exclusion criteria were articles that (1) focused on the use of self-diagnosing AI technology by health professionals; (2)

described the back-end development of a self-diagnosing platform (eg, neural networks and architecture); (3) focused on digital health platforms that provide general health information, advice for disease management or triage; (4) focused on a tool that entails a validated questionnaire rather than an algorithm; and/or (5) examined test kits or digital platforms requiring an image upload. To allow for a wide array of results to be included, quantitative, qualitative, and mixed-methods studies or reports were eligible for inclusion.

This scoping review systematically searched citation databases and the gray literature for relevant published and unpublished articles. The citation databases included PubMed (Medline), Scopus, Association for Computing Machinery Digital Library, Institute of Electrical and Electronics Engineers, and Google Scholar. To supplement the gray literature retrieved through Google Scholar (Haddaway et al., 2015), OpenGrey and ProQuest Dissertations and Theses were also searched. The final search strategy for each data source was defined and refined with the assistance of a librarian (Rebecca Hutchinson, University of Waterloo) and was finalized on November 19, 2018. The final search strategy for PubMed (Medline) can be found in **appendix 1**. The final search results were exported into RefWorks for screening.

Once duplicates were removed in RefWorks, the screening process was conducted independently by 2 researchers (SA and RHL). The decision tree in figure 1 was used as a guide to screen titles and abstracts (or executive summaries for reports and commentaries). Articles that were extracted from the title and abstract screening stage were read in their entirety (full-text review). For the full-text screening step, 2 researchers (SA and RHL) screened the same 30 articles to assess inter-rater reliability. Any uncertainty and disagreements were discussed and resolved through consensus. Following full-text review, the reference lists of eligible articles were systematically screened. Similarly, for any review paper screened at the full-text review stage, references were screened for potentially relevant articles meeting the inclusion criteria.

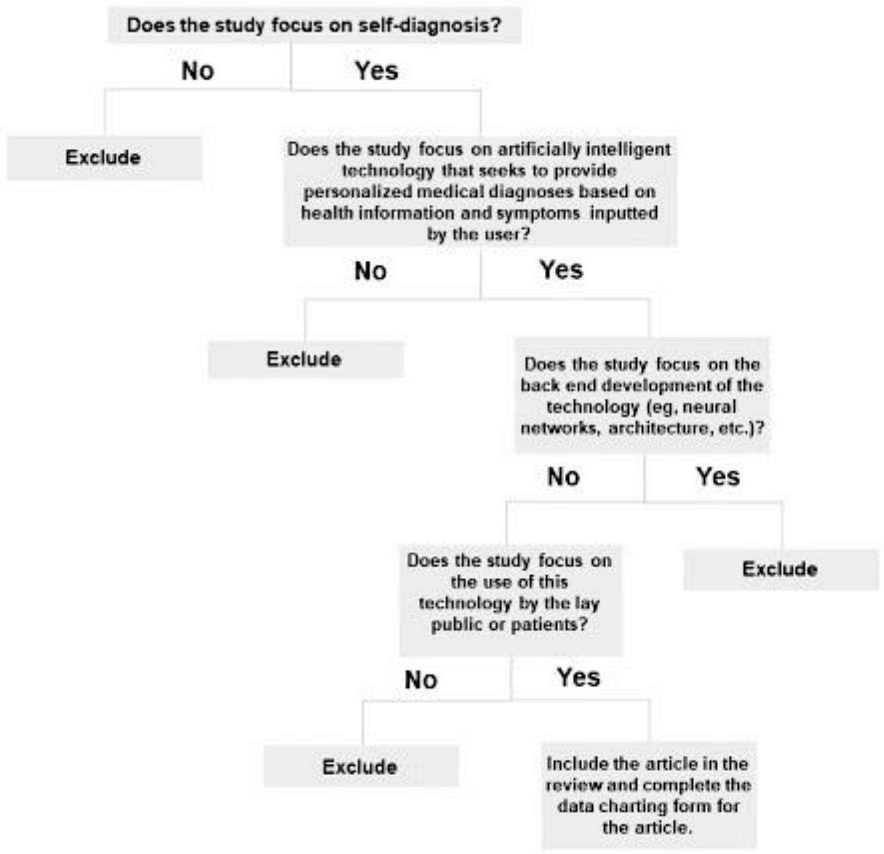

Figure 1. Decision tree for assessing article eligibility

Once the final number of articles was determined, a scan through these articles allowed the research team to gain a high-level understanding of the topics of interest in which self-diagnosing digital platforms were being examined (eg, accuracy and regulatory concerns). This allowed for the development of a data-charting form that captured all the relevant information, irrespective of the article type (eg, clinical trial or a qualitative study on user experience). The data-charting form was pretested with the same 5 articles to assess consistency. No changes were made to the form following this exercise.

The variables collected through the data-charting form included the following: country, year of publication, main objective, the main area of study (eg, clinical, legal, and ethical), study design, data sources used (if any), target population (if any), sample size and sample characteristics (if any), methods/statistical analyses (if applicable), main findings, and study limitations (if applicable).

Scoping reviews provide knowledge users with a concise overview on the literature available on a given topic of interest (Canadian Institutes of Health Research, 2016). Given the heterogeneity of the studies included in this review, studies were grouped based on a specific area of study. A concept map was used to illustrate the breadth of studies surrounding self-diagnosing AI technology. Tables were used to provide an overview on the types of articles found in the literature and the data extracted from each article. A thematic synthesis was used to outline the knowledge gaps in the literature and other key considerations.

2.4 Results

Figure 2 depicts the flow chart, which illustrates the selection process at each screening step. Our search identified a total of 2536 from which 217 were duplicates. In addition, 2 researchers independently screened the titles and abstracts of 2316 articles from which 2229 were excluded based on relevance and eligibility criteria. A total of 104 full-text articles were retrieved and assessed for eligibility. Of these, 76 articles were excluded for the following reasons: described the back-end development of the digital platform or the algorithm, examined the use of digitized questionnaires rather than algorithm-based digital platforms, the digital platform required the input of health professionals, provided the risk of disease, monitored symptoms, technology designed for health professionals, not in scope, and did not provide enough data or information. We excluded 12 additional articles because we were unable to retrieve them. Through reference screening of the included articles, we identified 17 potentially relevant articles from which 3 articles were included in the review. A total of 19 articles were considered eligible for this review. Inter-rater reliability was assessed at the full-text stage which resulted in a score of 0.82, an almost perfect agreement score, between the 2 reviewers (SA and RHL) (McHugh, 2012; Wongpakaan et al., 2013).

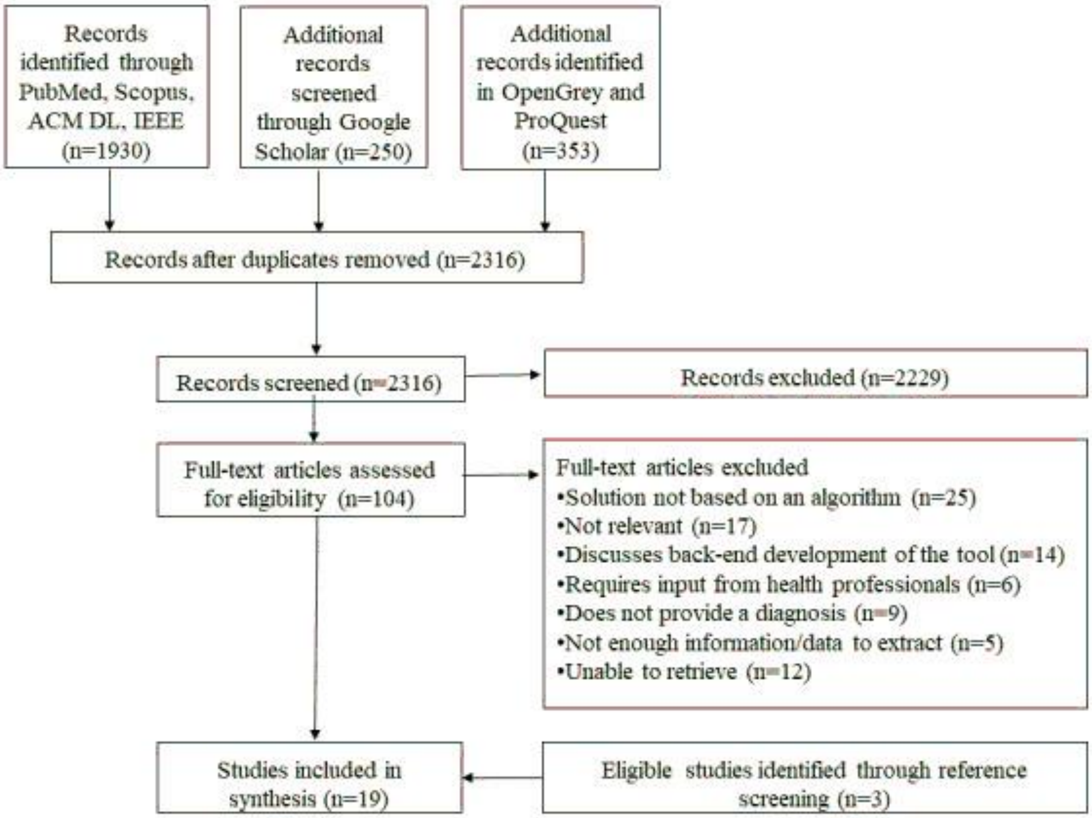

Figure 2. Preferred Reporting Items for Systematic Reviews and Meta-Analyses flowchart of included articles.

Notes: ACM DL: Association for Computing Machinery Digital Library; IEEE: Institute of Electrical and Electronics Engineers.

The concept map in **figure 3** provides an illustrative overview of the main topic areas surrounding the use of artificially intelligent self-diagnosing digital platforms by the general public. The articles were mainly conducted in the United States (n=10) or the United Kingdom (n=4). In total, 2 of the articles were commentaries and the rest focused on the following areas: accuracy or correspondence with a doctor’s diagnosis, regulation, sociological perspectives, experience, theory, privacy and security, ethics, and design. The concept map also outlines the main themes that emerged from the articles and the health conditions examined.

Figure 3. Concept map of the literature surrounding the use of artificially intelligent self-diagnosing digital platforms by the general public.
Notes: DCM: degenerative cervical myelopathy; ENT: ear, nose, and throat; FDA: Food and Drug Administration; HIPAA: Health Insurance Portability and Accountability Act; NHS: National Health Service.

Appendix 2 provides an overview of all included articles and outlines the following variables: the article type, topic area examined, main objective, and main findings (Lanseng & Andreassen, 2007; Ryan & Wilson, 2008; Farmer et al., 2011; Bisson et al., 2014; Boulos et al., 2014; Flaherty, 2014; Luger et al., 2014; Hageman et al., 2015; Jutel & Lupton, 2015; Lupton & Jutel, 2015; Bisson et al., 2016; Powley et al., 2016; Tudor et al., 2016; Weldegebrial, 2016 ; Bauer et al., 2017; Kao & Liebovitz, 2017; Morita et al., 2017; Copeland et al., 2018; Davies et al., 2019).

Table 1 provides additional information on studies that entailed participant recruitment to answer their research question. These articles tended to focus on accuracy of the digital platform or user experience.

Table 1. Synthesis of results of studies with participants

First author, year, reference, country	Sample size (n)	Target population	Data collection	Digital platforms used	Methods
Bisson, 2014 [26], United States	572	Individuals with knee pain	Primary data collection from patients and electronic medical records (EMRs)	A Web-based program developed by the research team	Sensitivity and specificity of the program's ability to provide a correct diagnosis for knee pain was tested, out of a possible 21 conditions in which the algorithm was trained to diagnose
Bisson, 2016 [27], United States	328	Individuals with knee pain	Primary data collection from patients and EMRs	A Web-based program developed by the research team	Sensitivity and specificity were calculated
Copeland, 2018 [29], United States	13	Users who tested the protocol (specifics not provided)	Primary data collection using the System Usability Scale and the Usability Metric for User Experience	Prototype developed by the research team	Descriptive statistics

Farmer, 2011 [32], United Kingdom	61	Patients coming in to the ENT[1] surgeon's office	Primary data collected from patients over 1 month	Boots WebMD Symptom	Not provided
Hageman, 2014 [33], United States	86	Patients coming into an outpatient hand and upper extremity surgeon's office	Primary data collection from patients and physicians	WebMD Symptom Checker	The Pearson chi-square test was used to determine the level of correspondence of the provided diagnosis by the diagnostic application and the final diagnosis of the physician
Lanseng, 2007 [36], Norway	160	Individuals between the ages of 18 and 65 years	Primary data collection using the Technology Readiness Survey (TRI)	N/A[2]	A survey with an Internet-based medical self-diagnosis application as the focal technology was conducted; The research hypotheses were tested by completing a scenario and then following-up with a questionnaire
Luger, 2014 [37], United States	79	Older adults (aged 50 years or older)	Primary data collection of think-aloud protocols	WebMD Symptom Checker	Participants received one of 2 vignettes that depicted symptoms of illness. Participants talked out loud about their thoughts and actions while attempting to

					diagnose the symptoms with and without the help of common Internet tools (The Internet and WebMD's Symptom Checker); Think-aloud content of participants was then compared with those who were accurate in their diagnosis versus those who were not.
Powley, 2016 [40], United Kingdom	34	Consecutive patients with newly presenting clinically apparent synovitis or a new onset of symptoms consistent with inflammatory arthritis	Primary data collection from patients	NHS and WebMD Symptom Checkers	Patients were asked questions about their Internet use in relation to their presenting symptoms. Subsequently, they completed the NHS and the WebMD symptom checkers and their answers as well as outcomes were recorded.

[1] Ear, nose, and throat

[2] Not applicable

2.5 Discussion

In this scoping review, 19 articles were included that examined artificially intelligent self-diagnosing digital platforms from various perspectives. Despite the popularity and accessibility of self-diagnosing AI technology by the public, it is noteworthy that research examining the accuracy of these platforms is limited. As such, it is unclear whether these platforms hinder or improve the health of users. Although some argue that the use of this technology may cause an individual to delay seeking care, it is important to recognize that delayed diagnoses are prevalent even without the use of this technology (Powley et al., 2016; Tudor et al., 2016; Behrbalk et al., 2013) Many factors contribute to a delayed diagnosis with the top-ranked issues being poor communication between secondary and primary care, a mismatch between patients' medical needs and health care supply, and a lack of access or use of health services (Tudor et al., 2016; Aboueid & Meyer, 2019). For example, Behrbalk et al found that the average time delay from initiation of symptoms to the diagnosis of cervical spondylotic myelopathy (CSM) was 2.2 (SD 2.3) years (Behrbalk et al., 2013). Although symptom checkers can potentially address delayed diagnoses, a review showed that this technology was suboptimal in diagnosing CSM (Davies et al., 2019).

Moreover, these platforms generally provide a list of potential diagnoses rather than a single diagnosis. In this case, the user must decide which condition describes their current state best. The likelihood of a user to accurately choose the right diagnosis is associated with the sociodemographic profile/variables of a user, such as education and gender (Hageman et al., 2015). For example, women and those with higher education were more likely to choose the correct diagnosis (Hageman et al., 2015). Therefore, although having a timely diagnosis is important, it may be counterproductive if the user considers the wrong treatment options owing to a misdiagnosis. Moreover, the patient may still require a visit to a PCP to receive treatment or a prescription. Issues may arise if patients already have a diagnosis in mind when visiting their PCP as it could translate into disagreements regarding their condition.

This scoping review suggests that there are prominent knowledge gaps in the literature; as such, a systematic review may not be worthwhile on this topic. Rather, concerted efforts are needed in producing research in this area related to accuracy, user experience, regulation, doctor-patient relationship, PCP perspectives, and ethics. Specifically, extensive research is needed in evaluating the accuracy of this technology while accounting for the fact that some platforms are designed for a wide area of conditions and others are specialized—as such, these platforms need to be evaluated accordingly. It is also important to distinguish the difference between accuracy and correspondence with a PCP's diagnosis as PCPs may misdiagnose or miss a diagnosis (Singh et al., 2017; Panesar et al., 2016; Nurek et al., 2015). Importantly, when developing self-diagnosing AI digital platforms, it is important to test them on users with a wide range of backgrounds and level of experience with technology. This will ensure that a high proportion of users will end up choosing the right diagnosis.

Along with the importance of accuracy in self-diagnosing applications, there also needs to be guidance on how these platforms should be regulated. Although regulations related to self-diagnosing AI technologies should focus on patient safety as well as privacy and security, they should not hinder innovation in this area; rather, they should allow innovative advancements that are safe and improve access to timely diagnosis. Overall, more knowledge is needed on how different types of users interact with this technology and how its use can impact the PCP-patient relationship. There is also a need for clarity on data management shared by users. Ethical concerns surrounding the digital economy is a main area of concern, and there is currently a debate surrounding the trade-offs pertaining to the use of these platforms.

Given self-diagnosing AI technology’s potential, it is worth understanding how it can be leveraged by health care systems to reduce costs and unnecessary medical visits. This scoping review aimed to map the literature surrounding the use of artificially intelligent self-diagnosing platforms. Given the direct-to-consumer approach of these platforms, it is worrisome that only a few studies have focused on the use of this technology. It is important that future research and resources are directed to understanding the accuracy and regulation of self-diagnosing AI digital platforms. These regulations may take different forms such as creating an application library which includes a list of platforms that have been deemed safe and provide highly accurate diagnoses from a credible health agency or organization. It should be noted that patient engagement is necessary in the development of these platforms to ensure that they allow a high proportion of individuals—irrespective of gender and education—to choose the right diagnosis. Importantly, user experience is crucial to consider as the public may be skeptical of this technology.

Key findings from this scoping review highlight that research is needed in all areas related to AI-enabled symptom checkers with a focus on technology acceptance being important to consider. The following chapter will provide an overview of key elements related to understanding the intention to adopt symptom checkers.

Chapter 3: Background

3.1 Pressing Issues in Healthcare

In most parts of the world, healthcare spending is continuing to increase at an alarming rate, especially in high income countries (Marchildon, 2013; Dieleman et al., 2017a; Dieleman et al., 2017b). Unnecessary care[1] and delaying seeking care[2] are two factors that contribute to higher system costs (Canadian Institute for Health Information, 2017; Institute of Medicine, 2013; Statistics Canada, 2016). Unnecessary care includes tests and treatments that are not helpful and expose patients to harm (CIHI, 2017). Importantly, it takes care away from those who actually need it – many Canadians (approximately 4.8 million) and individuals around the world do not have a regular primary care provider (PCP) (Statistics Canada 2017; WHO, 2019). Concomitantly, many patients who require medical care avoid or delay seeking it (Taber, Leyva, & Persoskie, 2015; Kannan & Veazie, 2014; Green, Johnson, & Yarborough, 2014). At the individual/user level, this delay is associated with worse health outcomes and higher mortality due to delays in diagnosis and treatment (Institute of Medicine 2004a; Prentice & Pizer, 2007). Given that a health condition is likely to get worse as the patient delays seeking care, the treatment(s) required will likely be more costly (Statistics Canada, 2016). In order to curtail increasing healthcare costs, inform necessary visits (i.e., reducing unnecessary ones and encouraging those who require care to visit their PCP), minimize overcrowding of emergency departments, and improve access to healthcare providers, it is important to ensure that those who seek and use health services truly need them. A 2015 national survey found that 67% of participants believed that unnecessary care is driven by misinformed patient demand rather than decisions by experienced/trained physicians/professionals (Choosing Wisely Canada, n.b.; CIHI, 2017). As such, one way to economize the healthcare system is to provide patients with reliable tools to inform better decisions on when to seek care (Choosing Wisely Canada, n.b.; CIHI, 2017).

3.2 The Internet and Health Information-Seeking Behaviours

Individuals are becoming increasingly more engaged in their health and one of the most commonly used tools for health information seeking is the Internet (Cline & Haynes, 2001; Masys et al., 2002; Epstein & Street, 2011). In fact, the Internet is often used as the first source of health

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[1] Unnecessary care is defined as care provided but not needed as indicated by clinical practice guidelines (CIHI, 2017).

[2] Patient delay in seeking care can be defined as the amount of time between the first awareness symptom(s) to the time of presentation for medical care (Safer et al., 1979).

information (Hesse et al., 2010) and 91% of Canadians use the Internet for reasons that include medical or health-related information (Statistics Canada, 2019). Many people use the Internet to assess if their health condition is severe (triage) or to identify a medical condition in oneself (self-diagnosis) (White & Horvitz, 2010; Mueller et al., 2017). Reasons for researching health information include the readily accessible health information available online, the increased engagement of people in their own health, and lack of access to health services (Bhandari et al., 2014; Amante et al., 2015; Case & Given, 2016).

Studies have shown that researching health information can have both positive and negative effects on individuals. Positive effects include patients feeling more empowered (Fox et al., 2005; Oh et al., 2012), more involved in their health decision-making (Edwards et al., 2009; Chen et al., 2018) as well as during consultations (Tan et al., 2017), more knowledgeable (Iverson et al., 2008; Tonsaker et al., 2014), and less isolated through access to community forums (Tonsaker et al., 2014). There are, however, certain negative effects of researching health information because not all health information on the Internet is of good quality. Importantly, given the vast amount of information, it is not always possible for individuals to elucidate which health information is reliable or applicable to them – this is especially an issue for those with low health literacy (Tonsaker et al., 2014). Patients might trust misleading information or make health decisions based on information that is not relevant to their health context (White & Horvitz, 2010). Moreover, diagnosing oneself before seeking advice from a health care provider could result in trust issues if the provider's advice or diagnosis does not align with the patient's preconceived mis-assessment (Karnam & Raghavendra, 2017).

3.3 Health Information-Seeking Behaviours by University Students

Generally, in Canada, young adults tend to be university students, a demographic that regularly engages in unhealthy behaviours, placing them at risk of developing serious health problems later in life (Heller & Sarmiento, 2016; Hopper & Moninger, 2017). It was found, however, that university students exhibited great interest in health topics, regularly used the Internet to access health information and used the Internet to self-diagnose (Escoffery et al., 2005; Basch et al., 2018). Importantly, a national study found that young adults (between the ages of 18 and 34) are the most eager adopters of technology to manage their health (CMA, 2018a) accentuating the need for the healthcare system to catch up to the requirements – convenience and timeliness – of young adults (CMA, 2019). This is in line with research that found that university students were more likely to use the Internet for health information than visiting a health or medical professional (Basch et al., 2018) – reasons for this include the vast amount of valuable information available; anonymity, privacy and confidentiality; ease of access; low cost; convenience; and less embarrassing than speaking to a health professional in-person (Asibey et al., 2017).

Moreover, university students can easily access the Internet on college campuses and are typically technology savvy (Escoffery et al., 2005). They also face busy schedules and financial issues, two factors that are known to be associated with health information seeking habits on the Internet (Bhandari et al., 2014). However, there is a concern that the information sought on the Internet can be unscientific, inaccurate, and hence, unreliable; it may also be beyond the university students' capabilities to discern information relevant to their individual situation (Tennant et al., 2015; Basch et al., 2018). This is worrisome given that risky behaviours are likely to develop during early adulthood (Heller & Sarmiento, 2016; Hopper & Moninger, 2017).

3.4 The Rise of AI-Enabled Digital Platforms for Self-Triage and Self-Diagnosis

More recently, to address the limitations of researching health information on the Internet and the concerns regarding the health workforce shortages, companies have developed more sophisticated digital platforms – such as artificially intelligent symptom checkers – to provide users with a more personalized health assessment. The term artificial intelligence (AI) dates back to the 1950s (Turing, 1950) and is described as the theory and development of computer systems that can perform complex and cumbersome tasks that would normally require human intelligence (Barr et al., 1981, p. 3). The explosion of medical knowledge in the 1970s led to physicians to specialize and highlighted the potential of AI in medicine (Clancey & Shortliffe, 1984). AI-enabled Clinical Decision Support systems (CDSSs) were initially developed for health professionals to assist with diagnosis and treatment (Gorry, 1967; 1968). While the concept of AI and machine learning (ML) is not new, improved computational algorithms and resources (e.g., data storage and security, query, and analysis) have enabled its resurgence. For example, the resurgence of ML, an AI method that can learn from data, was driven by developments in deep learning methods, which are based on neural networks (Lyell et al., 2021). Much progress has been in the past decade; however, the definition of what constitutes "real AI" is evolving and varies across disciplines and applications. This is partly because reaching success in a specific performance goal soon disqualifies that performance as constituting AI; for example, automated route planners were examples of advanced AI in the 1970s but have now become so pervasive that describing them as AI is less common (Yu et al., 2018).

Given the gap in the market for health information seeking, increased engagement of individuals in their health (Epstein & Street, 2011; Masys et al., 2002), and resurgence of AI, consumer-oriented health information technologies (CHITs) are emerging as promising tools (Eysenbach, 2000). CHITs can be defined as "consumer-centered electronic tools, technologies, applications, or systems that are interacted directly by health consumers (i.e., individuals who seek or receive healthcare services) to provide them with data, information, recommendations, or services for promotion of health and health care" (Tao et al., 2017).

While symptom checkers do not seek to replace a medical diagnosis made by a health professional, these relatively new digital platforms (especially those involving AI) are regarded as a means to advise users on the health condition they may have and next steps to manage their care (e.g., whether or not they should seek medical care) (Morita et al., 2017; Fraser et al., 2018). These direct-to-consumer (DTC) digital platforms are readily available to the general public and are defined in this thesis and by Semigran et al., (2015) as tools that use computer algorithms to help users with self-diagnosis or self-triage based on the health information they provide. These platforms are typically built on expert systems that consist of a medical knowledge base and an inference engine (Kao and Liebovitz, 2017). While developers of these platforms claim to use AI, it is unclear whether it could be truly categorized as "real AI", what kind of AI they are using (e.g., machine learning techniques). The lack of transparency may be due to intellectual property protection with some machine learning approaches used seen as "black boxes" to end-users. Nonetheless, the developers of AI-enabled symptom checkers promise many benefits including quality diagnosis and reduction of unnecessary visits (Babylon Health, 2018; Semigran et al., 2015). Examples of these platforms include the WebMD symptom checker (https://symptoms.webmd.com/), Babylon Health (https://www.babylonhealth.com/ask-babylon-chat), the Ada health app (https://ada.com), and the K Health app (https://khealth.com). Based on the medical information and symptoms provided by an individual, these digital platforms perform two main functions: (1) assist with triage and (2) provide individuals with a list of potential diagnoses (Semigran et al., 2015). Throughout this thesis, “symptom checkers” and “AI-enabled symptom checkers” will be used interchangeably.

Various institutions such as the National Health Service (NHS; UK) and the Government of Australia have adopted this technology for the purpose of triage and the provision of next steps to users (Akbar et al., 2020; Babylon GP at Hand, 2018; Government of Australia, 2018). Compared to other developing and developed countries, the UK has made strides in symptom checker adoption. Symptom checkers, however, have also gained traction in the Canadian market – in the fall of 2018, Telus Health announced their partnership with the London-based AI company Babylon to bring medical services to Canadians (the Globe and Mail, 2018; Telus Health, 2019). Given that the Canadian healthcare system is largely under the purview of the provinces and territories, the adoption and use of AI symptom checkers across jurisdictions differ with many of them encouraging the use of these platforms to reduce the burden on healthcare systems. Specific analyses on how various jurisdictions are faring regarding adoption and use at the population level are in early stages but required to understand the overall standing of SC use in Canada.

There is limited literature on AI-enabled symptom checkers in areas such as safety, accuracy, user experience, technology acceptance, and privacy and security, (Aboueid et al., 2019; Magrabi, 2019; Chambers et al., 2019; Gottliebsen and Petersson, 2020; Tsai et al., 2021) with most studies focusing on auditing these platforms’ accuracy and performance by using patient vignettes. While AI-enabled symptom checkers have the potential to improve diagnosis, quality of care, and system performance worldwide (Fraser et al., 2018), these platforms have limits as they do not explain why certain questions are being asked or why certain diagnoses are provided – this negatively impacts transparency in the platform (Pu and Chen, 2007). Transparency focuses on explaining and justifying the outcomes of AI-driven decisions or recommendations which in turn lead to improved user experience (i.e., higher trust, understandability, and satisfaction) (Gedikli et al., 2014; Tintarev and Masthoff, 2015). In addition to the limited studies on symptom checkers, research focusing on user perspectives is lacking (Aboueid et al., 2019; Chambers et al., 2019; Gottliebsen and Petersson, 2020; Tsai et al., 2021) – those that exist tested the Technology Trust Model which focused on the role of trust on symptom checker adoption (Samhan, 2019), identified top reasons for using symptom checkers (Meyer et al., 2020), examined the user experience of symptom checkers (You and Gui, 2020), and identified the types of explanations users would want to see in symptom checkers to improve transparency (Tsai et al., 2021). A national study conducted by the CMA found that 60% of Canadians have a positive outlook on the role of AI in healthcare and see it as a preventative tool for some illnesses and lead to better care from physicians (CMA, 2018). However, it was also found that while Canadians support investments of technology/AI in healthcare, they do not want to see these investments at the cost of fewer doctors and nurses with higher trust reported when AI-derived diagnosis and treatment recommendations are delivered by a physician (CMA, 2018).

While existing studies have advanced our knowledge, the literature notes that additional studies are required to understand other areas of inquiry such as how users interpret and use symptom checker outputs, how valid they assume the output to be, and what impact symptom checkers have on care-seeking behaviours (Tsai et al., 2021). Importantly, it is unclear how the use of symptom checkers may impact access and utilization of healthcare services – in this study, we are defining care as any service provided by a health professional irrespective of the healthcare setting (e.g., primary care or emergency room). This study seeks to leverage an innovative methodological approach to address some of these gaps among an understudied population and leverages the technology acceptance model to identify profiles associated with the intent to use symptom checkers among a relatively large cohort of potential end-users.

3.5 Technology Acceptance Models and their Applications

Failing to examine the factors associated with symptom checker acceptance and use will result in lost investments from both the public and private sectors. This is because users who do not accept a technology are not likely to use it; as such, users will not be able to fully benefit from innovative technologies (Davis, 1989; Venkatesh et al., 2003). The importance of assessing technology acceptance[3] is accentuated by prior research that demonstrated rejection of technology because health institutions failed to attend to key factors underlying user acceptance (Jimison et al., 2008; Kruse et al., 2015; de Grood et al., 2016). As such, to better economize investments in

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[3] Defined as "an individual's psychological state with regard to their voluntary or intended use of a particular technology" (Gattiker, 1984).

AI-enabled healthcare systems, it is of utmost importance to examine their acceptance by its prospective users.

Research on individual acceptance and use of information technology (IT) is one of the most established streams of research in IS (Venkatesh, Davis, & Morris, 2007). Stemming from theories in social-psychological and behavioural literature, mainly the Theory of Planned Behavior (Ajzen, 1988), Davis (1989) developed the technology acceptance model which states that the most proximal antecedent to actual technology use is behavioural intention, which is commonly known as the agent of acceptance. Behavioral intention is influenced by individuals' attitude, which in turn, is influenced by two key constructs (i.e., perceived usefulness (PU) and perceived ease of use (PEOU) of the technology) (Davis et al., 1989).

Davis's (1989) earlier work is ground-breaking but was in the context of a work environment in which the end-users were employees who may have been limited with their option of using or not using a technology. Over time, researchers have extended the technology acceptance model for different applications (Venkatesh, Thong, & Xu, 2016). In 2003, Venkatesh et al. synthesized these models into a Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT model identifies four key factors (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions) and four moderators (i.e., age, gender, experience, and voluntariness) related to predicting behavioural intention to use a technology and actual technology use (Venkatesh et al., 2016). The UTAUT was further refined to incorporate new constructs (i.e., hedonic motivation, price value, and habit) that focus on theoretical mechanisms in a consumer context (Venkatesh, Thong, & Xu, 2012).

3.6 The Baseline Technology Acceptance Model Guiding this Work

The UTAUT model has been widely used for its ability to explain 70% of the variance in behavioural intention (Venkatesh et al., 2012), which is the most common indicator of acceptance (Venkatesh et al., 2016). Behavioural intention considerably predicts actual behaviour, such as using a technology (Ajzen & Fishbein, 1980; Taylor & Todd, 1995; Venkatesh et al., 2003). Given the advantages of UTAUT/UTAUT2 in understanding technology acceptance, Venkatesh et al. (2016) provide a baseline model for the use of UTAUT in various contexts while allowing for flexibility on the inclusion of contextual factors of the setting and technology important for the research study at hand. In summary, the baseline model considers the effects of the following constructs on behavioural intention: *facilitating conditions, individual beliefs* (i.e., performance expectancy, effort expectancy, social influence, hedonic motivation, and price value), and *habit* (Venkatesh et al., 2016, p. 347).

The elements included in the baseline model are outlined and described in **table 2** and have informed the factors in **figure 4** which provides a visual depiction of the proposed model and the association between the various variables and constructs that were considered in this dissertation. Information on the factors outlined in **figure 4** is provided in **appendix 3.** It is important to note that variables in the figure changed based on findings from this work (i.e., which elements are significant in explaining technology acceptance and those that are not and thus, should be omitted). The dotted box in **figure 4** outlines the main effects of the baseline model proposed by Venkatesh et al. (2016). The other variables included in the figure were mainly derived from the works of Jung (2008), Kenny and Connolly (2017), and Lanseng & Andreassen (2007).

Table 2. Main Effects in the Baseline Model of Technology Acceptance and Use

Main effects	**Definition**	**Source**
Facilitating conditions	"*Consumers' perceptions of the resources and support available to perform a behaviour."* (Venkatesh et al., 2003; Brown & Venkatesh, 2005)	Venkatesh et al., 2012: Facilitating conditions in a consumer context vary – those who have access to a favourable set of facilitating conditions are more likely to have higher intentions of technology use.
Individual beliefs • Performance expectancy	"*Degree to which using a technology will provide benefits to consumers in performing certain activities*." (Venkatesh et al., 2003; Brown & Venkatesh, 2005)	Venkatesh et al., 2012: In an organizational context, performance expectancy is often the most significant predictor. In a non-organizational context, it was found that hedonic motivation was a more important driver than performance expectancy.
• Effort expectancy	"*Degree of ease associated with consumers' use of technology."* (Venkatesh et al., 2003; Brown & Venkatesh, 2005)	Venkatesh et al., 2012: It is hypothesized that those who perceive requiring little effort to use a technology are more likely to accept and use it.

• Social Influence	“*Extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology.*” (Venkatesh et al., 2003; Brown & Venkatesh, 2005)	Venkatesh et al., 2012: It is hypothesized that those who have a surrounding that encourages the use of a technology will be more likely to use it.
• Hedonic Motivation	“*The fun or pleasure derived from using a technology.*” (Holbrook et al., 1982)	Brown & Venkatesh, 2005; van der Heijden 2004; Thong et al., 2006; Childers et al., 2001: Perceived enjoyment has been found to be an important determinant of technology acceptance and use.
• Price Value	“*Consumers’ cognitive trade-off between the perceived benefits of the applications and the monetary costs for using them.*” (Dodds et al., 1991)	Venkatesh et al., 2012: The monetary cost/price is usually conceptualized together with the quality of products or services to determine their perceived value. The price value is positive when the benefits of using a technology are perceived to be greater than the monetary cost.
Habit	*“Extent to which people tend to perform behaviours automatically because of learning.”* (Limayem et al., 2007)	Ajzen, 2002 ; Kim & Malhotra, 2005 ; Limayem et al., 2007 : Prior use was a strong predictor of future technology use. Habit has a direct effect on technology use over and above the effect of intention.

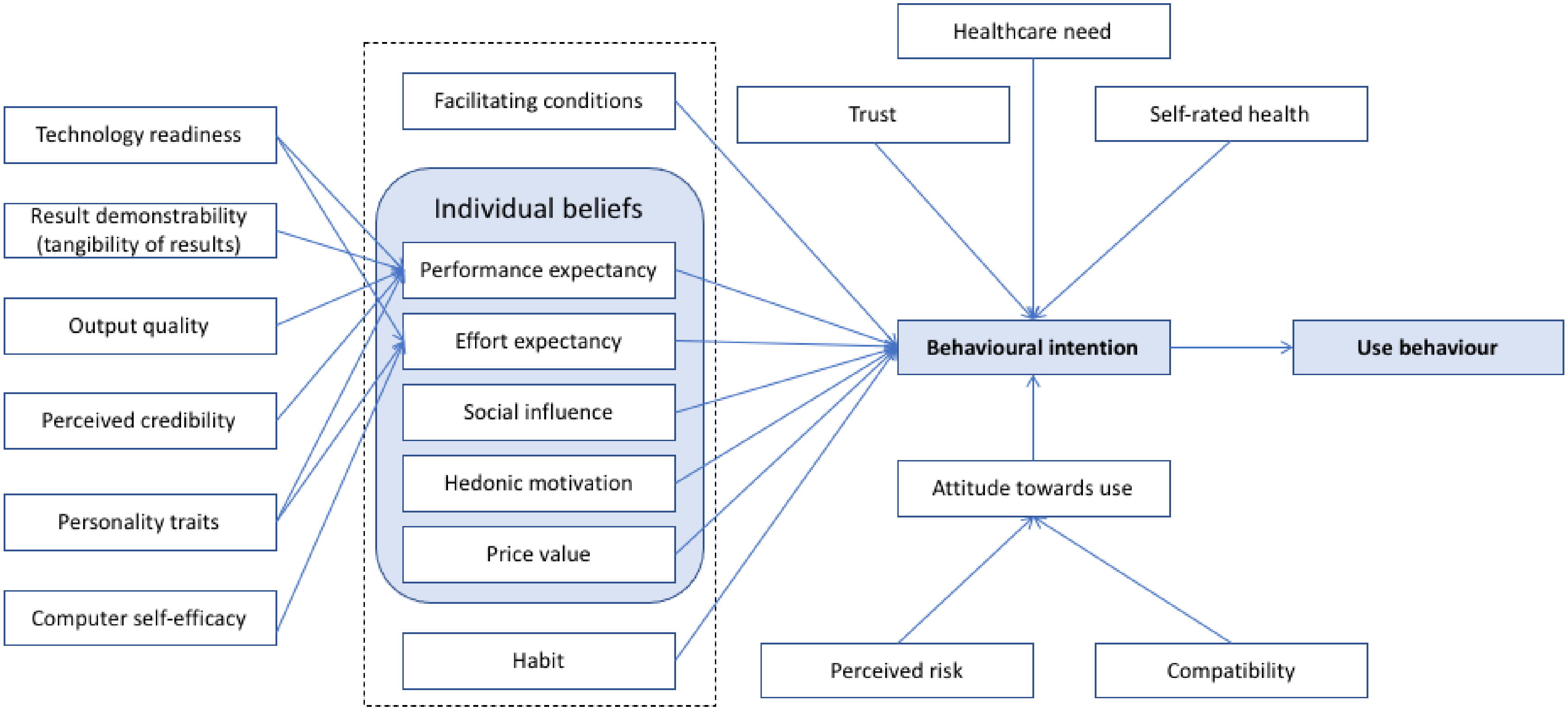

Figure 4. Proposed Model for Understanding University Students' Behavioural Intention of Using AI-Enabled Symptom checkers for Self-Triage and Self-Diagnosis

Notes: This figure was informed by the baseline model of Venkatesh et al., 2013 as well as other studies that examined self-serve technologies in the healthcare space.

3.7 Latent class analysis for identifying population subgroups

While previous studies have mainly focused on identifying the effect of individual variables on digital health platform use, it is unclear how a group of variables co-exist and in turn identify profiles that could help explain acceptance and use of such platforms. Select variables outlined in the technology acceptance model could be analyzed using Latent Class Analysis (LCA), a statistical and probabilistic method introduced in the 1950s (Lazarsfeld, 1968) that classifies individuals from a heterogeneous group into smaller more homogenous unobserved subgroups (Vermunt & Magidson, 2003). Examples of LCA applications in IT has focused on identifying classes based on Internet searching behaviours among older adults (van Boekel et al., 2017), segmenting mobile phone users based on attitude (Sell et al., 2014), and identifying patterns of technology and interactive social media use among adolescents (Tang and Patrick, 2019). The literature suggests that there is a wide range of possible bases to use in segmentation analysis, ranging from demographic data (simple to use but limited in utility), to lifestyle-related bases which are more complex but potentially more powerful (Wedel & Kamakura, 2000). Attitudes, for example, have been suggested as a useful basis for segmentation as they take into account a more affective dimension of consumers' choices (Wedel & Kamakura, 2000). It is also suggested that attitude-based segmentation can be used to explain consumer behaviour whereas socio-demographic segmentation can only be used to describe behaviour (Olsen et al., 2009).

An attitude can be defined as a consumer's evaluation of a product – in this case, symptom checkers. Attitudinal determinants for adoption have been described as consumers' subjective perceptions of different innovation characteristics and personality traits (De Marez et al., 2007). Attitudes often encompass beliefs (cognitive dimension of the attitude), feelings and emotions (affective component of the attitude), and behaviour (Pelsmacker et al., 2001; Evans et al., 2006). In IS literature, attitudes are often reduced to two constructs: "ease of use" and "perceived usefulness" (Sell et al., 2014); however, these are not sufficient for measuring consumer attitudes, especially when the target population had not yet been exposed to the platform. Therefore, it is important to consider additional variables – especially those in the UTAUT model – that may be relevant in attitude segmentation. Given the limited literature in this topic, it is important to apply LCA in attitude segmentation while considering relevant variables identified in the UTAUT model in order to understand symptom checker use.

Chapter 4: Research questions, contribution, and research design

Given the large investments in AI funded through Canadian taxpayers (UNESCO, 2017), it is important that we evaluate the extent to which/how/when AI can aid the healthcare system. To do understanding perspectives of end users, an important stakeholder, is pivotal to inform the factors associated with adoption and use. To narrow the scope of this thesis, the focus was on university students – the reasons for this are: 1) university students are typically young adults, a demographic that has been shown to be technology savvy; as such, they are the ideal target population for such platforms (Escoffery et al., 2005; CMA, 2019) – if they do not intend to use this technology or do not accept it, other population groups are unlikely to do so; 2) university students are usually undergoing a critical transition period as they have to start making decisions on their own, including decisions related to health; 3) university students tend to engage in risky health behaviours; and 4) health behaviours established during university years may persist later in life (Gardner et al., 2012; Epton et al., 2013); as such, if they accept the technology during these years, they may be more likely to continue using this technology in future years.

4.1 Research questions and contribution

Given the rise in healthcare costs, unnecessary visits, and lack of access to primary care providers, the overarching aim of this dissertation was to assess university students' behavioural intention of using AI-enabled symptom checkers for self-triage and self-diagnosis. To address this aim, three main research questions with their respective objectives were of interest. The rationale and significance for each research question are provided below.

Research Question 1: What are university students' perspectives towards the use of AI-enabled symptom checkers for self-triage and self-diagnosis?

Specifically, this question explored students' perspectives on:

a. the use of AI in healthcare,
b. researching the Internet search engine (e.g., Google) versus using AI-enabled self-diagnosing platforms for self-triage and self-diagnosis,
c. the enablers and barriers for using an AI-enabled self-diagnosing platform, and
d. areas for improving the platform.

Rationale and contribution: Given that the focus of this study was on AI-enabled symptom checkers, it was of interest to first understand how participants perceived the use of AI in healthcare to elucidate whether their perspectives regarding symptom checkers was being influenced by their general perspectives on AI (for example, a participant that has a negative perspectives regarding the use of AI in healthcare may also have similar perspectives on symptom checkers; as such, these negative perspectives would be due to the general perception related to the AI rather than the actual platform). Second, given the traditional use of the Internet to search for health information, it is of interest to understand if this habit is less or more favoured than using relatively new AI-enabled self-diagnosing platforms. This question also explores the enablers and barriers of using a symptom checker for self-triage and self-diagnosis in order to understand the factors that facilitate or hamper the use of this technology. Findings would allow health institutions to leverage the most appropriate health information source based on preferences and perspectives shared by individuals. Finally, by understanding how symptom checkers could be improved, adoption and use of symptom checkers can be maximized.

Research Question 2: What are university students' perspectives on the platform's influence on the use of health services?

Specifically, this question gathered university students' perspectives on:

a. how the use of an AI-enabled self-diagnosing platform may influence their health and use of health services,
b. factors that promote the use of AI-enabled symptom checkers, and
c. factors that influence trust towards the platform.

Rationale and contribution: Given that one of the main objectives of symptom checkers is to reduce unnecessary healthcare visits, it is important to go beyond understanding general perspectives on the use of symptom checkers to explore how participants perceive the use of these platforms to influence health services use. Second, to inform the second phase of this work, we identified the top five most chosen variables (e.g., computer self-efficacy, self-rated health) by participants to be important in deciding to use a symptom checker for self-triage – this informed the development of the survey which was employed in the second phase of this work. Trust, a variable that has been identified as an important deciding factor for technology adoption was explored further to understand how symptom checkers could be modified to improve user trust in the platform.

Research Question 3: What are the population profiles (latent classes) associated with university students' behavioural intention of using AI-enabled symptom checkers for self-triage? To answer this question, the following objective were addressed:

a. To identify the latent classes that exist among the sample, and
b. To assess the association between latent classes and the intent to use AI-enabled symptom checkers.

Rationale and contribution: The aim of this research question is to identify the latent classes associated with the behavioural intention of using symptom checkers. This approach is novel because previous studies have examined the effect of each variable on behavioural intention – it is thus unknown whether certain profiles exist among the population and if they do, what kind of effect they may have on intention to use symptom checkers. By understanding these profiles, tailored interventions could be developed to increase the adoption and use of symptom checkers.

4.2 Research design

In this thesis, a mixed methods research (MMR)[4] approach and an exploratory sequential study design were used (Creswell, 2014, p.35). MMR acknowledges the strengths and weaknesses of both qualitative and quantitative research methods and aims to neutralize the weaknesses through triangulation of data sources (Jick, 1979; Tashakkori & Teddlie, 2010). Given the limited knowledge available regarding the use of AI-enabled symptom checkers, an exploratory sequential study design was used which typically has two phases in which the qualitative data collection and analysis precedes the quantitative research design (Creswell, 2014, p.44; Berman, 2017). This study design allowed for the reduction of the number of variables depicted in **figure 4** to be included in the latter phase of this dissertation. As depicted in **figure 5**, research questions 1 and 2 were addressed during phase 1 whereas research question 3 was addressed in the second phase.

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[4] An approach to inquiry that involves collecting both qualitative and quantitative data with the "*core assumption that the combination of these approaches provides a more complete understanding of a research problem than either approach alone"* (Creswell, 2014, p.32).

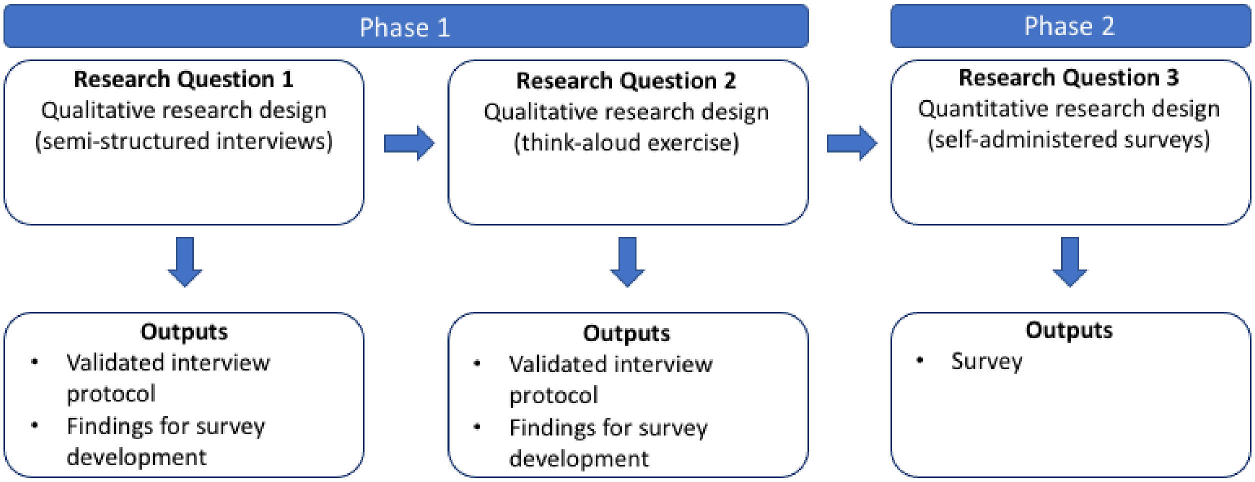

Figure 5. Data Collection Process and Outputs

Chapter 5: Phase 1 – Qualitative study examining the perspectives of university students on the use of AI-enabled symptom checkers

5.1 Research Design and Approach

Given the aim of exploring students' perspectives on the use of AI-enabled digital health platforms and identifying factors that could explain the use of symptom checkers, a qualitative research[5] design was employed to address research questions 1 and 2. Specifically, a case study research (CSR) design was used – a design that is typically differentiated by other research strategies (e.g., grounded theory, phenomenology) because of the focus on a bounded system or case (Creswell, 2013). In this work, the intent to use AI-enabled symptom checkers is the phenomenon of interest – this phenomenon is bounded by the university campus (case) and the selection of university students as participants. For this work, the descriptive type of case study was used over the other types (e.g., collective, explanatory) since it provided a description of the phenomenon of interest (i.e., the use of AI-enabled symptom checkers) in rich detail (Stake, 1995; Bogdan & Biklen; Merriam 2009; Yin 2014).

CSR first appeared around 1900 in the discipline of anthropology (Yin, 2014) and extended to other disciplines. Three notable researchers have described case studies with each having different philosophical positions (Merriam, 1998; Stake, 1995; Yin, 2012) – this thesis is in line with Yin's perspective which focuses on methodology and uses a post-positivist worldview. As described by Yin, a case study strategy has five components: the study's questions, its propositions which reflect on a theoretical issue, its unit(s) of analysis, the logic linking the data to the propositions, and the criteria for interpreting the findings (Yin, 2003). This thesis considered these five components and was guided by a conceptual framework (**figure 4**) that draws on prior research in the IS field. The research question reflects a theoretical issue related to technology acceptance and use and data were linked to propositions related to the use of symptom checkers.

In terms of the worldview utilized, there are multiple realities through which one can make sense of the world and acquire knowledge (Creswell, 2014, p.35). Post-positivism, the worldview utilized in this work, reflects the thinking after positivism, challenging the traditional notion of the

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[5] Defined as an "*approach for exploring and understanding the meaning individuals or groups ascribe to a social or human problem*" (Creswell, 2014, p.32).

absolute truth of knowledge (Phillips and Burbules, 2000). There are four philosophical assumptions which were considered throughout the first phase of this work and these include: ethics (axiology)[6], epistemology[7], ontology[8], and methodology[9] (Denzin and Lincoln, 2018). In line with a post-positivist worldview (Yin, 2003, 2009), the attempt is to control for bias by corroborating interview data with other sources of evidence. Post-positivists recognize that while there is a single reality, it cannot be fully understood due to hidden or unmeasured variables and the use of both quantitative and qualitative methods to approximate reality are typically used (Denzin and Lincoln, 2018). To understand complex social phenomena and retain holistic and meaningful characteristics of real-life events, the researcher was detached, neutral, and independent of what is being researched. This work is positioned in the post-positivist paradigm due to the use of a theory, the collection of data to either support or refute this theory, and the changes and revisions made to the theory as findings emerged.

5.2 Study Site, Study Population, and Sample

The study site was the University of Waterloo and the study population was university students. Ethics clearance was granted from the Research Ethics Board at the University of Waterloo (#41366). University students were purposively sampled to allow for a broad range of perspectives (on the use of this technology) to be gathered; as such, students across faculties (i.e., Applied Health Sciences, Arts, Engineering, Environment, Mathematics, and Science), in all levels of education, and year of study were eligible to participate. Given that this study focused on young adults, only students between the ages of 18 and 34 were eligible to participate. Students were notified of this study through flyers and recruitment posters (**appendix 4**) which were on the university campus and social media platforms. Participants were recruited until research saturation[10] was reached; this was possible to identify because data collection and analysis occurred concomitantly. A total of 24 participants were recruited to address research question 1 of which 22 were also included in the sample for research question 2 (objective b). Scope and replication were considered for determining when data saturation was reached. The

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[6] Answers the question: what is the role of values?

[7] Answers the question: what is the relationship between the researcher and the researched?

[8] Answers the question: what is the nature of reality?

[9] Answers the question: what is the process of research?

[10] Building rich data throughout the process of inquiry by focusing both on scope and replication to build theorical aspects of inquiry (Morse, 2015)

comprehensiveness of data collected, relatively large number of participants, semi-structured nature of the interview, and relatively homogenous sample (i.e., university students) allowed for a good coverage of scope (Morse, 2015). Replication was also observed, and this pertains to observing essential characteristics which were common across participants (Morse, 2015).

5.3 Data Sources and Procedures

For this study, the main data sources were gathered through one-on-one semi-structured interviews and a think-aloud protocol, and a researcher write-up following every interview. Most interviews took place virtually through a secured platform (Whereby) due to the COVID-19 pandemic. Recruitment scripts used can be found in **appendix 5 and 6**. An information letter (**appendix 7**) was provided to all participants, the study's objectives and procedures (including the technology of focus – i.e., AI-enabled symptom checkers) were clearly explained, and informed consent (**appendix 8**) was obtained from each participant.

To allow for comparability across participants, a semi-structured interview guide was used. This interview guide entails asking the same questions in the same order in the beginning of the interview and allows the interviewer to explore any subjects of interest in the latter parts of the interview (Patton, 2002). Such semi-structured interviews offer flexibility to the interviewer in determining when it is appropriate to explore certain subjects in greater depth or pose new questions that were not originally anticipated when the interview protocol was developed (Patton, 2002, p.347). For example, this allowed the researcher to explore lines of questioning related to the use of symptom checkers during the COVID-19 pandemic. All interviews, including the think-aloud exercise, were audio-recorded with the permission of the participant.

To ensure that all participants were familiar with symptom checkers, they were asked to conduct a think-aloud exercise during which they read a clinical vignette (**appendix 9**) which describes the symptoms of scarlet fever (Luger et al., 2014). Participants were asked to input symptoms from the clinical vignette into the platform while thinking out loud (Ericsson & Simon, 1993). In this method, participants are asked to report everything that goes through their mind while they are performing a task, and they are instructed not to interpret or analyze their thinking (Güss, 2018). The thinking aloud procedure helps in understanding the process of human reasoning while problem solving rather than investigating whether a person solved a problem or not (Güss, 2018). In this study, for example, the focus was to ensure that participants were familiar with the platform prior to answering questions related to their experience rather than to identify whether participants chose scarlet fever as a potential diagnosis. The principal investigator (SA) provided an example of how the procedure should be completed and participants were asked if they had any questions before beginning the task. Each participant had the chance of practicing the process and beginning once they felt comfortable.

In this study, 11 participants used the WebMD symptom checker while the rest (n=13) used Babylon Health. The choice of the platform used was based on a draw. WebMD (https://symptoms.webmd.com/) and Babylon Health (https://www.babylonhealth.com/ask-babylon-chat) were chosen based on popularity and adoption by credible institutions such as the NHS, respectively. Both platforms are similar in terms of their objectives and process (e.g., they both allow users to enter symptoms as free text and suggest symptoms from a drop-down list); however, there are key differences with Babylon: 1) requiring the user's full name, email address, country of residence, and date of birth, 2) probing more and thus taking longer to complete.

The questions in the semi-structured interview protocol were driven by the objectives of RQ.1 and RQ.2. The interview protocol was pilot tested with 11 participants (key learnings from the pilot can be found in **appendix 10)**. Based on these key learnings and the COVID-19 pandemic, additional dimensions were explored to assess how the pandemic may have influenced participant perspectives on the use of symptom checkers – results from this work can be found in Aboueid et al. (2021a). Another addition was a question that prompted participants to choose five factors they believed were associated with the use of symptom checkers – this allowed the understanding of the relative importance of factors and in turn, the factors that should be considered for the survey. As such, pilot participants were asked to participate in a second interview to allow for additional questions to be asked.

All participants were asked the same questions which are outlined in **appendix 11** – a rationale and alignment with the research objectives are also provided. The pre-interview questionnaire contains questions on demographic data and individual or contextual information including health literacy and self-perceived health. These variables were measured to assess whether responses differed based on these parameters. As it pertains to health literacy, the interest is on how people obtain, understand, and use health information to manage their health (WHO, 1998). With permission from the authors, questions from the Health Literacy Questionnaire (HLQ) developed by Osborne et al (2014) were administered to participants. As in other studies, to avoid respondent burden, not all domains from the HLQ were measured. Out of the 9 domains, four of them were measured and these include: 1) feel understood and supported by healthcare providers (HPS), 2) actively managing health (AMH), 3) ability to actively engage with healthcare providers (AE), and 4) ability to find good health information (FHI). For domains HPS and AMH, the four-point Likert scale ranged from strongly disagree to strongly agree with a higher number indicating a higher agreement. Domains AE and FHI were measured using a five-point scale which ranged from "cannot do or always difficult" to "always easy" with a higher number indicating an easier ranking for performing the task. The total average score for each of these domains are provided in **table 3 and 5**. Scores for each participant are outlined in **table 4**.

Self-perceived health (SPH) was also measured and refers to a person's perception of their own health. SPH was measured using one question which was shown to be a powerful measure in the meta-analysis conducted by DeSalvo and colleagues (2006). This construct is important to measure as it may influence the perspectives of participants on the use of technology for addressing their health needs.

Importantly, given that the ultimate aim of this dissertation was to identify which variables are significant in explaining the use of symptom checkers, a salient finding from the interviews was to identify the variables that participants believe are most important when deciding to use a symptom checker for self-triage and self-diagnosis. This approach is in line with what was used in the study by Jung (2008) during which the researcher asked interviewees to place variables in order based on their perceived importance in deciding on whether to use an e-health service. This methodology helped reduce the number of constructs to be included in the quantitative survey which will be used to address RQ.3.

5.4 Analysis Plan

The data were analyzed as new data were being collected. The analysis process involved many steps that were interlinked – some tasks were repeated to obtain a deeper and more refined understanding of responses. Thematic analysis was utilized to identify emerging themes that address the study's research questions and objectives. Four main steps were undertaken to identify themes: 1) compiling, 2) disassembling, 3) reassembling, and 4) interpreting (Castleberry and Nolen, 2018).

SA conducted all steps of the data analysis. The first step consisted of transforming data into a readable format; as such, all audio-recorded interviews were transcribed. The data were imported into NVivo 12 software (Version 12.6.0) – a sophisticated software developed to aid in organizing and analyzing qualitative data. To get a sense of the data as a whole, all transcripts were read in their entirety. This step is important to gain familiarity with the data and to start understanding the overarching themes (Bradley, Curry, & Devers, 2007; Creswell, 2014). In the second step of disassembling the data, a line-by-line coding approach was used. This step allowed for a careful read of the data, reduced the likelihood of superimposing preconceived notions on the data, and generated descriptive codes (Charmaz, 2006). These descriptive codes served as tags to retrieve and categorize similar data. Given the limited literature on this topic, the coding process was mainly inductive, but informed by the UTAUT. A codebook was developed throughout the coding process and contains all generated codes with their definitions and indication of when they should be used.

The third step consisted of reassembling the codes into main themes. Based on the themes and patterns that emerged from the data, hierarchies, diagrams, and tables were used to present findings. The final step was to interpret the data. While interpretation occurred throughout the data analysis process, the final step of the analysis was to provide analytical conclusions that stem from the data. By interpreting the data at a higher level than themes, it was possible to answer the research question and objectives. For each research question and their respective objectives, results are presented and supported by participant quotes.

The following approaches were used to ensure validity of the research conducted: a clear explanation of the data collection and analysis, triangulation of data through various means of data collection (i.e., self-administered questionnaires, think-aloud exercise, semi-structured interviews, and survey in phase 2), reflexivity, fair dealing, and intra-coder reliability (Mays and Pope, 2000; Morse, 1997; Saldana, 2016). The researcher aimed to provide a clear account of how research questions were developed and participants were recruited, conducted a pilot test to ensure that the interview protocol covers all relevant aspects, and provided a description of how data were analyzed and presented, as well as provided example quotes and explanation for emerging themes. To allow for a comprehensive understanding of the phenomenon, various data collection approaches were used including a think-aloud exercise which allowed the researcher to understand participant experiences with the use of symptom checkers followed by probing each participant about their experience.

Reflexivity was another approach that was utilized and allowed the researcher to assess whether their own experiences or characteristics such as age, sex, social class, and professional status influenced the analysis of data. By acknowledging that the researcher has an interest in technology as a health professional, it helped mitigate self-induced conscious biases in the data analysis process. Recognizing their biases, the researcher conducted the data analysis over two occasions to calculate intra-coder reliability – an approach that entails coding a portion of the data, waiting a few days, and re-coding the same data (Miles, Huberman, & Saldana, 2014) – and found an internal consistency of 92% in the coded themes (Castleberry & Nolen, 2018). This level of consistency in generated themes across two time points may be explained by the fact that the researcher conducted all the interviews, was immersed in the data, and had read the data carefully. Fair dealing was another approach that was undertaken by allowing for a broad range of perspectives to be included through the recruitment of students across faculties, level of education, and year of study.

5.5 Results

5.5.1 Participant Information

A total of 24 participants took part in the qualitative interviews. An overview of participant characteristics and symptom checker used during the interviews are provided in **table 3**. Nine participants from the pilot study were interviewed twice (please refer to section 5.3 for more details). Two participants from the pilot study did not agree to participate in a second interview and one participant was excluded because they were older than 34 years of age. Results from this section informed the publication of an article (see Aboueid et al., 2021b).

Table 3. Sample Characteristics for RQ.1

Characteristics	Count (n) or Mean
Gender	
Female	14
Male	9
Non-binary	1
Racial Group	
White	9
Asian	6
Chinese	3
Arab	2
Indian	2
Black	2
Highest Level of Education	
High school	2
Undergraduate degree	14
Master’s degree	8
Faculty	
Engineering	8
Sciences	6
Applied Health Sciences	3
Environment	3
Arts	3
Mathematics	1
Self-Perceived Health	
Excellent	2
Very good	13
Good	5
Fair	4
Poor	0
Health Literacy	
Feeling understood by healthcare providers (HPS)*	2.92
Actively managing my health (AMH)*	3.05
Ability to actively engage with healthcare providers (AE)**	3.64
Ability to find good health information (FHI)**	3.81
Symptom Checker	
WebMD	11
Babylon Health	13

*Maximum possible average is 4
**Maximum possible average is 5
Note: Reporting count for categorical variables and means (up to two decimals) for continuous variables

A total of 11 participants had used a symptom checker before the time of the interview, among which two participants used a symptom checker for the first time because of COVID-19.

Participants who had previously used a symptom checker heard about the platform through word-of-mouth or an Internet search.

Most participants scored high on health literacy dimensions; few exceptions were as follows – two participants had a low score on feeling understood by healthcare providers, one had a low score on actively managing their health, and two participants had a low score on ability to find good health information. Participant scores for each domain are provided in **table 4**.

Table 4. Participant Scores for Health Literacy Domains

Participant	Feeling understood by healthcare providers (HPS) mean score	Actively managing my health (AMH) mean score	Ability to actively engage with healthcare providers (AE) mean score	Ability to find good health information (FHI) mean score
1	2.50	3.00	3.40	4.60
2	3.00	3.20	3.80	3.60
3	2.50	3.20	4.00	2.75
4	4.00	3.80	3.60	3.60
5	3.00	3.80	4.60	4.80
6	2.25	2.60	3.80	4.60
7	3.75	3.80	3.40	3.60
8	4.00	4.00	4.20	4.60
9	2.25	2.80	3.00	4.00
10	3.75	2.40	4.60	5.00
11	3.50	3.20	4.00	3.40
12	2.25	3.00	3.00	4.00
13	2.75	2.60	3.00	3.20
14	3.75	3.00	4.60	4.20
15	1.50*	2.80	3.40	4.00
16	3.25	2.40	3.40	4.20
17	3.00	3.20	4.00	1.80*
18	2.50	2.60	4.20	3.20
19	4.00	3.00	3.40	3.80
20	2.75	2.80	4.00	5.00
21	2.00	3.80	3.20	2.40*
22	3.25	1.80*	2.60	3.00
23	3.00	4.00	3.60	4.20
24	1.50*	2.40	2.60	3.80
Total Mean Score	2.92	3.05	3.64	3.81

*less than 50% of the total possible score

The sample differs for the objective that focuses on the top factors perceived to be associated with the use of a symptom checker for self-triage (RQ.2, objective b.) as this was addressed through a question which was added following the pilot project. Two participants from the pilot project did not accept to be interviewed a second time; as such, the total number of participants recruited to address objective b) is 22 in total. Participant information for this sample is provided in **table 5**.

Table 5. Sample Characteristics for RQ.2

Characteristics	Count (n) or Mean
Gender	
Female	12
Male	9
Non-binary	1
Racial Group	
White	7
Asian	6
Chinese	3
Arab	2
Indian	2
Black	2
Highest Level of Education	
High school	2
Undergraduate degree	14
Master's degree	6
Faculty	
Engineering	8
Sciences	5
Applied Health Sciences	3
Environment	3
Arts	2
Mathematics	1
Self-Perceived Health	
Excellent	2
Very good	11
Good	5
Fair	4
Poor	0
Health Literacy	
Feeling understood by healthcare providers (HPS)*	2.90
Actively managing my health (AMH)*	3.04
Ability to actively engage with healthcare providers (AE)**	3.64
Ability to find good health information (FHI)**	3.78
Symptom Checker	
WebMD	10

Babylon Health	12

*Maximum possible average is 4
**Maximum possible average is 5
Note: Reporting count for categorical variables and means (up to two decimals) for continuous variables

5.5.2 Themes for Research Question 1

RQ.1. Objective a) University students’ perspectives on the use of AI in healthcare

Most participants had positive perspectives on the use of AI in healthcare and believed that the positives of using AI in healthcare outweighs its potential negative effects. Themes that indicated positive perspectives regarding the use of AI were related to the use of big data to inform decision-making and pattern recognition. While AI was thought by some participants to improve efficiency in healthcare, they were cognizant that its impact is limited by the quality and quantity of data used. Some were optimistic about the use of AI in healthcare, especially in the presence of regulations surrounding the use of personal information and data privacy.

Some participants expressed concerns regarding the ethical implications of the use of AI and biases that could be exacerbated from the use of AI if not regulated and monitored. For example, given that individuals develop algorithms, it is important to ensure that relevant information (e.g., medical conditions) are not missed and that bias is minimized. Moreover, some believed that AI is “overhyped” and that its use will limit human-to-human interaction which they believed could be an issue for the elderly population.

Figure 6 outlines the themes that emerged from the data which were grouped into positive, negative, and indecisive depending on their nature. **Table 6** provides example participant quotes to support identified themes.

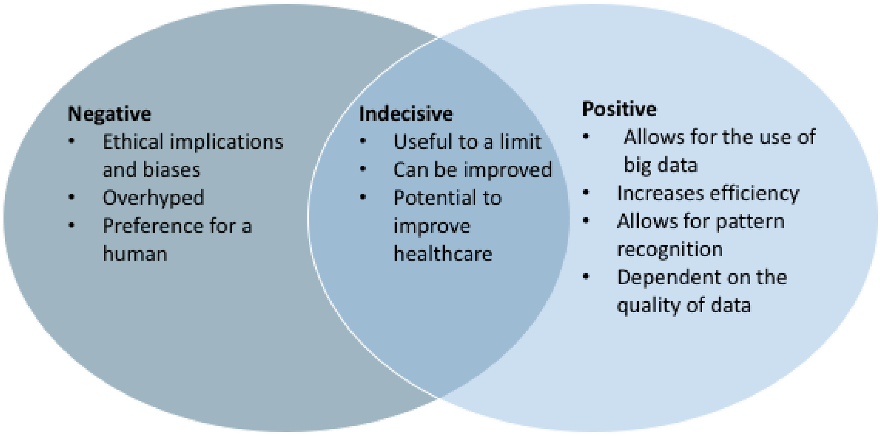


Figure 6. Diagram of Themes Related to the Use of AI in Healthcare

Table 6. Example Quotes Related to the Use of AI in Healthcare

Type of Theme	Theme	Example Quotes
Negative	Ethical implications and biases	*"I have done some research on artificial intelligence within my program for several projects – initially I am concerned with the ethical implications of using AI for health care. I guess especially because we know a lot of the time the kind of biases or assumptions that the humans who created the algorithms get baked into the AI system so I guess I would be concerned with some gender imbalances and racial imbalances in terms of how symptoms are interpreted or understood by the AI system. That's just based on what I know about ethics and AI – my concern would be around bias."* – P6
	"Overhyped"	*"I feel like AI seems to be one of those overhyped tech things that may or may not pan out. There is the craze about blockchain and self-driving cars but then they always die. There are a lot of obstacles in implementing these technologies."* – P20
	Preference for a human	*"Honestly, I always prefer real humans for any sort of information that I need. I would always prefer to be in contact with a real human whose expertise I trust and whom I have some rapport with."* – P23
Indecisive	Useful to a limit	*"I am hopeful, I think. With every technology there are going to be drawbacks but as a society in general, we*

		have to go forward. With time and enough development, AI can be hugely beneficial for the society.” – P21
	Can be improved	“*I guess it depends on how much you can customize the input of the symptoms. I think at some point AI will be very strong in pattern recognition to discern the symptoms and diagnoses but as it stands, you click sore throat plus this and gives the output. I don’t know if we will reach a point, well we will eventually reach a point where we actually understand some sort of text or voice input, but I don’t know if that’s in the near future*.” – P3
	Potential to improve healthcare	“*I have seen some pretty amazing breakthroughs for the use of AI, so I think that at least now and, in the future, there is the potential to really improve healthcare universally. It really depends on how we use it. At least right now, there are a lot of people who might not trust the output if they know AI is behind it but if we warm people up to it I think it had the potential to improve our healthcare system overall*.” – P18
Positive	Allows for the use of big data	“*I think it has large potential because if there is one doctor that sees 20 patients with a certain case every year, they have 20 cases to draw upon; however, if you have this one software that’s taking those 20 cases from all the doctors and combining them together, the one doctor can use that data pool of all the information of all the patients and say: you know what I have seen one case like this but it’s quite probable that you are similar to this patient because from this larger dataset that the AI can absorb and process then it could be more of an easy transition to say that it very good well be the case even though I am not experienced with it*.” – P4
	Increases efficiency	“*They [AI technologies] are super fast; they expand their data much more than a human so it will be useful and time-efficient if you actually have all of that being governed by AI. It just reduces time and energy for everyone – the doctors and the patients*.” – P10
	Useful for pattern recognition	“*I think it’s really great. It’s capturing experiences and disseminating information in a way that is smart and accessible. This is work that would have needed to be done anyways. Tracking symptoms and organization of it is good because patterns are a really big part of health and what health analysis should be looking into and I think AI can do that in a way that is faster and smarter*.” – P11
	Dependent on the quality of data	“*AI is pretty good if there are credible data to make those decisions then I think it is pretty good. I know if you have*

		a lot of data, the credibility of AI depends on the number of data you have." – P16

RQ.1. Objective b) University students' perspectives on researching the Internet versus using AI-enabled self-diagnosing platforms for self-triage and self-diagnosis

The data analysis elucidated themes related to the use of the Internet and symptom checkers for the input of symptoms. Codes and sub-themes related to the use of the Internet and symptom checker were grouped into positive or negative themes. Positive themes suggest a desirable attribute, function, or experience related to a platform whereas negative themes encompass themes that suggest the opposite. An overview of these themes is provided in **table 7**. Example quotes for themes can be found in **appendix 12.**

Table 7. Overview of Themes Related to the Use of the Internet Versus Symptom Checkers

<table>
<tr><th></th><th>Internet Search Engine</th><th>Symptom Checkers</th></tr>
<tr><td>Positive Themes</td><td>- Provides information without claiming a diagnosis
- More customizable
- Allows entry of all symptoms in the search engine</td><td>- More personalized
- More interactive due to chatbot feature
- Good for those who do not know how to use the Internet
- Straightforward design
- Easy to use
- Real time
- Makes the correlation between symptoms and potential conditions
- More intuitive
- More reliable
- More specific
- More structured</td></tr>
<tr><td rowspan="2">Negative Themes</td><td>- Absence of chatbot feature</td><td>- Accuracy is questionable
- Limits the number of symptoms that can be inputted
- Not widely known
- Thought process of the platform is unclear
- User more vulnerable when using this platform</td></tr>
<tr><td colspan="2">- Text input is insufficient
- Suboptimal reliability</td></tr>
</table>

Participants perceived the Internet's search engine and symptom checkers to be useful for mild symptoms; however, some perceived that using the Internet's search engine was faster than having to answer questions in a symptom checker.

> "*If you're googling something quick then it's easy, quick and straight-forward, you don't have to take ten minutes to answer all these questions […].*" – P2

Positive themes related to the use of the Internet mainly pertain to the perspective that an Internet search engine allows users to input as many symptoms as needed allowing for a more comprehensive search of potential conditions that may be relevant to their health context. Some users also mentioned that they preferred the platform did not claim that this is the condition they may have.

> "*On the other hand, I think it may be easier to get accurate results on symptoms through a google search because I can type multiple symptoms and see how they fit, I may get more garbage results, but I can use my judgment to decide what is true and not true. Whereas the symptom checker has only one piece of information which is fever. The symptom checker did not give me the opportunity to put in more from what I can recall.*" – P11

Nonetheless, some participants mentioned that the absence of a chatbot feature in the Internet search engine limits the platform's ability to ask follow-up questions based on symptoms inputted. As such, some users who may not be able to identify all symptoms experienced, may omit certain symptoms, or may not elaborate on symptoms which hinders the quality and comprehensiveness of the output.

> *"[…] if I were to google my symptom, I would just put in a fever and rashes that could be a million things. But with a symptom checker, I would put in fever and it asked me for a specific temperature and other specific questions which I would not know to search on my own.*" – P21

Symptom checkers were perceived by some participants to be a good option for individuals who are less proficient using the Internet for information retrieval. Some had a positive attitude towards symptom checkers because the platform asked questions regarding age and gender giving the impression that it is more personalized and in turn, in their perception, more accurate.

> *"[...] surfing through the* Internet and coming through a particular diagnosis takes a *lot of time although it might give you more information about other diseases that have similar symptoms, but this is not what I am looking for, I am looking for what I am suffering from. So, for which, I think a personalized software is helpful*." – P2

Some participants believed that the symptom checker "had more structure", "provided a greater level of detail", "was more interactive", and "was more reliable" than using the google search engine.

> "*So I think having that more structured approach to inputting symptoms and figuring out what is likely wrong with you would be a lot nicer for the user and the user would have more faith in the result rather than just going on google that brings up a whole bunch of results and the user thinking that they could have anything*." – P4

While having a more structured approach to symptom input was favoured, some participants were unable to enter all symptoms in the platform which led them to question the accuracy and reliability of the platform – this also hindered trust towards the platform.

> "*I feel like I don't like the symptom checker as much because it limits the number of symptoms. I did not have the chance to mention the thing with the red bumps; it just asked me a lot of questions about the one "symptom that was bothering me the most".*
> – P20

There was also a sense that participants would feel more vulnerable using a symptom checker due to the more personalized nature of the questions asked. Interestingly, some participants believed that their judgement and thought process to identify potential diagnoses was superior to using a symptom checker due to lack of knowledge about how symptom checkers arrive at an output.

> "*It feels more vulnerable and personal to put my symptoms into a list or generator of some kind. It feels like I am just looking at a series of articles I feel there's more of a distance [....] If I am typing in a symptom checker and it comes back at me with answers, I don't know how it came to that conclusion and I don't know what the process was to decide that 'yes, this is what you have' whereas if I am the one doing the analysis through a bunch of articles that I deem legitimate – whether or not they truly are legitimate – at least I know what the thought process was and I feel like I can trust that.*" – P6

Despite various shortcomings that were mentioned related to the use of symptom checkers, some participants believed that an important issue is the lack of awareness about the existence of the platform.

> "*But the issue is that we don't know about symptom checkers so making them widely available would be super helpful*." – P13

In addition, there was a consensus that consulting a primary care provider or nurse was superior than searching the Internet or using a symptom checker to assess the severity of symptoms – this was especially the case when certain symptoms required a physical examination and text input was insufficient. Reliability of the Internet search engine and symptom checker were also questionable and were perceived negatively by some participants.

> "*I think seeing a provider face to face is better than both options. I feel that you can't accurately portray all your symptoms and general health by text input. You need someone looking at you and take measurements and touch injured areas, I think that's far superior*." – P1

> "*I think google is a very wide platform so it's very hard to analyze the reliability or the source. In this case, it depends on the reliability of the symptom checker as well."* – P19

In sum, while consulting a primary care provider was perceived to be superior to both searching the Internet or using a symptom checker, most participants believed that these platforms could be useful for mild symptoms. Various positive and negative themes emerged related to the use of the Internet and symptom checker. While symptom checkers were perceived positively by most participants, some conveyed that its use would be justified on the basis that it has been rigorously tested and validated. There was also an acknowledgement that the results provided by symptom checkers can only be as good as the data that informed them. Nonetheless, symptom checkers were perceived to be more personalized, structured, and tailored thus improving the user experience. To increase adoption and ultimately, the use of symptom checkers, it was perceived to be important to increase awareness about the existence of the platform and increase the number of symptoms that could be inputted by users.

RQ.1. Objective c) University students' perspectives on the enablers and barriers for using an AI-enabled symptom checker

Barriers were defined as factors that hindered or would hinder the use of symptom checkers whereas enablers were defined as factors that would entice an individual to use symptom checkers. Participants enumerated many enablers and barriers for using symptom checkers – these factors pertained to the: 1) individual, 2) disease, 3) healthcare system, or 4) the symptom checker. Enablers that were related to the individual included health literacy or level of education, technical skills, lack of time, curiosity, convenience, and aversion to medical professionals. Given that a disease does not define the individual, disease-related enablers were considered separately and included having a "broad category of illness", an embarrassing issue, or an issue perceived to be minor. Individuals seemed to be more willing to use a symptom checker if they are experiencing non-specific symptoms (e.g., fatigue) due to the perceived notion that a symptom checker would allow the user to narrow down on a health condition. They are also more willing to use symptom checkers for issues perceived to be "embarrassing" such as conditions related to mental health or for conditions they are "uncertain about". Interestingly, symptom checkers were perceived to be useful in the context of seeking primary care services rather than informing emergency department visits.

Enablers related to the healthcare system included lack of access to care, having the symptom checker approved by the doctors' and nurses' associations, or incorporated in the public healthcare system. Some believed that this tool would work well in conjunction to the existing healthcare system to prevent those with minor issues from accessing medical care which would in turn allow for those with more serious conditions to receive care quicker. Most of the enablers that were mentioned pertained to the symptom checker platform and these included: accuracy; free of cost; a guarantee of anonymity, security, and privacy; a well-designed and easy-to-use platform; a personalized experience; short time to complete; and gamification of the platform. Interestingly, more than half of participants (13/24) were not aware of symptom checkers prior to the interview and believed that more advertisement was needed.

Most barriers mentioned were the opposite of the enablers explained above; however, some new factors that were not previously mentioned were perceived as barriers for using symptom checkers. These factors were grouped under the following overarching themes: 1) individual-level,

2) health-system level, or 3) factors related to symptom checkers. Health literacy was perceived to be both an enabler and barrier as those with high knowledge of diseases may be skeptical of this technology. Lack of access to the Internet, lack of trust in the results provided by the platform, and fear of the worst-case scenarios were all individual-level factors that would hinder the use of symptom checkers. Health-system level barriers include the dogma in healthcare and health professionals who may disapprove of symptom checkers.

The data suggest that barriers for using symptom checkers are the lack of transparency on how the data collected will be used – some mentioned that they would not have an issue with the data being used by governmental institutions to improve health services but did not want their data to be used to generate profits. While most participants understood the medical terms that were used by the digital platform, some believed that the average person may not understand some of the questions asked. Providing a brief description of medical terms would allow users to interact with the platform in a more informed manner. Participants also stressed the importance for the digital platform to elaborate on why certain questions were being asked. In contrast to seeing a health professional, users are unable to interject and ask the platform questions for further elaboration. Moreover, most platforms use a disclaimer claiming that they do not provide medical advice which undermines the platform’s credibility.

The platforms that were used during this study were in English; however, some mentioned the importance of having these platforms available in various languages to ensure that they are accessible to those who are less proficient in English. Lack of inclusivity measures do not allow persons with disabilities to use the platform and was also mentioned as a barrier to use. Other mentioned barriers were skepticism from the media regarding the use of AI and its unintended consequences, the lack of human interaction, and being disadvantaged which limits access to these platforms.

A full list of factors enabling or hampering the use of symptom checkers are listed in **tables 8 and 9** along with example quotes.

Table 8. Example Quotes of Enablers for Using Symptom Checkers

Individual-level enablers

Enabler	**Example Participant Quote**
Internet access	"*Access to the Internet.*" – P16
Low health literacy	"*…maybe if they just did not know a ton about health in general maybe they would be less critical than me*." – P11
Trust in the platform	"*If you want people to use symptom checkers more, there has to be development on the technology to make people trust it*." – P21
High technology literacy	"*Health literacy and technological literacy are big ones*." – P10
Younger age	"*The younger generation would be a lot more into doing this type of thing because I know that the older generation are less savvy with using new technology and programs*." – P2
Lack of time	"*Entirely be time and lack of availability of health services. Sitting at a drop-in clinic it sucks, obviously. So, if you don't have to go through that, it's great – from a time perspective but also from sheer stress and not being enjoyable to sit at a clinic*." – P1
Convenience	"*Just generally wait times with family practitioners I mean it can obviously take several weeks or longer to make an appointment with a practitioner and the inconvenience of the wait for the appointment and to get to where the appointment is.*" – P6
Lack of trust in doctors	"*If you don't trust the doctor, you may still end up using the symptom checker*." – P16
Curiosity	"*Curiosity, I think people are just generally interested in what's going to pop up based on the symptoms.*" – P4
Embarrassing topic	"*Some people are embarrassed of health issues so if they can have it diagnosed without having to see someone then they would be interested in that.*" – P1
Increase empowerment	"*I find it empowering to be able to identify what is going on with my own body so a symptom checker can allow me to get a sense of what might be going on – put words to something I cannot put words to*." – P23
Aversion to medical professionals	"*Perhaps an aversion to actual medical professionals. People generally don't like doctors it seems or healthcare professionals and that might be the environment of the medical office or the personal privacy standpoint of it. That will probably continue and so I see a benefit of these programs and why they exist.*" – P4
Having pre-existing conditions	"*If you have pre-existing conditions, if you know you're generally not well and generally anxious about your health, you will go ahead and use this to check the problem*." – P15
Unable to discuss the topic with a health provider	"*Embarrassment of discussing the topic or unable to discuss it with the doctor (so either lacking the knowledge back or doctors not being trained in informing their patients properly or not taking the time to inform patients).*" – P4
Uncertain about care required	"*I think people will use it when they are uncertain if something is serious and have to go to the emergency or if it's something that they can put off and take an appointment with the doctor*." – P13

Worried about health of oneself	“*If you know you’re generally not well and generally anxious about your health, you will go ahead and use this to check the problem. Being always worried about diseases and health*.” – P16
Disease-level enablers	
Mild symptoms	“*Something that is personal or lame [something minor] just to check if it’s abnormal.*” – Participant 3
A “broad category of illness”	“*…if it’s still a broad category of illnesses, then they would just go to a symptom checker.*” – P2
Symptoms can be easily described	“*Maybe if they have symptoms that can be easily described, and they know how to describe them properly*.” – P18
Health-system level enablers	
Approved by doctors	“*Advertised by a doctor, not advertised but you know in the doctor’s office where you have some papers and ads so having that there so it’s at the doctor’s and you have more confidence that it will be something useful and not just weird things that go on the Internet*.” – P13
Lack of access to health services	“*Entirely time and lack of availability of health services.*” – P1
Cost of health services	“*I think that maybe if they had to pay for healthcare wherever they are they would try to figure it out if it’s actually serious*.” – P11
Public education	“*Educating the public is very important because the older generation probably doesn’t trust the Internet stuff. I would trust it a bit more, but I am still hesitant because I do not know how this thing works and anything that deals with your health, people are a bit more cautious about it.*” – P21
Long wait times for health services	“*Just generally wait times with family practitioners I mean it can obviously take several weeks or longer to make an appointment with a practitioner and the inconvenience of the wait for the appointment and to get to where the appointment is*.” – P6
Reputable organizations recommend it	“*First of all, they have to somehow not only advertise but maybe if the website is promoted by the healthcare organization that is reliable for people then I can make sure that the platform is trusted by an authentic organization so for sure I would use it, why not*.” – P24
Symptom checker related enablers	
Increased advertisement	“*But I would say a very attractive platform and ads to make it known that these things exist. Especially during cold and flu season if there are advertisements in bathroom stalls or cafeterias*.” – P3
Easy interface	“*It sounds very interesting and it is very easy to use. Definitely I will use it again, I had a good user experience*.” – P24
Data privacy	“*They will use it if they know that their information is not going to be shared. These days people are very hung up on keeping their information private. To all their own but a lot of people do not feel comfortable putting their name and email address when they ask for it before you start or before you get your result.*” – P10

Free of charge	“*Cost, in the United States you have to pay to see a doctor and why pay if you can have something that may give you a better diagnosis or idea of what is going on.*” – P8
Good source of information	“*Something that I found really weird about health information sharing is that one of the key messages that you receive in anything health related is “talk to your doctor” but my experience has been that talking to my doctor, I would be talking to my doctor all the time. So, I feel that symptom checkers or other sources of health information that people have access to and can trust can help people get good healthcare information without constantly having to take an appointment and go to the medical office*.” – P23
Short to complete	“*And if it was short – I think if there were options “hey, do you want to take the shorter version and it might not be as accurate or do you want to take the longer one that will take more time but will be more accurate”. I think people want something quick but quick won’t be as accurate.*” – P9
Precision	“*This is a precise and confidential type of platform where you just have to put it in your age and gender*.” – P17
Use of AI	“*Maybe it would seem more comforting that there is an AI behind it rather than just Googling*.” – P20
Gamification	“*… there’s probably a gamification way to help people use it too – maybe a monthly check-in thing where you do a personal assessment, and you get points or badges for being on top of your own health. I feel like I would use that more if I had that.*” – P6
Integrated with an electronic health record	“*I think if the symptom checker was somehow able to send a report of the symptoms to your doctor, I think that would help*.” – P8
Useful in identifying potential conditions	“*So, this might be kind of a slightly less intense less scary less vulnerable less committed way of digging what condition it might be*.” – P6
Information about the creators of the platform	“*The experience of the practitioners who developed this tool and that have practiced for many years*.” – P19
Interactive platform	“*Some sort of interface that could be more user friendly. This is user friendly, but it should be a bit more interactive and should allow to ask questions*.” – P19
Reliability	“*I think if the symptom checkers are from sources which are reliable which again is a dicey statement to make because someone could find something reliable or not*.” – P19

Table 9. Example Quotes of Barriers for Using Symptom Checkers

Individual-level barriers	
Barrier	**Example Participant Quote**
Lack of Internet access	“*Also, if we are talking about people who do not have access. Even though it’s not as common as before, you still have people who don’t have access to the Internet or know that this service is possible.*” – P9

Low health literacy	"*Also, sometimes it's hard to articulate to have the proper term of how you feel. For example, in the fever or the lymph node, you don't know of things like that unless you have specific knowledge about it. So, it is hard for someone who does not have medical terminology to input what they have in there*." – P13
Lack of trust in the platform	"*People might not want to piss off their doctors or have a general distrust of things on the Internet. You never know who is putting out really bad information out there*." – P12
Low technology literacy	"*If you don't know how to use technology properly – elderly people may not know how to – I taught my grandmother how to use chrome – some people just don't know how to use the Internet. Some people don't know how to google properly – they will google a full sentence rather than googling 'symptom checker'.*" – P8
Older age	"*I know my grandma who has a lot of illnesses and medication does not use the Internet, so she does not even google anything*." – P2
Social influence	"*Family telling you not to use it because of previous bad experiences*." – P16
Not wanting to know	"*… just fear or avoidance – not wanting to know*." – P6
Previous bad experience	"*Misdiagnosis or a previous bad experience*." – P16
Disease-level barriers	
Severe condition	"*If something was serious, people would not want to use it, they would want to go to a doctor. Not just physically but also emotionally, I could see them go to the doctor right away*." – P13
Need for a physical examination	"*Can only be used for symptoms that can be described in words. I feel like this can act as a barrier for skin problems because it needs an assessment (physical one)*." – P17
Health-system level barriers	
Dogma in healthcare	"*A lot of dogma and a lot of doctors will say 'we are always the right ones, do not access these tools'. A lot of doctors are like that, they will say 'don't bother googling your symptoms just come and see me' and other doctors really appreciate that people try to educate themselves with whatever tool they have to their disposal which is often google or a tool like this*." – P10
Symptom checker related barriers	
Lack of awareness	"*Lack of knowledge – there are people who do not have an idea that there is service like this which gives results fast*." – P16
Poor design	"*Lack of user-friendly interface. The UX [user experience] was terrible, it was really frustrating. Too much information especially for someone who does not have the medical knowledge*." – P20
Asking identifiable questions	"*I might think 'Oh, what are they using my data for?'. It depends, as I said, I have not used a symptom checker before, so I don't know what kind of information they are asking for. I wouldn't mind giving them my age and gender but for example, if they are asking for date of birth and things like that, that might give a red flag*." – P3

Cost of the platform	"*Also cost might be a barrier*." – P9
Time to complete	"*I think another barrier is time depending on how long it can be. I am sure it can vary*." – P2
Lack of inclusivity measures	"*[…] or various disabilities being able to use the screen or use computers or any type of access issues would be a problem*." – P6
Lack of language options	"*Maybe also a barrier can be the language that is used in the software*." – P2
Lack of credibility	"*Lack of credibility*." – P18
Lack of human interaction	"*The human interaction and I know we are getting away from that because the way technology is designed, we don't have to talk to people in the grocery store anymore to buy our groceries so it's something we are getting more socialized to. But for seniors it's a barrier because of the trust component and human interaction but also technology literacy and I think that would also apply to people with disabilities who still need to see someone face to face to get a better idea of the issues*." – P7
Disclaimer	"*If they know not to take it seriously, they won't feel encouraged to do the test at all. If the disclaimer says this is not really a diagnosis, then what am I doing? I should just go to the doctor*." – P10
Inability to obtain elaboration on a question	"*I think it's the inability to get an elaboration on something. If you are talking to a person you can ask them questions and they hopefully elaborate on it and tell you what that means but with a symptom checker the onus is on you to go further*." – P4
Liability	"*Liability. Like if it was jumping to severe and worst-case scenarios*." – P1
Using data for profits	"*I would not want my data to be used to anything that would harm me. I don't know what it could be used for but if it is being used to find out the prevalence of a certain disease or whatever that is helpful for the healthcare system, I am fine with that but anything that would encourage the business part of it or pharmaceutical side of it or anything that is business related or goes back to making money, I would not like it*." – P3

RQ.1. Objective d) University students' perspectives on areas for improving the platform

Following the use of a symptom checker, participants were asked to provide their perspectives on how the platform could be improved. Additional capabilities or improvement areas were mostly related to the input of symptoms, the process used by the platform, and outputs provided. An overview of the various areas for improvement and additional capabilities are provided in **table 10** along with example quotes.

Table 10. Indication and Example Quotes for Themes Related to Areas for Improvement and Additional Capabilities for Symptom Checkers

Theme	Indication	Example Quotes
Input		
Provide a welcoming introduction	Used when a participant mentions that a welcoming introduction to the platform would be an area for improvement	"*One of the sentences aren't necessarily straightforward and that's fine but I feel like some of the beginning ones can be a little bit more personal and welcoming. I know that would appeal to my demographic or younger, for seniors as well – you would think it needs to be both friendly and professional somehow*." – P6
Ability to enter more symptoms	Used when a participant mentions that the platform providing the ability to input more symptoms is an area for improvement	"*I would like somewhere in the middle to add more symptoms and I would also like if the symptoms gave more information about the diseases*." – P18
Ability to enter symptoms as free text	Used when a participant mentions that the ability to enter symptoms as free text is an area for improvement	"*To improve there is a lot of room for it because if I am able to type in my symptoms in my own words and if it can search its database based on the symptoms I entered rather than choosing the options it has, then it's more useful because I will not be leaving out symptoms, so I think that's something to improve*." – P2
Ability to change units for measures asked (e.g., body temperature)	Used when a participant mentions that the ability to change units for measures such as body temperature to be an area for improvement	"*I guess being able to change the units (E.g., Fahrenheit to Celsius)*." – P18
Ability to upload images of affected body areas	Used what a participant mentions that the ability to upload images of affected body areas should be an added capability to the platform	"*If someone was able to take a picture and the AI can sort out certain matches for the rash. I think that would also be useful for skin cancer. If they can take a picture and map it to abnormalities could be really valuable*." – P14
Ability to assess user's health literacy prior to symptom checker use and modify the	Used when a participant mentions that an additional capability would be to assess each user's health literacy prior to the use of the	"*I guess a lot of comments or overall, I am not too sure how university students could change my answer but having the option of telling the platform how much knowledge the user has. So, for example, if the user has no*

experience accordingly	platform to modify questions and the user experience accordingly	*medical knowledge, it will have a different approach*." – P18
Allow users to select affected body areas on a human skeleton	Used when a participant mentions that an area for improvement is to allow users to click on affected body areas	"*If you can select body parts on the graphs, it would be more beneficial rather than typing words and selecting options*." – P16
Process		
Collect more data on the user	Used when a participant mentions that an area for improvement is collecting more data on the user to allow for a more informed assessment	"*Age, gender, allergic reactions, medication allergies and other information because it makes it better. We are surrounded with so much information that sometimes it gets so hard to find what is correct. If we need that much accuracy, we can add two or three more sections so that we feel that the system knows what the condition is*." – P17
Integrate with patient charts	Used when a participant mentions that an additional capability would be to integrate data inputted into the symptom checker with patient charts to allow for information sharing between the patient and provider	"*Integrated with information that physicians can access or triage folks at hospitals even if it generates a QR code at the end and you can show it to the doctor or nurse practitioner and they scan it with their phone and they can access that report so that you are not saying the same thing twice or the doctor can have a list of what was said already so that they can glance over it and say 'ok, so what I am getting from this is that you have this, this, and this – did I miss anything?' The doctor could then capture things that the symptom checker could not*." – P10
Make it friendly for users who have visual impairment	Used when a participant mentions that an additional capability would be to add a voice option for users who have visual impairment	"*Umm, is there a way to have the questions read to you? For like visually impaired people. Being able to press a button to have a voice read you the question might be good*." – P6
Partner with health services	Used when a participant mentions that an area for improvement is to partner with health services	"*Partnership with health services would be helpful – that's the only way I see it working*." – P12
Provide information about how the platform works	Used when a participant mentions that an area for improvement is to provide users with information about how	"*Having, at least for me, having patient studies accessible might be helpful just to show how it works, what it uses, and information about the backend. It might make*

	the platform works (i.e., information about the data, algorithm, process used)	*us trust it a bit more if we know how it's working*." – P18
Output		
Provide an option to speak to a health provider based on severity of symptoms	Used when a participant mentions that an added capability would be to provide an option for users to speak to a health provider following the use of a symptom checker based on need	"*I guess if the symptom checker can eventually lead to a doctor appointment. That would be hugely beneficial because you can take as long as you want on a symptom checker. If that information can be used to not only diagnose your condition but refer you to a doctor in the end and the doctor already has all the information in the symptom checker, I think that could be very beneficial*." – P21
Improve accuracy and confidence in potential conditions provided	Used when a participant mentions that an area for improvement is to improve confidence in the results (or matches) provided by the platform	"*It has to be some sort of more defined outcome with a certain level of confidence – more confident outcomes. You want to make sure that the results indicate what is actually happening rather than a broad scope where it could be several things*." – P4
Provide information about others in similar contexts	Used when a participant mentions that an area for improvement is to provide users with information about other users who may be in similar contexts to provide reassurance	"*Maybe if it had 'if you have this type of fever, X percentage of people your age has this fever' and this is what they do to fix it. Then the user would feel that a lot of people have this condition, not just me*." – P3
Provide information about potential conditions	Used when a participant mentions that an area for improvement is to provide users with information and definitions about the conditions that match with the inputted symptoms	"*I would really like to know what the diseases might be or what is happening with my body. A short definition of what I may have would be helpful as well as options at the end*." – P19
Provide the likelihood that the user has a condition listed	Used when a participant mentions that an area for improvement is to provide users with the likelihood of having each of the conditions provided by the	"*Another feature is to give some sort of probability based on the massive data that it has and say ok 'there is only 0.1% chance of people getting this condition.' That could potentially be beneficial, just as a piece of mind to the patient when they are looking at the result. Because when you look at the conditions, you quickly appoint them equal*

	platform based on inputted symptoms	*probabilities, so you are scaring yourself unnecessarily*." – P21
Recommend nearby locations for accessing tailored health services	Used when a participant mentions that an added capability is to provide users with information on the nearest health services based on needs and inputted symptoms	"*If it can give recommendations of where students should go or the types of services that health services offer*." – P4
Other capabilities and areas for improvement		
Develop an easier user interface	Used when a participant mentions that the user interface is an area for improvement	"*If it has a really easy user interface to interact with – I think that would be nice*." – P3
Ensure that a mobile option is available	Used when a participant mentions that an added capability would be to ensure that the symptom checker could be accessed through mobile	"*Some people are big on apps which I am sure already exists*." – P22
Provide a fun fact each day	Used when a participant mentions that an added capability would be to provide a health-related fun fact each day	"*I feel like sometimes university students like random facts so if you had this app and it gives you a health-related fact of the day, that could be fun*." – P3
Enable sign-off on school-related matters	Used when a participant mentions that an added practical capability would be to provide an official sign-off for school-related matters	"*For Waterloo specifically, you have to get the sign out by a doctor for anything school related so if it had a functionality like that, I could see it really useful. Like it is an actual official thing, talk to a doctor and get a certificate. Having a practical functionality rather than it just being informational because that limits the number of times that I will use it*." – P20
Provide information about medications	Used when a participant mentions that an added capability would be to provide an option to search for the usefulness of medications	"*I have to be able to search the usefulness of medications and what they are useful for. There is not information about the medication. There is only information on diagnostics*." – P24
Allow users to enter symptoms and a condition to	Used when a participant mentions that an added capability would be to allow for users to enter	"*If someone gave me the name of the illness or the diagnostics results. Let's say I know the symptoms, and someone gave me the result,*

assess if they match	an illness and symptoms to assess whether they match	*now I want to search if this is the case really*." – P24

5.5.3 Themes for Research Question 2

RQ.2. Objective a) University students' perspectives on how symptom checkers may influence their health and use of health services

Influence on health

Most participants believed that university students would be fast adopters of symptom checkers; however, most believed that current efforts to advertise the platform are lacking. This perspective is justified by the fact that more than half of participants (n=13) were unaware that these platforms existed. Some believed that if tested and validated, symptom checkers could be utilized to improve the health of university students. Only a few believed that the platform would have a negative or neutral influence on their health due to the suboptimal understanding of the user's contextual factors, overall health status, and the reactive nature of the platform.

> "*I think at least in my case, I usually get the 'don't be so concerned about this' when I actually should be concerned about it. I have a weakened immune system and I don't think symptom checkers take that into account. There are people who are just naturally sicker than other people and the symptom checker may not take into consideration other conditions that I may already have. If I have diabetes and the symptom checker says I have diabetes – well then, that doesn't help me there*." – P9

> "*I don't really think it would [influence university students' health] because peoples' health is more than just their symptoms. It's a range of factors, it's how you eat, how you feel, how you exercise and if you get symptoms, you're already at a point where you feel that your health is a little bit lower I guess so it's a reactive thing so I don't really think it would influence very much*." – P11

Symptom checkers were also perceived, by some participants, to be useful for "sensitive" and "personal" health conditions that participants would not feel comfortable sharing with a health professional. Interestingly, some participants assumed that symptom checkers would have a positive influence on their health because they had the perception that doctors were designing these platforms.

> "*It will improve it. A little bit but it can help improve. This software was designed by doctors, right? … So, it may improve health if the diagnosis is right and its assumptions are right.*" – Participant 5

Symptom checkers were perceived to have the potential to improve the health of university students through the integration of health reminders, enablement of proactive care seeking, and mental health. Most participants believed that these platforms should be leveraged to address mental health on university campuses to enable preventative care.

> "*I think it could actually be really helpful in mental health awareness because I think often people who are starting to deal with a mental illness or crisis it manifests as physical symptoms like fatigue. So, if you had a place where you could put the symptoms in thinking that you're just sick and then maybe getting this suggestion that there could be psychological issues, that might suggest to them a pathway of treatment that they have not thought of before – as part of a whole care option.* – P6

A few participants believed that the platform would be useful for reassuring university students that their symptoms warrant them to forego attending class or missing an assignment.

> "*I think the one thing that university students struggle with is that students always push themselves to go to school while they're sick because they don't want to miss a midterm or assignment. It shows the bias in me but if opportunities like symptom checkers were used to show that I really am sick and I need to take the day off, it can give a sense of self-assurance that missing school for a day is OK.*" – P10

Influence on the use of health services

While most believed that symptom checkers can improve health, some were unsure if these platforms would be useful for the healthcare system. After having used a symptom checker, most participants believed that the platform needed improvement. Given that some participants were unable to enter all the symptoms mentioned in the clinical vignette, their statement indicates that improvement to the platform's accuracy is needed. As such, the influence of symptom checkers on health services were strongly dependent on the perceived reliability and accuracy of the platform.

> "*If it is sloppy like this, I don't think anyone would use this. If at least I am able to enter all my symptoms, I wouldn't have had this reliability issue with it, but I think if its not so good then I would think that people will start using the healthcare services.*" – P2

Nonetheless, participants believed that symptom checkers could influence the use of health services through its usefulness in triage, communication enablement with health providers, access to care, knowledge improvement, and proactive care seeking.

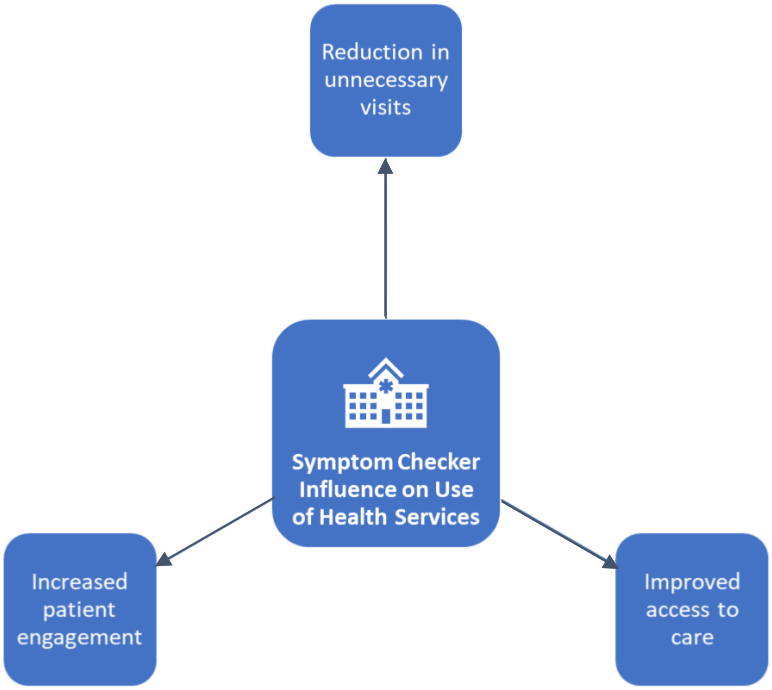


Figure 7: Perspectives on the Impact of Symptom Checkers on Healthcare Use

Reduction in unnecessary visits

Some participants believed that symptom checkers could be the "first line of defense" for the healthcare system – similar to Telehealth – and that it would be useful for triage which would in turn reduce healthcare costs and wait times as well as save users time and money related to transportation. By reducing unnecessary visits, participants believed that the platform would improve access for those who require medical attention; specifically, they perceived the tool to be useful for prioritizing appointments based on severity of reported symptoms. It was also perceived to be helpful for determining whether an annual check-up is necessary.

> "*So, I imagine it could be more effective than telehealth kind of things because the telehealth operator isn't really allowed a solid diagnosis anyway but even if there is*

> *a hint of something more serious, then they just tell you to see a doctor or just go to the ER [emergency room].*" – P6

> *"I think it is [symptom checker] perfect when it comes to triage. For self-*diagnosis, *it can be made more accurate if we added more columns to it [more variables].*" – P17

Some participants believed that this tool is useful for mild symptoms and is more suitable for certain populations (i.e., younger population groups and individuals who do not have pre-existing medical conditions). Most participants believed that this technology cannot replace a primary care provider; however, it can work in conjunction with health providers to improve efficiency in healthcare systems by reducing unnecessary medical visits.

> "*If someone is younger, healthy and got a rash for the first time after going on a hike, a checker may be good to use… if I can take the burden off the healthcare system by checking my symptoms online, maybe that's me clearing the way for someone who needs more access to care*." – P12

Improved access to care

The tool was thought to be a convenient and quick approach for assessing symptoms during after-clinic hours. This is also in line with another theme which emerged related to the platform's potential ability in increasing accessibility by providing an option to individuals who may not have a regular primary care provider.

> "*There is definitely an opportunity to use this with individuals who may otherwise lack access to healthcare. And I can see this combined with a telemedicine approach – if you combine those in a way that makes sense and sensitive to contextual factors, I can see it improving access to care*." – P10

Increased patient engagement

Moreover, given the questions asked by the platform, some perceived the platform to be useful for providing ideas on the types of questions they should ask when seeking medical care. The platform was also perceived to be useful in improving health knowledge of users and potentially allowing for regular health monitoring.

> "*I think along with the rest of the Internet, symptom checkers would be a way to get your hands-on knowledge that you may not have access to, so it is good for satisfying your curiosity or knowledge acquisition in general. It can also make people more knowledgeable*." – P19

In general, participants believed that symptom checkers could be useful for self-triage and if designed properly, would allow for proactive care, including for mental health.

RQ.2. Objective b) University students' perspectives on factors that promote the use of AI-enabled symptom checkers

A total of 22 participants were given a self-administered questionnaire (**appendix 11**) in which they were asked to pick the top five factors that they believed are most important when deciding to use a symptom checker for a) self-triage, and b) self-diagnosis. The factors included in the questionnaire were informed by the UTAUT and literature in IS. The number of participants who chose the most important factors for **self-triage** are provided in **table 11**.

Table 11. Number of Participants Choosing Factors that are Important for Using a Symptom Checker for Self-Triage

Factor	Number of participants
1. Your ability to perform **tasks on the computer**	4
2. Your **self-rated health**	6
3. Your **perceived accessibility** of symptom checkers	8
4. Your **propensity or tendency** of using new technology	2
5. Your **individual personality traits**	3
6. Your perception of the **supports and resources** available to you	2
7. Your **perception of risk** associated with using symptom checkers	5
8. Your perspectives on the **perceived benefits** of using symptom checkers	7
9. Your **trust** towards symptom checkers	13
10. Your perspectives on the **effort expected** to use symptom checkers	6
11. Your perception of the **credibility** of symptom checkers	12
12. Your **social surroundings**	2
13. Your perception of the **output quality** provided by symptom checkers	7
14. Your perspectives on the **fun or pleasure** derived from using symptom checkers	0
15. Your perception of the **tangibility of the result(s)** provided by symptom checkers	8

16. Your perspectives on the **trade-off between costs and value** (applies if a fee is associated with the use of a symptom checker)	6
17. Your perception on the symptom checker's **compatibility** with your values, past experiences, and needs	6
18. Your **habit** in adopting new technology	3
19. Your level of **healthcare need**	12

Based on a frequency analysis, the top five factors that seemed to be chosen most often for self-triage are:

- **Trust** towards symptom checkers
- Perception of the **credibility** of symptom checkers
- Level of **healthcare need**
- Perception of the **tangibility of the result(s)** provided by symptom checkers
- **Perceived accessibility** of symptom checkers

The number of participants who chose the most important factors for **self-diagnosis** are provided in **table 12**.

Table 12. Number of Participants Choosing Factors that are Important for Using a Symptom Checker for Self-Diagnosis

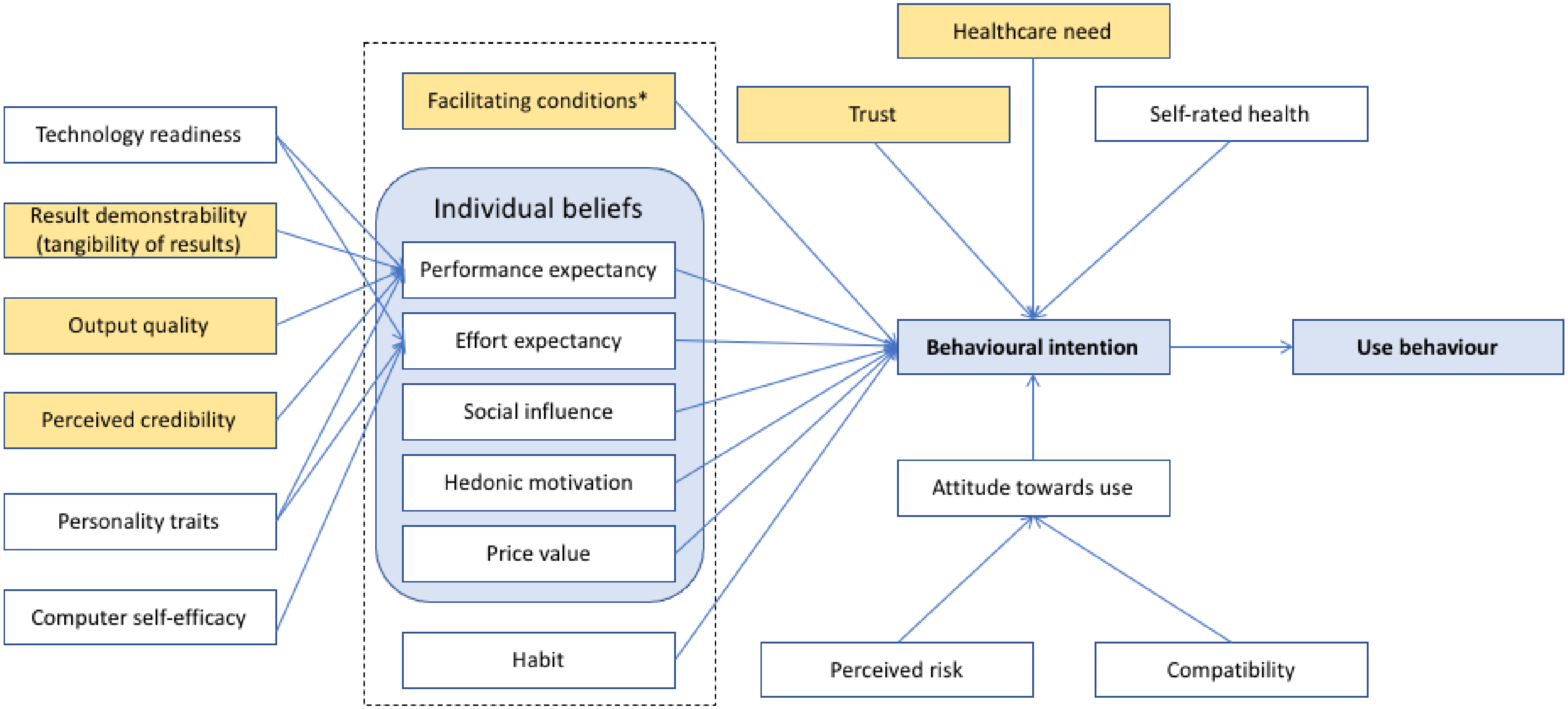
Factor	Number of participants
1. Your ability to perform **tasks on the computer**	3
2. Your **self-rated health**	7
3. Your **perceived accessibility** of symptom checkers	2
4. Your **propensity or tendency** of using new technology	1
5. Your **individual personality traits**	7
6. Your perception of the **supports and resources** available to you	7
7. Your **perception of risk** associated with using symptom checkers	7
8. Your perspectives on the **perceived benefits** of using symptom checkers	7
9. Your **trust** towards symptom checkers	13
10. Your perspectives on the **effort expected** to use symptom checkers	2
11. Your perception of the **credibility** of symptom checkers	12
12. Your **social surroundings**	1
13. Your perception of the **output quality** provided by symptom checkers	12
14. Your perspectives on the **fun or pleasure** derived from using symptom checkers	0
15. Your perception of the **tangibility of the result(s)** provided by symptom checkers	8

16. Your perspectives on the **trade-off between costs and value** (applies if a fee is associated with the use of a symptom checker)	4
17. Your perception on the symptom checker's **compatibility** with your values, past experiences, and needs	6
18. Your **habit** in adopting new technology	0
19. Your level of **healthcare need**	11

Based on a frequency analysis, the top five factors that seemed to be chosen most often for self-diagnosis are:

- **Trust** towards symptom checkers
- Perception of the **credibility** of symptom checkers
- Perception of the **output quality** provided by symptom checkers
- Level of **healthcare need**
- Perception of the **tangibility of the result(s)** provided by symptom checkers

Trust, credibility, healthcare need, and tangibility of the results were the most chosen by participants as being important in deciding to use a symptom checker both for self-triage and self-diagnosis. Accessibility and output quality were chosen most times for self-triage and self-diagnosis, respectively. A visual depiction of the most frequently chosen factors is highlighted in orange in **figure 8**.



*This includes perceived accessibility

Note: Factors highlighted in orange were the most frequently chosen as important by participants

Figure 8. Proposed Model of Factors to Consider in Explaining University Students' Behavioural Intention of Using AI-Enabled Symptom checkers for Self-Triage and Self-Diagnosis
Notes: The variables highlighted in orange were used as attitude-based variables for the latent class analysis.

RQ.2. Objective c) Trust: an important factor influencing the use of symptom checkers

Following the use of a symptom checker, participants were asked if they trusted the platform. The perspectives of participants varied widely with some trusting it as much as they would trust a doctor. While most participants did not perceive this tool to replace a doctor, some believed that even doctors could make mistakes – the lack of expectation for "perfection" seems to strengthen a participant's trust towards symptom checkers.

> "*If I had to rate out of 10, I would give a 7.5, if not a complete 9. Of course, I cannot give a 10 because nothing is perfect because even a doctor can fail to detect the right issues*." – P18

Others mentioned that they trust the symptom checker as they trust another website that provides health information.

> "*I think I would trust it as much as I would trust medical websites like webpages you see through university. Like Cornell or Harvard where they are describing symptoms*." – P14

Others mentioned that they would trust it to a certain extent and solely use a symptom checker as a source of information. In line with this reasoning, another participant mentioned that trust in this context is irrelevant since in their perspective, the symptom checker is not used for a definite answer but rather as a source of information.

> "*I don't think it will be the main source of information, let's put it that way. Even if I do check it, depending on how, according to my own knowledge, and how serious the symptoms are, I might double or triple check rather than rely on one source. I would also google or ask my friends in medicine*." – P13

> "*I don't think of them in the context of trust. I think they are just validating. I think of them of a context of an information provider so it's not necessarily trust. I never thought of my google searches in the context of trust. It's more about doing research about what I think I have - more about information*." – P22

Interestingly, some mentioned that they would trust the platform if it provided diagnoses that were in line with the health condition that the participant believed to have.

> "*If it was something close to what I thought it was then I would think it was impressive – it's something that I would try a few more times before diving into it but if it was repeatedly showing me what I felt I had then I would trust it more*." – P8

Some participants mentioned that they would trust the platform for minor or common conditions that are not too worrisome.

> “*I mean I would trust it with more common things – yeah, I don’t think I would trust it if we are going into anything related to chronic illness or cancer or liver or heart disease or any of the bigger ones. It might point me to consider some of those larger things but at that point I certainly wouldn’t trust a self diagnosis, but it would hopefully point me to looking further at getting more practitioner care.*” – P6

Most factors that influenced participants’ trust towards the platform related to input of symptoms, process used by the platform, and outcomes provided. An overview of themes related to input, process, and output as they influence participants’ trust is provided in **figure 9**.

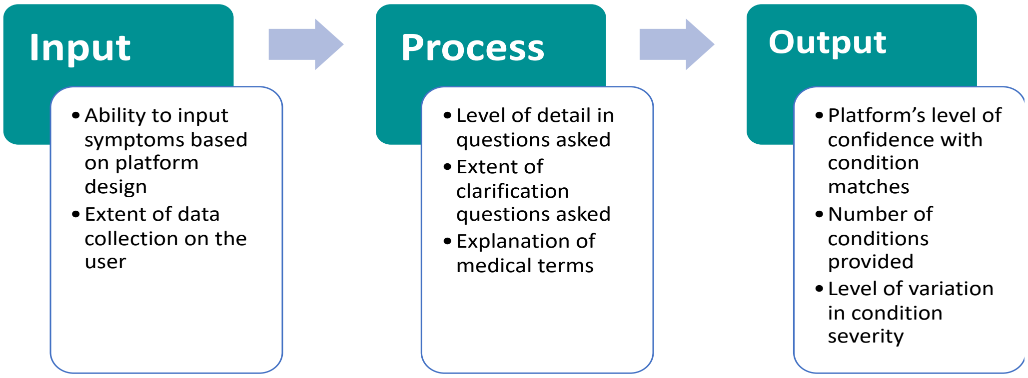


Figure 9. Factors Related to Input, Process, and Output as Influencing Trust Towards Symptom Checkers

Table 13 provides an explanation of the themes presented in **figure 6** as well as example quotes. It also provides additional factors that were mentioned to influence trust, and these included: reviews provided by users, established credibility of the platform, knowledge about the creators of the platform, and visual appearance of the platform.

Table 13. Explanation and Example Quotes of Factors Influencing Trust (Positively or Negatively) as they Relate to Input, Process, and Output

Factor Group	Factor	Explanation	Example Quotes
Input	Ability to enter symptoms based on platform design	- Some participants were not able to enter all symptoms in the clinical vignette which	“*I would say on a scale of 0 to 10 I would say 5 or even less because for the symptoms I was suffering from I couldn’t enter*

		hindered their trust towards the result provided by the symptom checker - This theme was most relevant for a platform that uses a drop-down menu for symptom input rather than free text	*some of them so it's not a representation of what symptoms I have and the diagnoses it gives are not representative of what I have so I wouldn't trust it. I prefer google search because the symptom checker restricts me*." – P2
	Extent of data collection on the user	- Some participants believed that the platform did not collect enough or comprehensive information to allow for a well-informed assessment	"*I do not trust them. To increase my trust in them, they need to demonstrate that they are collecting different pieces of information and that it's comprehensive, my medical history, all the symptoms I am feeling and then it would have to state things with a certain amount of confidence*." – P11
Process	Level of detail in questions asked	- A few participants believed that the questions asked by the platform regarding symptoms were quite exhaustive	"*Um, it was asking a lot of questions I feel to get a proper diagnosis – some questions I haven't thought about, so I think that was valuable*." – P8
	Extent of clarification questions asked	- A few participants believed that clarification questions regarding symptoms reported were insufficient for the provision of a well-informed assessment	"*It asked me one questions about my rash and focused more or less on cardiovascular and respiratory system questions, but it didn't ask me how the rash looked like. It only asked me if it changes colour when I click on it. I can't be confident if it didn't ask me more questions about the rash. It would be good to have images of different types of rashes and asking what the rash looks like*." – P10
	Explanation of medical terms	- A few participants believed that the quality of results provided by the platform depends on the information they input; this is hindered	"*I didn't know what they meant [words used by the platform] and when I hovered over them, it did not give me a description of what those symptoms are. There are medical terms that weren't just a give*." – P3

		if the platform does not provide a description of some medical terms to lay users	
Output	Platform’s level of confidence with condition matches	- Participants who got fair matches of conditions based on the symptoms inputted expressed that the suboptimal level of confidence exhibited by the platform’s output limited their trust towards the platform	“*What I got was just fair, fair, fair and I mean that doesn’t really mean a ton to me. It’s not enough confidence for me to really trust the results*.” – P11
	Number of conditions provided	- Some participants believed that the substantial number of potential conditions that are provided by the platform limits the user’s trust towards the results	“*They had a lot of fairly moderate connections to what I could have had. There were a lot of ones with moderate matches and I was not interested in looking through all of them and if that one is the one that I may have, I would have missed it because I would not go through 17 different conditions of words that I don’t know what they are to see if they are my diagnosis*.” – P3
	Level of variation in condition severity	- The level of variation in severity between the potential conditions provided limits trust towards the platform	“*It gives you a variance of severity of symptoms like there is a big difference between influenza and sepsis. One will immediately kill you so not very confident and it was missing some of the key features from the diagnosis*.” – P4
Additional Factors	Reviews provided by users	- The type of reviews found online related to symptom checkers was a factor that was mentioned to influence user trust	“*I will go on google, see the review, and check if it’s valid. I will trust it if it’s been there for years and tested on a number of people*.” – P17
	Established credibility of the platform	- Studies pertaining to the platform’s accuracy was	“*I tend to be skeptical overall on a lot of things until I see tests or a lot of documented evidence*

		mentioned to be another factor influencing user trust	*that when we use a symptom checker as compared to a real doctor, there is an X percentage accuracy rate but if I don't see that, then I would not be able to trust it.*" – P18
	Knowledge about the creators of the platform	- Knowing the people who designed the platform, including their level of expertise, was mentioned to be a factor to influence user trust	"*I need to know that it was developed by a team of people who really know what they're doing.*" – P11
	Visual appearance of the platform	- A professional visual appearance was mentioned to be important to garner trust – a platform that uses less colours was mentioned to be more trustworthy	"*The design made me think that I was not going to get anything professional. It looked more user friendly, but I think when I am looking for something when I am sick, I wouldn't want to use something that makes me think that I am buying a shampoo product that's best for my hair type. I want to know that I am getting my medical information handled well.*" – P8

To further understand participants' trust towards symptom checkers, they were asked whether they would seek care from a health provider following the use of a symptom checker. Most participants (14 out of 24) mentioned that they would visit a primary care provider following the use of a symptom checker. Some participants believed that the platform could potentially be a good "pre-screening tool" or for self-triage and could help inform the tests that may need to be ordered.

> "*If it was good, then I think it would be a good pre-screening because there are a lot of people that to go to the doctor when they don't need to*." – P1
>
> "*I actually think the symptom checker would be very good because sometimes the doctors do not listen to you and symptom checkers would be good to tell the doctors what to potentially test you for. If you think that the healthcare provider is not doing enough tests, you can tell them that this is a possibility, can you test me for this*?" – P22

Factors which seemed to be associated with the decision of visiting a PCP following the use of a symptom checker were: level of confidence with the results provided by the platform, the platform's approval by the medical community, level of severity of the conditions provided on the platform, the user's level of discomfort with symptoms experienced, and persistence of symptoms following the use of home-based treatments. An explanation of these themes and example quotes are provided in **table 14**.

Table 14. Themes Related to Seeking Medical Care Following the Use of a Symptom Checker

Themes	Indication	Example Quotes
Credibility of the platform		
Trust or confidence with the results provided by the platform	Used when a participant mentions that their decision of visiting a PCP following the use of a symptom checker depends on their level of confidence with the platform	"*To be honest I think that would be determined on how confident I am with the results. So, if I believe that the result was probably right. So, if it tells me that this is what is probably wrong with you and how to treat it, I will see how it goes. But if I am skeptical with the result and I wasn't sure how to answer one of the questions, then I wouldn't have confidence in the result because I didn't have confidence in my answers prior to the output*." – P3
Approval of the platform by the medical community	Used when a participant mentions that their decision to visit a PCP following the use of a symptom checker depends on whether the platform is approved by the medical community	"*Yes [to visiting a PCP], and I think that's because the technology itself is not yet fully approved by the medical community*." – P8
Symptoms		
Persistence of symptoms	Used when a participant mentions that they will visit a PCP following the use of a symptom checker if symptoms persist even after treating oneself for a condition that the platform provided	"*Basically, I would try home treatments based on the insights I get from the symptom checkers and see if the symptoms persist, I will see a doctor*." – P22

Discomfort resulting from symptoms	Used when a participant mentions that one of the deciding factors for visiting a PCP following the use of a symptom checker is the feeling of discomfort resulting from symptoms	"*If the symptom checker there are three potential conditions you may have and none of them are really severe at all then I probably would not go to a doctor, especially if I am not in discomfort or anything*." – P21
Condition Severity		
Level of severity of the conditions provided by the platform	Used when a participant mentions that a deciding factor in visiting a PCP following the use of a symptom checker is the level of severity of the condition	"*It depends on the diagnosis. If it's a flu, then it's fine, I don't need to visit a healthcare provider but if it's something more serious and you don't know about then yes, I would*." – P13

5.6 Key takeaways

Overall, participants seemed to have positive, indifferent, or negative perceptions regarding the use of AI and symptom checkers for healthcare purposes. Variables such as self-perceived health and health literacy were perceived to influence the use of symptom checkers. Interestingly, more than half of participants were not aware about the existence of symptom checkers. In addition to the need for increasing awareness of symptom checkers, identifying key factors in the TAM are important in understanding the intention to- and use of- a symptom checker. Given the perceptions that symptom checkers required various improvements, they were perceived to be most useful for self-triage rather than self-diagnosis. Aforementioned findings and key takeaways informed the survey development which is explained in more detail in the following chapter.

Chapter 6: Phase 2 – Quantitative study to determine and assess latent classes of attitudes towards AI symptom checkers and their association with the intent to use symptom checkers

6.1 Research Design and Approach

An observational quantitative research design was used to address the final research question which seeks to identify the classes of attitudes among university students and their association with the intent to use symptom checkers. To address this question, Latent Class Analysis (LCA) was used to identify patterns in the observed data. LCA is a statistical technique that identifies underlying latent variables based on observed measured categorical variables. This technique helped identify the latent classes among university students based on attitude-based variables which were measured and categorized. The selection of the best fitted latent class model(s) for attitudes towards symptom checker functionality and AI in health was based on key fit statistics and interpretability. Once latent classes are determined, a subject's membership to a certain class is estimated via probabilities attributed to the eight attitude-based variables. For models assessing association between latent classes and intent to use, our General Linear Logit models considered various types of latent classes, and their effect on the outcome variable.

6.2 Study Site, Study Population, and Sample

As for RQ.1 and RQ.2, the study site was the University of Waterloo and the study population was any young adult (between 18 and 34 years of age) enrolled at the University. Prior to participant recruitment, ethics clearance was granted from the Research Ethics Board (#41366) and approval was obtained from the Institute of Analysis and Planning at the University of Waterloo. A total of 35,643 undergraduate university students received an email invitation (**appendix 13**) for the survey through the Registrar's office. A total of 1,547 students completed the web survey which was available online on January 11, 2021 and closed the following day because the estimated required sample size was reached. Respondents who clicked on the web survey link and did not complete the survey were classified as either screened out or a drop out. Respondents who were screened out were those not meeting the eligibility criterion of being between the ages of 18 and 34. There were 12 and 2 respondents who indicated they were under 18 or over the age of 34, respectively – they were deemed ineligible and screened out of the survey. Drop-outs were defined as respondents who clicked on the web survey link but did not complete the survey. There was a total of 558 dropouts with just over half (57%) having occurred at the introduction page – this could indicate that the respondents clicked the survey link by mistake or were not interested in completing the survey. The rest of the dropouts occurred throughout the survey with most occurring within the first several questions. There was a total of 180 respondents who had used symptom checkers in the past 12 months and were thus categorized as “users”. The remaining sample (n=1,367) who had not used the platform were identified as “non-users” and are the focus of this thesis.

Having a large enough sample size is important to avoid underextraction (i.e., choosing a number of classes (K) that is too small) (Dziak et al., 2014). Estimating the sample size required prior to data collection would necessitate the researcher to specify a value for K; while this can be informed by theory, there is a tendency in research to use the data to guide the choice on number of classes – this is important to avoid both underextraction and overextraction. Given the dependency of the required sample size on the number of items and classes, researchers often assess whether the sample achieved provides sufficient power after data have been collected (Dziak, 2014). A simulation study conducted by Dziak et al. (2014; see table 8 pp. 34), recommended a sample size range for a three to five latent class model categorized by 8 items and a power=.80 to be between 293 and 2640. Available studies that have used LCA in information systems were able to identify three to four distinct classes with samples sizes used varying from n=340 to n=1,418 (Sell et al., 2014; Tang & Patrick, 2019; Mok et al., 2014; Okazaki & Romero, 2010). For our objectives, the sample recruited for this study falls within the suggested range of having sufficient power to detect profiles.

6.3 Data Sources and Procedures

Given the limited knowledge on the topic, findings from the qualitative phase of this thesis (RQ.1 and RQ.2) and literature on construct measurement were used to inform survey development. While the literature and construct measurement were useful in informing how survey questions should be developed, the choice of variables from RQ.2 informed which variables should be measured. For example, trust was one of the top chosen factors and was measured in the survey by leveraging survey questions used in previous studies that sought to measure the same construct. Importantly, given that participants were more accepting to use a symptom checker for self-triage rather than self-diagnosis, survey questions were limited to focus solely on self-triage. The survey used in this study was developed and reviewed in collaboration with the Survey Research Center (SRC) at the University of Waterloo. The SRC is comprised of experts in survey design and methodology who work in developing expertise in rigorous and specialized research (University of Waterloo, n.b.). Survey development began in August and was finalized the same year, in December 2020. Once the survey was approved by the Research Ethics Board and the Institute of Analysis and Planning at the University of Waterloo, it was sent to the SRC for programming. The survey email invitation was drafted by the principal investigator (SA) and sent to the Registrar's office to be sent to university students.

The survey has five sections, is comprised of closed ended questions and was administered to participants at one time point. The first question was used as a screener to identify whether the university student is within the target age group (i.e., between 18 and 34 years of age). Individuals under 18 and over 34 would not be eligible to start the survey. The survey begins with a figure and description of AI-enabled symptom checkers to familiarize participants with the platform. Participants were then asked whether or not they had used the described platform in the past 12 months for self-triage. The response to this question categorized respondents into "users" or "non-users" and survey questions (starting from section 4) were adapted accordingly to ensure relevance. Section 2 of the survey measured respondents' self-perceived health, health literacy, wait times, and healthcare need. A justification for measuring these variables is provided in **table 15.** Section 3 focused on measuring students' perspectives on the use of AI in healthcare. Questions in section 4 differed based on whether the respondent was determined to be a "user" or "non-user" of symptom checkers. Section 4 measured attitudes towards symptom checkers. For users, questions were asked related to the quality of information provided by the platform. For non-users, participants were asked to rely on the platform description to answer questions that were framed in the future tense (e.g., "symptom checkers would perform well for self-triage"). The fifth and final section of the survey collected demographic data (e.g., age, gender), employment data, and data on Internet access. As previously mentioned, the focus of these analyses was conducted on the "non-users" sample (n=1,365).

6.3.1 Measures for LCA and Regression Models

6.3.1.1 Outcome variable: Intent of SC Use

The outcome variable of interest was whether participants would, in the future, regularly use a symptom checker for self-triage (i.e., intent to use a symptom checker). This was measured by the statement "I would regularly use symptom checkers for self-triage" with a 5-point Likert scale. Response options were collapsed into three categories (i.e., yes, no, and neutral).

6.3.1.2 Variables for latent class modeling

The variables considered for latent class modeling were inspired by the literature and findings from the qualitative phase. These attitude-based variables are listed and described in **table 15**.

6.3.1.3 Covariates

Once latent classes were identified, the effect of confounders on the latent classes was assessed. The list of confounders is described in **table 16**.

Table 15. Variables considered for identifying latent classes

Variable	**Definition**	**Source**	**Corresponding Question(s) in the Survey (appendix 14)**
Perceived accessibility	*"Captures an individual's perception of the ease or difficulty to gain access to or reach something."* (Jung, 2008)	It has been argued that perceived accessibility is a powerful predictor of choice of information source rather than actual quality of the information (O'Reilly, 1982; Rice & Shook, 1988).	Question 25
Trust	*"Willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party".* (Mayer et al., 1995, p. 712)	Gefen et al., 2003 demonstrated the importance of trust in understanding the acceptance of e-commerce. Klein et al. (2007) demonstrated the importance of trust in the acceptance of health services online.	Question 23
Perceived output quality	*"Judged by observing intermediate or end products of using the system, such as documents, graphs, calculations, and the like."* (Davis et al., 1992)	Song et al. (2006) state that the quality of the information is the most important attribute for users seeking information. Venkatesh & Davis (2000) outline that output quality positively influences perceived usefulness. In the case of e-health, this is the quality of the healthcare response given to the request; the health information obtained (Jung, 2008).	Questions 32, 34, 36, and 38

Result demonstrability	*"Tangibility of the results of using the innovation."* (Moore & Benbasat, 1991, p. 203; adapted by Venkatesh and Davis, 2000)	Venkatesh & Davis (2000) outline that result demonstrability is correlated with usage intentions.	Question 30
Perceived ease of use (or effort expectancy)	*"degree to which a person believes that using a particular system is free of effort*" (David, 1989, p.320)	While this construct has been theoretically shown to influence technology use; a study conducted by Jung (2008) showed that perceived ease of use had limited effect on using e-health services – a reason for this however, may be that the services were not perceived difficult to use.	Question 21
Perceived usefulness (or performance expectancy)	"*Degree to which a person believes that using a particular system would enhance his or her job performance*" (Davis 1989, p. 320)	Perceived usefulness has been shown to be a stronger determinant than perceived ease of use (Davis, 1989; Venkatesh and Davis, 2000; Jung, 2008)	Questions 18, 27, 28, 42, and 44
Perspectives on AI in healthcare	Captures the perspectives of respondents on the use and application of AI in healthcare	This variable was added based on findings from the qualitative phase which suggests that use of AI-enabled symptom checkers may be influenced by perspectives on AI in general.	Questions 13 and 14
Perceived credibility	"*The extent to which one believes that the other has the required expertise to perform effectively and reliably."* (Lanseng & Andreassen, 2007, p.402).	This variable was identified to be an important factor in the qualitative phase of this work.	Questions 32, 34, and 46

Table 16. Potential covariates

Variable	**Definition**	**Source**	**Corresponding question(s)**
Self-perceived health	"…*a summary statement about the way in which numerous aspects of health, both subjective and objective, are combined within the perceptual framework of the individual respondent."* (Tissue, 1972, p.93)	This construct may have an important influence on the use of self-service technology. For example, those who perceive their health to be poor may be more incline to use the technology (Kenny and Connolly, 2017).	Question 3
Health literacy	"*Degree to which individuals have the capacity to obtain, process, and understand basic health-related decisions*." (Institute of Medicine, 2004b)	Health literacy measures whether an individual is able to find health information, easily understand the information, use the information to make decisions, and make good choices about their lifestyle and healthcare (University of Arkansas for Medical Sciences, 2017).	Questions 4 to 7
Healthcare use	Defined in this study as the frequency of using healthcare services (excluding overnight hospital stays)	Questions that measure whether healthcare services (excluding hospital stays) were used in the past 12 months and if so, the number of times healthcare services were sought (Statistics Canada, 2020).	Question 8A and 8B
Wait times	Captures wait times to schedule a medical appointment and at the medical appointment.	Questions that measure the number of days that the individual has to wait prior to getting an appointment with a family physician or nurse as well as the time that the individual waits at the office (Statistics Canada, 2020).	Questions 9 to 11
Healthcare need	Defined as the need to use healthcare services due to an individual's health condition(s).	A question that measures the number of "long-term health conditions" which are expected to last or already lasted 6 months (Statistics Canada, 2020).	Question 12

6.4 Statistical Analyses

The dataset was divided into two groups based on whether the respondent was a "user" or "non-user" of symptom checkers. The dataset for "non-users" was used to conduct the analyses described below as they are the intended target for our analyses. The group of "users" was measured for supplementary/future objectives during the survey and is not within the scope of this dissertation. All analyses were performed using SAS 9.4.

6.4.1 Descriptive and exploratory analyses

Exploratory data analysis was conducted to understand the data through sample profiles and frequency of responses. Descriptive statistics and bivariate analyses were conducted to provide an overview of the sample. Items used to determine latent classes were coded with binary variables such that 1 denoted "no or neutral" and 2 denoted "yes". In determining latent classes, Lanza et al. (2007) recommend conducting a preliminary exploration on the overall relations among pairs of profile-determining items to identify highly related items that may be partially redundant indicators of a latent variable – to address this, chi-square tests were conducted to assess potential associations (redundancy) among pairs of items. Chi-square tests were also used to assess potential associations between each of the independent variables and the common outcome variable.

6.4.2 Latent class analysis to determine latent classes

LCA grouped attitude-based variables into latent classes reflecting underlying response patterns. As described by Collins and Lanza (2010) the latent class model is directly analogous to factor analysis as both models posit an underlying latent variable that is measured by observed variables with the key differentiator being the nature of the variables. In LCA, observed variables and the latent classes are categorical; a detailed explanation of LCA is provided by Lanza et al. (2007). For non-users, PROC LCA was used to identify response patterns that define latent classes. In order to identify an optimal baseline model, the procedure was repeated for different numbers of latent classes. The parameter ρ is used to represent probabilities that can range from 0 to 1 and expresses the relation between manifest and latent variables as well as form the basis for interpreting latent structure (Lanza, 2017). When a latent variable completely predicts the manifest variable, $\rho = 0$ or $\rho = 1$. ρ is used to assess homogeneity (i.e., degree to which ρ parameters for a particular latent class are close to 0 or 1); for example, a homogenous class would have all items close to 0 or 1 (Lanza, 2017). Latent class separation is another aspect that ρ parameters allow us to assess. In our work, we first assessed if the classes were homogenous and then if the classes were easily distinguishable. Our LCA algorithm used the default starting values of $\gamma=1/K$ and $\rho=0.5$.

Once latent classes were determined for the various number of classes, relative model fit statistics were used to select the model (i.e., the number of classes) that best describes the data. Model selection for best latent class model was based on goodness of fit measures such as Bayes Information Criterion (BIC) and entropy (Allison et al., 2016). A low BIC value, a high entropy value, and interpretability of the classes informed our model selection (Lanza et al., 2007). Grouping by gender in LCA was considered, but the determining profiles were unaffected; as such, our LCA ignored the consideration of grouping variables.

6.4.3 Regression analyses

General Logit Models were used for our nominal outcome of interest since the three categories do not have a natural order. Intent to use symptom checkers was the nominal outcome of interest with categories “neutral”, “yes” and “no”, where the “neutral” category was the referent group. The “neutral” category was chosen as the reference since the interest was to understand the odds-like of either intending or not intending to use symptom checkers in the future.

6.5 Results

6.5.1 Sample Characteristics and Descriptive Statistics

A total of 1365 respondents had not used an AI-enabled symptom checker in the past 12 months and were thus considered to be SC “non-users”; however, there were missing data across variables for interest for 62 participants which brought down the total sample to n=1305. In sum, the sample of non-users is somewhat evenly split across men and women, non-white, enrolled in an undergraduate program, and often have access to the Internet. An overview of this sample in terms of demographics (gender, age, race), academic/professional environment (education level, faculty, employment status), self-perceived health, health literacy, healthcare access, healthcare use, healthcare use frequency, wait time, and healthcare need are shown in **table 17**. The counts and percentages of the outcome variable and items used to determine latent classes are presented in **table 18**.

Table 17. Sample Characteristics for RQ.3.

Characteristics	Count (%)
Gender	
- Women	710 (54)
- Men	556 (43)
- Other	39 (3)
Age group	
- 18 – 24 years	1256 (96)
- 25 – 29 years	37 (3)
- 30 – 34 years	12 (1)
Racial group[1]	
- White	370 (28)
- Non-white	935 (72)
Current education level[2]	
- Undergraduate	1272 (97)
- Other	33 (3)
Faculty	
- Engineering	358 (27)
- Sciences	247 (19)
- Applied Health Sciences	112 (8)
- Environment	77 (7)
- Arts	212 (16)
- Mathematics	299 (23)
Employment status	
- Employed	469 (36)
- Not employed	785 (60)
- Prefer not to disclose	51 (4)
Self-perceived health[3]	
- Good	1156 (89)
- Poor or do not know	149 (11)
Health literacy[4]	
- High	1140 (87)
- Average or low	165 (13)
Healthcare access	
- Same day to 2 weeks	948 (73)
- 2 weeks to 1 month	85 (7)
- One month or more	24 (2)
- Do not know	248 (19)
Healthcare use[5]	
- Yes	664 (51)
- No or do not know	641 (49)
Healthcare use frequency[6]	
- None to few	501 (75)
- Sometimes	120 (18)
- Often	43 (7)
Wait time[7]	
- Short	982 (75)

- Medium or long	323 (25)
Healthcare need[8]	
- Low	1289 (99)
- Medium or high	16 (1)

Notes: all percentage values are rounded to the nearest integer.

[1] Race captures the self-perceived racial or cultural group of participants. Prevalent racial groups include South Asian and Chinese. The response options were collapsed into two categories (white and non-white) for data analysis.

[2] Most participants are currently enrolled in an undergraduate program. Masters and PhD programs were grouped into "other".

[3] There were five categories for self-perceived health (i.e., excellent, very good, good, fair, poor) which were grouped into two categories (i.e., good and poor) for data analysis. Eight participants indicated "don't know"; they were grouped with the "poor" self-perceived health group for analysis purposes.

[4] Four questions with five-response option Likert scale were used for measuring health literacy. The mean of the responses was calculated and grouped into three options (i.e., high, average, and low).

[5] Healthcare use was measured by asking whether participants saw a family doctor or nurse in the past year (before COVID-19).

[6] Healthcare use frequency was answered by 664 participants who had utilised healthcare in the past year. Zero to 2 visits were categorized as "none to few"; 3 – 5 categorized as "sometimes"; and more than 5 visits categorized as "often".

[7] Wait time was measured as the amount of time participants had to wait between the time of their appointment and the time seen by the primary care provider. Less than 15 minutes to 2 hours was categorized as low; 1 to 2 hours was categorized as medium; and 3 hours or more was categorized as long. Eighty-two participants reported long wait times.

[8] Healthcare need was measured by the number of health conditions reported with "no chronic health conditions" and 1 – 2 health conditions categorized as "low"; 3 – 5 health conditions categorized as medium; and 6 or more conditions categorized as "high". Four participants were identified to have "high" healthcare need and were grouped with those with medium healthcare need.

6.5.2 Perspectives on the use of AI and use of symptom checkers

Table 18. Descriptive statistics on the intent to use symptom checkers

Characteristics	Count (%)
Intent of SC use (outcome variable)	
- No	215 (16)
- Neutral	391 (30)
- Yes	699 (54)
Perspective on the use of AI	
- Negative or neutral	480 (37)
- Positive	825 (63)
Perceived SC ease of use	
- Low or neutral	469 (36)
- Yes	836 (64)
Perceived access to SC	
- Low or neutral	397 (30)
- High	908 (70)
Demonstrability	
- Low or neutral	644 (49)
- High	661 (51)

Trust	
- Low or neutral	827 (63)
- High	478 (37)
Usefulness	
- Low or neutral	318 (24)
- High	987 (76)
Output quality	
- Low or neutral	442 (34)
- High	863 (66)
Credibility	
- Low or neutral	161 (12)
- High	1144 (88)

Notes: all percentage values are rounded to the nearest integer; variables in the table were measured using Likert scale response options.

6.5.3 Exploratory data analysis

The Pearson chi-square statistic provides evidence of association between each pair of independent variables. The Phi coefficient, a measure of association between binary variables and derived from the Pearson chi-square suggests that the associations among our profile-determining items of interest are weak with coefficient ranging between 0.072 and 0.405 **(see appendix 15, table 1)**. This suggests that the items are not highly correlated indicating low redundancy among these items (Lanza et al., 2007). The Pearson chi-square statistic also provides evidence of association between each independent variable and the common outcome of intention to use suggesting that each of the eight items are important determinants **(see appendix 15, table 2)**.

Associations between potential confounders **(from table 17)** and the common outcome (intention of using symptom checkers) were also examined to identify whether they need to be accounted for in the regression analyses **(see appendix 15, table 3)**. All associations were considered weak as per Cramer's V coefficients (a measure of association derived from the Pearson chi-square test and used for variables with more than two categories as is the case for Gender). Nonetheless, these variables were included in the model to identify how the association between the main independent variable (i.e., latent class) and the intent to use symptom checkers may change when controlling for these confounders. Results from the exploratory data analysis (EDA) also suggest that overall perspectives are similar across gender and race except for some significant differences (**see appendix 15, table 4 for** an overview of the Cramer's V (for gender) or phi-coefficient (for race)). Furthermore, latent class analyses showed that profiles did not differ based on these grouping variables; as such, stratification by these variables were not conducted. To account for the impact of gender and race on the intent to use symptom checkers, they were controlled for in the regression analysis. This allowed us to assess whether the effect of latent classes persists even after controlling for these variables.

6.5.4 Latent class modeling

Eight items (i.e., trust, usefulness, credibility, demonstrability, output quality, perspectives about AI, ease of use, and accessibility) were used for latent class modelling. The number of latent class considered were K=2, 3, … 7. **Table 19** displays the fit statistics for the LCA for the top three models arising from K= 3,4, and 5 based on fit statistics and interpretability. These models had relatively lower BIC values and higher entropy as shown in **table 19**. A discussion of these model follows next.

Table 19. Fit statistics for the latent class analysis

	Number of latent classes					
	2	3	4	5	6	7
Fixed effects model						
Degrees of freedom	238	**229**	**220**	**211**	202	193
Log likelihood	-5882.62	**-5837.06**	**-5802.22**	**-5786.55**	-5776.10	-5768.13
G-squared	392.99	**301.87**	**232.19**	**200.85**	179.96	164.01
AIC	426.99	**353.87**	**302.19**	**288.85**	285.96	288.01
BIC	514.95	**488.40**	**483.28**	**516.51**	560.18	608.80
Adjusted BIC	460.95	**405.81**	**372.10**	**376.74**	391.83	411.85
Entropy	0.74	**0.65**	**0.61**	**0.63**	0.63	0.66

Note: The bolded text represents models (3, 4, and 5 latent classes) that have been interpreted further for their potential in being selected as the preferred model.

For the model with three classes, the profile description of these classes is given in **table 20**. The first profile describes a group with positive attitudes towards various aspects of symptom checkers and were thusly labeled *tech acceptors*. The second group were the opposite, having a low probability of answering positively on any of the items assessed, and were labeled as *tech rejectors*. The third group had a mixed response pattern showcasing some negative perceptions, particularly related to trust, demonstrability, and output quality – this group was labeled as *skeptics*.

Table 20. Three-latent-class model: Probability of positive perceptions for each subgroup

	Latent Class (count; %)		
	Tech acceptors (756; 58%)	Tech rejectors (110; 8%)	Skeptics (439; 34%)
Trust	**0.5559**	0.0644	0.1448
Credibility	**0.9914**	0.3127	**0.8475**
Output quality	**0.8849**	0.0789	0.4625
Usefulness	**0.9456**	0.0908	**0.6356**
Demonstrability	**0.7362**	0.1042	0.2484
Accessibility	**0.7779**	0.1806	**0.7058**
Ease of use	**0.7179**	0.2014	**0.6375**
Perspectives about AI	**0.7466**	0.3385	**0.5292**

Note: Item-response probabilities >0.5 are bolded to facilitate interpretation.

The four-class-model identifies similar groups as the three-class model (i.e., "*tech acceptors*", "*tech rejectors*", and "*skeptics*") but includes an additional sub-group that had some positive perspectives related to the output but did not trust the platform and perceived it to be difficult to access and use – this group was labeled as "*unaware acceptors*".

Table 21. Four-latent-class model: Probability of positive perceptions for each subgroup

	Latent Class (count; %)			
	Tech acceptors (578, 44%)	Tech rejectors (138, 11%)	Skeptics (360, 27%)	Unaware acceptors (229, 18%)
Trust	**0.5480**	0.0624	0.1300	0.4824
Credibility	**0.9929**	0.3765	**0.8191**	**0.9813**
Output quality	**0.8835**	0.0974	0.4149	**0.8422**
Usefulness	**0.9726**	0.1422	**0.6073**	**0.8532**
Demonstrability	**0.7184**	0.1046	0.2226	**0.6743**
Accessibility	**0.9933**	0.1499	**0.8211**	0.2892
Ease of use	**0.8221**	0.1935	**0.7059**	0.4598
Perspectives about AI	**0.7626**	0.3410	**0.5340**	**0.6636**

Note: Item-response probabilities >.5 are bolded to facilitate interpretation.

A similar pattern is observed in the five-class model with *tech acceptors, tech rejectors*, and *skeptics* being recurring classes. The five-class model dissects the *unaware acceptors* further to suggest that there are some differences among the group. The fourth subgroup (*tech seekers*) has positive perceptions related to all aspects of symptom checkers but do not find the platform to be accessible whereas the fifth group (*unsure acceptors*) does not perceive access to be an issue but rather have some negative perceptions about AI and other aspects of symptom checkers.

Table 22. Five-latent-class model: Probability of positive perceptions for each subgroup

	Latent Class (count; %)				
	Tech acceptors (621, 48%)	Tech rejectors (137, 11%)	Skeptics (190, 14%)	Unsure acceptors (185, 14%)	Tech seekers (172, 13%)
Trust	**0.5428**	0.0675	0.1217	0.1887	**0.5521**
Credibility	**0.9927**	0.3112	**0.7544**	**0.9744**	**0.9724**
Output quality	**0.8824**	0.0924	0.3572	**0.5811**	**0.8679**
Usefulness	**0.9671**	0.0989	**0.5600**	**0.7480**	**0.8479**
Demonstrability	**0.7195**	0.1102	0.2649	0.1678	**0.8359**
Accessibility	**0.9939**	0.1905	**0.8921**	**0.5369**	0.1311
Ease of use	**0.8036**	0.2076	**0.8729**	0.3697	**0.5082**
Perspectives about AI	**0.7557**	0.3517	**0.5774**	0.4656	**0.7249**

Note: Item-response probabilities >.5 are bolded to facilitate interpretation.

Tech acceptors and *tech rejectors* make up the biggest and smallest proportion across models, respectively. *Skeptics* are the second most prevalent group with additional granularity provided in models with additional classes. Based on the fit statistic and interpretability, the five-class model was chosen. While the BIC and adjusted BIC were slightly higher for the five-class model as compared to the three- and four-class models, the entropy was higher as compared to the 4-class model. Importantly, the five-class model provides more detailed information regarding the classes that exist in the population with *tech seekers* being an important class that is in line with findings from the qualitative phase which highlights the key barrier related to lack of perceived access to symptom checkers. As such, the five-class model will be used for the regression analysis.

6.5.5 General Logit Models for assessing association between latent classes and intent to use symptom checkers

The general linear models for the nominal variable future use are given by:

$$\log[Odds(Yes \text{ vs. } Neutral)] = \beta_0 + \beta_1(LatentClass)_i + \beta_2(Gender)_i + \beta_3(Race)_i + \beta_4(HCUse)_i + \beta_5(Wait\ time)_i + \beta_6(HL)_i + \beta_7(GenHealth)_i ;$$

$$\log[Odds(No \text{ vs. } Neutral)] = \gamma_0 + \gamma_1(LatentClass)_i + \gamma_2(Gender)_i + \gamma_3(Race)_i + \gamma_4(HCUse)_i + \gamma_5(Wait\ time)_i + \gamma_6(HL)_i +$$

$$\gamma_7 (GenHealth)_i \text{ ;}$$

where,

$$Odds(Yes \text{ vs. } Neutral) = \frac{\text{Pr } (FutureUse = Yes)}{\text{Pr } (FutureUse = Neutral)}$$

$$Odds(No \text{ vs. } Neutral) = \frac{\text{Pr } (FutureUse = No)}{\text{Pr } (FutureUse = Neutral)}$$

$FutureUse_i$ is a nominal outcome for subject i;
β_0 and γ_0 $are\ the\ corresponding\ model\ intercepts$;
$LatentClass_{i,}\ Gender_{i,}, Race_{i,}\ HCUse_{i,}\ Wait\ time_{i,}\ HL_{i,}\ GenHealth_{i,}$ are (fixed) $seven$ explanatory variables for subject i;
$\beta_1, \beta_2,\ \beta_3, \beta_4,\ \beta_5, \beta_6,\ \beta_7, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \gamma_6, \gamma_7$ are the (fixed) unknown regression coefficients for each of the predictors

The reference category for each independent variable is as follows:
Latent class: *Tech rejectors*
Gender: Other
Race: White
HCUse: No or do not know
Wait time: Medium or long
HL: Low or average
GenHealth: Poor or do not know

The GLM procedure in SAS was used to the fit the above General Logit model. As mentioned in the previous section, the five-class model was used for the regression analysis. We additionally ran the above models without the covariates (i.e., gender, race, healthcare use, wait time, health literacy, and self-perceived health). Detailed outputs of these model are provided in **appendix 16**. Discussed next is the model that was selected as best in summarizing the association while elucidating interesting features of the latent classes.

Table 23. Output for the five-class model without confounders

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
Latent Class	8	142.8164	<.0001

Odds Ratio Estimates				
Effect	Future Use	Point Estimate	95% Wald Confidence Limits	
Acceptors vs. tech rejectors	Yes	5.556	3.448	8.954
Acceptors vs. tech rejectors	No	0.592	0.367	0.956

Skeptics vs. tech rejectors	Yes	2.772	1.586	4.844
Skeptics vs. tech rejectors	No	1.400	0.826	2.374
Tech seekers vs. tech rejectors	Yes	7.510	4.210	13.397
Tech seekers vs. tech rejectors	No	0.640	0.316	1.294
Unsure acceptors vs. tech rejectors	Yes	2.090	1.217	3.590
Unsure acceptors vs. tech rejectors	No	0.532	0.301	0.939

Interpretation of intending to use symptom checkers as compared to the “neutral” referent group (without confounders)

The output suggests a significant effect of latent classes on the intent to use symptom checkers. The odds of intent to use in *tech acceptors* are 5.5 times higher than the odds of intent to use in *tech rejectors* [CI: (3.448, 8.954); p-value < .0001]. The odds of intent to use in *skeptics* are 2.7 times higher than the odds of intent to use in *tech rejectors* with a [CI: (1.586, 4.844); p-value < .0001]. The odds of intent to use in *tech seekers* are 7.5 times higher than the odds of intent to use in *tech rejectors* [CI: (4.210, 13.397); p-value < .0001]. The odds of intent to use in unsure *tech acceptors* are 2 times higher than the odds of intent to use in *tech rejectors* [CI: (1.217, 3.590); p-value = 0.0076].

Interpretation of not intending to use symptom checkers in the future as compared to the “neutral” referent group (without confounders)

The output suggests that *tech acceptors* have lower odds of not intending to use symptom checkers in the future as compared to those categorized as *tech rejectors* [CI: (0.367, 0.956); p-value = 0.03]. The odds of reporting not intending to use symptom checkers in the future are 1.4 times higher in *skeptics* than the odds of not intending to use symptom checkers in *tech rejectors* [CI: (0.826, 2.374; p-value = 0.2]. *Tech seekers* have lower odds of not intending to use symptom checkers as compared to *tech rejectors* [CI: (0.316, 1.294); p-value = 0.2]. *Unsure acceptors* have lower odds of not intending to use symptom checkers as compared to *tech rejectors* [CI: (0.301, 0.939); p-value = 0.02].

The effect of latent classes on intention to use symptom checkers remains significant and of similar magnitude even after controlling for our confounders. This finding is critical since it suggests latent classes have an independent association to intention to use SCs. **Table 24** provides the output for the model that includes latent class with the full output with the seven other control variables being in **appendix 16 (table 2)**.

Table 24. Output for the five-class model with confounders

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
Latent Class	8	143.3710	<.0001
GenHealth[1]	2	2.7162	0.2572
HL[2]	2	0.6488	0.7230
HC Use[3]	2	5.6047	0.0607
Wait time[4]	2	5.0084	0.0817
Gender[5]	4	5.8547	0.2103
Race[6]	2	12.3150	0.0021

[1] Self-perceived health, [2] Health literacy, [3] Healthcare use, [4] Wait time, [5] Gender, [6] Race

Odds Ratio Estimates				
Effect	Future Use	Point Estimate	95% Wald Confidence Limits	
Tech acceptors vs. tech rejectors	Yes	5.603	3.458	9.078
Tech acceptors vs. tech rejectors	No	0.565	0.346	0.922
Skeptics vs. tech rejectors	Yes	2.615	1.491	4.586
Skeptics vs. tech rejectors	No	1.384	0.808	2.371
Tech seekers vs. tech rejectors	Yes	7.669	4.276	13.752
Tech seekers vs. tech rejectors	No	0.662	0.325	1.352
Unsure acceptors vs. tech rejectors	Yes	2.080	1.207	3.584

Unsure acceptors vs. tech rejectors	No	0.538	0.302	0.958

Interpretation of intending to use symptom checkers as compared to the "neutral" referent group (with confounders)

After controlling for confounders, the effect of latent classes on the intent to use remains significant (p-value < .0001) with the odds of intent to use in *tech acceptors* being 5.6 times higher than the odds of intent to use in *tech rejectors* [CI: (3.458, 9.078); p-value < .0001]. The odds of intent to use are 2.6 times higher in *skeptics* than the odds of intent to use in *tech rejectors* [CI: (1.491, 4.586); p-value = .0008]. The odds of intent to use are 7.6 times higher in *tech seekers* than the odds of intent to use in *tech rejectors* [CI: (4.276, 13.752); p-value = < .0001]. The odds of intent to use in *unsure acceptors* are 2 times higher than the odds of intent to use in *tech rejectors* [CI: (1.207, 3.584); p-value = .008]. In sum, latent class membership is a significant predictor of the intention to use symptom checkers. *Tech seekers* and *unsure acceptors* were the latent classes with the highest and lowest odds of intending to use symptom checkers, respectively.

Interpretation of not using symptom checkers in the future as compared to the "neutral" referent group (with confounders)

The output suggests that *tech acceptors* have lower odds of not intending to use symptom checkers in the future as compared to those categorized as *tech rejectors* [CI: (0.346, 0.922); p-value = 0.02]. The odds of reporting not intending to use symptom checkers in the future are 1.4 times higher in *skeptics* than the odds of not intending to use symptom checkers in *tech rejectors* [CI: (0.808, 2.371; p-value = 0.2]. *Tech seekers* have lower odds of not intending to use symptom checkers as compared to *tech rejectors* [CI: (0.325, 1.352); p-value = 0.2]. *Unsure acceptors* have lower odds of not intending to use symptom checkers as compared to *tech rejectors* [CI: (0.302, 0.958); p-value = 0.03].

6.6 Key takeaways

While university students tend to be young adults and thus eager adopters of technology, there exists homogenous groups within this population which suggests that a deeper understanding of profiles is required. Based on our study’s sample, we found five latent classes characterized by probabilities of attributing a high or positive response to the eight attitude-based variables. When regressing intention to use symptom checkers in the future on latent classes, this predictor remains significant even after controlling for confounders. This suggests that latent classes have an independent association with the outcome of interest. Interestingly, while *tech seekers* scored positively on all attributes, *tech seekers* (those who scored positively on all items except for “perceived accessibility”) had the highest like-odds of intending to use symptom checkers for self-triage. A summary of thesis findings, contrast with the literature , and other key discussion points are in the following chapter.

Chapter 7: Discussion

7.1 Research question 1

In contrast to the limited literature available on public perspectives on the use of AI in healthcare (Xu et al., 2018; Hengstler et al., 2016; Aicken et al., 2016), most participants in this study had positive perspectives related to its use in the healthcare context. Most participants believed that AI has huge potential in healthcare – a viewpoint that is shared by various experts in the field (Hinton, 2018; Israni and Verghese, 2019; Naylor, 2018). This was especially the case when the use of AI is being used by Governmental institutions that were perceived to be using data to improve overall health and well-being of the population. The positive outlook on the use of AI in healthcare was due to the use of big data which would allow for pattern recognition, decision-making, and efficiency optimization.

Many, however, either exhibited indecisiveness or negative perspectives about the use of AI owing to its reliance on the quality of data which cannot be guaranteed. Importantly, participants shared comments which suggested that they were skeptical about the use of AI due to biases (e.g., racial profiling) that could manifest with its use. Some believed that AI is “overhyped” and that its popularity will subside in the upcoming years similar to previous trends in the scientific domain. Negative perspectives were also shared regarding the use of AI by corporations to generate profit – this finding is in line with a study conducted by Paprica et al. (2019) which highlighted the general public’s concern related to privacy and security of data, especially where there is private sector involvement. Findings from this work are also in line with work conducted by the Canadian Medical Association showing that while the public support investments in AI and technology, they do not want to see these investments occur at the expense of the health workforce (CMA, 2018). Importantly, most participants shared a common viewpoint that the output provided by AI-enabled technology can only be as good as the data used to teach these machines (Digital Journal, 2018).

Despite some skepticism related to the use of AI in healthcare, most participants had a positive outlook on the use of AI-enabled symptom checkers for self-triage. It is noteworthy that more than half of participants were not aware of the existence of the platform prior to their participation in the qualitative study. These participants were able to use the platform for the first time during the interview. As compared to the use of the Internet search engine for health-information seeking, symptom checkers were better perceived due to their more personalized and interactive nature; straightforward design; and perceived reliability. While the Internet has been historically used for searching health information for self-assessment, symptom checkers – especially more sophisticated ones that utilize AI – are becoming more widespread and adopted by the general public (Hill et al., 2020, Aboueid et al., 2019). This can be explained by some of the findings highlighted in the present work which suggests that users may perceive symptom checkers as more personalized, reliable, and accurate due to their approach in collecting data. It is important to note, however, that not all symptom checkers are equal. In a study conducted by Hill et al. (2020), it was found that the proportion of correct diagnosis results was larger for programs that use AI algorithms – as compared to those that do not – and those that require demographic information. This suggests that AI-enabled symptom checkers may be more accurate; however, all symptom checkers – irrespective of whether or not they utilize AI – are perceived to be more accurate than conducting a general Internet search (Semigran et al., 2015).

In line with previous published literature (Verzantvoort et al., 2018; Hill et al., 2020; Semigran et al., 2015), most participants in this study believed that symptom checkers would be useful for self-triage rather than self-diagnosis. This can be explained by various reasons outlined in this study which include the disclaimer provided by most platforms which states that the information cannot substitute medical advice. A common perspective is that getting the exact diagnosis may not be as important as getting the correct advice about whether or not and how quickly one should consult a primary care provider (The Harvard Gazette, 2015; Semigran et al., 2015). The limitations of symptom checkers – with the most notable being suboptimal accuracy – suggests that triage advice may be the more important function of symptom checkers. This is because diagnosis is (most often) not a single assessment, but rather a process that requires knowledge, experience, clinical examination and testing, and the passage of time (Hill et al., 2020), which is impossible to replicate in a single online interaction. Given that unnecessary care and overuse of health services are a widespread and costly issue in many parts of the world, optimizing symptom checkers to improve its performance in triage is important to reduce healthcare costs (CIHI, 2017; Brownlee et al., 2017) and improve patient safety (Akbar et al., 2020). Interestingly, the use of symptom checkers was perceived useful to inform healthcare visits in primary care rather than the emergency room – this may be due to less frequent use of emergency services by university students.

While symptom checkers have been highlighted as useful for self-triage, understanding the factors associated with their use is important to optimize their benefits. Factors that would enable or hinder the use of a symptom checker were identified – these factors were related to the individual, disease, healthcare system, or the symptom checker itself. Individual-level factors that entice individuals to use a symptom checker include having Internet access, low health literacy, trust towards the platform, and high technology literacy. In Canadian rural and remote regions, access to Internet is lacking; speeds of 50/10 Mbps are available to 84% of Canadian households (Government of Canada, 2019). Efforts are outlined in the 2019 Canadian budget – the government announced its commitment of reaching a target in which 95% of Canadian homes and business have access to Internet speeds of at least 50/10Mbps by 2026 and 100% by 2030 (Government of Canada, 2019). Lack of connectivity is also an issue worldwide, especially in developing countries (UNESCO, 2019). Interestingly, the lack of connectivity is related to poor literacy and digital skills rather than lack of affordability (Government of Canada, 2019). This was also found in our study and highlights the importance of ensuring that populations have the means of accessing these platforms. Failing to do so will undermine the purpose and mission of many of these technology companies that aim to reach those that are disadvantaged and in developing countries (Morita et al., 2017).

There was a perception that having low health literacy is an enabler for using a symptom checker. This is contradictory to findings from previous studies which found that those with low health literacy reported less Internet use, including online health information seeking (Jensen et al., 2010) and that patients with more limited cognitive abilities, less education, and older age showed greater anxiety with adopting new technologies (Czaja et al., 2006). These differing findings can be explained by age where younger adults who have lower health literacy may be less critical of symptom checkers and hence use them, while older adults with low health literacy may not be familiar with the technology (Fischer et al., 2014).

As found in other studies (Bahmanziari, Pearson, Crosby, 2016; Söllner, Hoffmann, Leimeister, 2016), trust was identified as an important component in technology acceptance and adoption. Participants mentioned that they would be more trusting of platforms if they provided them with a diagnosis that they thought they had – this demonstrates that as found in another study, (Mueller et al., 2017) confirmation bias was present. This phenomenon can pose some issues, especially when the user believes to have false beliefs about their symptoms/potential condition(s). Another issue that could arise is that users conduct the self-assessment (i.e., answers questions on the symptom checker) in a way that would prove their own beliefs – even if they were false.

Another enabler perceived to play a role in symptom checker use was technology literacy – a term that goes beyond understanding how to use computers; it refers to one's ability to use, manage, evaluate, and understand technology (ITEA, 2002). Studies suggest that this ability seems to be more pronounced in younger adults as they are the population group most eager to adopt technology (Pew Research Center, 2016). This is in line with the literature which highlights that an important factor that seems to influence symptom checker acceptance is age with younger populations exhibiting higher acceptance (Meyer et al., 2020; Healthwatch Enfield, 2019). A UK-based study that engaged with 1,071 patients found that more than 70% of individuals between the ages of 18 and 39 would use a symptom checker as compared to 51% for ages between 55 and 69 (Healthwatch Enfield, 2019).

Lack of time and convenience were important enabling factors for using symptom checkers – these factors also explain the use of Internet search engines for health information (Asibey et al., 2017). University students tend to have busy schedules which may push them to use symptom checkers for self-assessment more than other population groups. Importantly, while preventive care visits involving screening and counseling for risky behaviours (e.g., tobacco and alcohol use as well as sexually transmitted infections) are important during young adulthood, sensitivity surrounding these topics impede young adults from accessing health services (Santelli et al., 2019). Some participants are more honest with a computer as compared to a health professional (Wyatt, 2015; Joinson et al., 2007; Hewson et al., 2007). This may explain why participants mentioned they would be more likely to use a symptom checker to assess symptoms or health conditions if they are perceived to be sensitive in nature.

Experiencing mild or non-specific symptoms (e.g., a cough which may indicate the presence of one of many diseases) were other reported enablers for using symptom checkers. A study that sought to understand the characteristics of symptom checker users found that among 26,646 assessments, the top 10 most common initial symptoms were abdominal pain, cough, headache, sore throat, dizziness, fatigue, chest pain, lower pack pain, diarrhea, and painful urination (Morse et al., 2020). While symptom checkers were perceived to be useful for mild symptoms, a study found that most assessments conducted resulted in a recommendation to seek out care; specifically, a study that examined the characteristics of 26,646 assessments provided by a symptom checker found that only 20% of assessments directed the user to low-acuity care (i.e., care provided to individuals who do not have a severe illness) with the remaining 51% and 29% directed to medium or high acuity care, respectively (Morse et al., 2020). This suggests that symptom checkers are being used for more severe symptoms and that these platforms are risk averse.

The need to narrow down potential causes for experiencing non-specific symptoms was also found in another study which showed that users most commonly used a symptom checker to better understand the causes of their symptoms (232/304, 76.3%) (Meyer et al., 2020). Participants mentioned, however, that using the platform is contingent on them knowing how to easily describe their symptoms. This finding accentuates the importance of health literacy in the adoption of health technology. Interestingly, there were conflicting perspectives on the ideal users of symptom checkers. While some believed that these platforms are most suited for individuals who have less complex health problems, others believed that those with existing health conditions would be most likely to use such a platform. Those with pre-existing or complex health problems may be more likely to worry about their health and hence use symptom checkers; however, there is limited evidence to confirm or disprove this hypothesis. We do know, however, that users of symptom checkers tend to be female and younger – the latter has a lower correlation with complex health problems as the number of health conditions increases with older age (Morse et al., 2020; Singer et al., 2019).

Lack of access to health services emerged as an enabler for symptom checker use even though this sample has relatively good access to healthcare services both off and on campus. Evidently, while this is mentioned as an enabler, it should not be capitalized on as a factor to increase use of symptom checkers. In line with findings from a Canadian national study, while most participants have a positive outlook on the integration of technology and AI in the healthcare system, they do not want these investments to occur at the expense of the health workforce (Canadian Medical Association, 2018b). Rather, there should be an integration of both with the notable example of the University of California Symptom Checker (UCSC) – one of the many symptom checkers that are fully integrated with patient medical records (Judson et al., 2020). The benefits reaped from using the UCSC were evident during the COVID-19 pandemic during which patients using the platform were triaged and scheduled for an appointment (if needed) in a median of two minutes (Judson et al., 2020). It seems that the pandemic has made individuals more receptive of symptom checkers due to the potential risks of infection associated with in-person medical visits. For a more detailed analysis and discussion on participant perspectives on the use of symptom checkers for COVID-19 related symptoms, please refer to the paper by Aboueid et al., 2021a.

The integration of symptom checkers with patient medical records is one of many ways of showing approval of such platforms – a factor that was mentioned to be important for deciding whether to use symptom checkers. This study has shown that the approval (or disproval) of such platforms by primary care providers and health organizations plays a key role in an individual's decision to use a symptom checker. Given the mounting number of symptom checkers available and questionable credibility of many, skepticism among health professionals is well justified; however, this skepticism should not stifle innovation that could potentially provide benefits to the healthcare system. A study by Meyer et al. (2020) found that 51.6% (110/213) choosing not to discuss the findings with their physicians due to concerns including the belief their doctors would not approve of such a platform. Among those who visited physicians after having used the tool (213/304, 70.1%), half discussed the findings with their physicians (103/213, 48.4%) with 40.8% (42/103) and 23.3% (24/103) having reported positive and negative experiences, respectively (Meyer et al., 2020).

While less applicable in the Canadian context, cost of healthcare services was mentioned to be a factor that would entice an individual to use a symptom checker. Many mentioned that this platform would be ideal for countries in which healthcare services are not publicly funded as individuals would be able to assess whether they truly need to seek care prior to paying for the service. Future studies exploring the utilization rate of such platforms across countries that differ based on level of access to healthcare services (primarily defined as cost of care) could help in understanding the correlation between utilization and cost of healthcare. Long wait times in health clinics were mentioned to be an enabler for using symptom checkers. Results from the Commonwealth Fund's 2016 International Health Policy Survey of Adults in 11 countries found that Canada continues to perform below the international average for timely access to patient care with only 43% of Canadians reporting that they were able to get a same- or next-day appointment at their regular place of care the last time they needed medical attention – the lowest percentage of all countries[1] (CIHI, 2016). As such, while most Canadians (93%) have a regular doctor or place of care, they generally report longer wait times for medical care than adults in comparable countries (CIHI, 2016). Interestingly, Canadian patients are not seeing improvements in timely access to primary care, which is contrary to what primary care physicians reported in the Commonwealth Fund's 2015 survey. This contradiction in perspectives could potentially be explored as a reason for leveraging technology to address patient concerns.

An important factor to consider, however, is the level of awareness related to symptom checkers. Our study stresses the need to increase advertisement related to these platforms with social media being a potential avenue (Uhls et al., 2017). A myriad of factors was identified as important for enabling symptom checker use. Many symptom checkers are free of charge to the user due to companies' other revenue streams enabled by data collected. This study suggests, however, that while users value a platform that is free of charge, they do not want their data to be used for revenue generation. Despite this, health data collected through these platforms have been identified as a promising revenue stream for corporations. For example, health data may be sold to pharmaceutical companies to help them understand the prescribing behaviours of primary care providers (Scientific American, 2016; The Guardian, 2017).

In this study, participants stressed the importance of anonymity and data privacy. Legal challenges such as the one resulting from a collaboration between Google and the University of

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[1] Netherlands, New Zealand, Australia, United Kingdom, Switzerland, France, Germany, US, Sweden, Norway

Chicago Medical Center highlight the need to address privacy issues – for example, with the University's medical records' data, Google's DeepMind is capable to reidentify individuals (CMAJ News 2019; US Action Lawsuit Case 1:19-cv-04311; 2019). Some participants believed that these practices could have repercussions on health technology users as some information may be used for discriminatory purposes. Nonetheless, one factor that was identified as a means of enabling use of symptom checkers was providing information about the creators of the platform. A quick review of some of the top symptom checkers (i.e., Isabel, Ada, Babylon, WebMD) highlights that only high-level information is provided about how the platform was developed – the individuals behind the platform are rarely introduced to users. This is important as some participants mentioned wanting to know whether doctors were involved in developing these platforms.

Participants believed that the use of symptom checkers would be maximized if it was perceived to be a good source of health information and if AI is used to provide personalized results. It is important to note that while the use of AI is important, it has been shown that AI-enabled technology may fall short partly due to the type of data used. For example, a relatively recent scandal of unsafe and incorrect cancer treatment recommendations provided by IBM's Watson was traced to engineers training the AI on hypothetical cases rather than real patient data (CMAJ News, 2019).

An interactive platform and easy to use interface were mentioned to be important deciding factors for symptom checker use. For example, being able to ask questions was perceived to be important by some participants – this feature; however, is not readily available given the more rigid nature of symptom checkers (as compared to the Internet and conversation with a medical provider). Therefore, it is important for symptom checker developers to consider as patient-centered communication has been shown to be important for patient outcomes (King and Hope, 2013). Moreover, gamification – known as the application of game-design elements in non-game contexts – was mentioned to be a potential enabler for symptom checker use; however, although gamification has been used in various health apps (Cotton and Patel, 2019), it may be inappropriate for symptom checkers as these platforms are typically used by individuals experiencing signs and symptoms.

A factor that was mentioned to hinder the use of symptom checkers is the disclaimer used by most platforms which indicate that the platform is not providing a diagnosis but rather health information that is based on the information entered, and not a personalized assessment. Given the risks associated with false negatives when assessing medical risks as well as the little or no regulatory oversight of medical apps, disclaimers are used to warn users in a simple language regarding the app's diagnostic limitations (Boulos et al., 2014). While disclaimers were mentioned to decrease participants' likelihood of symptom checker use, it was not identified as an important factor in another qualitative study that explored the factors associated with initiating and continuing the use of such platforms (Vaghefi and Tulu, 2019). It is worth noting that in some countries, symptom checkers are considered a medical device and are thus regulated by Governmental entities.

Inclusivity measures for health apps have often focused on reaching populations with low health literacy (UNESCO, 2018); however, little to no research has been conducted to understand how populations with different types of disabilities may be able to access and use symptom checkers. Concerted effort is needed to address this important gap in research and application.

Participants also mentioned that lack of human interaction may be a potential barrier for older adults but did not believe it to be a barrier for them. The importance of integrating human support in technology has been recommended for improving adherence, communication with care teams, and improving quality of the tool. While some symptom checkers solely rely on AI for providing the final output to users, some platforms are integrating an option to speak to a health professional virtually should it be needed based on severity of symptoms. Given these user preferences, a digital formulary (i.e., a list of digital symptom checkers that would enable a provider to distinguish between preferred or non-preferred symptom checkers based on several factors including cost and clinical value) could be beneficial (Gordon et al., 2020). A digital formulary would also be able to mitigate bad experiences that could have resulted from false negatives or poor user experience – factors that have been identified in this study as a barrier for using symptom checkers.

7.2 Research question 2

Despite the barriers related to symptom checker use, most participants in our study had a positive outlook on the use of symptom checkers and believed that these platforms could have a positive effect on their health, as well as health services by reducing unnecessary medical visits, increasing patient engagement, and improving access to care. Importantly, however, most participants believed that the accuracy of these platforms would have to improve substantially before benefiting the healthcare system (e.g., through reducing health system burden). A few participants believed that it may have a negative influence on health due to a suboptimal understanding of the user's contextual factors, overall health status, and the reactive nature of the platform (i.e., focus on symptoms). This is in line with studies and literature reviews showing that symptom checkers are suboptimal in terms of accuracy, coverage, and safety (Semigran et al., 2015; Aboueid et al., 2019; Chambers et al., 2019; Gilbert et al., 2020; Munsch et al., 2020). For example, a study that compared the coverage (i.e., is the condition modelled), suggested condition accuracy (i.e., is the condition listed as one of the top three conditions), and urgency advice accuracy (i.e., at gold standard level, more conservative, or no more than one level less conservative) of 8 popular symptom checkers (i.e., Ada, Babylon, Buoy, K Health, Mediktor, Symptomate, WebMD, and Your.MD) found that none of these platforms were able to outperform a GP; however, some symptom checkers came close (Gilbert et al., 2020). Another study that focused specifically on web-based COVID-19 symptom checkers found that the number of correctly assessed COVID-19 and control cases varied considerably between symptom checkers, with only two platforms having achieved a good balance of sensitivity and specificity (Munsch et al., 2020). Moreover, a study that evaluated the advice given by a self-assessment triage system in a university health center found that there was only a 39% agreement between the platform and the GP with the former being more risk averse (Poote et al., 2014). In sum, the literature suggests that software improvements could improve symptom checker performance overtime and in turn, meet user expectations.

In this study, credibility of the platform was among the top five most important factors in deciding whether to use a symptom checker for self-triage and its importance has been stated throughout this dissertation. For symptom checkers to improve their credibility, there is a need to increase transparency about the developers and medical experts involved in developing the platform. Interestingly, while user reviews were identified as a factor influencing the credibility of a platform, it has been shown that consumer ratings poorly reflect clinical utility and usability (Singh et al., 2016). Therefore, while some elucidated factors may be deemed legitimate in improving the perceived credibility of a symptom checker, some may be misleading which suggests that there is a need for an unbiased assessment of symptom checker credibility.

Importantly, findings from this study suggest that credibility of the platform will influence trust in the results as participants mentioned that they are more likely to trust a symptom checker that is perceived to be credible. Understanding the role of trust in public health research has been proven to be fundamental, especially when it takes into account the social factors (e.g., socio-economic status, class, and age) that may play a role in willingness to trust (Meyer et al., 2008). Trust is important to consider because the literature suggests that people shape their attitudes, beliefs, and behaviours based on health information sources they trust (Clayman et al., 2010; Chen et al., 2018). In fact, a lack of trust in healthcare professionals and health systems is thought to make patients turn to unregulated health technology (Meskó et al., 2017). Just as healthcare professionals have to gain patient trust to enable data collection of personal health information (Russell, 2005), symptom checkers have to assume a similar role; as such, building trust with users is critical for the collection of complete and sensitive data. While the qualitative work of this study did not consider the role that social factors play in willingness to trust symptom checkers, key factors related to the design of digital platform and that influence user trust were identified **(see table 12)**.

Tangibility of results is another important factor to consider as the positive outcomes claimed to be delivered by the symptom checker needs to be obvious to users (Venkatesh and Davis, 2000). Tangibility is captured in result demonstrability and is perceived to be positively correlated with health technology use (Jung, 2008). To achieve result demonstrability, symptom checkers should not only state the positive outcomes of using the platform but also assess how these outcomes can be achieved. For example, if a symptom checker claims that it can save time for an individual by providing a quick assessment of their symptoms, it would achieve result demonstrability if users truly thought that this claim was substantiated.

While a higher level of healthcare need was identified in the literature as a driver for healthcare technology use (Kenny and Connolly, 2017), this was not be the case in this study as findings from qualitative data suggest that participants believe symptom checkers to be useful for individuals with less complex health issues and hence, healthcare need. These perspectives were explained by the belief that a symptom checker may not be able to capture all relevant health data which can be problematic, especially for those who have pre-existent health conditions or a higher level of healthcare need.

Perceived accessibility – defined as an individual's perception of the ease or difficulty to gain access to or reach something – will play a key role in an individual's decision to use symptom checkers. In this study, the following factors seemed to influence accessibility: 1) knowing about the technology, 2) having access to the Internet, 3) having financial means (applies if a fee is associated with platform use), 4) understanding the medical terms used by the platform, 5) understanding the language used by the platform, and 6) the platform having inclusivity measures. As such, while the literature suggests that health technology is readily accessible (Meskó et al., 2017), this may not be the case, especially for technologies that may not be as known by the target population. Governments and corporations should consider these factors to improve accessibility of such platforms. It is important to ensure, however, that accessibility is improved for platforms that have been deemed safe ad credible.

7.3 Research question 3

To the author's knowledge, this thesis study is the first to employ latent class analysis to understand how a group of variables or a membership to a certain class would influence the use of symptom checkers. It is noteworthy finding that the effect of latent classes remained significant even after controlling for confounders; this is not always the case since from a statistical perspective, the effect of a variable can lose its significance when controlling for other variables (Simons-Morton et al., 2016). Other studies in the field of information technology have employed LCA to identify the types of classes that exist based on attitude-based variables – these researchers found three distinct latent classes (i.e., conservative users, average users, and innovative users) categorized by the array of mobile services used. (Sell et al., 2014). In our study, attitude-based variables were also found to be significant in identifying population profiles that exist among university students; these variables covered perspectives on the functionality of symptom checkers as well as AI. Another large-scale study by Tang and Patrick (2019) went beyond identifying latent classes by regressing these latent classes – which were categorized by technology and interactive social media use – on two key outcomes (academics and substance use) with the most media-intensive profiles at greater risk for poor academic outcomes and substance use. In line with their study, our analyses found latent classes of attitudes towards AI to be significantly associated with the outcome (intent to use) with or without controlling for confounders.

Previous studies have applied the TAM to identify the factors associated with the adoption and use of health apps and health technologies; for example, a study found that adolescents found wearable activity trackers to be useful, but the efforts required to use these technologies may influence overall engagement and technology acceptance (Drehlich et al., 2020). In our study perceived ease of use was also found to play a role in defining latent classes and in turn, the latent class association with the intention to use symptom checkers. For example, *tech rejectors* and *unsure acceptors* did not perceive the use of symptom checkers to be easy which was evident by their lower odds of intending to use symptom checkers in the future. While age was not explored in our study due to the young age of our sample, another study found that younger populations displayed more confidence with the use of mHealth apps and were less concerned about compromising the confidentiality of their health records (Shemesh and Barnoy, 2020). Answers to TAM-related questions among mHealth apps users were significantly more positive compared with non-users (Shemesh and Barnoy, 2020). Interestingly, as found in our study, the endorsement of health apps by health organizations can play an influential role in technology acceptance and utilization (Shamesh and Barnoy, 2020).

Our study merged the TAM and LCA literature to identify profiles among university students and regress these profiles on intention to use symptom checkers. Interestingly, while young adults are perceived to be technology savvy, most of the participants recruited had not used a symptom checker in the past year – this may be due to, as outlined in the qualitative findings, the lack of awareness regarding the existence of these platforms. Among those who have not used a symptom checker and thus identified as non-users, most had positive perspectives regarding the use of AI in health and symptom checkers' functionality. However, some skepticism and issues related to perceived accessibility and functionality may hinder the future adoption and use of symptom checkers. Five distinct latent classes were identified: *tech acceptors*, *tech rejectors*, *skeptics*, *unsure acceptors,* and *tech seekers*. Even after controlling for potential confounders, the effect sizes remained similar suggesting that these profiles are independently able to explain the variation in the outcome (i.e., intention to use symptom checkers) with *tech seekers* and *unsure acceptors* having the highest and lowest odds of intending to use symptom checkers, respectively. While confirmatory latent class analysis was not performed, the nature of the latent classes was similar to the qualitative findings which outline the three key positions which are defined as having positive, indecisive, or negative perceptions. Importantly, it was found that *tech seekers* (those who have positive perspectives related to symptom checker functionality and AI but do not perceive to have access to the technology) had the highest odds of intending to use a symptom checker, even more so than *tech acceptors* (those who have positive perspectives related to all aspects and perceive to have access to the technology). This nuance was highlighted through five latent classes but lost when approaching the same objective with three or four latent classes. These classes could serve as a starting point in similar studies targeting other population groups.

7.4 Strengths

This study has several strengths that relate to the technology studied, choice of target population, theoretical framework and methodological approach used, tools developed, and practical implications for key stakeholders in the public health arena. Firstly, the development and use of an interview protocol and survey will enable other researchers in the field to adapt and use these tools. In terms of contribution to the literature, this study contributed to developing the literature on an understudied technology that has real potential in addressing key healthcare challenges. Symptom checkers, along with other digital platforms that allow for self-care, have been named as one of the top 10 emerging technologies in 2020 (World Economic Forum, 2020) and their importance has been accentuated during the COVID-19 pandemic. While understanding symptom checker use among various population groups is important, the bounded case used in this study was justified by the notion that young adults (between 18 and 34 years of age) may be the user group most accepting of such technology – and thus the ideal target group. Therefore, understanding the factors that they believe hinder or enable the use of symptom checkers should be seriously considered by symptom checker developers. For example, if participants mentioned that the design of the platform could be improved for better clarity (which was the case for some participants), this means that this is an improvement that should definitely be considered as other population groups – that are not ideal targets for this technology – are likely to have a similar perspective.

Importantly, an influential theoretical framework (the technology acceptance model or TAM), has been applied in this study to inform factors that should be considered in understanding symptom checker acceptance and use. Many studies have used the TAM either in its original form (Davis, 1989) or in the extended model (Venkatesh & Davis, 2000). This study adds to the TAM literature while focusing on a novel technology and understudied target population. Moreover, the methodological approaches used which included the designing, collection and analysis of qualitative followed by quantitative data. Such an extensive study and approach allowed for a deeper understanding of the technology and its prospective users/consumers. The methods employed for collecting qualitative data (i.e., semi-structured interview protocol and think-aloud exercise) allowed for the principal investigator to explore questions that were not considered when the protocol was being developed.

The application of latent class analysis also allows for the identification of profiles associated with symptom checker use; this provides a more comprehensive understanding of drivers of use, rather than assessing factors individually. Our study allowed for the identification of five latent classes that may need to be targeted differently to promote the use of promising symptom checkers. Finally, findings from our study have practical implications to health systems, governmental entities, and private sector players which are discussed in section 7.6.

7.5 Limitations

Some limitations of the scoping review warrant mention. Artificially intelligent self-diagnosing platforms that require individuals to upload an image or a scan were excluded from the review. Test kits or platforms that would require the user to perform medical tests were also excluded. Our scoping review's focus was on platforms that required the least amount of effort from the user (i.e., simply entering their symptoms into the platform to obtain potential diagnoses). It is also possible that some potentially relevant articles were missed because they could not be retrieved. To counteract this limitation, the authors systematically reviewed the references of relevant articles and held multiple meetings to assess consistency and to discuss any discrepancies in the screening process.

It should be noted that the study occurred during the pandemic which may have influenced participants' perspectives regarding the platform. Also, findings stem from a bounded case which is categorized by a sample that is highly educated and perceived to have a good health status thus limiting the transferability of findings to other populations with a wide range of age groups, education levels, self-perceived health, and health literacy. For the first phase (qualitative study), it was assumed that all participants had previously used the Internet for health information; as such, participants were not asked to use the Internet search engine (e.g., Google) during the interview meaning that they had to rely on their memory to answer questions. In addition, while participants were asked if they had previously used a symptom checker, questions about frequency of use were not asked which limited the ability to assess whether responses differed based on this potentially important factor. Also, responses were not distinguished based on the digital platform used since the main focus of this thesis was to understand perspectives on the use of symptom checkers in general – these perspectives may have differed if participants used another symptom checker than those used in this study (i.e., WebMD or Babylon Health). If the symptom checkers used in this study claims to use AI, this was taken at face value – assessing this was outside the scope of this thesis. In line with this, we did not examine whether participants chose the correct diagnosis based on the clinical vignette as the focus of the study was on the process of obtaining the list of diagnosis and getting participants familiar with the platform.

The second phase of this work (quantitative study) also has limitations. It is important to note that items used for LCA were based on factors chosen by participants in this study; as such, conducting the study again with a different sample may result in different attitude-based variables. Individuals who opted to participate in the survey may be different than the rest of the sampling frame. Though our qualitative findings aligned with the latent classes, this does not constitute a formal validation method of the determined latent classes. The outcome of interest was the intent to use, not actual use; as such, the intention to use a symptom checker in the future may change due to various factors.

7.6 Implications

7.6.1 Implications for Governmental Entities

While many Governmental entities around the world have developed their own symptom checkers, especially for COVID-19-related symptoms, and that digital adoption and transformation have been brought at the forefront of political agendas, there remains a long way to go for optimizing technology adoption – including platforms such as symptom checkers. Governments play a key role in enabling the success of innovative and new technologies by preparing the population, health professionals, healthcare systems, and other key stakeholders on how to leverage technological advances in a responsible way. As found in this thesis, users may be more likely to accept symptom checkers if they were endorsed by Governmental entities. In order for Governmental entities to endorse such platforms, various factors should be considered. In Canada, for example, provincial and territorial Governments should first assess the reliability and credibility of the platform as well as how symptom checkers could address some of their most pressing challenges at the population level, the profile of their population, how receptive/trusting the population would be of such a platform, and how healthcare systems within their jurisdictions could benefit from such a technology.

As explained later in this section, symptom checkers may need to be adapted based on the end-user (e.g., if it is a young adult or elderly) and healthcare system (e.g., the type of services provided); however, to reduce redundancy in work and optimize consistency across a given province or territory, it is optimal to develop a strategy for symptom checker adoption at a regional level. For example, given that some symptom checkers may be more credible than others or more appropriate for certain outcomes and populations/groups, Governments should consider developing a digital formulary that could be shared with healthcare systems. The formulary would be similar to a drug formulary and would be used as a guide for health professionals in prescribing which symptom checker is safer/reliable to use – of course, this would come with a disclaimer that these platforms do not replace individual medical advice. In parallel, to optimize and inform the use of the digital formulary, Governments would also be responsible in working in conjunction with regulatory bodies, healthcare systems, and the educational system to:

- Identify best practices for health technology adoption and use (this could include identifying factors and profiles with the biggest effect on symptom checker adoption – profiles identified in this work can serve as a starting point for future latent class analyses)
- Encourage the inclusion of end-users in health technology development to improve technology adoption and use
- Understand which population groups would benefit most from such a technology (for example, based on the qualitative interviews in this study, participants believed that symptom checkers may be more suited to a younger population with less severe health conditions)
- Consider privacy and data protection related issues (this was found to be an important consideration by participants in their decision to use symptom checkers)
- Develop a database that could be used by the population for checking a symptom checker's degree of credibility, inclusiveness, and safety
- Assess how the digital divide could be mitigated to ensure that all population groups could benefit from the technology

7.6.2 Implications for Health Systems

As for health systems, it has been suggested that symptom checkers have the potential to address various challenges facing health systems today. These challenges include lack of access to care, rising healthcare costs, unnecessary care, spread of communicable diseases (especially during pandemics), and shortage of health professionals. If well-designed and adopted by health systems, symptom checkers have the potential to improve access to care by encouraging only those who need care to access health services. In turn, this reduces unnecessary care – a pervasive issue that can cause harm to patients. Moreover, it could play a key role in reducing the burden on- and shortage of- health professionals by ensuring that tasks that could be performed by AI are carried out by the platform therefore allowing health professionals to shift their focus on other aspects that technology would not be able to emulate. All recommendations could play a key role in reducing healthcare costs by economizing existing resources. It is important to acknowledge, however, that not all symptom checkers are created equal and health systems across regions and countries should assess which platform would be best suited to meet the needs of their populations and healthcare system. Irrespective of the symptom checker chosen, it is evident that adopting a symptom checker that could be linked to a patient's electronic health record or other health information can provide a more comprehensive and informed assessment. If health systems consider partnering with corporations responsible for designing these platforms, transparency and patient consent will be critical for ensuring or maintaining patient trust.

Health systems around the world have already adopted symptom checkers into their clinical practice with some showing positive outcomes, especially during the COVID-19 pandemic, and with others experiencing issues related to data leakage and privacy concerns. The decision of adopting a symptom checker in a healthcare system is multidimensional and should be informed by the assessment of various factors, including those mentioned in this study, that could hinder or enable its success. As such, while it is evident that symptom checkers have the potential to address various healthcare challenges, there are certain factors that should be considered which include:

- Understanding if the population group served would be accepting of this technology
- Assessing the various platforms that exist and deciding on whether the healthcare system wants to develop their own platform or partner with an existing company
- Ensuring that the platform chosen or developed contains certain elements that users look for – findings from this study can help as a starting point
- Deciding whether the platform should be integrated with the electronic health record
- Ensuring that privacy and confidentiality could be uphold and develop a contingency plan in a potential case of a data breach
- Educating health professionals regarding the platform to ensure that they understand the complimentary nature of the platform
- Educating health professionals on how symptom checkers should be positioned with patients to ensure that the platform is being used appropriately
- Optimizing the platform by learning more about users as more data are collected

7.6.3 Implications for Symptom Checker Developers

Symptom checker developers – which include corporations and, in some cases, Governments – have many stakeholders they need to consider with the first being the end-user of the platform. Failing to understand the drivers of symptom checker adoption and use renders the accuracy of these platforms irrelevant because drivers of symptom checker use extend beyond accuracy. Developers should consider the factors identified in this study, including those that play a role in influencing a user’s trust towards the platform. Applying some of the recommendations related to symptom input, process for determining potential conditions, and quality of output are key for improving trust. Given that symptom checkers are continuously evolving as new findings emerge, it is critical to include end-users, health professionals, and other key stakeholders in platform development. Importantly, the platform should undergo various iterations to include the latest scientific evidence. Addressing some of the barriers identified in this study could help symptom checker developers in increasing symptom checker adoption and use. Increasing awareness about symptom checkers and educating population groups about their existence will also be pivotal for their success with data privacy and safety remaining at the forefront of all endeavours. Importantly, understanding the profiles that exist among the population can allow for a more targeted approach to increase adoption and use by addressing the variables that hinder certain groups from using symptom checkers.

7.7 Directions for Future Research

Future studies could explore demographic differences across latent classes (e.g., the gender proportion or the overall self-perceived health across each latent class) as it would allow us to further understand each latent class from a demographic perspective. Importantly, studies should explore symptom checker acceptance and use among other population groups such as older adults, individuals with chronic diseases, as well as population groups with varying levels of health literacy and self-perceived health – this will help identify how acceptance and use may change based on demographic characteristics and across the wider population. Future studies could also assess participants' membership to a class identified in this study by measuring the eight attitude-based variables – this would inform future sampling survey designs. Longitudinal studies that capture the length for which symptom checkers are used and the factors associated with continued use could be conducted – applying latent class analysis on longitudinal data could highlight if and how latent classes may change overtime. Research should also examine how barriers for symptom checker use identified in this study could be addressed or mitigated to optimize the benefits of the technology. This includes conducting additional clinical studies that seek to assess and improve the accuracy of these platforms.

Notably, to improve acceptance and use of symptom checkers, it will be important to conduct studies that examine how symptom checkers could be integrated into healthcare systems.

An important component of this is to gather the input of key stakeholders (i.e., end users, Governmental entities, health professionals, and symptom checker developers) to ensure an optimization of symptom checker adoption and use. In parallel, research on regulation and procedures for symptom checker validation and adoption should be developed and refined to ensure that studies that seek to optimize acceptance of symptom checkers are being utilized responsibly. Ethical implications surrounding the optimization of symptom checker adoption are important to highlight and require further study all the while considering key factors such as conflicts of interest between stakeholders. In line with the premise of this thesis, it is recommended that future studies are conducted as a means to understand how promising technology could help address healthcare challenges rather than optimizing the adoption of a technology that does not render benefits for the public as a whole. Moreover, while adopting symptom checkers can have many benefits such as reducing healthcare costs; it is important to acknowledge that this adoption can also come at a cost. Health systems should consider and assess the long-term cost savings to make decisions related to digital adoption. Given the ample symptom checkers available, studies focused on developing criteria for including a symptom checker in a digital formulary should be considered.

Chapter 8: Conclusion

Symptom checkers are promising tools that seem to be accepted by this study's participants; however, various improvements have to be made to improve acceptance and use. As improvements are made, symptom checkers may be the preferred option as compared to the conventional Internet search engine. Addressing barriers to symptom checker use, engaging key stakeholders in symptom checker development and adoption, and symptom checker endorsement by credible institutions will be key for the widespread use of the platform. The significance of this thesis was both theoretical and practical. Theoretically, it contributed to the technology acceptance literature by exploring the behavioural intention of using a technology that has not been studied before (i.e., symptom checkers) in a population that has been understudied (i.e., university students). From a practical standpoint, findings from this work will be useful to various stakeholders such as policymakers, health professionals, the lay public, health organizations, and companies or individuals developing symptom checkers.

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Appendices

Appendix 1 – Search strategy

Step 1. Isolate the main concepts of the research topic. (Add/subtract columns as needed). List all relevant search terms for each concept. Include author keywords and subject headings (i.e. MeSH headings)

Concept 1	**Concept 2**	**Concept 3**
Self diagnosing[tiab] OR self diagnosis[tiab] OR self evaluation*[tiab] OR self appraisal*[tiab] OR symptom check*[tiab] OR check your symptom*[tiab] OR check their symptom*[tiab] OR self triage[tiab] OR self-triage [tiab]	Technolog*[tiab] OR technology[mesh:noexp] OR website*[tiab] OR online[tiab] OR computing methodologies[mesh] OR computer* [tiab] OR algorithm*[tiab] OR mhealth[tiab] OR m-health [tiab] OR ehealth[tiab] OR e-health [tiab] OR app[tiab] OR apps[tiab] OR mobile application[tiab] OR smartphone[mesh] OR smart phone*[tiab] OR smartphone*[tiab] OR cell phone*[tiab] OR cellular phone*[tiab] OR mobile phone*	Population [tiab] OR person*[tiab] OR patient [tiab] OR patients [tiab] OR individual*[tiab] OR consumer* [tiab] OR people [tiab] OR patients[mesh:noexp]

Step 2. Translate the above list into a search statement. Create one search strategy rather than multiple searches. Combine the search terms using AND/OR and brackets ( ). Use Line #s to organize longer searches.

((((Self diagnosing[tiab] OR self diagnosis[tiab] OR self evaluation*[tiab] OR self appraisal*[tiab] OR symptom check*[tiab] OR check your symptom*[tiab] OR check their symptom*[tiab] OR self triage[tiab] OR self-triage [tiab]) AND ((English[lang] OR French[lang])))) AND ((Technolog*[tiab] OR technology[mesh:noexp] OR website*[tiab] OR online[tiab] OR computing methodologies[mesh] OR computer* [tiab] OR algorithm*[tiab] OR mhealth[tiab] OR m-health [tiab] OR ehealth[tiab] OR e-health [tiab] OR app[tiab] OR apps[tiab] OR mobile application[tiab] OR smartphone[mesh] OR smart phone*[tiab] OR smartphone*[tiab] OR cell phone*[tiab] OR cellular phone*[tiab] OR mobile phone*) AND ((English[lang] OR French[lang])))) AND ((Population [tiab] OR person*[tiab] OR patient [tiab] OR patients [tiab] OR individual*[tiab] OR consumer* [tiab] OR people [tiab] OR patients[mesh:noexp]) AND ((English[lang] OR French[lang])))

Step 3. Retrieve articles (n=611)

Step 4. Filter by language: English and French

Table 1. Overview of included studies related to self-diagnosing AI digital platforms.

Appendix 2 – Overview of included studies related to self-diagnosing artificial intelligence (AI) digital platforms

First Author (Year) [Reference]	Article type, Topic area	Main objective	Main findings/discussion points
Bauer M (2017) [24]	Review, Ethical	To increase understanding and promote discussion on the ethical issues of the digital economy that affect the treatment of patients with mental illness	Privacy is rarely guaranteed; There are societal pressures to disclose personal information; Usage of invalidated apps involve medical risks; Physicians should be aware of these apps to guide patients appropriately
Weldegebrial T (2016) [25]	Review, Legal	To examine the FDA[1] and HIPAA[2] regulations for health care apps and to suggest additional regulation requirements that could be used globally	Many health apps are unregulated by the FDA and HIPPA; Enforcing strict regulations might stifle innovation of beneficial apps
Bisson L (2014) [26]	Comparative, Accuracy	To design and evaluate an Internet-based program that generates a differential diagnosis based on a history of knee pain entered by the patient	High sensitivity corresponding to correct knee pain diagnosis; Low specificity is expected owing to differential diagnosis; Missed diagnosis owing to program limitation, error, and incorrect inputs by users
Bisson L (2018) [27]	Comparative, Accuracy	To evaluate a patient's ability to self-diagnose their knee pain from a list of possible diagnoses	Patients were able to correctly identify the cause of their knee pain in 315 out of 543 cases (ie, 58% of the time); The accuracy of a program to

		supplied by a symptom checker	generate a diagnosis may not be able to be improved without the ability to gather data from a physical examination
Boulos M (2014) [28]	Narrative, Legal/Regulation	To describe the range of apps on offer as of 2013 and then present a brief survey of evaluation studies of medical and health-related apps that were conducted to date, covering a range of disciplines and topics	App development should include medical experts and requires maintenance and regular updating which may entail significant costs; Lack of regulation undermines the population's safety; To ensure user safety, education regarding the use of these apps should be a first-line solution
Copeland C (2018) [29]	Cross-sectional, User experience	To create a simple interface for a symptom checker and evaluate the design by surveying users	Mobile health (mHealth) symptom checker was well received; It works well on a modest range of common ailments; It can be used conditionally to disseminate appropriate medical information
Davies BM (2018) [30]	Cross-sectional/ Accuracy	To investigate whether online symptom checkers are able to recognize relevant symptoms of Degenerative Cervical Myelopathy (DCM) differential returned and to evaluate the	DCM symptoms perform inadequately in symptom checkers; With the required optimization, symptom checkers are still attractive; Language barrier, computer proficiency, and the algorithms are some of the hindering

		diagnostic performance of its recognized symptoms	factors limiting usability of symptom checkers
Flaherty JL (2014) [31]	Narrative/ Legal	To examine regulations in which mHealth apps such as self-diagnosing apps are subjected to and the privacy/security concerns related to them	Many apps are unregulated by FDA or HIPAA; Unclear usage of consumers' information; The regulation leniency to allow for innovation comes with information risk
Farmer SEJ (2011) [32]	Prospective/ Accuracy	To report the findings of a study that examined the accuracy of Boots WebMD symptom checker in diagnosing ENT complaints	The median number of differential diagnoses provided per patient was 13 (range 1-20); The symptom checker correctly diagnosed 43 out of 61 patients
Hageman MGJS (2014) [33]	Prospective observational study/ Correspondence of diagnosis from the symptom checker with one of the surgeons	To test the null hypothesis that there are no factors associated with correspondence between online diagnosis and the hand surgeon's diagnosis in an outpatient hand and upper extremity surgeon's office	Factors associated with a web-based diagnosis corresponding to the hand surgeon's diagnosis included sex (women) and patients who studied their symptoms online prior to the visit; Considering the uniqueness of various symptom clusters and the probability of specific disease may improve diagnosis accuracy of symptom checkers
Jutel A (2015) [34]	Review of apps/ Sociological perspective	To describe and catalogue available diagnosis apps and	The 4 app categories are diagnosis, diagnosis coding, e-documents, and medical education; These apps are

		explore their impact on the diagnostic process	improving access to medical information, but credibility is a concern
Kao CK (2017) [35]	Narrative/ Unsure	To describe the current state, barriers, and future directions of mHealth apps and eventually take the leading role to drive the change	Lack of regular supervision, limited evidence-based literature, and privacy and security concerns are the barriers to efficacy of mHealth apps; Despite the barriers, there exists potential for evolution of these apps
Lanseng EJ (2007) [36]	Cross-sectional survey/ Theoretical	To examine the introduction of self-service technology (SST) in health diagnosis as a means to reduce costs and improve quality in the health care sector at the same time	People might accept the use of self-diagnosis technology; Consumers' expectation, convenience, ease of use, and trust are the key drivers for adoption and usage of SST
Luger TM (2014) [37]	Cross-sectional (qualitative)/ User experience	To describe the processes that a sample of older adults may use to diagnose symptoms online as well as the processes that predict accurate diagnosis	Participants relied on their experience and rejected the diagnosis if it was discordant; Confusion with the process, untrusting the diagnosis, tendency to rely on past experience are reasons for inaccurate diagnosis
Lupton D (2015) [38]	Review/ Sociological perspective	To examine the ways in which self-diagnosis apps were portrayed on	Even if many apps lack a description statement, they denote a sense of authority, scientific objectivity, and

		the Apple App store and The Internet Play websites	accuracy; Many apps added the tag *for entertainment purpose* which may undermine their credibility
Morita T (2017) [39]	N/A[3]/ Letter to the editor	To introduce the possible benefit of symptom checkers on public health	Symptom checkers can help community health workers in resource-limited countries; With incorporation of feedback from health professionals, symptom checkers can be improved
Powley L (2016) [40]	Comparative/ Accuracy	To evaluate how patients with inflammatory arthritis and inflammatory arthralgia use the Internet to look for health information and to assess the advice given and diagnoses suggested by the NHS and WebMD symptom checkers in relation to the patients' actual diagnoses	Only 4 out of 21 patients with inflammatory arthritis were given a first diagnosis of rheumatoid arthritis or psoriatic arthritis; Help-seeking advice given online is often inappropriate and the diagnoses suggested are frequently inaccurate
Ryan A (2008) [41]	Review/ Expert Opinion	To describe the possible impact of the use of self-diagnosis websites.	Affluence and higher education attainment increased the interest in self-care
Semigran HL (2015) [42]	Audit study/ Accuracy	To determine the diagnostic and triage accuracy of online symptom checkers.	Symptom checkers provided the correct diagnosis first for 262 out of 770 patient vignettes; The correct

			diagnosis was listed within the top 3 diagnoses, 394 out of 770 patient vignettes; The correct diagnosis was, however, listed first more often for patient vignettes of common diagnoses as compared to those of uncommon ones.

[1] Food and Drug Administration
[2] Health Insurance Portability and Accountability Act
[3] Not applicable

Appendix 3 – Rationale for factors considered in the proposed technology acceptance model

To ensure that all relevant constructs are included in the technology acceptance model, a rapid review of the literature of similar research (i.e., that focused on CHIT) was conducted. An interesting element that was not considered in the baseline model is the impact of *personality* on behavioural intention to accept and use technology. For example, Ozbek et al. (2014) assessed the association between the big five personality dimensions (i.e., extraversion, agreeableness, conscientiousness, neuroticism and openness) (Goldberg, 1992) and technology acceptance. Findings from their work highlights the influence of personality traits on acceptance of smart phones among university students. It was found, for example, that neuroticism is negatively influenced perceived usefulness of a technology, which in turn, hinders technology acceptance (Ozbek et al., 2014). Similarly, Tao et al. (2019) conducted a meta-analysis and demonstrated that *self-efficacy*, *trust*, and *perceived behavioural control* are important to consider in CHIT acceptance. Trust and self-efficacy were also considered to be important constructs in other studies (Becker, 2016; Pavlou & Fygenson, 2006; Or & Karsh, 2009; Wu et al., 2011; Mou et al., 2017). Interestingly, Tao et al. (2019) also identified ethnicity to be an important moderator.

Work conducted by Jung (2008) highlighted the importance of *computer self-efficacy*, *access to care*, *trust*, *credibility of healthcare provider (or in this case, symptom checker)*, *perceived output quality*, *result demonstrability*, and *compatibility* on acceptance of online healthcare services (i.e., online consultations provided by healthcare providers). For example, it was found that *perceived output quality*, which is defined as "*an individual's perception of the quality of the outcome of using a service*" was an important antecedent to perceived usefulness (Jung, 2008). Other potentially important variables are *healthcare need* and *self-rated health* which were found to be associated with intention to use m-health technologies (Kenny and Connolly, 2017). They found that healthcare need is positively associated with the use of m-health technologies whereas self-rated health is negatively associated with adoption (Kenny & Connolly, 2017). In other words, those who have higher healthcare needs are more likely to adopt m-health technologies (these findings are supported by Klein, 2007) and those with lower perceived health are less likely to adopt these technologies – an explanation for the latter may be that those with low self-perceived health may not feel that these technologies can adequately address their health condition (Kenny & Connolly, 2017).

Lanseng and Andreassen (2007) argued the importance of including the technology readiness index (TRI) in addition to the TAM. The TRI is an index used to measure people's propensity to embrace and use new technology for accomplishing their goals (Parasuraman, 2000). The reason for including TRI was explained by the fact that when people are asked to state their beliefs and express their attitudes concerning a service that they have virtually no experience in, the responses will provide little value. As such, using TRI provides an indication on the population's propensity to embrace and make use of new technology – high TRI scores suggest that the general public will have reached a certain level of comfort with technology through usage in other areas (e.g., banking) (Lanseng & Andreassen, 2007). Lanseng and Andreassen state that the TRI score will be an indication that responses in TAM are based on experience and knowledge, which will result in more valid predictions of actual technology adoption (2007). The TRI consists of four dimensions (i.e., *optimism*, *innovativeness*, *discomfort*, and *insecurity*) – with the two former dimensions being drivers of technology readiness and the two latter being inhibitors (Parasuraman, 2000).

In summary, the baseline TAM, additional relevant constructs, and the TRI will be used to assess technology acceptance of symptom checkers among university students. It is important to note that many constructs and variables may be relevant in assessing technology acceptance; for example, Or and Krash (2009) identified 94 potential predictors of adoption. The large number of potentially relevant variables can be problematic as it leads to a sporadic body of knowledge (Kenny & Connolly, 2017). I seek to address this limitation by drawing on the baseline TAM model – a practice that is recommended by experts and leading researchers in the field – and incorporating relevant constructs in the field of CHIT. **Table 2** outlines a list of additional preliminary independent variables that will be considered in my model, along with their definitions, operationalization, and source. The relationship between variables have been shown to be influenced by moderators (i.e., variables that affect the strength of the relationship between the independent and dependent variable) – these moderators include age, gender, experience, and voluntariness (Venkatesh & Davis, 2000). Experience is defined as "*the level of experience with using a target system*" whereas voluntariness is "*the extent to which potential adopters perceive the adoption decision to be non-mandatory.*" (Venkatesh & Davis, 2000).

Construct/variable	**Definition**	**Source**
Personality	"*Individual differences in characteristics, patterns of thinking, feeling, and behaving*" (Roberts, 2009).	Ozbek et al., 2014: studied the impact of personality on acceptance of smart phones among university students.
Computer self-efficacy	"*Perceptions of internal control and represents one's belief about her/his ability to perform a specific task.*" (Compeau & Higgins, 1995; Venkatesh & Davis, 2000, p.347)	Jung (2008) considered computer self-efficacy to be important when assessing the intention to use online consultations. Koufaris (2002) outlined that web skills are a similar construct to computer self-efficacy and affects usage intention.
Perceived accessibility	"*Captures an individual's perception of the ease or difficulty to gain access to or reach something.*" (Jung, 2008)	It has been argued that perceived accessibility is a powerful predictor of choice of information source rather than actual quality of the information (O'Reilly, 1982; Rice & Shook, 1988).
Perceived risk	"*The probability of certain outcomes given a behaviour, and the danger and severity of negative consequences from engaging in those behaviours.*" (Curran & Meuter (2005, p.105)	Pavlou, 2003; Jung, 2008: Risk perceptions tend to be high in situations where there is uncertainty, this is especially the case in online environments related to health.
Trust	"*Willingness of a party to be vulnerable to the actions of another party based on the*	Gefen et al., 2003 demonstrated the importance of trust in understanding the acceptance of e-commerce.

	expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party”. (Mayer et al., 1995, p. 712)	Klein et al. (2007) demonstrated the importance of trust in the acceptance of health services online.
Credibility of healthcare provider (or, in this case, credibility of the platform)	“*The extent to which one believes that the other has the required expertise to perform effectively and reliably.”* (Lanseng & Andreassen, 2007, p.402).	Perceived credibility has been shown to influence individuals’ perceptions on usefulness (Jung, 2008).
Perceived output (or information) quality	“*Judged by observing intermediate or end products of using the system, such as documents, graphs, calculations, and the like.”* (Davis et al., 1992)	Song et al. (2006) state that the quality of the information is the most important attribute for users seeking the information. Venkatesh & Davis (2000) outline that output quality positively influences perceived usefulness. In the case of e-health, this is the quality of the healthcare response given to the request; the health information obtained (Jung, 2008).
Result demonstrability	“*Tangibility of the results of using the innovation.”* (Moore & Benbasat, 1991, p. 203; adapted by Venkatesh and Davis, 2000)	The initial four-item scale (Moore & Benbasat, 1991) was used and adapted by Jung (2008) – the researcher dropped an item to improve reliability.
Compatibility	“*The degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters.”* (Rogers, 1995, p.224)	Chen et al. (2002) and Wu and Wang (2005) demonstrated that compatibility is the strongest determinant for usage intentions of online services.
Healthcare need	The degree to which an individual uses healthcare services and has health conditions that require medical care. (Wilson & Lankton, 2004)	It has been demonstrated that those with higher healthcare needs express higher intentions to use these technologies (Kenny & Connolly, 2017; Klein, 2007).
Self-rated health	“*…a summary statement about the way in which numerous aspects of health, both subjective and objective,*	This construct may have an important influence on the use of self-service technology. For example, those who perceive their health to be poor may be

	are combined within the perceptual framework of the individual respondent." (Tissue, 1972, p.93)	more incline to use the technology (Kenny and Connolly, 2017).
Technology Readiness Index	"*People's propensity to embrace and use new technologies for accomplishing goals in home life and at work."* Parasuraman (2000)	Parasuraman, 2000; Lanseng & Andreassen, 2007: The TRI consists of four dimensions: optimism and innovativeness are drivers of technology readiness whereas discomfort and insecurity are inhibitors.

Appendix 4 – Recruitment poster for research questions 1 and 2

PARTICIPANTS NEEDED FOR RESEARCH ON THE USE OF DIGITAL PLATFORMS FOR SELF-DIAGNOSIS

We are looking for volunteers to take part in a study that seeks to understand the use of artificially intelligent symptom checkers by university students.

As a participant in this study, you would be asked to participate in a semi-structured interview and a think-aloud exercise. During the think-aloud exercise, you will be asked to think aloud while using a symptom checker.

Your participation would involve *1* session which will be approximately 75 minutes in length.

In appreciation for your time, you will be given a $10 coffee shop gift card.

This study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee.

For more information about this study, or to volunteer for this study,
please contact:

Stephanie Aboueid
School of Public Health and Health Systems
at
Email: *seaboueid@uwaterloo.ca* or
519-888-4567. 38093

Appendix 5 – Recruitment email script for research questions 1 and 2

Dear students,

This email is being sent on behalf of Dr. Ashok Chaurasia and his student and PhD candidate, Stephanie Aboueid. They are seeking participants for a study that is being conducted on the use of digital platforms for self-diagnosis. Stephanie, a graduate student in the faculty of applied health sciences, is looking for volunteers to take part in a study that seeks to understand the use of artificially intelligent symptom checkers by university students.

As a participant in this study, you would be asked to participate in a semi-structured interview and a think-aloud exercise. During the think-aloud exercise, you will be asked to to think aloud while using a symptom checker. Your participation would involve *1* session which will be approximately 75 minutes in length. In appreciation for your time, your name will be added to a draw for 1 of 10, $10 Tim Hortons gift card.

This study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee.

For more information about this study, or to volunteer for this study, please contact: *Stephanie Aboueid (School of Public Health and Health Systems)* at seaboueid@uwaterloo.ca or 519-888-4567 Ext. 38093.

Sincerely,

University administrator (TBD)

Appendix 6 – Recruitment verbal script for research questions 1 and 2

Hello,

We are looking for participants for a study that is being conducted on the use of digital platforms for self-diagnosis. A graduate student in the faculty of applied health sciences is looking for volunteers to take part in a study that seeks to understand the use of artificially intelligent symptom checkers by university students.

As a participant in this study, you would be asked to participate in a semi-structured interview and a think-aloud exercise. During the think-aloud exercise, you will be asked to to think aloud while using a symptom checker. Your participation would involve 1 session which will be approximately 75 minutes in length. In appreciation for your time, your name will be added to a draw for 1 of 10, $10 Tim Hortons gift card.

This study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee.

If you are interested or require more information, please let me know right now (in person) or contact me at (Stephanie Aboueid) at seaboueid@uwaterloo.ca or 519-888-4567 Ext. 38093.

Thank you for your time,

Stephanie

Appendix 7 – Information letter for research questions 1 and 2

University of Waterloo

Date

Dear ***(insert participant's name):***

This letter is an invitation to consider participating in a study I am conducting as part of my Doctoral degree in the Department of Applied Health Sciences at the University of Waterloo under the supervision of Professor Dr. Ashok Chaurasia. I would like to provide you with more information about this project and what your involvement would entail if you decide to take part.

Researching the Internet for health information is common. It is often used by individuals to identify if their symptoms are severe and to self-diagnose. Information on the Internet, however, may not be reliable and it is difficult for individuals to identify which health information is relevant to their context. New advances in artificial intelligence have resulted in the development of symptom checkers that provide users with personalized information regarding the severity of their symptoms and a list of potential diseases they have. Given that these technologies are new, studies examining the perspectives and use of this technology are lacking. The purpose of this study, therefore, is to understand university students' perspectives regarding this technology as well as to understand the thought process that university students use while using this technology for triage or self-diagnosis.

Participation in this study is voluntary. It will involve an interview and thinking-aloud protocol of approximately 75 minutes in length to take place in a mutually agreed upon location or online. During the think-aloud exercise, you will be provided with a clinical vignette and asked to enter the information from the vignette into the symptom checker while thinking out loud. You may decline to answer any of the interview questions and to conduct the think-aloud exercise if you so wish. Further, you may decide to withdraw from this study at any time without any negative consequences by advising the researcher. With your permission, the interview and think-aloud exercise will be audio recorded to facilitate collection of information, and later transcribed for analysis. Demographic information (e.g., gender, age, education) will be collected to describe the study sample. Shortly after the interview has been completed, I will send you a copy of the transcript to give you an opportunity to confirm the accuracy of our conversation and to add or clarify any points that you wish.

Your identity will be completely confidential. Your name will not appear in any thesis or report resulting from this study, however, with your permission anonymous quotations may be used. Data collected during this study will be retained for 7 years in a locked office in my supervisor's lab. Only researchers associated with this project will have access. There are no known or anticipated risks to you as a participant in this study. It is important to note that When information is transmitted over the Internet privacy cannot be guaranteed. There is always a risk your responses may be intercepted by a third party (e.g., government agencies, hackers). University of Waterloo researchers will not collect or use Internet protocol (IP) addresses or other information which could link your participation to your computer or electronic device without first informing you.

In appreciation of the time, you have given to this study, you can enter your name into a draw for 1 of 10 prizes. The prizes include a $10 Tim Horton's gift card. Your odds of winning one of the prizes is based on the number of individuals who participate in the study. We expect that approximately 30 individuals will take part in the study. Information collected to draw for the prizes will not be linked to the study data in any way, and this identifying information will be stored separately, then destroyed after the prizes have been provided. The amount received is taxable. It is your responsibility to report this amount for income tax purposes.

This study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee (study number: 41366). If you have questions for the Committee contact the Office of Research Ethics, at 1-519-888-4567 ext. 36005 or ore-ceo@uwaterloo.ca.

For all other questions or if you would like additional information to assist you in reaching a decision about participation, please contact me at 519-888-4567 ext. 38093 or by email at seaboueid@uwaterloo.ca. You can also contact my supervisor, Professor Ashok Chaurasia at 519-888-4567 ext. 38093 or email a4chaura@uwaterloo.ca.

I hope that the results of my study will be of benefit to health organizations and organizations that are trying to reduce the burden in our healthcare system, as well as to the general public, and the broader research community.

I very much look forward to speaking with you and thank you in advance for your assistance in this project.

Yours Sincerely,

Stephanie Aboueid

Appendix 8 – Consent form for research questions 1 and 2

CONSENT FORM

By signing this consent form, you are not waiving your legal rights or releasing the investigator(s) or involved institution(s) from their legal and professional responsibilities.

I have read the information presented in the information letter about a study being conducted by Stephanie Aboueid and Dr. Ashok Chaurasia of the Department of Applied Health Sciences at the University of Waterloo. I have had the opportunity to ask any questions related to this study, to receive satisfactory answers to my questions, and any additional details I wanted.

I am aware that I have the option of allowing my interview to be audio recorded to ensure an accurate recording of my responses.

I am also aware that excerpts from the interview may be included in the thesis and/or publications to come from this research, with the understanding that the quotations will be anonymous.

I was informed that I may withdraw my consent at any time without penalty by advising the researcher.

This study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee (study number: 41366). If you have questions for the Committee contact the Office of Research Ethics, at 1-519-888-4567 ext. 36005 or ore-ceo@uwaterloo.ca.

For all other questions contact Stephanie Aboueid at 519-888-4567 ext. 38093 or seaboueid@uwaterloo.ca.

With full knowledge of all foregoing, I agree, of my own free will, to participate in this study.

☐YES ☐NO

I agree to have my interview audio recorded.

☐YES ☐NO

I agree to the use of anonymous quotations in any thesis or publication that comes of this research.

☐YES ☐NO

Participant Name: ______________________________ (Please print)

Participant Signature: ______________________________

Witness Name: ________________________________ (Please print)

Witness Signature: ______________________________

Date: ____________________________

Appendix 9 – Clinical Vignette

Please read the following story

I’ve been feeling sick for almost a week. I have a high fever and the lymph nodes in my neck are swollen. I also have this weird, red rash on my neck and arms. My tongue has red bumps on it too. I wish I would feel better soon.

Appendix 10 – Overview of Pilot Study Participants and Key Learnings

Description of the Pilot Study and Overview of Participants

In light of understanding university students' perspectives on the use of symptom checkers for self-triage and diagnosis, a pilot study was conducted to test the interview protocol. The questions in the semi-structured interview protocol were driven by the objectives of RQ.1, which are to understand university students' (i) attitudes toward the use of symptom checkers, (ii) perspectives on the enablers and barriers related to the behavioural intention of using the technology, and (iii) perspectives on how the platform may influence their health and health services. A total of 11 participants were recruited with the following characteristics:

- Age range: 20 – 50 years old;
- Gender: Female (n=6), Male (n=4), non-binary (n=1);
- Racial group: White (n=8), Arab (n=2), South Asian (n=1);
- Highest level of education: High School (n=1), Undergraduate degree (n=5), Master's (n=5);
- Faculty: Science (n=6), Arts (n=3), Environment (n=2);
- Self-perceived health: Excellent (n=1), Very Good (n=8), Good (n=1), Fair (n=1).

While the sample was predominantly white, highly educated, and perceived their health to be very good, the pilot study allowed for the emergence of other relevant questions that were not considered when the protocol was developed. Interestingly, most participants applied an equity lens to each question by first responding to questions as it related to them and then acknowledging that others who experience inequities may not have the same perspective.

Description of the Interview Protocol Used in the Pilot Study

The interview protocol had two parts in which some questions regarding symptom checkers were asked before the think-aloud exercise (i.e., when the participant used a symptom checker) and some questions that were asked after the exercise. In the first part, the questions focused on university students': 1) general thoughts on the use of the Internet to find health information, 2) current use of symptom checkers, 3) perspectives on symptom checkers, 4) thoughts on symptom checkers as compared to the use of the Internet, 5) their outlook on the use of AI in healthcare, 6) thoughts on visiting a primary care provider following the use of a symptom checker, 7) perspectives on the enablers, barriers, and opportunities associated with the use of symptom checkers, 8) perspectives on the factors that would entice the use of symptom checkers among university students.

Interview Protocol – Part 1 Questions

- What are your thoughts on the use of the Internet to find health information for triage or self-diagnosis?
- Do you currently use symptom checkers?
    - If so, how long have you used this technology for?
    - How did you hear about it?
- Based on the definition I provided, what are your perspectives on this technology?

- What are your thoughts on this technology as compared to conducting a general search on the Internet?
- What is your outlook on the use of artificial intelligence in health care?
- Would you still want to visit a primary care provider to review the diagnosis following the use of this technology?
- How would you react if the diagnosis provided by the doctor or nurse practitioner is different than the diagnoses provided by the digital platform?
- How do you think this technology will influence your relationship with your primary care provider?
- What do you believe are the enablers (factors that facilitate) for using symptom checkers?
- What do you believe are the barriers (factors that hinder) for using symptom checkers?
- What do you believe are the opportunities with this technology? How do you think symptom checkers can influence the health of university students?
- What do you believe are the factors that would make students to use a symptom checker?

Following this set of questions, the participant was asked to use a symptom checker and was then asked a series of questions that focused on university students' perspectives on: 1) trusting the technology, 2) having to choose among the multiple diagnoses presented on the platform, 3) how they believe this technology will influence the use of health services, 4) the additional capabilities that would make university students want to use a symptom checker, 5) any concerns related to the use of symptom checkers.

Interview Protocol – Part 2 Questions

1. How much do you trust this technology?
2. How do you feel about having to choose one of the diagnosis provided on the platform?
3. How do you see this technology influencing the use of health services?
4. What do you believe are the other capabilities that would make symptom checkers more useful or attractive to university students?
5. Can you tell me about any concerns you might have about using a symptom checker to diagnose and treat a health issue?
6. Is there a question you feel I should have asked but did not?
7. Is there anything you would like to add?

Findings from the Pilot Study

Interview Questions

1. **Thoughts on the use of the Internet to find health information for triage and self-diagnosis**

   Most participants believed that using the Internet for health information is useful, especially in regions where healthcare is private and there is a limited ability to pay for healthcare services. They believed that using the Internet is useful for understanding if their symptoms are severe and if they truly need to seek care. They also thought that it was a good source of information that would inform their discussions with their PCPs (they would know what to ask for during a medical visit etc.). Some mentioned that they did not trust the Internet and that it is frustrating to see all the advertisements when they are trying to search for something. The use of the Internet for self-triage was more accepted than self-diagnosis. Even if they were to use the Internet to self-diagnose, they would still require visiting a PCP to get a prescription or other treatment. Using the Internet for self-diagnosis was found useful for sensitive topics that participants may not want to share with their PCPs.

2. **Current use of symptom checkers**
   Half of participants were not aware of the existence of symptom checkers. Those who did know about them mostly used them for "fun" and mostly used them out of curiosity.

3. **General perspectives on symptom checkers**
   Symptom checkers were described to be more personalized than searching the Internet for health information. It was also thought to be more accurate and that it should be part of the healthcare system. Some believed that the structure of questions was useful to get participants to think about the symptoms that they have; for example, the symptom checker will ask the participant if the cough is dry or wet which will get people to think more about how they are actually feeling. While people believed that it may have potential, especially in areas where healthcare access is limited, concerns regarding accuracy and data privacy were raised. Moreover, given the recent media related to AI and discrimination, some believed that this would also be an issue in symptom checkers since the algorithms used to develop this technology is not shared with the public. Some shared that this technology should minimize the "worst-care scenario" to avoid panic among those using the platform and thought that it would prompt users to access the healthcare system when needed.

4. **Thoughts on symptom checkers as compared to conducting a general search on the Internet**
   In cases where participants believed their symptoms to be less severe and wanted a quick answer, both the Internet and the symptom checker were a viable option, but each seemed to be more appropriate in specific cases. For example, some perceived that using the Internet to search symptoms in the search engine was faster than having to input symptoms in a symptom checker. There was also a sense that participants would feel more vulnerable using a symptom checker due to the more personalized nature of the questions asked and the fact that symptoms had to be inputted into a list. Interestingly, some participants believed that their judgement and thought process to identify potential diagnoses was superior to using a symptom checker due to lack of knowledge on how a symptom checker works. Participants explained that the use of a symptom checker would be justified on the basis that it has been rigorously tested and validated. There was also an acknowledgement that the results provided by a symptom checker can only be as good as the data that informed them. Some had a positive attitude toward symptom checkers due to the fact that the platform asked questions regarding age and gender giving the impression that it is more personalized and in turn, in their perception, more accurate. There seemed to be a belief that the platform "had more structure", "had a greater level of detail", "was more personalized", and "was more accurate" than using the Internet.

5. **Outlook on the use of artificial intelligence in healthcare**

   Participants expressed both positive and negative perspectives on the general use of AI in healthcare. Many believed that AI is still in its infancy and that it has potential; however, there are certain limitations that need to be addressed. For example, given that it is people who code the algorithms, it is important to ensure that relevant information (e.g., medical conditions) are not missed and minimize potential bias. Moreover, some believed that AI is “overhyped”. Some feared that the use of AI will limit human-to-human interaction which they believed is not an issue for them but could be an issue for the elderly population. As for the positives, some believed that it would improve the ability to diagnose given the big data that can be used to inform decision-making. The use of AI was found to be more useful for the medical community as compared to the general public as they would have the critical thinking skills to either agree or disagree with a decision. The use of AI was also thought of as a potential time saver in healthcare.

6. **Visiting a primary care provider following the use of a symptom checker**

   Almost all participants said that if the symptom checker indicated a minor condition and that the symptoms subsided after two days, they will not go see a PCP; however, most participants mentioned that they would still visit a PCP to confirm the potential diagnosis.

   a. **Reaction to a different diagnosis provided by the doctor or nurse practitioner is different than the diagnoses provided by the digital platform**

      While most participants mentioned that they would trust the diagnosis of a PCP over the conditions provided by a symptom checker, some mentioned that PCPs are not perfect and that they may have the wrong diagnosis; as such, they would consult another doctor. This was especially the care if the PCP and participant did not have a pre-existing relationship (e.g., if they went to a walk-in clinic).

   b. **Influence on the patient-PCP relationship**

      Some believed that the use of symptom checkers will negatively influence the PCP-patient relationship because of the dogma in healthcare and the “physician is always right” mentality that was mentioned to be exhibited by some physicians. Others believed that it would improve the relationship because the patient will be more knowledgeable which would improve the conversation between the PCP and the patient.

7. **Enablers for using symptom checkers**

   Factors that were mentioned to enable the use of symptom checkers were related to the individual, disease, health system, and symptom checker itself. Enablers at the individual level include: level of education, technical skills, curiosity, convenience, lack of time and aversion to medical professionals. Disease-level enablers were: a “broad category of illness”, having a condition to be perceived as “embarrassing”, and a condition perceived to be minor. Health-system level enablers included: lack of access to care, symptom checker approval by nurses’ and doctors’ associations, incorporated in the health system. Enablers to use that were related to the symptom checker itself were: accuracy, free of cost, increased awareness, guarantee of anonymity, privacy and security, well-designed and easy-to-use platform, personalized experience, short time to complete, and gamification of the platform.

8. **Barriers for using symptom checkers**
   Factors that would hinder the use of symptom checkers were associated to the individual, health system, the symptom checker itself, or an “other category”. Individual-level barriers were: high health literacy, lack of access to the Internet, computer access issues, lack of trust, and fear of the worst-case scenario. Health-system level barriers was the “dogma in healthcare”. Barriers related to symptom checkers were: lack of transparency on the use of data, medical jargon, lack of elaboration on why certain questions are asked, lack of credibility, and lack of availability in different languages. Other mentioned barriers included the skepticism that is found in the media, the lack of human interaction, and being disadvantaged which limits computer access.

9. **Opportunities with symptom checkers**
   The opportunity that was mentioned by most participants is the reduced number of people accessing the healthcare system when they don’t need to. They also envisioned that the use of symptom checkers would make accessing the health system faster. They also believed that symptom checkers were better than Telehealth because the latter does not provide the possibility of getting a diagnosis. Some believed that it would also be useful for tracking one’s health (e.g., useful for check-ups). Some believed that this technology would be more useful for the medical community than the general public.

10. **Perspectives on how symptom checkers can influence the health of university students**
    Some believed that the use of symptom checkers would influence university students’ health positively as it would improve access to health services. Some believed that this technology was designed by doctors which made them have a positive outlook on its use. It was believed that university students would be fast adopters of this technology as they do not like going to walk-in clinics and being surrounded by people who are sick. Moreover, this technology seemed to be more convenient and less time-consuming – this is of useful to university students given their busy schedules. This technology was mentioned to be useful for mental health and specifically, someone mentioned that it could be used as a tool by counselors in universities to identify those who need to be seen. It was also found to be useful in cases where someone would think they have a minor condition, but they actually have something more serious – the symptom checker may prompt them to seek care proactively. At the same time, some believed that symptom checkers may exaggerate and provide serious potential diagnosis when in reality, the condition is mild. In general, symptom checkers were thought to be useful for preventative health – for example, tracking students’ health and for yearly check-ups.

11. **Factors that would make students want to use a symptom checker**
    The factors mentioned that would entice students to use symptom checkers included: ease of use, lack of time, lack of access to health services, gamification of the platform/reward system, ease of accessibility to the platform, curiosity exhibited by university students, Instagram ads and other advertisements that would inform university students about symptom checkers (many did not know that they existed), good design, access through mobile, few questions asked/easy and short time to complete, and ensured anonymity.

12. **Trusting symptom checkers**

    After having used the platform, participants were asked about how much they trusted the results provided by the symptom checker. Differing opinions were provided with some trusting the symptom checker more after having used it while others trusting it less. Those who did not trust the symptom checker mentioned that they were unable to enter all the symptoms that were in the clinical vignette, so it was not possible for the platform to provide an adequate diagnosis option. Some did not like the drop-down menu of the platform as it limited the range of symptoms that they were able to input. These participants mentioned that because of this reason, conducting a general The Internet search is better as they would be able to enter all symptoms. Some did not understand the words and questions used in the platform which limited their ability to provide informed answers. The platform also lacked clarification questions; for example, it did not ask a sufficient number of questions regarding the rash that was reported by participants (e.g., how it looks like, if it hurts etc). The symptom checkers provided a wide variation of conditions with some being really minor to others being really severe; for example, it ranged from the common cold to having sepsis. Moreover, there were many potential diagnoses that were labeled as “moderately fair match” which reduced the credibility of the platform. Some did not believe that the layout was appropriate for a medical website – some felt like they were buying a shampoo rather than trying to assess their health condition.

    Some participants mentioned trusting the platform for mild conditions. Others did not realize that the symptom checkers was so detailed and long to use – their perspectives regarding the detailed questions asked by the platform increased their level of trust with the results. Moreover, those who were able to match all the symptoms in the clinical vignette were more likely to trust the results provided by the platform. Participants were also more likely to trust the platform if one of the conditions provided is similar to the condition that the participant thought they had based on the clinical vignette.

13. **Perspectives on having to choose among the multiple diagnoses presented on the platform**

    Surprisingly, most participants thought it was good to have more than one potential condition listed on the platform. This allowed them to read the description for each and identify which ones are more relevant. However, the wide variation of conditions provided may lead to fear, panic, and unnecessary access to the healthcare system. Some thought that it was good to have the match level to each condition (e.g., strong, fair and weak match). However, some believed that it was time consuming.

14. **Perspectives on how this technology will influence the use of health services**

    Some believed that the platform was “sloppy” and if it remained so, it would not be useful for the healthcare system as no one would use it. Some also believed that it would not benefit the healthcare system as it would create more confusion among users and could lead to unnecessary medical testing. Nonetheless, some believed that using symptom checkers would be useful as a first line of defense (e.g., used for triage), may save time, may provide more information on the types of questions that should be asked by the patient when visiting a PCP, and useful for prioritizing medical appointments based on the severity of the reported symptoms by the user.

15. **The additional capabilities that would make university students want to use a symptom checker**

    Many additions were mentioned to improve symptom checkers, and these include:

    - A way to share information with health professionals; for example, after using the symptom checker, it would generate a code that could be shared with the health professional – this code would grant access to the user's data that were inputted in the platform (this would save time during the medical visit)
    - Make the platform accessible to those with visual impairment by having an audio button option
    - Make the platform accessible through university portals and webpages such as Learn
    - Make the platform more accurate and provide more information on who built it (increase transparency)
    - Make the platform available through the computer and mobile for convenience
    - Make sure the platform is covered by university insurance plans
    - Easy to find online
    - Easy to use
    - Provide a fun fact for the day to all users based on their demographics (for example, a fun fact that university students would be interested in knowing every day)
    - Include images to demonstrate how the signs and symptoms should look like to make the process easier
    - Ask more information on the medical history of the individual above age and gender (e.g., pre-existing health conditions, diet history etc)
    - Provide long-term health advice for those showing symptoms that are linked with future negative health outcomes rather than just focus on triage
    - Make sure that the sequence of questions make sense based on the answers provided by the user
    - Provide more confident results to the users rather than providing many potential conditions
    - Use more friendly and familiar language
    - Provide recommendations on where to go for testing based on location
    - Allowing the user to type the symptoms rather than select from a drop-down menu
    - Provide information on how people with similar background information have coped with the fever (or other symptoms) and how they recovered to provide a sense of assurance

16. **Any concerns related to the use of symptom checkers**

    - Lack of credibility of the platform
    - Data being sold to third parties/data privacy concerns
    - False sense of security if the platform provides non-severe conditions when the condition is actually severe
    - Confusion due to the symptoms not lining up with the results
    - Indicating a more severe condition when the condition is minor
    - Limited data used to build the platform
    - The user not knowing the diseases presented by the platform
    - Not personalized

    - People starting to feel that they have certain symptoms when they don't due to the questions asked by the platform
    - Biases in diagnosis – people choosing the less severe condition for a false sense of security
    - SC not considering the medical history of the user which may influence the results provided
    - Targeted ads
    - A user treating themselves for a condition they do not actually have

Learnings from the Pilot Study

- While most participants were not aware of symptom checkers, they were interested to learn about them and to use it. This further accentuates the importance of conducting this research.
- Some questions in the interview protocol seemed to be redundant; for example, the following questions yielded similar answers:
    - What are the opportunities of using symptom checkers?
    - How do think the use of symptom checkers will influence health services?
- Nonetheless, no questions will be deleted as each question yielded additional insights/findings that are useful to answering the research questions.
- The order of the questions will change – most of the questions will come after the participant has used the symptom checker. This is important because most participants did not use one before taking part of the interview and they should be aware of how the platform works before being asked questions about the platform. Importantly, the answers that participants provided after the think-aloud exercise tended to be more negative as some thought that the platform was suboptimal and lacked credibility.
- Throughout the interview, it would have been good to probe more; for example, when people mention that the platform should be "easy to use", I should have probed more on what "easy to use" actually looks like. How can the platform change to make it "easy to use"?

Implications for the Second Version of the Interview Protocol

- Keep the same questions in order to be able to validate the interview protocol for future studies that may want to use the protocol
- Add a question in the pre-interview questionnaire that asks participants to list the factors they believe are important for explaining the behavioural intention of using symptom checkers; this will help inform the constructs that should be measured in the survey
- Change the order of the questions so that they are asked after the think-aloud exercise
- Probe more based on answers provided
- Potentially add a question regarding how university students would want to use symptom checkers in times of pandemics such as COVID-19

Appendix 11 – Semi-structured interview protocol for research questions 1 and 2

Interviewer: I first want to thank you for accepting to take part in this interview. I will now explain the information letter and consent form. I will also provide you with time to read the information. Please take as much time as you need to fully understand the study and feel free to ask any questions for clarification. Once you have signed the consent form, we can begin the interview. **Interviewer explains the information letter and consent form verbally and provides time for the participant to read the information carefully.*

Interviewer: Now that you have signed the consent form, we can begin the interview.

PRE-INTERVIEW QUESTIONNAIRE	
Questions	**Rationale and link to research questions/objectives**
Demographic information • How old are you? • What is your self-perceived gender? • What is your self-perceived racial or cultural group? • What is your highest level of education? • In which faculty do you currently study? • Do you currently work? • If so, how many hours do you work a week (unrelated to schoolwork)?	Age, gender, ethnicity, level of education, and field of study can all influence health information seeking and the use of the technology.[1] Having this information will enable me to understand if responses differ based on these characteristics. If discernable differences exist, it further justifies the need to measure these demographic data in the survey. Current work status and number of hours worked a week were identified to be important following the pilot study. Participants believed that a busy schedule was an enabler for using symptom checkers.
Contextual/individual information **Self-perceived health** • Compared to others your age, how would you rate your health? Poor; fair; good; very good; excellent **Health literacy** The tool has been requested from the authors Osborne et al., 2013. It asks questions on: 1) Feeling understood and supported by healthcare providers	This question has proved to be a powerful measure as outlined in the meta-analysis conducted by DeSalvo and colleagues (2006)[2]. This construct may have an important influence on the use of self-service technology. Health literacy pertains to how people obtain, understand, and use health information to manage their health.[3] It would be interesting to understand if health literacy influences the responses provided

<table>
<tr><td>2) Having sufficient information to manage my health
3) Actively managing my health
4) Social support for health
5) Appraisal of health information
6) Ability to actively engage with healthcare providers
7) Navigating the healthcare system
8) Ability to find good health information
9) Understanding health information well enough to know what to do</td><td>by participants. The questions are based on the Health Literacy Questionnaire (HLQ) developed by Osborne et al.[4]

As in other studies, to avoid respondent burden, not all domains from the HLQ will be measured. Four domains will be measured, and these are number 1, 3, 6, and 8.</td></tr>
<tr><td colspan="2">**Interviewer:** I first want to provide the standard definition of artificially intelligent symptom checkers (or symptom checkers) before we begin the interview. These platforms allow users can enter their health information and symptoms, and these platforms provide the user with information regarding the severity of their symptoms and a list of potential diagnoses they have. This technology was developed to address the lack of access to a primary care provider and the need for more personalized health information. They are relatively new and are highly accessible through the Apple Store or The Internet Play.</td></tr>
<tr><td colspan="2">**INTERVIEW QUESTIONS FOR RESEARCH QUESTION 1**</td></tr>
<tr><td>**Internet and symptom checker usage**

• What are your thoughts on the use of the Internet to find health information for triage?
• What are your thoughts on the use of the Internet to find health information for self-diagnosis?
• Do you currently use symptom checkers?
  ○ If so, how long have you used this technology?
  ○ How did you hear about it?
• Based on the definition I provided, what are your perspectives on this technology?</td><td>These questions address **objective a)** of the first research question. These questions will help me understand the participants' attitude towards using the Internet for triage and self-diagnosis and then probes regarding the use of symptom checkers.

It is important to understand if the participant currently uses a symptom checker as their level of knowledge and comfort with the technology will be different than those who do not.</td></tr>
<tr><td colspan="2">**THINK-ALOUD EXERCISE**</td></tr>
<tr><td colspan="2">**Interviewer: The first part of the interview is now complete, and we will now begin the second portion which entails a think-aloud exercise.**

Interviewer: For the second part of the interview, we are interested in understanding the thought process of university students while they use a digital platform for triage or self-diagnosis. To complete this task, please read the following vignette and use the WebMD symptom checker (or Babylon) to enter in the relevant information and symptoms. During the process, please say out loud everything that you are thinking without synthesizing your thoughts. It will be important for you to keep talking as you perform the task.</td></tr>
</table>

**Interviewer provides an example of how the thinking-aloud exercise should be performed.*

Interviewer: Do you have any questions about this exercise? Please feel free to practice thinking out loud before starting. You can start whenever you feel comfortable.

**Participant completes the task*

Interviewer: I now have a few questions about the use of this platform.

Interviewer provides participants with a self-administered questionnaire to choose the top five factors they believe are most important when deciding to use a symptom checker for: 1) self-triage and 2) self-diagnosis.

1) **Please highlight or circle the top five factors that you believe are important for you to use a symptom checker for <u>self-triage</u>. If you require any clarification or further information about the factors, please let me know.**

Factor	
1. Your ability to perform **tasks on the computer**	2. Your **self-rated health**
3. Your **perceived accessibility** of symptom checkers	4. Your **propensity or tendency** of using new technology
5. Your **individual personality traits**	6. Your perception of the **supports and resources** available to you
7. Your **perception of risk** associated with using symptom checkers	8. Your perspectives on the **perceived benefits** of using symptom checkers
9. Your **trust** towards symptom checkers	10. Your perspectives on the **effort expected** to use symptom checkers
11. Your perception of the **credibility** of symptom checkers	12. Your **social surroundings**
13. Your perception of the **output quality** provided by symptom checkers	14. Your perspectives on the **fun or pleasure** derived from using symptom checkers
15. Your perception of the **tangibility of the result(s)** provided by symptom checkers	16. Your perspectives on the **trade-off between costs and value** (applies if a fee is associated with the use of a symptom checker)
17. Your perception on the symptom checker's **compatibility** with your values, past experiences, and needs	18. Your **habit** in adopting new technology
19. Your level of **healthcare need**	

2) **Please highlight or circle the top five factors that you believe are important for you to use a symptom checker for <u>self-diagnosis</u>. If you require any clarification or further information about the factors, please let me know.**

Factor	
1. Your ability to perform **tasks on the computer**	2. Your **self-rated health**
3. Your **perceived accessibility** of symptom checkers	4. Your **propensity or tendency** of using new technology
5. Your **individual personality traits**	6. Your perception of the **supports and resources** available to you
7. Your **perception of risk** associated with using symptom checkers	8. Your perspectives on the **perceived benefits** of using symptom checkers
9. Your **trust** towards symptom checkers	10. Your perspectives on the **effort expected** to use symptom checkers
11. Your perception of the **credibility** of symptom checkers	12. Your **social surroundings**
13. Your perception of the **output quality** provided by symptom checkers	14. Your perspectives on the **fun or pleasure** derived from using symptom checkers
15. Your perception of the **tangibility of the result(s)** provided by symptom checkers	16. Your perspectives on the **trade-off between costs and value** (applies if a fee is associated with the use of a symptom checker)
17. Your perception on the symptom checker's **compatibility** with your values, past experiences, and needs	18. Your **habit** in adopting new technology
19. Your level of **healthcare need**	

Barriers, facilitators, and opportunities • What are your thoughts on the use of symptom checkers as compared to conducting a general search on the Internet? • What do you believe are the enablers (factors that facilitate) for using symptom checkers? • What do you believe are the factors that would make students to use a symptom checker? • What do you believe are the barriers (factors that hinder) for using symptom checkers? • What do you believe are the opportunities with the use of symptom checkers? • Did you use a symptom checker to check for symptoms related to COVID-19? Why or why not? If so, how would you describe your experience?	These questions address **objectives b) and c)** of the first research question. Given the limited research on symptom checkers, understanding the barriers, facilitators, and opportunities regarding their use. It will also provide valuable information university students' perspectives on how this technology will influence their health and health services. The question related to COVID-19 will help us understand if a sense of urgency or a situation such as a pandemic would be a factor that is associated with use or beginning of use of a symptom checker.

(If the person replies that they did not use one because they did not develop symptoms, then ask): Would you have used one if you did develop symptoms? • How do you think symptom checkers can influence the health of university students? • How do you believe symptom checkers will influence the use of health services?	
INTERVIEW QUESTIONS FOR RESEARCH QUESTION 2	
Use of AI in health care and trust • What is your outlook on the use of artificial intelligence in health care? • How much do you trust this technology? • What do you think about the output provided by the platform? • Would you still want to visit a primary care provider to review the diagnosis following the use of this technology?	These questions address **objectives b) and c)** of the second research question. Following the pilot study, it was evident that the media played a role in shaping participants' perspectives on AI. I decided to add this question to highlight the importance of the media in shaping peoples' perspectives. Trust seemed to be an important construct to explore further – a construct that has been shown to influence health seeking behaviours.[9]
User experience and concerns • How do you feel about having to choose one of the diagnosis provided on the platform? • What do you believe are the other capabilities that would make symptom checkers more useful or attractive to university students? • Can you tell me about any concerns you might have about using a symptom checker for triage or self-diagnosis?	The last questions of the interview will pertain to the participant's thoughts on the process of using a symptom checker, concerns they have with the platform, and ways in which the platform can be modified to improve the user experience.
• Do you believe that your answers would have been different if you were interviewed before the COVID-19 pandemic?	This question will be asked to understand if the participants' perspective would have been different pre-pandemic. Given that people seem to be more hesitant to seek care in person due to the risk of infection, it would be useful to know if this factor (risk of infection) is a factor that is associated with the use of symptom checkers.
CLOSING QUESTIONS	
• Is there a question you feel I should have asked but did not? • Is there anything you would like to add?	These questions will allow the participant to express their perspectives on a related topic that was not discussed.

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Appendix 12 – Participant quotes for research question 1

Table 1. Example Quotes Related to the Use of The Internet Versus Symptom Checkers

The Internet
Positive Themes: - Provides information without claiming a diagnosis “*When I search on the Internet though, I can usually point it in a direction, and no one is claiming ‘oh you have this’ but it gives you a starting point so if you go to a doctor you can say ‘I am experiencing symptoms that are in line with meningitis’*.” – P12 - More customizable “*For a person who is more savvy Googling I feel like right now at least with this system, the Internet is the preference because I can tweak the search terms to my liking*.” – P18 - Allows entry of all symptoms in the search engine “*On the other hand, I think it may be easier to get an accurate result on symptoms through a The Internet search because I can type multiple symptoms and see how they fit, I may get more garbage results, but I can use my judgment to decide what is true and not true. Whereas the symptom checker has only one piece of information which is fever. The symptom checker did not give me the opportunity to put in more from what I can recall. It only asked for my main symptom and age and gender*.” – P11
Negative Themes: - Absence of chatbot feature “*I might still have the same perspective because on the Internet when I do the search myself, I might not include every single symptom*.” – P2

Symptom Checkers
Positive Themes: - More personalized “*Instead of giving generalized information, something that gives personalized information in a short period of time is good because surfing through the Internet and coming through a particular diagnosis takes a lot of time although it might give you more information about other diseases that have similar symptoms, but this is not what I am looking for, I am looking for what I am suffering from. So, for which, I think a personalized software is helpful*.” – P2 - More interactive due to chatbot feature “*I think it’s a lot more logical for sure because the online checker at least tries to get more information out of you as opposed to you just Googling it because if I were to The Internet my symptom, I would just put in a fever and rashes that could be a million things. But with a symptom checker, I would put in fever and it asked me for a specific temperature and other specific questions which I would not know to search on my own*.” – P21 - Good for those who do not know how to use The Internet “*For someone who just wants one system to go through. This seems good for someone who does not know how to The Internet too well*.” – P18 - Straightforward design “*I think that it can be helpful to use symptom checkers, I am a bit surprised at the simplicity of the questions they ask. I mean they basically ask you 4 or 5 questions which are basically what*

your symptoms are, are you pregnant, what are your conditions. It is surprising that you only require that much information to decide what kind of disease you have but at the same time it is pretty straightforward so it's helpful." – P13

- Easy to use

"*This platform is very easy. I can convey to the system what I am facing because it asked me questions, so I just need to click. The Internet does not understand my problem, but this platform does because it asks me questions regarding if I have something else to ask*." – P15

- Real time

"*I like that it asked me questions that you can answer in real time like about the rash. Like on your arm, you can press it and see if it's lighter*." – P12

- Makes the correlation between symptoms and potential conditions

"*When I the Internet online, I don't know how to phrase it to be specific enough to even give me a diagnosis. But a symptom checker asks you questions and more specific questions, so it mimics a real doctor rather than a The Internet search. And the conditions are logical, and it correlates the symptoms to the conditions whereas in The Internet you are trying to make that correlation yourself*." – P21

- More intuitive

"*Well, this is much more intuitive. Instead of looking at bunch of problems, you can actually type in or go through each problem one by one rather than going through all the sets of problems… At the end, it also gives a suggestion which is better than deciding by yourself what to do next*." – P16

- More reliable

"*The symptom checker would give me more reliable information and I can go right to the symptoms and the causes and it's easy to understand*." – P11

- More specific

"*I think this is probably much better than using The Internet because right away if you The Internet rash it would give you information on all types but this one gives specifications, and it gives specifications about having fever which The Internet would not give*." – P14

- More structured

"*So, I think having that more structured approach to inputting symptoms and figuring out what is likely wrong with you would be a lot nicer for the user and the user would have more faith in the result rather than just going on The Internet that brings up a whole bunch of results and the user thinking that they could have anything*." – P4

Negative Themes:

- Accuracy is questionable

"*Hopefully this information is accurate, I don't know if the website is authentic*." – P24

- Limits the number of symptoms that can be inputted

"*I feel like I don't like the symptom checker as much because it limits the number of symptoms. I did not have the chance to mention the thing with the red bumps; it just asked me a lot of questions about the one "symptom that was bothering me the most". It does look tailored, but I think I would have gotten the same information if I did The Internet search and The Internet does not limit my options. I guess it's comforting to have AI say yes or no though*." – P20

- Not widely known

"*But the issue is that we don't know about symptom checkers so making them widely available would be super helpful*." – P13

- Thought process of the platform is unclear

“*If I am typing in a symptom checker and it comes back at me with answers, I don’t know how it came to that conclusion and I don’t know what the process was to decide that ‘yes, this is what you have’ whereas if I am the one doing the analysis through a bunch of articles that I deem legitimate – whether or not they truly are legitimate – at least I know what the thought process was, and I feel like I can trust that*.” – P6

- User more vulnerable when using this platform

“*It feels more vulnerable and personal to put my symptoms into a list or generator of some kind. It feels like I am just looking at a series of articles I feel there's more of a distance there and I can assess that objectively and I can do a comparative analysis of my own symptoms and what is shown in the article*.” – P6

Negative Themes Related to the Internet search engineand Symptom Checkers

Negative Themes:

- Text input is insufficient

“*I think seeing a provider face to face is better than both of these options. I feel that you can’t accurately portray all your symptoms and general health by text input. You need someone looking at you and take measurements and touch injured areas, I think that’s far superior*.” – P1

- Suboptimal reliability

“*I think The Internet is a very wide platform so it’s very hard to analyze the reliability or the source. In this case, it depends on the reliability of the symptom checker as well. Yes, I find it to be more catered, but it depends on the symptom checker, but the symptom checker did not allow me to input more symptoms or ask questions. In the Internet you can ask questions and find more about the underlying conditions but again, it could be confusing and overwhelming*.” – P19

Appendix 13 – Survey email invitation for research question 3

Subject: Invitation to complete University of Waterloo survey on online health technology

Good morning,

As a University of Waterloo student, you are invited to participate in a research survey about the use of artificially intelligent symptom checkers by young adults. All university students between the ages of 18 and 34 are eligible to participate. For participating, you will be eligible for entry into a draw for a chance to win an iPad OS14 valued at $429.

The survey is being conducted by the University of Waterloo Survey Research Centre (SRC) on behalf of a PhD candidate in the School of Public Health and Health Systems. The purpose of the study is to understand university students' perspectives on the use of symptom checkers for health assessments. **The data collected will be used to inform the use of health care technology in healthcare settings, specifically related to reducing unnecessary medical visits and enabling convenience in healthcare**. Your opinion is important to us!

The online survey should take about 10 minutes to complete. Your identity will be kept confidential. The results of this survey will be shared only in aggregate form. Demographic information such as age and gender will be collected to assess whether responses differ based on this information. No individuals will be identified, nor individual survey information shared. This study has been reviewed by, and received ethics clearance through a University of Waterloo Research Ethics Committee (ORE#: #41366).

You can access the survey by clicking on this link:

<insert survey link here>

Please copy and paste the URL into any browser if you are unable to access the survey through the link listed above.

Questions related to the survey can be directed at Stephanie Aboueid at seabouei@uwaterloo.ca.

If you have any technical problems with completing the online survey, please contact the Survey Research Centre by email at srcccinb@uwaterloo.ca.

Please note, deadline to complete the survey is March 13, 2021.

Thank you for considering participating in this important study.

This message was sent by *Stephanie Aboueid*, whose mailing address is *200 University Avenue West]* and whose email address is *seabouei@uwaterloo.ca.* It is sent on behalf of the School of Public Health and Health Systems at the University of Waterloo, whose contact information may be accessed at https://uwaterloo.ca/public-health-and-health-systems/. If you no longer wish to receive messages specific to this subject line, you may unsubscribe by sending an email to seabouei@uwaterloo.ca

Sent on behalf of:

Stephanie Aboueid, MSc, RD
PhD (c) in Public Health and Health Systems
University of Waterloo

200 University Ave. W.,
Waterloo, Ontario
Canada N2L 3G1
seaboueid@uwaterloo.ca

Appendix 14 – Survey

Online Health Technology Survey

Introduction

Thank you for participating in this survey. The purpose of this study is to understand university students' perspectives on the use of artificially intelligent digital platforms for self-assessing their health and symptoms. The survey will take about 10 minutes to complete. In appreciation for the time given to this study, you can enter your name into a draw for a chance to win an iPadOS 14 valued at $429. Your odds of winning the prize is based on the number of individuals who participate in the study. We expect that approximately 500 individuals will take part in the study. The amount received is taxable. It is your responsibility to report this amount for income tax purposes.

All University of Waterloo students between the ages of 18 and 34 are eligible to participate. Demographic information such as gender and age will be collected to assess if differences in response exist based on this information. Information collected to draw for the prize will not be linked to the study data in any way, and this identifying information will be stored separately, then destroyed after the prize has been provided.

Participation in this survey is voluntary and you can decline to answer any question by leaving it blank. Withdrawing from the study does not disqualify you from the draw as you can, at any time, skip to the end of the survey to enter the draw. When provided to the researcher, the survey data will be anonymized so that no individual can be identified. The survey responses will be stored on a restricted access, secure server at the University of Waterloo and electronically archived for at least seven years. When information is transmitted over the Internet, privacy cannot be guaranteed. There is always a risk your responses may be intercepted by a third party (e.g., government agencies, hackers). The SRC temporarily collects your computer IP address to avoid duplicate responses in the dataset.

There are no known or anticipated risks associated with participation in this study. Your participation in this study will help advance our knowledge on how digital platforms could potentially be used to reduce the burden on healthcare systems.

This study had been reviewed and received ethics clearance from the University of Waterloo Research Ethics Committee (ORE #41366). If you have questions for the Committee, contact the Office of Research Ethics, at 1-519-888-4567 ext. 36005 or ore-ceo@uwaterloo.ca. If you have questions about the study, please contact Stephanie Aboueid at seabouei@uwaterloo.ca.

By providing your consent, you are not waiving your legal rights or releasing the investigator(s) or involved institution(s) from their legal and professional responsibilities.

I consent to participate in this survey

01 Yes
02 No

Section 1: Age and self-perceived health

SCREENER

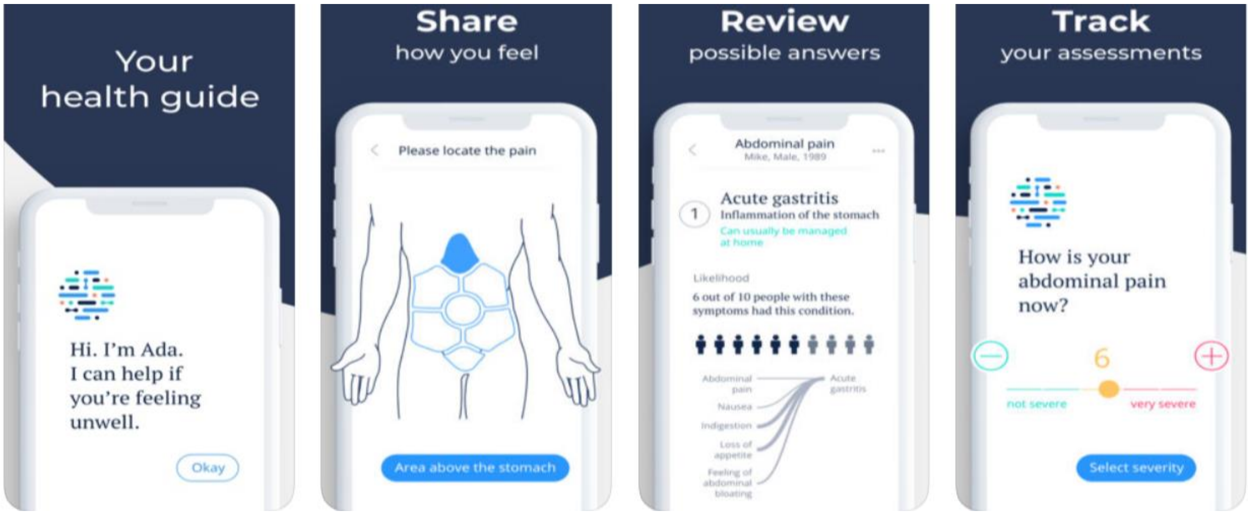
Q1
How old are you?

01 Younger than 18 years old → **GO TO INELIGIBLE**
02 18-24 years old
03 25-29 years old
04 30-34 years old
05 Older than 34 years old → **GO TO INELIGIBLE**

INELIGIBLE
Thank you for your time but we are interested in interviewing University of Waterloo students aged 18-34.

New page

Artificially intelligent symptom checkers are smart digital platforms available online via desktop or through a mobile application. Users can enter a list of symptoms they are experiencing, and the app helps them identify whether or not they should seek medical care and provides a list of potential medical conditions that the user could be having. These platforms are typically free of charge and examples include **Babylon**, **Isabel**, and **mediktor** symptom checkers. These do not include the COVID-19 standard self-assessment tools.



Hi. I'm Ada. I can help if you're feeling unwell.

6 out of 10 people with these symptoms had this condition.

How is your abdominal pain now?

Q2a
In the past 12 months, have you used artificially intelligent symptom checkers to assess whether or not you needed to seek medical services?

01 Yes – Code as Users for Section 4 questions
02 No – Code as Non-Users for Section 4 questions – **GO TO SECTION 2**

New page

Q2b
In a typical year, how many times do you use artificially intelligent symptom checkers to assess whether or not you need to seek medical services?

01 0
02 1-2
03 3-5
04 More than 5

Section 2
Preamble
The first few questions will focus on your health and your use of healthcare.

Q3
How would you describe your general health?

01 Excellent
02 Very good
03 Good
04 Fair
05 Poor
06 Don’t know

Q4
How often do you have someone help you read hospital materials?

01 Always
02 Often
03 Sometimes
04 Occasionally
05 Never
06 I have never had to read hospital materials

Q5
How often do you have problems learning about your medical condition because of difficulty understanding written information?

01 Always
02 Often
03 Sometimes
04 Occasionally
05 Never
06 I don’t have a medical condition - **GO TO Q7**

Q6
How often do you have a problem understanding what is told to you about your medical condition?

01 Always
02 Often
03 Sometimes
04 Occasionally
05 Never

Q7
How confident are you filling out medical forms by yourself?

01 Always
02 Often
03 Sometimes

04 Occasionally
05 Never

Q8a
In the 12 months before COVID 19 (March 1, 2020), did you see or talk to a family doctor or nurse about your physical, emotional or mental health? Please do not include any overnight stays in a hospital.

07 Yes
08 No → **GO TO Q9**
09 Don't know → **GO TO Q9**

KEEP Q8b ON SAME PAGE

Q8b
How many times (in the past 12 months before COVID-19)?

01 0
02 1-2
03 3-5
04 More than 5

Q9
When you need immediate care for a minor health problem, how long do you usually have to wait before you can have an appointment with a family physician or nurse?

01 The same day
02 The next day
03 In 2 to 3 days
04 In 4 to 6 days
05 In 1 to 2 weeks
06 Between 2 weeks and one month
07 One month or more
08 Don't know

Q10
When you visit your primary care provider in their office, how often are you seen at your scheduled appointment time?

01 Always → **GO TO Q12**
02 Often
03 Sometimes
04 Rarely
05 Never

Q11
How long do you typically wait between the time of your appointment and the time you are seen by the primary care provider?

01 Less than 15 minutes
02 15 to less than 30 minutes
03 30 minutes to less than one hour
04 1 to less than 2 hours
05 2 hours or more
06 Refuse to answer
07 Don’t know

Q12
How many chronic health conditions do you have? We are interested in ‘long-term conditions’ which are expected to last or have already lasted 6 months or more and that have been diagnosed by a health professional. Some examples include asthma, diabetes, high blood pressure, heart disease.

01 No chronic health conditions
02 1 – 2
03 3 – 5
04 6 or more

Section 3: Perspectives on artificial intelligence

Artificial intelligence is defined as the theory and development of computer systems that can perform tasks that would normally require human intelligence. AI can be used to process a large set of data and its application in healthcare includes diagnosis and treatment recommendations, patient engagement, etc.

Q13

I believe that the application of artificial intelligence in healthcare has a positive effect on healthcare services.

01 Strongly disagree
02 Disagree
03 Neither disagree nor agree
04 Agree
05 Strongly agree
06 I don’t know

Q14

I believe that the use of artificial intelligence leads to bias in healthcare because the data used may lead to predetermined ideas, prejudice or influence in a certain direction.

01 Strongly disagree
02 Disagree
03 Neither disagree nor agree
04 Agree
05 Strongly agree
06 I don’t know

Section 4: The use of symptom checkers

Preamble
This section will assess your perspectives on the use of artificially intelligent health symptom checkers. These platforms ask for questions related to age, gender, symptoms, and some also ask about medical history. These platforms use artificial intelligence to help tailor the user experience by changing the question based on answers provided by users. The aim of these platforms is to help users identify whether or not they should consult a primary care provider based on the severity of their symptoms.

FOR SECTION 4 ONLY:

IF Q2 = 02 (No) → DISPLAY ALL QUESTIONS IN BLUE AND BLACK
- **THIS INCLUDES → Q15, Q16, Q18, Q19, Q21, Q23, Q25, Q27, Q28, Q30, Q32, Q34, Q36, Q38, Q40, Q42, Q44, Q46**

IF Q2 = 01 (YES) → DISPLAY ALL QUESTIONS IN GREEN AND BLACK
- **THIS INLCUDES → Q17, Q18, Q20, Q22, Q24, Q26, Q27, Q29, Q31, Q33, Q35, Q37, Q39, Q41, Q43, Q45, Q47**

QUESTIONS IN BLACK (Q18, Q27) → DISPLAY FOR ALL

Q15
If available, I would try out an artificially intelligent symptom checker for self-triage (i.e., to determine if I need to see a healthcare provider or can manage my own health).

01 Strongly disagree
02 Disagree
03 Neutral
04 Agree
05 Strongly agree

Q16
If available, I would use an artificially intelligent symptom checker regularly for self-triage.

01 Strongly disagree
02 Disagree
03 Neutral
04 Agree
05 Strongly agree

Q17
I use an artificially intelligent symptom checker regularly for self-triage.

01 Strongly disagree
02 Disagree
03 Neutral
04 Agree
05 Strongly agree

Q18 → DISPLAY FOR ALL
I would recommend an artificially intelligent symptom checker to a friend for self-triage.

01 Strongly disagree
02 Disagree
03 Neutral
04 Agree
05 Strongly agree

Q19
I would like to use an artificially intelligent symptom checker for self-triage.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q20
I like to use an artificially intelligent symptom checker for self-triage.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q21
An artificially intelligent symptom checker would be easy to use.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q22
An artificially intelligent symptom checker is easy to use.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q23
I would trust artificially intelligent symptom checkers with my health information.

01 Strongly agree
02 Agree
03 Neutral

04 Disagree
05 Strongly disagree

Q24
I trust artificially intelligent symptom checkers with my health information.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q25
I would be able to easily access artificially intelligent symptom checkers.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q26
I can easily access artificially intelligent symptom checkers.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q27 → DISPLAY FOR ALL
The advantages of using artificially intelligent symptom checkers are obvious to me.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q28
Symptom checkers will provide me with high quality information.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q29
Symptom checkers provide me with high quality information.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q30
Artificially intelligent symptom checkers would perform well for self-triage.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q31
Artificially intelligent symptom checkers perform well for self-triage.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q32
Artificially intelligent symptom checkers would offer accurate information.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q33
Artificially intelligent symptom checkers offer accurate information.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q34
Artificially intelligent symptom checkers would offer up-to-date information.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q35
Artificially intelligent symptom checkers offer up-to-date information.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q36
Artificially intelligent symptom checkers would offer information relevant to my health context.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q37
Artificially intelligent symptom checkers offer information relevant to my health context.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q38
The information provided by the artificially intelligent symptom checker would reflect my health status.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q39
The information provided by the artificially intelligent symptom checker reflects my health status.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q40
I would be more likely to use an artificially intelligent symptom checker if I felt my personal health information was protected.

01 Strongly agree

02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q41
I would be more likely to continue using an artificially intelligent symptom checker if I felt my personal health information was protected.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q42
Using an artificially intelligent symptom checker would help me assess the severity of my symptoms.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q43
Using an artificially intelligent symptom checker helps me assess the severity of my symptoms.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q44
Using an artificially intelligent symptom checker would be beneficial for my health.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q45
Using an artificially intelligent symptom checker is beneficial for my health.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q46
I would use an artificially intelligent symptom checker if it was endorsed by doctors or a health organization.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Q47
I would continue using an artificially intelligent symptom checker if it was endorsed by doctors or a health organization.

01 Strongly agree
02 Agree
03 Neutral
04 Disagree
05 Strongly disagree

Section 5: Other questions

The last few questions are about you and your household. The answers to these questions are used only for broad analysis purposes only. When analyzed, all of the data will be summarized, and the data will be anonymized so that no individual can be identified from these summarized results.

Q48
What is your gender?

01 Woman
02 Man
03 Non-binary
04 Prefer not to disclose
05 Prefer to self-describe ________________________

Q49
What is your self-perceived racial or cultural group? (please select all that apply)

01 First Nations, Inuit or Métis
02 White
03 South Asian (e.g., East Indian, Pakistani, Sri Lankan)
04 Chinese
05 Black
06 Filipino
07 Latin American
08 Arab
09 Southeast Asian (e.g., Vietnamese, Cambodian, Malaysian, Laotian)
10 West Asian (e.g., Iranian, Afghan)
11 Korean
12 Japanese
13 Other (please specify): ___________

Q50
What is the highest level of education that you have completed?

01 High school
02 Undergraduate degree
03 Master's
04 PhD
05 Other, please specify: ______________

Q51
What program are you currently enrolled in?

01 Undergraduate degree
02 Master's
03 PhD
04 Other (please specify): ____________

Q52

In which faculty do you currently study at the University of Waterloo?

01 Applied Health Sciences
02 Arts
03 Engineering
04 Environment
05 Mathematics
06 Science

Q53
Are you currently employed?

01 Yes
02 No → **GO TO Q55**
03 Prefer not to disclose → **GO TO Q55**

Q54
How many hours (on average), do you currently work within a week period?

01 1 – 5 hours
02 6 – 10 hours
03 11 – 15 hours
04 16 – 20 hours
05 21 – 25 hours
06 26 – 30 hours
07 31 – 35 hours
08 36 – 40 hours
09 41+ hours

Q55
How often do you have access to the Internet?

01 Always
02 Often
03 Occasionally
04 Rarely
05 Never

That is the end of the survey.

Q56
Please indicate below if you would like to be entered into a draw for a chance to win an iPad.

01 Yes → **GO TO SEPARATE DRAW ENTRY PAGE**
02 No → **GO TO THANK YOU PAGE**

Draw Entry Page:

To be entered into the draw for a chance to win an iPad, please provide the information indicated below. Your name and contact information will be collected separately and will not be associated with your responses to the survey questions. Please see below for the Draw Rules and Regulations and the Privacy Policy.

First Name:
Last Name:
Phone Number:
Phone Extension:
E-mail address:
E-mail address (confirmation):

Incentive Rules and Regulations

Incentive offered*:* For participating, you will be eligible for entry into a draw for a chance to win an iPad OS14 valued at $429. If you decide to withdraw your participation, you will still be eligible to enter the draw.

Eligibility: All university of Waterloo students between the ages of 18 and 34 enrolled in the Winter 2021 term who have completed the survey.

Eligibility to receive/win the prize begins on January 5, 2021, at 8:00 a.m. E.S.T. and closes on February 15, 2021, at 11:59 p.m. E.S.T.

$429 iPad OS14 Draw: The winner of the iPad will be selected in a random draw from eligible entries on February 15, 2021. Your odds of winning the iPad will depend on the number of individuals who enter the draw. The award winner will be contacted by the researcher, Ms. Aboueid, by email (through the selected entrant's UWaterloo e-mail address) within 10 business days of the draw. Before being awarded the iPad, the selected entrant must respond by the timeframe provided in Ms. Aboueid's email (usually within 5 business days of being contacted by Ms. Aboueid) and correctly answer a time-limited skill-testing mathematical question. Failure to respond within the identified timeframe or a failed skill-testing question will result in the opportunity to win being passed on to the next eligible entrant.

Please note:

- The University is not responsible for any incomplete, failed or delayed transmission of your submission due to technical difficulties, including interruption or delays caused by equipment or software malfunction.
- If you have any questions about the survey, please contact Stephanie Aboueid at seabouei@uwaterloo.ca. If you have any technical problems with completing the online survey, please contact the Survey Research Centre by email at srcccinb@uwaterloo.ca.

The University reserves the right to disqualify any entry not conforming to these Rules and Regulations at any time. The University assumes no responsibility for entry fraud committed by an entrant and reserves the right to demand the return of the prize and all costs associated with remedying any prize awarded to an ineligible entry or entrant.

Participation in the survey is confidential and voluntary. You may opt out of the survey at any time by closing the survey, with no loss of your chance to win the prize.

Privacy Policy

The Survey is being administered by the Survey Research Center on the behalf of a PhD candidate at the School of Public Health and Health Systems at the University of Waterloo. The purpose of the survey is to obtain information about university students' perspectives related to the use of digital health technology for self-triage.

Only authorized staff tasked with analyzing and interpreting the results, and who have signed a data sharing and confidentiality agreement meant to ensure secure and appropriate handling of data, have access to the survey data.

Please note that when information is transmitted over the Internet, privacy cannot be guaranteed. There is always a risk your responses may be intercepted by a third party (e.g., government agencies, hackers). See Waterloo's guidelines on secure data transmission for more information.

University of Waterloo Information, Privacy and Record Retention

The University of Waterloo is committed to protecting your personal information and respecting the privacy of respondents.
All personal information is collected under the authority of the University of Waterloo Act (1972) and will be processed in compliance with Ontario's Freedom of Information and Protection of Privacy Act, as well as the University of Waterloo's Information and Privacy policies.

Questions about the collection, use, and disclosure of information associated with this survey should be directed to the Survey Research Center (519-888-4567 ext. 35071). Questions about the collection, use, and disclosure of personal information by the university, should be directed to the Privacy Officer at fippa@uwaterloo.ca.

The collected data and reports will be managed according to the University records classification scheme, WatClass, and will be securely destroyed when no longer needed by the University.

Thank You Page

Thank you for participating in the survey! Your feedback is extremely valuable. The draw winner will be selected and notified once the survey closes.

If you would like a copy of the results, please email the researcher at seabouei@uwaterloo.ca. They will be provided by 25/12/2021.

This study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee (ORE#41366). If you have questions for the Committee contact the Office of Research Ethics, at 1-519-888-4567 ext. 36005 or ore-ceo@uwaterloo.ca.

For all other questions or if you have general comments or questions related to this study, please contact Stephanie Aboueid, School of Public Health and Health Systems at seabouei@uwaterloo.ca or Dr. Ashok Chaurasia, School of Public Health and Health Systems at a4chaurasia@uwaterloo.ca.

Appendix 15 – Results from exploratory data analysis

Table 1: Associations among pairs of independent variables

	Trust	**Credibility**	**Usefulness**	**Output Quality**	**Demonstrability**	**Perspectives on AI**	**Perceived ease of use**	**Perceived accessibility**
Trust	1.00	0.18	0.20	0.25	0.25	0.16	0.07	0.09
Credibility	0.18	1.00	0.40	0.33	0.22	0.11	0.14	0.19
Usefulness	0.20	0.40	1.00	0.36	0.28	0.17	0.15	0.24
Output Quality	0.25	0.33	0.36	1.00	0.28	0.12	0.12	0.15
Demonstrability	0.25	0.22	0.28	0.28	1.00	0.16	0.14	0.08
Perspectives on AI	0.16	0.11	0.17	0.12	0.16	1.00	0.10	0.11
Perceived ease of use	0.07	0.14	0.15	0.12	0.14	0.10	1.00	0.32
Perceived accessibility	0.09	0.19	0.24	0.15	0.08	0.11	0.32	1.00

Notes: Phi coefficients are presented in the table. All associations were significant at a p-value of 0.2.

Table 2: Associations between independent variables and the outcome

	Trust	Credibility	Usefulness	Output Quality	Demonstrability	Perspectives on AI	Perceived ease of use	Perceived accessibility
Future Use	55.99	91.81	137.28	75.32	134.35	17.78	5.74	8.24

Notes: Chi-square values are presented in the table. All associations were significant at a p-value of 0.2.

Table 3: Associations between between the outcome and potential covariates

	Self-perceived health	Health literacy	Healthcare use	Wait times	Healthcare need
Future Use	0.04	0.04	0.06[1]	0.04[1]	N/A[2]

[1] Significant as per a p-value <0.2.

[2] Healthcare need was not considered a covariate in the regression analysis due to low cell counts; most participants were identified to have low healthcare need.

Table 4: Associations between between the outcome and potential grouping variables

	Trust	Credibility	Usefulness	Output Quality	Demonstrability	Perspectives on AI	Perceived ease of use	Perceived accessibility
Gender[1]	**0.08**	**0.07**	**0.08**	**0.11**	**0.05**	**0.04**	0.04	**0.05**
Race[2]	**-0.40**	0.00	0.01	0.03	**0.04**	0.01	-0.03	**-0.04**

[1] Cramer's V coefficients are presented.

[2] Phi coefficients are presented.

Coefficients in bold were identified to be significant as per a p-value < 0.2.

Appendix 16 – Detailed output of the PROC GLM procedure

Table 1. Model with the five-class model as a predictor

Model Fit Statistics		
Criterion	Intercept Only	Intercept and covariates
AIC	2594.716	2454.289
SC	2605.064	2506.029
-2 Log L	2590.716	2434.289

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
Latent Class	8	142.8164	<.0001

Analysis of Maximum Likelihood Estimates						
Parameter	Future Use	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	Yes	1	-0.7758	0.2244	11.9535	0.0005
Intercept	No	1	-0.3365	0.1952	2.9718	0.0847
LC acceptors	Yes	1	1.7149	0.2435	49.6191	<.0001
LC acceptors	No	1	-0.5237	0.2442	4.5978	0.0320
LC skeptics	Yes	1	1.0195	0.2848	12.8135	0.0003
LC skeptics	No	1	0.3365	0.2694	1.5600	0.2117
LC tech seekers	Yes	1	2.0163	0.2953	46.6259	<.0001
LC tech seekers	No	1	-0.4463	0.3594	1.5420	0.2143
LC unsure acceptors	Yes	1	0.7371	0.2760	7.1333	0.0076
LC unsure acceptors	No	1	-0.6318	0.2900	4.7468	0.0294

Odds Ratio Estimates				
Effect	Future Use	Point Estimate	95% Wald Confidence Limits	
Tech acceptors vs. tech rejectors	Yes	5.556	3.448	8.954
Tech acceptors vs. tech rejectors	No	0.592	0.367	0.956

Skeptics vs. tech rejectors	Yes	2.772	1.586	4.844
Skeptics vs. tech rejectors	No	1.400	0.826	2.374
Tech seekers vs. tech rejectors	Yes	7.510	4.210	13.397
Tech seekers vs. tech rejectors	No	0.640	0.316	1.294
Unsure acceptors vs. tech rejectors	Yes	2.090	1.217	3.590
Unsure acceptors vs. tech rejectors	No	0.532	0.301	0.939

Table 2. Model with the five-class model as a predictor and confounders

Model Fit Statistics		
Criterion	Intercept Only	Intercept and covariates
AIC	2594.716	2449.931
SC	2605.064	2574.106
-2 Log L	2590.716	2401.931

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
Latent Class	8	143.3710	<.0001
GenHealth	2	2.7162	0.2572
HL	2	0.6488	0.7230
HC Use	2	5.6047	0.0607
Wait time	2	5.0084	0.0817
Gender	4	5.8547	0.2103
Race	2	12.3150	0.0021

Analysis of Maximum Likelihood Estimates						
Parameter	Future Use	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	Yes	1	-0.6534	0.5069	1.6617	0.1974
Intercept	No	1	-1.0934	0.6537	2.7979	0.0944
LC acceptors	Yes	1	1.7233	0.2462	48.9998	<.0001
LC acceptors	No	1	-0.5710	0.2498	5.2239	0.0223

LC skeptics	Yes	1	0.9614	0.2866	11.2564	0.0008
LC skeptics	No	1	0.3250	0.2747	1.3999	0.2367
LC tech seekers	Yes	1	2.0371	0.2980	46.7329	<.0001
LC tech seekers	No	1	-0.4118	0.3640	1.2799	0.2579
LC unsure acceptors	Yes	1	0.7322	0.2777	6.9519	0.0084
LC unsure acceptors	No	1	-0.6206	0.2947	4.4364	0.0352
GenHealth Good	Yes	1	0.0190	0.2034	0.0088	0.9255
GenHealth Good	No	1	0.4466	0.2867	2.4273	0.1192
HL High	Yes	1	-0.0398	0.1966	0.0409	0.8396
HL High	No	1	0.1759	0.2818	0.3895	0.5326
HC Use	Yes	1	0.3023	0.1342	5.0731	0.0243
HC Use	No	1	0.0593	0.1773	0.1118	0.7381
Wait time Short	Yes	1	-0.2901	0.1585	3.3492	0.0672
Wait time Short	No	1	-0.4003	0.1993	4.0337	0.0446
Gender Men	Yes	1	-0.0570	0.3919	0.0211	0.8844
Gender Men	No	1	0.4993	0.5242	0.9074	0.3408
Gender Women	Yes	1	-0.00540	0.3875	0.0002	0.9889
Gender Women	No	1	0.1584	0.5206	0.0926	0.7610
Race White	Yes	1	-0.0184	0.1509	0.0149	0.9028
Race White	No	1	0.5676	0.1871	9.2065	0.0024

Odds Ratio Estimates				
Effect	Future Use	Point Estimate	95% Wald Confidence Limits	
Tech acceptors vs. tech rejectors	Yes	5.603	3.458	9.078
Tech acceptors vs. tech rejectors	No	0.565	0.346	0.922
Skeptics vs. tech rejectors	Yes	2.615	1.491	4.586

Skeptics vs. tech rejectors	No	1.384	0.808	2.371
Tech seekers vs. tech rejectors	Yes	7.669	4.276	13.752
Tech seekers vs. tech rejectors	No	0.662	0.325	1.352
Unsure acceptors vs. tech rejectors	Yes	2.080	1.207	3.584
Unsure acceptors vs. tech rejectors	No	0.538	0.302	0.958
GenHealth good vs. Poor or do not know	Yes	1.019	0.684	1.518
GenHealth good vs. Poor or do not know	No	1.563	0.891	2.741
HL high vs. low or average	Yes	0.961	0.654	1.413
HL high vs. low or average	No	1.192	0.686	2.071
HC Use yes vs. no or do not know	Yes	1.353	1.040	1.760
HC Use yes vs. no or do not know	No	1.061	0.750	1.502
Wait time short vs. medium or long	Yes	0.748	0.548	1.021
Wait time short vs. medium or long	No	0.670	0.453	0.990
Gender men vs. other	Yes	0.945	0.438	2.036
Gender men vs. other	No	1.648	0.590	4.603
Gender women vs. other	Yes	0.995	0.465	2.126
Gender women vs. other	No	1.172	0.422	3.250
Race white vs. non-white	Yes	0.982	0.730	1.320