Eye-Tracking Online Health Information-Seeking Behaviour: Investigating eHealth Literacy Measurement and the Impact of an Inoculation Message.

Bradley Crocker

Department of Kinesiology and Physical Education

McGill University, Montreal

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Abstract

The internet is a prominent source people use to inform health-related decisions, likely to grow more commonplace as internet accessibility continues to improve globally. Online health information quality is highly variable; whether someone stands to benefit from this source depends largely on their ability to locate, evaluate, and utilize online health information, or in other words their eHealth literacy. Little is known about how eHealth literacy may mechanistically contribute to resistance against online health misinformation (via observable differences in information-seeking behaviour), in part due to methodological limitations that may be addressed with eye-tracking technology. Inoculation messages are an effective means of promoting resistance to misinformation, supported by a large and growing body of literature, and thus may function to promote favourable changes in online health information-seeking behaviour. The overall purpose of my dissertation is to conceptualize what existing measures of eHealth literacy tell us about people's information-seeking behaviour, and to use this mechanistic understanding of health information-seeking to test whether an inoculation message can favourably alter the process. Study 1 involved a systematic scoping review to identify tools used by researchers to measure eHealth literacy based on objective performance, and to quantify the prevalence of these measures within the literature in contrast to subjective measures. The findings showed nearly 90% of studies measuring eHealth literacy have used exclusively self-report measures, despite growing evidence that self-assessment has little correlation with actual ability in this domain. Study 2 used a mixed-methods comparative analysis to observe online health information-seeking behaviour in an unrestricted online environment using screen-recording and eye-tracking technology, with the goal of identifying correlations between quantifiable behaviour and the most popular subjective measure of eHealth literacy. Consistent

with the hypothesis, the self-report eHealth literacy measure correlated significantly with just 4 of the 21 behaviour-related variables measured, and these 4 related more to source-type preferences rather than procedural differences in information-seeking behaviour. Study 3 involved a randomized controlled trial to test whether an inoculation message would favourably alter online health information-seeking behaviour, using the same participants and similar search task and data collection procedures to Study 2. The findings demonstrated the brief inoculation message led participants to spend significantly more time evaluating sources, though this did not translate into a significant difference in the reliability of sources accessed. Overall, the findings of my dissertation, empowered by novel methodological approaches, contribute to a stronger holistic understanding of the relationship between eHealth literacy measurement and the online health information-seeking process. Additionally, my research provides support for inoculation messages leading to favourable procedural differences in the online information-seeking process.

Résumé

L’Internet est une source importante que les gens utilisent pour prendre des décisions en matière de santé, et qui deviendrait plus en plus en courante à mesure que l’accessibilité à l’Internet continue de s’améliorer à l’échelle mondiale. La qualité des informations de santé en ligne est très variable; le fait qu’une personne puisse tirer profit de cette source dépend en grande partie de sa capacité à localiser, évaluer et utiliser les informations de santé en ligne, ou en d’autres termes de sa littératie en santé électronique. On sait peu de choses sur la manière dont la littératie en santé électronique peut mécaniquement contribuer à la résistance à la désinformation en ligne sur la santé (par des différences observables dans le comportement de recherche d’informations), en partie en raison de limites méthodologiques qui peuvent être résolues grâce à la technologie de l’oculométrie. Les messages d’inoculation sont un moyen efficace d’améliorer la résistance à la désinformation, soutenu par un corpus de littérature, et peuvent donc servir à promouvoir des changements favorables dans le processus de recherche d’informations de santé en ligne. L’objectif général de ma thèse est de conceptualiser ce que les mesures existantes de la littératie en santé électronique nous disent sur le comportement de recherche d’informations des gens, et d’utiliser cette compréhension mécaniste de la recherche d’informations de santé pour tester si un message d’inoculation peut modifier favorablement le processus. L’étude 1 a consisté à une revue systématique de la portée afin d’identifier les outils utilisés par les chercheurs pour mesurer la littératie en santé électronique en fonction des performances objectives et de quantifier la prévalence de ces mesures dans la littérature par rapport aux mesures subjectives. Les résultats ont montré que près de 90 % des études mesurant la littératie en santé électronique ont utilisé exclusivement des mesures d’auto-évaluation, malgré des preuves que disent que l’auto-évaluation a peu de corrélation avec les capacités réelles dans ce domaine. L’étude 2 a

utilisé une analyse comparative à méthodes mixtes pour observer le comportement de recherche d'informations sur la santé en ligne dans un environnement en ligne sans restriction en utilisant l'enregistrement d'écran et la technologie de l'oculométrie, dans le but d'identifier les corrélations entre le comportement quantifiable et la mesure subjective la plus populaire de la littératie en santé électronique. Conformément à l'hypothèse, la mesure de la littératie en santé électronique auto-évaluée était significativement corrélée avec seulement 4 des 21 variables comportementales mesurées, et celles-ci étaient davantage liées aux préférences de type de source qu'aux différences procédurales dans le comportement de recherche d'informations. L'étude 3 consistait en un essai contrôlé randomisé visant à déterminer si un message d'inoculation modifierait favorablement le comportement de recherche d'informations sur la santé en ligne, en utilisant les mêmes participants et des procédures de recherche et de collecte de données presque identiques à celles de l'étude 2. Les résultats ont démontré que le bref message d'inoculation a conduit les participants à passer beaucoup plus de temps à évaluer les sources, bien que cela ne se soit pas traduit par une différence significative dans la fiabilité des sources consultées. Ensemble, les résultats de ma thèse, renforcés par de nouvelles approches méthodologiques, contribuent à une meilleure compréhension holistique de la relation entre la mesure de la littératie en cybersanté et le processus de recherche d'informations sur la santé en ligne. De plus, mes recherches soutiennent l'idée que les messages d'inoculation conduisent à des différences procédurales favorables dans le processus de recherche d'informations en ligne.

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Contributions to Original Knowledge

My dissertation is composed of three original manuscripts, each with unique contributions to the literature. My first study was the first published literature review to specifically identify existing performance-based measurement tools of eHealth literacy. The table within Study 1 can serve to direct researchers towards existing eHealth literacy measurement tools based on demonstrated online health information-seeking behaviour or relevant knowledge; something research suggests as key to accurately assessing people's ability to find relevant and trustworthy health information on the internet. Additionally, my scoping review is the first to quantify the approximate prevalence of performance-based versus self-report measurement tools of eHealth literacy in the literature broadly. With the internet representing a dominant driver of health discourse amongst the public, this is a key finding to highlight that current scholarship in the area may be falling short by relying on convenient self-report measures to assess online health information-seeking skill.

My second study, which examined correlations between self-reported eHealth literacy and observable online health information-seeking behaviour, augments the literature with quantitative evidence that perceived eHealth literacy has little bearing on how people behave during an online health information-seeking task. The combined use of eye-tracking technology and open-ended information-seeking prompts in Study 2 contributed a novel approach to eHealth literacy assessment literature, representing a method of quantifying day-to-day online health information-seeking behaviour with relatively high ecological validity. My third study made a meaningful contribution to the literature by applying this ecologically valid methodology to evaluating the impact of an inoculation message on online health information-seeking behaviour. In contrast to past inoculation message research that has predominantly evaluated the effectiveness of inoculation messages by testing participants' ability to discern false or misleading information from factual information presented to them, Study 3 examines how inoculation message exposure can alter the processes participants used to select relevant and reliable sources to inform themselves during an internet search task. Our participants exposed to an inoculation message spent significantly more time evaluating sources prior to selecting them from search results pages; to the best of our knowledge this represents the first quantitative evidence of a procedural information-seeking behaviour change resulting from inoculation message exposure. In addition to this mechanistic insight into how inoculation messages may confer misinformation resistance to a broad range of topics, findings from Study 3 also highlight that information-seeking behaviour changes resulting from inoculation message exposure may be highly specific to that message's content.

Overall, the findings of my dissertation, empowered by novel methodological approaches, contribute to a stronger holistic understanding of the relationship between eHealth literacy measurement and the online health information-seeking process. Specifically, my findings have contributed to furthering our academic understanding of how eHealth literacy is currently measured, how well these measures correlate with online health information-seeking behaviour, and how inoculation messages impact online health information-seeking behaviour.

Contributions of Authors

My dissertation includes three original manuscripts, conceptualized and written by me, with supervision and contributions made by my supervisor, Dr. Lindsay R. Duncan, and my co-authors, who are my graduate student lab-mates from the Healthy Living Lab in the Department of Kinesiology and Physical Education at McGill University.

Contributions to Study 1

The manuscript entitled "Performance-based measurement of eHealth literacy: A systematic scoping review" is published in the *Journal of Medical Internet Research* co-authored by myself, Olivia Feng, and my supervisor Dr. Lindsay R. Duncan.

- Bradley Crocker: As first author, I led the conceptualization, ethics board application, data collection, data analysis, and all phases of writing the manuscript. I was responsible for submitting the manuscript for publication, including all revisions and elements of the peer-review process. I serve as the corresponding author on the publication.
- Olivia Feng: Olivia contributed to the data collection, data analysis, and played a major role in editing and refining the manuscript before its initial submission to the journal.
- Lindsay R. Duncan: Dr. Duncan contributed to conceptualization of the study, the ethics board application, data analysis, and played a major role in editing and refining the manuscript up to publication.

Contributions to Study 2

The manuscript entitled "What does self-reported eHealth literacy tell us about online health information-seeking behaviour?: An eye-tracking study." is currently being prepared for submission to an academic journal. It is co-authored by myself, Emily V. Pike, and my supervisor Lindsay R. Duncan.

- Bradley Crocker: As first author, I led the conceptualization, ethics board application, data collection, data analysis, and all phases of writing the manuscript.
- Emily V. Pike: Emily made a major contribution to the data analysis phase of the study.
- Lindsay R. Duncan: Dr. Duncan contributed to the conceptualization of the study, the ethics board application, data analysis, and played a major role in editing and refining the manuscript.

Contributions to Study 3

The manuscript entitled "A randomized controlled trial examining the effects of inoculation message exposure on online health information-seeking behaviour" is currently being prepared for submission to an academic journal. It is co-authored by myself, Emily V. Pike, and my supervisor Lindsay R. Duncan.

- Bradley Crocker: As first author, I led the conceptualization, ethics board application, data collection, data analysis, and all phases of writing the manuscript.
- Emily V. Pike: Emily made a major contribution to the data analysis phase of the study.
- Lindsay R. Duncan: Dr. Duncan contributed to the conceptualization of the study, the ethics board application, data analysis, and played a major role in editing and refining the manuscript.

Preface

I structured my dissertation using a manuscript-based format, including a literature review section, three original studies, and a general discussion section. The literature review section provides a brief synopsis of past literature related to online health information-seeking, eHealth literacy, and inoculation messages, as well as the overall rationale and purpose statement of my dissertation. Study 1 consists of a systematic scoping review of performance-based eHealth literacy measurement tools. Study 2 consists of a mixed-methods comparative analysis examining correlations between self-reported eHealth literacy and quantifiable online health information-seeking behavioural outcomes of participants while searching the internet for information on 'immune boosting'. Study 3 consists of a randomized controlled trial, using a similar protocol to Study 2, examining the effects of inoculation message exposure on online health information-seeking behaviour. The general discussion section situates the findings from the three manuscripts within the current literature, including discussion of the contribution of their findings, their limitations, and how they might inform future research.

List of Tables

All tables in this document are embedded within their respective manuscripts. The following tables are included in this document (accompanied by page numbers):

Study 1

Study 2

Study 3

Introduction

The internet is a predominant source of information people use to inform their attitudes, beliefs, and behaviour in essentially all aspects of their lives, including how they manage their health and well-being. While the widespread and accessible nature of online health information presents an opportunity for people to benefit from up-to-date knowledge produced in the health sciences, the internet also has high potential to misinform the public by exposing them to false, misleading, and potentially harmful health-related content. Those who seek to benefit from venturing online for health information must be proficient at identifying relevant and credible sources; an ability known in academic circles as eHealth literacy (Norman & Skinner, 2006b). Proficient online health information-seeking requires a wide range of relevant knowledge and skills, making eHealth literacy assessment a challenging task. A bulk of research that has assessed participants' eHealth literacy has done so using self-report instruments (Griebel et al., 2018; Karnoe & Kayser, 2015), despite research indicating limited utility of self-report measurement to predict actual skill performance in similar domains. The continued popular use of such measurement tools may be in part due to gaps in knowledge surrounding the extent to which self-reported eHealth literacy correlates with observable health information-seeking behaviour.

Recognizing the urgent need to promote peoples' ability to differentiate between reliable and unreliable online health information, researchers have tested different interventions to promote resistance to health misinformation, primarily through the lens of inoculation theory. This theory posits that by exposing people to weakened forms of persuasive misinformation, we can enhance their resistance to persuasion by misinformation in the future (McGuire, 1964; McGuire & Papageorgis, 1961). Inoculation messages have been shown to effectively promote resistance to persuasion by misinformation across a large variety of topics; however, there remains much to be known regarding how specific features of inoculation messages play a role in this effect, and regarding the cognitive mechanisms by which different types of inoculation messages function to improve misinformation resistance. Understanding the mechanisms by which inoculation messages function to improve resistance to online misinformation has been partly constrained by research focused on information-seeking outcomes rather than information-seeking behaviour, something that could potentially be addressed using methods supplemented with eye-tracking technology.

Overall Purpose

The overall purpose of my dissertation is to conceptualize what existing measures of eHealth literacy tell us about people's demonstrable information-seeking behaviour, and to use this mechanistic understanding of health information-seeking to test whether an inoculation message can favourably alter the process. To accomplish this goal, three studies were conducted that each address specific research questions. The purpose of Study 1 was to identify tools that currently exist to measure eHealth literacy based on objective performance. A secondary purpose of Study 1 was to characterize the prevalence of performance-based measurement of eHealth literacy in the literature, as compared to self-report measurement. The purpose of Study 2 was to observe relationships between perceived eHealth literacy and online health information-seeking behaviour during an unrestricted internet search task. The purpose of Study 3 was to compare how an inoculation message changes online health information-seeking behaviour of young adults compared to those not exposed to that inoculation message.

Literature Review

In the pursuit of better health, people seek out high quality and relevant pieces of information to inform their beliefs and the way they live their lives. While there is a plethora of variables beyond a person's beliefs that contribute to how they behave (e.g., environmental factors, socioeconomic status), beliefs are a nearly universal component of all major theories validated to predict health-related behaviour (Bandura, 2001; Johnson, 1999; Rosenstock, 1977). Although people are informed to some extent about generally healthy behaviour, such as regular exercise and a varied diet, through formal grade school education, the science underpinning many health-related topics is constantly evolving and requires updating knowledge and beliefs. Accordingly, people consult various sources to inform themselves, including physicians, family members, and peers (Lau et al., 1990; Mollborn & Lawrence, 2018). Of all available information sources, research indicates the internet is the first place people turn to for health information (Gualtieri, 2009; Wang et al., 2021), and its influence over health discourse is constantly growing. Roughly 5 billion people, or 67%, of the global population are internet users (Statista, 2024), and around 94% of the Canadian population has internet access at home (Statistics Canada, 2023). As a source of health information, the internet provides many affordances that make it more attractive than traditional sources (i.e., in-person healthcare, books, pamphlets). The popularity of online health information can be attributed to 24-hour access from the comfort of one's own home, it can come at no cost (apart from those associated with general internet access), and requests for information can be made anonymously and without the bureaucracy common to accessing formal healthcare (Lee & Lin, 2020; Starcevic, 2024). A particularly attractive factor of the internet as a health information source is that it allows individuals to actively select information from a variety of viewpoints, including both traditional and alternative sources. This empowers individuals to act as 'experts' of their own health concerns by actively selecting the information they will use to address it (Lee & Lin, 2020). In these ways, the internet presents a promising health communication medium to boost public awareness of new research findings, treatment guidelines, and public health advisories.

Although the affordances of the internet as a health information resource are plentiful, locating high quality health information on the internet can be challenging. With increasing rates of internet access and climbing internet literacy levels, the internet has transitioned from a medium where the average user can only access information to a medium where everyday users experience remarkably low barriers to publishing their own information. Particularly compared to traditional channels of health information, the internet presents minimal gatekeeping to share information via personal websites, business websites, forums, and social media accounts. This has contributed to a massive and perpetually increasing volume of health information online; a Google search made today for "sore throat treatment" returns nearly 2 billion results. In this largely unregulated information landscape, the quality of health information on the internet is, perhaps unsurprisingly, highly variable (Cooke, 2017; Kitchens et al., 2014). In a perfect world, the internet stands to immensely benefit public health outcomes through convenient and widespread access to up-to-date health information related to both treatment and prevention. In reality, locating such information online can be immensely challenging due to the necessity of sifting through an ocean of information with highly variable accuracy and reliability.

Online Health Misinformation

Operationalizing "misinformation" in the context of research, and health-related research in particular, can prove challenging when it comes to quantifying the degree to which certain statements or beliefs are accurate (El Mikati et al., 2023; Vraga & Bode, 2020). Misinformation was named the Dictionary.com word of the year in 2018, which they define as "false information that is spread regardless of whether there is intent to mislead" (Dictionary.com, 2018). Traditionally scholars have suggested defining information's accuracy as the degree to which it is supported by clear evidence and expert opinion, two factors that each exist on broad spectrums in the domain of health information (Nyhan & Reifler, 2010; Vraga & Bode, 2020). The quality and quantity of scientific evidence supporting a claim can shift over time, meaning its degree of accuracy can shift as well. This is especially relevant for emerging topics in health and wellness for which a considerable body of research supporting or refuting a claim may not yet exist. For example, it has been hotly contested whether e-cigarette use (or "vaping") should be promoted as a healthier alternative to smoking given a lack of longitudinal research on its health risks (Ghuman et al., 2024; Laucks & Salzman, 2020), making it inherently difficult to quantify the accuracy of claims or beliefs on the topic. Deciphering prevailing expert opinion on a health-related topic first requires deciding who the relevant and trustworthy experts are; a task that has seemingly become more controversial and less straightforward in recent years (Nichols, 2017). Trust in healthcare institutions across North America has fallen considerably in recent years (Perlis et al., 2024; Proof Strategies, 2024), though trust in medical scientists, and scientists broadly, has remained relatively high with over three quarters of Americans reporting a fair amount or a great deal of trust (Pew Research Center, 2022). Even if it can be reasonably agreed upon that medical scientists are the most relevant experts to weigh-in on health-related topics, it can still be challenging to gauge the level of consensus among them on emerging trends. So, while there are many health-related claims that can reasonably be deemed accurate or inaccurate based on relatively "settled" science, there are many others for which judging accuracy can be challenging, even for those with relevant medical or scientific training.

This issue of health misinformation had perhaps never been more salient than during the COVID-19 pandemic, where misinformation surrounding the nature and treatment of the virus spread widely across many online platforms (Brennen et al., 2020). In a content analysis of 227 webpages from Google search results using the search terms ‘immune boosting’ and ‘coronavirus’, Rachul and colleagues (2020) found that 85.5% of webpages featured an unsupported claim that one could better protect themselves against COVID-19 using strategies such as the consumption of zinc, ginger, or probiotics. In an analysis of the top 75 YouTube videos related to COVID-19 on March 21st 2020, Li and colleagues (2020) found that videos containing non-factual information had amassed over 62 million combined views. While health misinformation was perhaps exacerbated by the pandemic, several health-related topics have had misinformation disseminate widely online over the past decade. The rapid growth in popularity of health trends with scant scientific evidence to support their effectiveness, such as ‘detox cleanses’ or ‘essential oils’, has been largely attributed to campaigns of online health misinformation (Bossalini & Neiner, 2020; de Regt et al., 2020; Klein & Kiat, 2015). A resurgence of vaccine-preventable illnesses in Europe and the United States has been attributed to anti-vaccine rhetoric promoted online, including a frequent (and unfounded) assertion that vaccines commonly cause autism and brain injury (Hotez, 2019; Navar, 2019). In a content analysis of 480 anti-vaccine websites, Moran and colleagues (2016) noted that vaccine misinformation was often communicated with a battery of sophisticated persuasive tactics including fear appeals supported by cherry-picked scientific and anecdotal evidence, co-promotion of known healthy behaviours to feign legitimacy, and conflation with values of freedom or living ‘naturally’.

Under the wide umbrella of health information, topics related to wellness lend themselves particularly well to spreading inaccurate information due to commonly unclear scientific consensus, low regulation (compared to medical treatments), and a high online presence of pseudoscientific theories and claims lacking rigorous evidence. Distinct from medical information that generally pertains to explaining and solving an acute symptom or condition, wellness culture is largely centered around the pursuit of self-optimization or self-mastery through holistic approaches, such as nutrition, fitness, and lifestyle regimens (Baker, 2022). Large contingents of the wellness industry position maintaining good health as an individual responsibility which can be enhanced through marketable, but often unfounded, solutions like supplements, superfoods, cleanses, or detoxes (Baker, 2022). Multi-billion-dollar companies in this sector are known to leverage celebrity sponsorship (Caulfield, 2017) and to use powerful narrative messaging techniques (Caulfield et al., 2019) to disseminate misinformation widely on online platforms. While many products and wellness techniques offered by these businesses may be relatively harmless (even if useless), others can lead to dangerous behaviour or the forgoing of much-needed evidence-based healthcare (Balogh et al., 2021; Murdoch et al., 2016).

The spread of misinformation is by no means a novel issue to society, however widespread access to the internet has initiated a fundamental change in how swiftly it proliferates and thus its societal impact (Wang et al., 2019). False information tends to spread faster than factual information across social media platforms, even despite those sharing the false information typically having smaller online followings (Vosoughi et al., 2018). Advances in photoshop and artificial intelligence technology stand to make deciphering the authenticity of content even more difficult in ensuing decades; ‘deepfake’ videos, in which one video is almost seamlessly superimposed upon another creating the image of a fictional event, have already started to appear across popular social media platforms and fooled many users into believing them (Maras & Alexandrou, 2019). Advances in machine learning have also made way for more sophisticated 'bot' accounts on social media able to mimic the behaviour of human users, which when controlled in large numbers can provide powerful influence upon public discourse by small groups of individuals (Unlu et al., 2024; Yang et al., 2019). Recent research has demonstrated that people who use the internet to evaluate misinformation can counterproductively increase their confidence in its veracity (Aslett et al., 2024), contributing to a line of scholarship that has questioned whether online health information-seeking is even a worthwhile endeavor for the general public (Johnson, 2014).

Regardless of its potentially problematic impacts, people going online to learn about health-related topics is inevitable and likely to only increase as global internet access becomes more abundant (McLean, 2023; Thapa et al., 2021). Improving public access to high-quality health information regarding treatment and prevention has the potential to make a dramatic positive impact on public health outcomes. However, the realization of this positive impact on health-related behaviour largely depends on how the internet is used by information-seekers.

Online Health Information-Seeking Proficiency

Online Information-Seeking Frameworks

Given most people use the internet as a primary source of health information, and yet many arrive at different understandings of what constitutes healthy behaviour, the online health information-seeking process is evidently not identical between users. Models of information-seeking behaviour evolved in academic literature for several decades prior to common use of the internet, however the dynamic, interactive, and complex information environment online necessitates new ways of understanding this process. Whereas former models of information-seeking behaviour were created to describe the strategies of formally trained or partially-trained individuals seeking print sources from libraries or other finite collections of literature (Wilson, 1999), present models must account for largely untrained information-seekers facing an almost infinite collection of sources that utilize various media (i.e., audio, video, interactive elements) (Knight & Spink, 2008). The internet has evolved tremendously in its own right since it debuted in upper- and middle-class households in the late 1990's; the ability to publish information online has shifted from being an exclusive capability of those with formal coding training (often hired by particular companies and organizations), to being a skill accessible to virtually anyone with internet access (Aghaei et al., 2012). This reduction in gatekeeping along with consistent growth in global internet access has made the internet a primary destination for the sharing of diverse perspectives on virtually any topic imaginable; setting the stage for variable information quality (Cooke, 2017; Kitchens et al., 2014). In this constantly evolving informational landscape, contemporary information-seeking behaviour likely differs substantially from older literature, however some broad elements of existing models may still be usefully drawn upon (Allam et al., 2019).

One of the earliest information-seeking behaviour models explicitly targeting a virtual setting is Marchionini's Information Seeking in Electronic Environments Model (Marchionini, 1995). This model posits eight components of information-seeking that occur in a relatively linear process: (a) Recognizing an information problem, (b) defining an information problem, (c) selecting a search engine, (d) formulating a query, (e) executing the search, (f) examining results, (g) extracting information, and (h) reflecting (Marchionini, 1995). Reflection may then result in a new information problem, re-definition of the same information problem, deciding to use a different search engine or query, or (ideally) complete satisfaction of the initial information problem (Marchionini, 1995). Spink (1997) noted later that different types of feedback occurred throughout an electronic search process such that users may move between stages in a less linear fashion. For example, users often reformulate their search terms based on the magnitude of results initially obtained, which in Marchionini's model would represent a move from the 'examining results' stage to the 'formulating a query' stage without necessarily completing the process. Popular online information-seeking behaviour models henceforth consistently include non-linear links between components. Choo and colleagues (1999) created a list of online information-seeking behaviours termed "web moves", several of which break from a linear process of information-seeking such as using hyperlinks between content-related websites and returning to 'favourite' sites directly without engaging in another full search process. In his non-linear model of information-seeking, (Foster, 2004) describes fluid transition between three core processes: Opening (e.g., keyword searching and browsing), orientation (e.g., problem (re)definition and information review), and consolidation (e.g., verifying and incorporating information into beliefs). In their version of a macro model of online information-seeking behaviour, Knight and Spink (2008) differentiate between information searching behaviour (interactions with a search engine) and information seeking behaviour (interactions directly with online sources), which influence each other in a constant and cyclical fashion until the user ultimately decides on which information to retrieve. In this model, it is also emphasized that information seeking and searching strategies are directly influenced by characteristics of the user (e.g., perspectives on the topic, perceptions of their own capabilities, cognitive style) (Knight & Spink, 2008). In summary, scholars generally agree that non-linear information-seeking behaviour models are necessary to account for the interactive nature of the online environment;

however, they have yet to arrive at consensus on a conclusive model that fully embodies how users obtain information online (Allam et al., 2019).

Since around the mid-1990s, researchers have also employed a variety of models to conceptualize the discrete actions involved in the health information-seeking process (Lambert & Loiselle, 2007). In their seminal review of health information-seeking behaviour research, Lambert and Loiselle (2007) differentiate between models focusing on the information dimension (characteristics of information sought by individuals), and the method dimension (discretionary actions individuals use to obtain health-related information). When applying this lens to current models of internet-related health information-seeking behaviour, it is clear most have focused on the information dimension, as well as broad determinants of online health information-seeking (Jia et al., 2021; Marton & Choo, 2012; Wang et al., 2021). Search engines may be considered an appropriate starting point to study online health information-seeking, as they are the most common means by which users actively seek health information on the internet (Jia et al., 2021; Maon et al., 2017; Sbaffi & Zhao, 2020). For the purposes of quantifying time spent on particular information-seeking stages in this research, I have consolidated components from broad online information-seeking models into four categories: query formulation (a user's decision of which search engine to use and which keywords to input), source selection (a user's strategy of selecting a source from a search engine results page), content navigation (a user's behaviours related to consuming information from a source), and verification (a user's tactics to gauge the relevance and trustworthiness of sources and content).

eHealth Literacy

Health literacy is defined as "the cognitive and social skills which determine the motivation and ability of individuals to gain access to, understand and use information in ways which promote and maintain good health" (Nutbeam, 2000). Synthesizing this and other definitions throughout the literature, Berkman and colleagues (2010) define health literacy more succinctly as "The degree to which individuals can obtain, process, understand, and communicate about health-related information needed to make informed health decisions" (p. 16). Health literacy can thus be considered a dynamic ability, as the health decisions people are faced with and the forms of health information available change over their lifespan (Berkman et al., 2010). Research indicates low levels of health literacy may contribute significantly to a range of unfavourable health outcomes and behaviour, including lower rates of influenza vaccination, higher rates of hospitalization, higher rates of mortality, and higher rates of poor health status (Berkman et al., 2011; Fabbri et al., 2020). Health literacy has often been applied to functioning in a healthcare environment via comprehending and applying information passed on by healthcare providers (Berkman et al., 2010). However, this conception of health literacy may have limited usefulness outside of clinical environments where terms used to discuss health-related topics (and to market health-related products) may deviate significantly from standard medical practice (Nutbeam, 2009).

Recognizing the critical importance of the internet to the health information-seeking process, Norman and Skinner (2006b) introduced the construct of eHealth literacy, defined as "the ability to seek, find, understand, and appraise health information from electronic sources and apply the knowledge gained to addressing or solving a health problem" (p. 2). They based this construct on the "Lily Model" of six foundational literacies: traditional literacy, information literacy, media literacy, health literacy, computer literacy, and scientific literacy (Norman & Skinner, 2006b). The former three literacies are grouped together as 'analytic' literacy skills; broadly applicable to navigating the virtual informational context. The latter three literacies are deemed ‘context-specific’ to eHealth; proximal to the phenomena of navigating health-related information on the internet. Norgaard and colleagues (2015) later extended this model to identify seven domains that ultimately contribute to an individual’s eHealth literacy: Ability to process information (locating, interpreting, and applying health information), engagement in own health (interest and basic knowledge of personal health and healthcare systems), ability to actively engage with digital services (competency with technology and navigating the internet), feel safe and in control (confidence and knowledge of securing personal health information), motivated to engage with digital services (accepting attitude towards online health resources and services), access to digital services that work (having the hardware and software to access online health resources and services), and digital services that suit individual needs (online health resources exist that are accessible and understandable to the individual user). Taken together, these models of eHealth literacy depict a diverse combination of critical skills needed to effectively acquire health information online.

eHealth Literacy Measurement and Limitations

Concurrent with their publication coining eHealth literacy, Norman and Skinner (2006a) published the eHealth Literacy Scale (eHEALS), an 8-item questionnaire wherein each item is rated using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating higher eHealth literacy. In a systematic review of eHealth Literacy measurement tools, Karnoe and Kayser (2015) noted this was the only tool used in multiple studies at the time of publication, and it remains the most widely-used instrument across the literature to assess eHealth literacy (Griebel et al., 2018). As a short self-report assessment tool, the eHEALS is attractive for healthcare providers looking to optimize clinical efficiency, and is convenient for researchers to minimize participant burden. However, the self-report nature of this measure may limit its usefulness at giving an accurate depiction of how well people critically engage with online health information in today's internet landscape.

While self-report measurements have functioned as invaluable research tools in several settings, the efficacy of using self-report to evaluate one's own skills, abilities, or proficiency in many contexts has been criticized for decades (Dunning et al., 2004; Mabe & West, 1982). In their seminal review and meta-analysis of self-evaluations of ability across 55 studies, Mabe and West (1982) found only a very modest (mean $r = 0.29$) relationship between self-reported ability and performance-based measurement. Several psychological mechanisms may contribute to the considerable gap in estimates of ability and actual ability, many of which have been supported by research across a variety of cognitive skills (see Dunning (2005)). For example, individuals have a tendency to be confident in skills where they feel fluent (Dunning, 2005), meaning people may mistake the ability to fluidly perform a skill with the ability to perform that skill well. In the context of online health information-seeking, people may mistake the ability to seamlessly locate some health information on the internet with the distinct ability to retrieve accurate, trustworthy, and relevant online health information. Consider that many avid followers of the anti-vaccine movement have spent several hours surfing the internet for health-related information (Hussain et al., 2018; Kata, 2012). Their relatively high amounts of experience of online health information-seeking may lead them to feel fluent in the skill, yet they are evidently not equipped to judge the quality of online information by the standards of evidence-based medicine.

Relating to online information-seeking, ample literature indicates people have a tendency to overestimate their ability with computers (Merritt et al., 2005; Palczyńska & Rynko, 2021) as well as their ability to locate and understand information online (Eysenbach & Köhler, 2002; Mahmood, 2016). Overestimation of ability in this context may result from overlap between the cognitive skills necessary for the task itself and the meta-cognitive skills necessary for accurate self-assessment, meaning those without the competence to consistently identify trustworthy information online are unlikely to have the capacity to recognize their lack of competence. Put more plainly by Dunning (2005): “If they had the skill to know they were making consistent mistakes, they would also have the skill to avoid those blunders in the first place” (pp. 16). Fittingly, in the context of online health information-seeking, Stellefson and colleagues (2012) found that the least proficient searchers commonly exhibited high confidence in their searching abilities, indicating that self-efficacy is not a consistent predictor of eHealth literacy skills. Similarly, Maitz and colleagues (2020) found that adolescents who reported higher eHEALS scores did not perform better at selecting higher-quality websites to access health information. Illustrating this point further, Brown and Dickson (2010) found that a group of occupational therapy graduate students reported lower average eHEALS scores than the high school participants in Norman and Skinner’s (2006a) original paper. Taken together, this literature indicates that intellectual hubris may play a bigger role in self-rated eHealth literacy than actual knowledge or ability, and so it should come as little surprise that a bulk of studies have noted no or little association between eHEALS scores and demonstrated eHealth skills (Neter & Brainin, 2017; Quinn et al., 2017; Van Der Vaart et al., 2011). That is not to say perceived eHealth literacy is a meaningless construct; a systematic review and meta-analysis by Kim and colleagues (2023) indicates self-assessed eHealth literacy has a moderate correlation with healthy behaviour, and other studies have demonstrated correlations with higher rates of internet use for health information-seeking (Heiman et al., 2018; Tennant et al., 2015). Still, measures of eHealth literacy that involve more objective, performance-based measurement of eHealth skills and abilities may be more promising at assessing how people actually behave online; however, such measures seem to be more scarcely used among researchers to date (Griebel et al., 2018). Particularly given the complex informational landscape users face seeking health information online, it seems particularly imperative to gauge their skill at identifying trustworthy sources by which to inform their health-related beliefs and decisions; a skill many are likely to lack the metacognitive awareness to accurately self-assess. Smith and colleagues (2015) found people with the most inaccurate beliefs related to antibiotic resistance tended to be the most likely to express and act on their misinformed beliefs.

Conferring Resistance to Health Misinformation

Drawing Attention to Accuracy

Recognizing that misinformed beliefs are notoriously persistent and resistant to correction (Chan & Albarracín, 2023; Ecker et al., 2022), many scholars have turned to pre-emptive interventions with the goal of reducing users' misinformation susceptibility and minimizing its spread. One promising approach to improve misinformation resistance has been spearheaded by Pennycook and colleagues, who have rigorously demonstrated that momentary attention to accuracy profoundly impacts willingness to share or engage with online misinformation (Pennycook et al., 2021; Pennycook & Rand, 2019, 2020). The mechanism is framed within a dual-process model of cognition, which implies that humans differentially engage in analytic (deep) or heuristic (shallow) modes of information processing, reasoning, and decision-making depending on their relationship with the information stimuli (Evans, 2008; Gerrard et al., 2008). In a study in which participants were asked to evaluate the validity of a series of news headlines, Pennycook and Rand (2019) found that participants who engaged in more analytic thinking performed better irrespective of whether the headline aligned with their stated ideological biases. Their type of thinking was assessed using a cognitive reflection test, which has participants answer prompts such as this from Frederick (2005): "If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? ___ minutes" (p. 27). Those engaging in only heuristic processing would likely answer 100 minutes, however upon deeper reflection (analytic processing) most will realize the answer is 5 minutes. From their findings, Pennycook and Rand (2019) posit that one's ability to identify misinformation may be based more on willingness to exert the cognitive resources to deeply consider it, than it is based on pre-existing knowledge or user-related factors. In this optimistic viewpoint, it is asserted that most people have the innate ability to evaluate source validity, they just lack the necessary thoughtfulness or willpower to apply it consistently.

To test this theory further, Pennycook and colleagues (2020) investigated whether participants would perform better at evaluating the validity of COVID-19 related news headlines following a 'nudge' to think about accuracy. Participants who were asked to rate the accuracy of a single news headline unrelated to COVID-19 prior to completing a series of news headlines evaluations were far better at identifying fake news (Pennycook et al., 2020). This research indicates that when users are provided a brief reminder that some of the content they see might not be accurate, they will tend more towards analytic processing and thus exhibit better resistance to online misinformation. Extending from these findings, Pennycook and colleagues (2021) suggest that reminding users to be cognizant of accuracy as they browse the internet can prime them to engage in analytic processing, potentially reducing their likelihood of engaging with misinformation.

Inoculation Theory

Inoculation theory, initially posited by McGuire and Papageorgis (1961), is based on an analogy between resistance to attitude change and resistance to contagious disease. In a similar way that bodies with little exposure to foreign contaminants develop minimal immunity, those with little exposure to counterarguments develop minimal resistance to attitude change (McGuire & Papageorgis, 1961). Just as one may protect their health by avoiding exposure to pathogens, one may protect their beliefs by avoiding exposure to argumentation, however in the modern context where people are bombarded constantly with information, this is not a feasible strategy. Instead, akin to vaccination, a more promising approach to harden people against persuasive messaging may be to inoculate them through exposure to weakened, defense stimulating forms of the counterarguments (McGuire & Papageorgis, 1961). The inoculation process involves two major components: a threat (participants are made aware that counter-attitudinal parties exist), and refutational preemption (participants are exposed to counter-attitudinal message and provided counterarguments and to help resist persuasion attempts) (McGuire, 1964).

Inoculation Messages Against Health Misinformation

A large volume of literature has found inoculation messages to be more effective at conferring resistance to persuasion than pro-attitudinal messaging in a variety of contexts, including for health-related topics (Banas & Rains, 2010; Compton et al., 2016). For example, Parker and colleagues (2012) found that inoculation messages featuring common persuasive techniques to engage in unprotected sex hardened the resolve of young adults against counter-attitudinal pressures to do so. Godbold and Pfau (2000) similarly found that anti-alcohol public service announcements using inoculation messaging made children more resistant to persuasion to engage in underage drinking. Relating more specifically to deceptive misinformation, Mason and Miller (2013) found inoculation messaging to be effective in making undergraduate students more resistant to deceptive health claims used by some commercial food and supplement advertisers. Inoculation theory has proven to be a useful tool to promote the formation of robust attitudes about health-related behaviour that can resist some forms of marketing tactics and peer pressure; however, less is known about how inoculation messages may be used to confer resistance to the insidious forms of online misinformation one may encounter today (Roozenbeek & van der Linden, 2019). In a content analysis of over 90,000 online news articles, Carrasco-Farré (2022) found that misinformation content tends to be significantly easier to cognitively process through use of simpler language, meaning those less willing or less able to engage in information evaluation processes may be at higher risk of persuasion by unreliable sources online (Lazer et al., 2018). To date, inoculation message researchers have predominantly evaluated intervention effects by measuring changes in participants' attitudes, their (mis)information sharing intentions, and their ability to accurately assess (mis)information credibility (Banas & Rains, 2010; Lu et al., 2023). Little, if any, inoculation message research to date has investigated how exposure may impact participants' information-seeking behavioural processes; which may provide a more holistic picture of how equipped people truly are to discern information reliability during their daily internet browsing.

Inoculation Message Components

The use of inoculation messages specifically to increase resistance against online misinformation is a relatively young field of research, and as such there remains much to learn regarding advantages and disadvantages of modifying specific components of the message. Some scholars have pointed out that many existing inoculation interventions are limited to providing only topic-specific protection against misinformation, which is only marginally useful as people engage in online-information seeking on other topics (Roozenbeek & van der Linden, 2019). Scholars have suggested this may be largely attributed to inoculation interventions primarily using fact-based refutations (demonstrating misinformation is wrong by identifying factually inaccurate components) rather than logic-based refutations (demonstrating misinformation is wrong by identifying misleading rhetorical techniques and logical fallacies) (Cook et al., 2022; Ecker et al., 2022; Ivanov, 2017). Inoculation approaches that teach users about common features of online misinformation, such as questionable source credibility and misleading persuasive techniques, may offer broad protection against many types of misinformation employing similar tactics (Ecker et al., 2022; Hruschka & Appel, 2023). Another potentially relevant feature of inoculation messages to providing broad misinformation protection is whether they utilize passive refutation (participants being provided counterarguments) or active refutation (participants developing their own counterarguments) (Banas & Rains, 2010). Passive refutation can arm users with the conceptual capacity to resist persuasion by misinformation, while active refutation has users engage in building and practicing reasoning skills as to why a particular piece of information may be false or untrustworthy (Cook et al., 2022).

A promising intervention incorporating both active and logic-based refutation was created by Roozenbeek and van der Linden (2019) who tested a gamified version of inoculation messaging targeting ‘fake news’ relating to a salient topic at the time (the European refugee crisis). In this game, participants played the role of misinformation-spreader in which they actively select strategies and produce content to mislead the masses, receiving informational prompts throughout the game that note common misinformation cues. Through active engagement in the inoculation messaging this intervention was successful at reducing perceived credibility and persuasiveness of fake news articles related to the refugee crisis, and later the authors found the intervention to be effective at protecting individuals against a broader range of misinformation (published in a separate study) (R. Maertens et al., 2020). In this follow-up research, Maertens and colleagues (2020) also noted a decay in the inoculation effect within two months if nothing was done to retain it; however, they found a significant inoculation effect still present three months following the intervention in a group tested 1 week, 5 weeks, and 13 weeks following the initial intervention. From these findings, Maertens and colleagues (2020) suggest a 'booster dose' of misinformation inoculation, even just in the form of a short evaluation, is necessary to maintain resistance to misinformation.

The exact mechanism by which inoculation messages improve broad resistance to misinformation have not been rigorously established, though scholars have posited that bolstered critical thinking directed towards information quality and source credibility stimulated by inoculation messages may contribute (Compton et al., 2021). Researchers have also suggested the "blanket of protection" against misinformation afforded by inoculation message exposure may be due to practicing the skill of counterarguing and familiarization with common logical fallacies (Cook et al., 2017; Cooke, 2017; Ecker et al., 2022; Parker et al., 2012, 2016). Research methods with the capacity to examine precise changes in users' information-seeking behaviour stimulated by exposure to inoculation messages, in contrast to simply testing users' ability to distinguish true and false headlines or statements, may help to clarify the nuances of the inoculation process (Banas & Rains, 2010; Compton, 2024).

Eye-Tracking

Given the complex nature of the online information-seeking process, research methods that provide a more nuanced understanding of objective search behaviour are needed. In the research presented in this dissertation, we opted to record online health information-seeking behaviour using screen-recording and eye-tracking technology. Screen-recording allows researchers to observe what participants are visually exposed to throughout their search, while eye-tracking records participants' precise visual attention. The ability to measure participants' gaze on the screen may be pivotal to conceptualizing information-seeking behaviour, as it is well-established individuals often attend to only parts of the information they are presented (Petty & Cacioppo, 1986; Reyna & Brainerd, 1995), including in health-related contexts (Schumann et al., 2012). Recording visual attention allows for a relatively objective (compared to self-report) understanding of what users notice and engage with throughout their search, providing a clearer picture of their information-seeking process than can be achieved with screen-recording alone. In the context of health information-seeking, most research has focused on search results page behaviour with particular focus on how the digital environment, such as the position of a source on a search results page, impacts behaviour. For example, Granka and colleagues (2004) were among the first to use eye-tracking to demonstrate that users pay more attention and are more likely to click sources based on early positioning on a search results page. In more recent eye-tracking work, it has been noted that today's users, who generally have more internet experience, tend to select more objective information over subjective or commercial sources (Kammerer & Gerjets, 2012), and consider relevance more important than search results page position when deciding what to click on (Schultheiß et al., 2018). Lopes and Ramos (2020) also applied eye-tracking methods along with performance-based measurement of health literacy to establish that those with superior health literacy were generally more attentive to search results pages and author information during online health information-seeking.

While measuring visual attention via eye-tracking can provide considerable insight into the information-seeking process, combining the method with qualitative data, such as verbal protocols, can improve external validity (Lewandowski & Kammerer, 2021; Orquin & Holmqvist, 2018). Muntinga and Taylor (2018) supplemented eye-tracking with gaze-cued retrospective think-aloud interviews, helping them establish that paying attention to URL addresses on a search results page resulted in better success identifying licensed (versus unlicensed) pharmacy websites, and this strategy was employed more consistently by users who reported having more internet experience. Chang and colleagues (2021) applied similar methods to study the indicators people use to evaluate health-related webpages and find that content-related indicators were consistently used more often than source-related indicators. These studies, and indeed all eye-tracking studies mentioned thus far, have utilized a purposefully designed internet-like simulation for participants to navigate rather than observing behaviour in an authentic online environment. While a controlled environment facilitates comparisons between participants' behaviour, limiting their decisions to a few webpages instead of the effectively endless expanse of the internet comes at the expense of ecological validity (Lewandowski & Kammerer, 2021). This limitation was addressed in recent work by Chang (2022) who utilized eye-tracking in an open-internet environment to study associations between self-assessed eHealth literacy and online health information-seeking behaviour during four fact-finding internet tasks. Their findings demonstrate relatively minor differences in strategies employed by low- and high-eHealth literacy groups; however, the author notes this may have been due to the relative simplicity of the search task. In this way, Chang (2022)'s study provides a setting to meaningfully analyze information-seeking behaviour related to locating straightforward medical facts, but may have limited applicability for nuanced health and wellness topics for which there exist multiple perspectives and highly variable information quality online.

Rationale and Purpose

The internet is a prominent source people use to inform themselves on health-related topics, likely to grow more commonplace as internet accessibility continues to improve globally.

The quality of online health information is highly variable, meaning users hoping to accurately inform their health-related decisions using the internet must be proficient in identifying relevant and credible sources; an ability known to researchers as eHealth literacy (Norman & Skinner, 2006b). A bulk of research involving eHealth literacy measurement has done so using self-report instruments (Griebel et al., 2018; Karnoe & Kayser, 2015), despite research indicating limited utility of self-report measurement to predict actual skill performance in similar domains. There remains much to be known about how self-reported eHealth literacy correlates with observable health information-seeking behaviour, in part due to methodological limitations in past research that may be addressed using eye-tracking technology. Inoculation messages are an effective means of promoting resistance to misinformation, supported by a large and growing body of literature, and thus can function to promote favourable changes in the online health information-seeking process. The insight offered by eye-tracking technology may be useful to assess potential mechanistic impacts of inoculation messages on online health information-seeking behaviour. The overall purpose of my dissertation is to conceptualize what existing measures of eHealth literacy tell us about people's information-seeking behaviour, and to use this mechanistic understanding of health information-seeking to test whether an inoculation message can favourably alter the process.

Bridging Text I

In the literature review, I provided a detailed summary of literature relevant to online health information-seeking, eHealth literacy measurement, and health-related inoculation message interventions. In the domain of eHealth literacy measurement, I put particular emphasis on the potential shortcomings of self-report assessment in terms of its utility at giving an accurate depiction of how well people can use the internet to locate, evaluate, and utilize reliable health information. Though other scholars have published research syntheses related to eHealth literacy measurement instruments and their properties (e.g. Karnoe & Kayser, 2015; Lee et al., 2021) no synthesis to date has specifically examined performance-based measurement of eHealth literacy. Given the distinct advantages these tools may provide, Study 1 offers a systematic scoping review with specific emphasis on performance-based tools for measuring eHealth literacy.

Study 1

Performance-based Measurement of eHealth Literacy: A Systematic Scoping Review

Bradley Crocker, Olivia Feng, Lindsay R. Duncan

Department of Kinesiology and Physical Education, McGill University, Montreal, Canada

*Corresponding author
Bradley Crocker
Department of Kinesiology and Physical Education
475 Pine Avenue West, Montreal, QC, H2W 1S4
bradley.crocker@mail.mcgill.ca

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Abstract

Introduction: eHealth literacy describes the ability to locate, comprehend, evaluate, and apply online health information to a health problem. In studies of eHealth literacy, researchers have primarily assessed participant's perceived eHealth literacy using a short self-report instrument, for which ample research has shown has little to no association with actual performed eHealth-related skills. Performance-based measures of eHealth literacy may be more effective at assessing actual eHealth skills, yet such measures appear to be scarcer in the literature.

Objectives: The primary purpose of this study was to identify tools that currently exist to measure eHealth literacy based on objective performance. A secondary purpose of this study was to characterize the prevalence of performance-based measurement of eHealth literacy in the literature, as compared to subjective measurement.

Methods: We conducted a systematic scoping review of the literature, aligning with the PRISMA-ScR extension checklist, in three stages: Conducting the search, screening articles, and extracting data into a summary table. The summary table includes terminology for eHealth literacy, description of participants, instrument design, health topics used, and a brief note on evidence of validity for each performance-based measurement tool. A total of 1444 unique articles retrieved from six relevant databases (MEDLINE, PsycINFO, CINAHL, LISA, LISTA, ERIC) were considered for inclusion, 313 of which included a measure of eHealth literacy.

Results: We identified 33 articles that reported on 29 unique performance-based eHealth literacy measurement tools. The types of tools ranged from having participants answer health-related questions using the internet, to having participants engage in simulated internet tasks, to having participants evaluate website quality, to quizzing participants on their knowledge of health and the online health information-seeking process. We additionally identified 280 articles that

measured eHealth literacy using only a self-rating tool, representing 89.5% of our sample of the literature.

Discussion: This study is the first research synthesis looking specifically at performance-based measures of eHealth literacy, and may direct researchers towards existing performance-based measurement tools to be applied in future projects. We discuss some of the key benefits and drawbacks of different approaches to performance-based measurement of eHealth literacy. Researchers with an interest in gauging participants' actual eHealth literacy (as opposed to perceived eHealth literacy) should make efforts to incorporate tools such as those identified in this systematic scoping review.

Introduction

Individuals form beliefs, make decisions, and enact behaviour based on what they perceive to be high-quality and relevant information [1]. Ideas and beliefs about healthy and unhealthy behaviour are shaped from various sources, but above all the internet plays an increasingly prominent role in people's information diet regarding health-related topics. Research indicates the internet is the first source people turn to for health information [2] and in some cases is deemed more credible than physician diagnoses [3]. The internet provides several affordances for accessing health information that cannot be matched by other resources; it is available 24 hours, queries are answered immediately, queries can be made anonymously, multiple points of view can be accessed and considered by the information-seeker, and all of this is offered from the comfort of one's own home [4]. Improved public access to health-related information related to treatment and prevention has the potential to make a dramatic positive impact on public health outcomes. However, the realization of this positive impact on health-related behaviour largely depends on how the internet is used by the information-seeker.

Although the affordances of the internet as a health information resource are plentiful, locating high quality health information on the internet can be challenging. The volume of health information online is massive and perpetually increasing; a Google search for "sore throat treatment" returns nearly 2 billion results. Within this plethora of information, users' search results are often clouded with misleading, inaccurate, or unsubstantiated information [5]. For example, in a sample of 227 webpages related to "immunity boosting" and "coronavirus", Rachul et al.[6] found that 85.5% of sources portrayed "immune boosting" as beneficial for preventing COVID-19 infection despite no existent scientific evidence. Information-seekers are tasked with sifting through search engine results to locate something relevant, trustworthy, and in an accessible format to inform their decisions. Norman and Skinner [7] describe this ability as eHealth literacy, which they define as “the ability to seek, find, understand, and appraise health information from electronic sources and apply the knowledge gained to addressing or solving a health problem” [7](pp.2).

The construct of eHealth literacy was initially derived from six underlying foundational literacies: traditional literacy, information literacy, media literacy, health literacy, computer literacy, and scientific literacy[7]. Norgaard et al.[8] extended this model further to identify seven domains that ultimately contribute to an individual’s eHealth literacy: Ability to process information (locating, interpreting, and applying health information), engagement in own health (interest and basic knowledge of personal health and healthcare systems), ability to actively engage with digital services (competency with technology and navigating the internet), feel safe and in control (confidence and knowledge of securing personal health information), motivated to engage with digital services (accepting attitude towards online health resources and services), access to digital services that work (having the hardware and software to access online health resources and services), and digital services that suit individual needs (online health resources exist that are accessible and understandable to the individual user). Taken together, these models of eHealth literacy depict the diverse combination of critical skills needed to effectively acquire health information online.

Concurrent with their publication coining eHealth literacy, Norman and Skinner[9] published the eHealth Literacy Scale (eHEALS), an 8-item questionnaire wherein each item is rated using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating higher perceived eHealth literacy. In a systematic review of eHealth Literacy measurement tools, Karnoe and Kayser[10] noted this was the only tool used in multiple studies at the time of publication, and it remains the most widely-used instrument across the literature to assess eHealth literacy[11]. As a short self-report assessment tool, the eHEALS is attractive for healthcare providers looking to optimize clinical efficiency, and is convenient for researchers to minimize participant burden. However, the self-report nature of this measure may limit its usefulness at giving an accurate depiction of how well people critically engage with online health information in today's internet landscape.

While self-report measurements have functioned as invaluable research tools in several settings, the efficacy of using self-report to evaluate one's own skills, abilities, or proficiency in many contexts has been criticized for decades[12,13]. In their seminal review and meta-analysis of self-evaluations of ability across 55 studies, Mabe and West[12] found only a very modest (mean $r = 0.29$) relationship between self-reported ability and performance-based measurement. Several psychological mechanisms may contribute to the considerable gap in estimates of ability and actual ability, many of which have been supported by research across a variety of cognitive skills (see Dunning[14]). For example, individuals have a tendency to be confident in skills where they feel fluent[14], meaning people may mistake the ability to fluidly perform a skill with the ability to perform that skill well. In the context of online health information-seeking, people may mistake the ability to seamlessly locate some health information on the internet with the distinct ability to retrieve accurate, trustworthy, and relevant online health information. Consider that many avid followers of the anti-vaccine movement have spent several hours surfing the internet for health-related information[15,16]. Their relatively high experience of online health information-seeking may lead them to feel fluent in the skill, yet they are evidently not equipped to judge the quality of online information by the standards of evidence-based medicine.

Relating to online information-seeking, ample literature indicates people have a tendency to overestimate their ability with computers[17,18] as well as their ability to locate and understand information online[19,20]. Frequent overestimation of ability in this context may result from overlap between the cognitive skills necessary for the task itself and the meta-cognitive skills necessary for accurate self-assessment, meaning those without the competence to consistently identify trustworthy information online are unlikely to have the capacity to recognize their lack of competence. Put more plainly by Dunning[14]: “If they had the skill to know they were making consistent mistakes, they would also have the skill to avoid those blunders in the first place” (pp. 16). Fittingly, in the context of online health information-seeking, Stellefson et al.[21] found that the least proficient searchers commonly exhibited high confidence in their searching abilities, indicating that self-efficacy is not a consistent predictor of eHealth literacy skills. Similarly, Maitz et al.[22] found that adolescents who reported higher eHEALS scores did not perform better at selecting higher-quality websites to access health information. Illustrating this point further, Brown and Dickson[23] found that a group of occupational therapy graduate students reported lower average eHEALS scores than the high school participants in Norman and Skinner’s[9] original paper. Taken together, this literature indicates that intellectual hubris may play a bigger role in self-rated eHealth literacy than actual knowledge or ability, and so it should come as little surprise that a bulk of studies have noted no or little association between eHEALS scores and demonstrated eHealth skills [(Neter & Brainin, 2017; Quinn et al., 2017; Van Der Vaart et al., 2011)]. Measures of eHealth literacy that involve more objective, performance-based measurement of eHealth skills and abilities may be more promising at assessing how people actually behave online; however, such measures seem to be more scarcely used among researchers to date[11].

While research syntheses have been undertaken related to eHealth literacy measurement instruments and their properties (e.g. Karnoe & Kayser[10]; Lee et al.[27]), no synthesis to date has looked specifically at performance-based measures of eHealth literacy. This work is needed to assist researchers in identifying performance-based measurement tools in the literature that may be applied in future projects.

Purpose

This study has two main purposes. The first purpose is to identify tools that currently exist to measure eHealth literacy based on objective performance. Within this purpose, we are interested in the design of these tools, their intended population, and whether their authors include some evidence of validity. The second purpose of this study is to characterize the prevalence of performance-based eHealth literacy measurement tools amongst the literature broadly, as compared to subjective eHealth literacy measurement tools.

Methods

We conducted a systematic scoping review of the literature. A scoping review was deemed appropriate for the purpose of this study given its broad focus on how research involving eHealth literacy measurement is conducted[28]. This scoping review was conducted in three main stages, aligning with the PRISMA extension for scoping reviews (PRISMA-ScR) checklist[29]. In the first stage, we devised an electronic search protocol that was completed by two researchers. We used the below search string, modified from that used in a systematic review conducted by Karnoe and Kayser[10].

(“eHealth literacy” OR “electronic health literacy” OR “e-health literacy” OR “digital health literacy” OR (“health literacy” AND “digital literacy”) OR (“health literacy” AND “computer literacy”)) AND (scale OR measure OR survey OR questionnaire OR test OR assessment)

We applied this string to search six relevant databases (MEDLINE, PsycINFO, CINAHL, LISA, LISTA, ERIC) selected in consultation with a university librarian. All searches were conducted in June 2021. Across these six databases, 1735 search results were obtained, which was reduced to 1444 unique articles after duplicates were removed.

In the second stage, we conducted three screening phases to narrow down the search results. In each screening phase articles were sought that met the inclusion criteria of 1) written in English, 2) published in peer-reviewed journals, and 3) create, revise, or utilize an eHealth literacy assessment tool (in accordance with Norman and Skinner's[7] definition of eHealth literacy, quoted earlier in this paper). The first screening phase involved screening all articles using their titles, which was carried out by the first author. After this phase, 788 articles were retained for possible inclusion. The second screening phase involved screening all remaining articles using their abstracts, which was carried out by the first and second author. If either author opted to include the article, it was kept for phase three. After this phase, 374 articles were retained for possible inclusion. The third screening phase involved reading the full text of all remaining articles, which was carried out by the first and second author. During this phase, each author also classified each included article as containing only a subjective eHealth literacy measure (based on self-rated assessment), or as containing a performance-based eHealth literacy measure (based on practical skill or knowledge assessment).

After the third screening phase, 311 articles were retained for inclusion in this scoping review; 31 of which contained a performance-based measure of eHealth literacy. In cases of disagreement between the first and second author during the third screening phase, the third author was consulted and discussion ensued until consensus was reached. Throughout the entire screening process, all authors only excluded articles that very evidently did not meet the inclusion criteria. At this point, the first author read the bibliographies of the 31 articles containing a performance-based measure of eHealth literacy and highlighted titles that could meet the inclusion criteria of this scoping review. After discarding studies that had already been considered in the screening process, six new studies were selected and read in full by the first and second author. Of these six new studies, two were included in the scoping review, and both contained a performance-based measure of eHealth literacy. Thus, the total number of articles included in this scoping review is 313; 33 of which contain a performance-based measure of eHealth literacy. The scoping review process we undertook is summarized in Figure 1.

In the third step, we extracted data from each of the articles containing a performance-based measure and summarized it into a table. The first and second authors each re-read the 33 articles containing a performance-based measure of eHealth literacy and input information from each into a comprehensive table devised by all three authors. This table was later simplified into the headings outlined in Table 1, selected in the interest of providing a concise and relevant summary of findings in this paper. In judging evidence of validity, we considered three relevant types of validity: Ecological validity, criterion validity, and construct validity. Ecological validity describes the extent to which a measure represents or predicts behaviour in real-world settings[30]. In the context of measuring performance-based eHealth literacy, we considered a measure to be ecologically valid if it involved participants accessing real or authentically simulated websites to gather or evaluate health information. Criterion validity describes the extent to which the scores of a measure predict scores of another established measure of interest[30]. We stated that a measure had criterion validity if the authors found statistically significant correlations between scores of their objective eHealth literacy measure and scores from another relevant construct or validated measure (e.g., higher scores on this measure correlate with higher scores of another validated measure of computer-related skills). Construct validity describes the extent to which the scores of a measure reflect the actual phenomena intended by the measure[30]. This concept has some overlap with criterion validity, however for our purposes we stated that a measure had construct validity if significant differences were reported based on relevant lifestyle or demographic factors, or reported between groups who can be reasonably assumed to have different levels of eHealth literacy (e.g., those with more health-related education score consistently higher). We also noted whether the performance-based measurement tool described in the article was included in its full form, partial form (examples provided but some parts omitted), or not at all.

Results

Performance-based eHealth Literacy Measurement Tools

Our scoping review identified 33 peer-reviewed studies utilizing a tool to measure eHealth literacy that incorporated a performance-based aspect. Within these studies there were just two measures used more than once; Three articles utilized the eHealth literacy assessment toolkit (eHLA) created by Karnoe et al.[31], and another three utilized the Research Readiness Self-Assessment (RRSA) created by Ivanitskaya et al.[32]. We thus identified a total of 29 unique performance-based measures of eHealth literacy. It is notable that many of these studies use differing terminology to describe the construct of eHealth literacy, as outlined in Table 1; however, all studies included in this review measure constructs aligning with the definition of eHealth literacy originally proposed by Norman and Skinner[7] as judged by the authors of this scoping review.

We categorized the 29 unique performance-based measurement tools identified in this scoping review into five broad categories according to the structure of their main measurement technique. It should be noted that several of the measurement tools have components that fall within two or more of these categories; for instance the RRSA-h[33] measures declarative knowledge about the internet and has participants respond to questions that simulate using online health information. We describe the instrument design of each performance-based measurement tool in Table 1, such that readers can gain a fuller understanding of each tool as compared to the brief descriptions within the body of this manuscript.

Table 1. Summary of included articles containing a performance-based measure of eHealth literacy (Organized alphabetically by category)

Article	Terminology for Measured Construct	Participants / Context	Instrument Design	Health Topics	Evidence of Validity	Instrument Availability
Health-Related Questions Using The Internet						
Agree et al., 2015[34]	Online health literacy	323 participants aged 35-90.	Six health-related questions were answered by performing online searches on a computer, limited to 15 minutes per task. Answers were coded by two researchers for response accuracy (0 or 1) and specificity (0, 1, or 2) to form a score from 0-18.	Diet/nutrition guidelines, skin cancer, alternative medicine, vaccines, assistive health technology, over-the-counter genetic testing.	Construct validity demonstrated in that having a college degree and daily Internet use were positively associated with more successful health information searches, and the oldest age group had significantly lower success scores relative to younger participants. Criterion validity demonstrated in that higher health literacy was positively associated with success on some search tasks.	Partly.

Blakemore et al., 2020[35]	eHealth literacy	A massive open online course run eight times.	Participants responded to one health-related question and were asked to list the resources they used to inform that answer. Answers were coded according to the extent that quality resources were used in this question.	Epigenetics and Cancer.	Ecological validity via having participants access online resources to inform answers to a health-related question.	Yes.
Chang et al., 2021[36]	Searching performance	11 older adult participants.	Participants were asked to search for specific health information using a web browser on a computer. Search completion time and problem correctness were measured by researchers during live observation.	Vaccination for older adults, stroke, and angina.	Ecological validity via participants accessing real-world online health information to answer health-related questions.	No.
Freund et al., 2017[37]	eHealth literacy	79 older adult participants.	Participants were asked to answer six questions (three each for two health scenarios) while being given option of using links to online medical databases with relevant information.	Hypertension, high blood pressure, osteoporosis, breast cancer, prostate cancer.	Construct validity demonstrated in that test scores for the intervention group significantly improved. Ecological validity demonstrated in that participants responded to questions by referencing an online resource.	Yes.

Kordovski et al., 2020[38]	eHealth search skills	56 undergraduate students enrolled in psychology courses.	Participants were instructed to find the answer to five short questions and one vignette-based question using an internet browser of their choice. Participants' accuracy, time to complete each task, and total number of search queries were recorded.	Headaches/migraines, Lyme disease.	Criterion validity demonstrated in that long answer accuracy was associated with better performance on a learning and memory composite test. Construct validity demonstrated in that lower performance on short questions associated with lower maternal education and lower socioeconomic status.	Yes.
Loda et al., 2020[39]	Online searching behaviour	140 medical students.	Students were randomly assigned to use a specific search engine (Google, Medisuch, or free choice) and had ten minutes to fill in a worksheet outlining a diagnostic recommendation. To pass, students needed to give at least one of three recommendations matching a clinical expert.	Histamine intolerance.	None.	No.
Quinn et al., 2017[25]	eHealth literacy	54 adults.	Participants were presented six health questions, which they could use the internet to answer. Each answer	Various topics.	Criterion validity demonstrated as scores significantly	Yes.

			was scored as correct or incorrect, with a final sum score out of six.		correlated with health literacy.	
Sharit et al., 2008[40]	Internet search task performance	40 older adults.	Participants answered six health-related information problems, which they could use the internet to answer. Participants had 15 minutes to solve each problem, and problems were progressively more complex. Problems were scored as incorrect, partially correct, or correct by the researcher to create a task performance score. Scores were weighted by difficulty, and participants' completion times for each problem were also measured and factored into the score such that faster times indicate better performance.	Various.	Criterion validity demonstrated in that higher performance correlated with higher knowledge of the internet, as well as with measures of reasoning, working memory, and perceptual speed.	Yes.
Sharit et al., 2015[41]	Search accuracy	60 adults.	Participants were given a health scenario followed by a series of questions related to it, which they could answer using the internet. To assess accuracy, researchers	Multiple sclerosis.	Criterion validity demonstrated as search accuracy significantly correlated with reasoning, verbal ability, visuospatial	Yes.

			assigned a score for each question. Questions were weighted based on their difficulty (differed in complexity and number of subtasks).		ability, processing speed, and executive function.	
Van Deursen & Van Dijk, 2011[42]	Internet skills performance	88 adults.	Participants completed nine health-related assignments using a computer with high-speed internet. Assignment was deemed successfully completed if a correct answer was provided; deemed unsuccessful if no correct answer was provided in the given timeframe.	Various.	Ecological validity demonstrated via participants using unrestricted online searching to answer health-related questions.	Yes.
Van Deursen, 2012[43]	Internet skills performance	88 adults.	Participants completed nine health-related assignments using a computer with high-speed internet. Assignment was deemed successfully completed if a correct answer was provided; deemed unsuccessful if no correct answer was provided in the given timeframe.	Various.	Ecological validity demonstrated via participants using unrestricted online searching to answer health-related questions. Construct validity demonstrated as education was predictive for making incorrect decisions based on information found.	Yes.

Simulated Internet Tasks

Camiling, 2019[44]	Actual eHealth literacy (distinct from "Perceived eHealth literacy)	40 grade 10 students from public and private schools.	Participants completed 10 simulation tasks: two researchers used a rubric to rate eHealth literacy based on task performance.	Not specified.	Ecological validity via use of simulated internet research tasks resembling a realistic environment.	No.
Chan & Kaufman, 2011[45]	eHealth literacy	20 adult participants between 18-65 years of age.	Participants completed eHealth tasks while verbalizing their thoughts (think-aloud protocol). Researchers observed their performance, rated accuracy and denoted barriers based on video capture, audio recording, and notes taken during observation.	Comparing hospital ratings.	Ecological validity via participants actively completing health-related internet tasks in a realistic environment.	Partly.
Maitz et al., 2020[22]	Health literacy* * "Our understandin g of health literacy includes internet-based	14 secondary school students aged 12-14.	Participants were asked to give health-related advice in response to a short narrative text. Students were asked to take screenshots of all searches and webpages opened. Webpages were later classified by researchers as good, fair, poor, or bad.	Rhinoplasty, skin cancer.	None.	Yes.

	information literacy”					
Neter & Brainin, 2017[24]	eHealth literacy (performed)	88 older adults.	Participants completed 15 computerized simulation tasks assessing digital and health literacy skills. Tasks were rated as completed or not completed by the researcher upon reviewing recorded performance. Time needed to perform the task also recorded. Two researchers provided overall observational judgment on participants’ performance ranging from 1 (poor) to 5 (good). A third researcher evaluated if disagreements were present.	Various topics.	Construct validity demonstrated as lower performers had significantly fewer years of experience using the internet.	Yes.
Van der Vaart et al., 2011[26]	eHealth literacy	88 adults.	Participants completed nine health-related assignments using a computer with high-speed internet. Assignment deemed successfully completed if a correct answer was provided; deemed unsuccessful if no correct answer was	Various.	Ecological validity demonstrated via participants using unrestricted online searching to answer health-related questions.	Yes.

			provided in the given timeframe.			
Van der Vaart et al., 2013[46]	eHealth literacy	31 adult patients.	In Study 1, participants completed six health-related assignments which they could use the internet freely to complete. In Study 2, participants completed five health-related assignments using specific websites. Researchers coded whether the assignment was completed and whether help was needed. Additionally, the time needed to perform each assignment was recorded. The performance was ultimately scored as good, reasonable, or poor according to the skills participants used to execute the assignment.	Various.	Construct validity demonstrated through correlations of higher performance with higher education.	Yes.
Witry et al., 2018[47]	eHealth task performance	100 adult COPD patients.	Participants completed a series of timed eHealth simulation exercises using a laptop computer and two different tablets. The time to complete each task was measured and used to	COPD.	Construct validity demonstrated as those who reported using video chat took less time than nonusers to complete most of the tasks.	No.

			indicate task performance, where faster times indicate better performance.			
Website Evaluation Tasks						
Kalichman et al., 2006[48]	Health information evaluation skills	448 adults who used the internet fewer than three times in the month before screening.	Participants rated two pre-selected web pages, one from a medical association and one with scientifically unsupported claims, on five dimensions of website quality. A larger difference in scores indicates higher health information evaluation skills.	HIV/AIDS Treatment.	Construct validity demonstrated in that those receiving internet skills training had better discrimination.	Yes.
Mitsuhashi, 2018[49]	eHealth literacy evaluation skills	300 adult participants.	Participants were shown a search engine results page with five websites and asked which should be viewed first. The list included two commercial websites, two personal healthcare websites, and one government website. Participants choosing the government website were assigned one point, others were assigned zero points.	Not specified.	Construct validity demonstrated in that evaluation skills improved significantly in an e-learning intervention group compared to control group.	No.

Schulz et al., 2021[50]	Health literacy	362 adults.	Participants rated two health information websites (one high quality and one low quality) using three seven-step semantic differential scales. As well, participants were asked to choose beneficial depression treatments from a list of relevant and non-relevant treatments.	Depression treatment.	Criterion validity demonstrated in that those with high health literacy and accurate recognition of low-quality website demonstrated good judgment for depression treatment.	Partly.
Trettin et al., 2008[51]	Website evaluation	142 high school students.	Two measures: One brief two-item pre-test of knowledge about how to evaluate a website. Second, participants ranked two different websites (assigned to students from a list of twelve) using six credibility factors, from a score of 1 (very bad) to 5 (very good).	Not specified.	Ecological validity demonstrated in that participants ranked authentic health-related websites according to their credibility.	Yes.
Xie, 2011[52]	e-Health literacy	124 older adults.	Participants were asked to evaluate the quality of 20 health websites; 10 selected from the Medical Library Association's recommended sites and 10 from a commercial search engine. Each correct assessment received one	Not specified.	Construct validity demonstrated as scores improved after an educational intervention.	No.

			point; incorrect or uncertain assessments received zero points.			
Knowledge Of The Online Health Information-Seeking Process						
Hanik & Stellefson, 2011[53]	E-health literacy	77 Undergraduate health education majors.	RRSA-h was used, which is a questionnaire that tests participants' declarative knowledge of concepts, skills, and thinking strategies related to using the internet to find health information.	Various.	Demonstrated in study by Ivanitskaya et al. (2006).	No.
Hanna et al., 2017[54]	eHealth literacy	165 adult dental patients.	Participants were asked to circle online health information quality seals they recognized, and to report purpose of one circled figure.	Third molar knowledge.	Criterion validity demonstrated in that eHEALS scores correlated with the dental procedural online information-seeking measure. Construct validity demonstrated in that online dental procedural information seeing was significantly associated with educational attainment and dental decisional control preference.	Yes.

Ivanitskaya et al., 2006[55]	Health information competency	400 college-aged students.	RRSA-h was used, which uses a quiz to assess declarative and procedural knowledge related to online health information-seeking.	Various.	Ecological validity demonstrated in that some questions had participants access real health-related websites to assess their credibility.	No.
Ivanitskaya et al., 2010[33]	eHealth literacy skills	1914 undergraduate and graduate students enrolled in health-related courses.	RRSA-h was used, which uses a quiz to assess declarative and procedural knowledge related to online health information-seeking. Proxy measure of critical judgment skills related to pharmacies also included.	Pharmaceuticals, various others.	Construct validity demonstrated in that evaluation skills positively correlated with number of earned college credits and being a health-related major.	Partly.
St. Jean et al., 2017[56]	Digital health literacy	19 adolescents.	Participants were given 13 questions related to searching for health information. Researchers analyzed responses using thematic analysis. No evident scoring system used.	Type 1 diabetes.	None.	Yes.
Van der Vaart & Drossaert, 2017[57]	Digital health literacy /	200 adults.	Participants completed a 28-item questionnaire. 21 items are self-report items,	Various.	None for performance-based items.	Yes.

	eHealth literacy		and 7 are performance-based items for which there is a correct answer.			
Health-Related Knowledge						
Holt et al., 2019[58]	eHealth literacy	246 adults, patients with diabetes, other endocrine conditions and/or gastrointestinal diseases.	Used eHLA performance tests (Tools 1 and 4). Tool 1 is a performance-based health literacy test based on an information leaflet; tool 4 is a performance test for knowledge of health and healthcare.	Various.	Construct validity demonstrated in that educational level was positively correlated with tool 4.	Partly.
Holt et al., 2020[59]	eHealth literacy	366 nursing students.	Used eHLA performance tests (Tools 1 and 4). Tool 1 is a performance-based health literacy test based on an information leaflet; tool 4 is a performance test for knowledge of health and healthcare.	Various.	Construct validity demonstrated in that graduate-level students scored higher than entry-level students, and performance on tools 1 and 4 were correlated with having at least one parent with experience in social or healthcare system.	Partly.
Karnoe et al., 2018[31]	eHealth literacy	475 adults used as	The eHLA consists of 7 tools, two of which are objective measures. Tool 1	Various.	None.	Partly.

		validation sample.	is a performance-based health literacy test based on an information leaflet; tool 4 is a performance test for knowledge of health and healthcare.			
Liu et al., 2020[60]	Digital health literacy	1588 adult participants.	Participants were provided five randomly selected items from a large online health information bank, and asked whether the information was right or wrong. Two of the items were designed to be relatively easy to judge accurately, two moderate, and one difficult. Participants scored 1 for each accurate judgment, and zero for being incorrect or unsure.	Various.	Ecological validity demonstrated in that online health information bank was generated from real online sources. Construct validity demonstrated as participants at high risk for misjudging health information had lower education level, poorer health, and used the internet less.	Partly.

Health-Related Questions Using The Internet

One of the most common types of performance-based measurement identified in this scoping review involved participants answering health-related questions using the internet; questions for which responses could be scored according to correctness, completeness, and/or specificity. In the majority of studies using this assessment method, participants were allowed open access to the internet to inform their answers. An exception was a study by Freund et al.[37], in which participants were provided expert-checked links to helpful resources they could choose to use for answering health-related questions. In addition to the correctness of participants' responses, some researchers additionally factored completion time into participant scores, such that faster completion time indicated greater proficiency[40,41]. Chang et al.[36] similarly considered faster completion times indicative of better online search performance, provided the responses were correct. The health questions posed in these measurement tools ranged from encompassing several diverse topics to being focused on one topic in depth. For example, both Agree et al.[34] and Quinn et al.[25] asked participants about six diverse health topics, while Kordovski et al.[38] and Loda et al.[39] asked participants to perform one in-depth medical diagnosis relating to symptoms of Lyme disease and histamine intolerance, respectively.

An advantage of eHealth literacy measurements where participants use the internet to answer health-related questions is that participants can be assessed without the need for researcher observation and/or video recording, except in cases where completion time is additionally factored into scores. With these measurement tools, participants' responses to questions were graded by one or multiple researchers according to a pre-determined rubric. The majority of measurement tools in this category coded responses as simply correct (1 point) or incorrect (0 points); however, Agree et al.[34] also examined specificity (on a scale from 0-2 points) and Kordovski et al.[38] gave partial credit (1 out of 2 points) for coming close to the correct response by diagnosing something similar to Lyme disease. In contrast to considering response correctness, Blakemore et al.[35] gauged participant's eHealth literacy skills based on whether they included a "detailed list of resources," had "written about using resources," or had no reference to online health resources in their response to a health-related question.

Simulated Internet Tasks

Another common type of performance-based eHealth literacy assessment identified in this scoping review involved online information-seeking simulations, where participants' online behaviour was observed (either in real time or via recording) and assessed for proficiency by researchers. Proficiency was determined by assessing whether participants were able to complete a set of tasks, and many went further by also assessing the degree of efficiency and/or "correctness" they exemplified throughout each simulated task. For example, in a study by Van Der Vaart et al.[26], participants' task performance was simply coded as successful or unsuccessful, depending on whether the participant accomplished the end result of the task (e.g., adding a specified website as a bookmark, downloading a specific image). Whereas in a study conducted by Camiling[44], a rubric was developed and utilized to rate participants' proficiency while observing them completing 10 health-related tasks on an internet-connected computer. Similarly, Neter and Brainin[24] viewed recordings of participants completing 15 simulation tasks on an internet-connected computer and rated each task on whether it was completed and additionally on the quality of task performance from 1 (poor) to 5 (good). Video and/or audio recording were commonly used to record participants' actions and thoughts in simulation-based measurement tools, with the notable exception of Maitz et al.[22] who had participants record screenshots of the websites they visited.

eHealth literacy assessments based on simulated internet tasks tended to be the most time consuming for participants; Neter and Brainin's[24] 15 simulation tasks took about 90 minutes for each participant to complete, and Van Der Vaart et al.'s[46] five or six simulation tasks took an approximate median time of 30 minutes for participants to complete. A notable exception is a study by Witry et al.[47] in which the assigned eHealth simulation tasks were far simpler and could be completed in one minute; however, it should be noted that participants' completion time was the only metric used to gauge participants' eHealth literacy in this study. It also stands to reason that evaluating the proficiency of participants' recorded online behaviour is quite time consuming for researchers, as compared to assessment methods scored based on correct or incorrect responses to questions. In studies conducted by Chan and Kaufman[45] as well as Van Der Vaart et al.[26], researchers factored in correctness of responses in addition to researcher-observed performance to gauge participants' eHealth literacy, combining task simulation with the "health-related questions using the internet" methods previously discussed.

Website Evaluation Tasks

A third prominent type of performance-based eHealth literacy assessment identified in this scoping review involved participants evaluating the quality of health-related websites. In studies conducted by Kalichman et al.[48], Schulz et al.[50], and Trettin et al.[51], participants rated two different websites on five, seven, and six dimensions related to their credibility, respectively. In each of these studies, the authors presented participants with one website of high quality and another of low quality, and participants' eHealth literacy was determined based on whether they rated the websites accordingly (with a larger difference between high- and low-quality website ratings indicating greater proficiency).

Deviating from the structure of these studies but still related to evaluating website quality, Mitsuhashi[49] had participants select which website they should view first from a search results page with five options (two commercial websites, two personal healthcare websites, and one government website), in which participants who selected the government site were said to have proficient evaluation skills. Xie[52] collected twenty websites to present to participants, ten from a commercial search engine and ten from a medical association's recommended websites, and had participants assess each website as high or low quality. Correct assessments earned participants one point, whereas incorrect or uncertain assessments earned zero points, for a maximum score of twenty.

Participants rating the quality of real health-related websites carries significant ecological validity in terms of participants' knowledge of how to recognize signifiers of credible health information online; however, in contrast to the simulated internet task measurement tools, these tools do not require participants to form queries nor to extract information to apply to health-related problems. While evaluating the credibility of an online source is undoubtedly a pivotal component of eHealth literacy, it does not encompass all components of eHealth literacy as defined by Norman and Skinner[7].

Knowledge Of The Online Health Information Seeking Process

Distinct from measurement tools where participants demonstrate eHealth literacy skills through task completion or by correctly answering health-related questions using the internet, other tools tested participants on their knowledge of procedural internet skills and information-seeking strategies to gauge their eHealth literacy. The most used tool in this category is the Research Readiness Self-Assessment (RRSA), a tool first developed by Ivanitskaya et al.[32] and later tailored to health information specifically (the RRSA-h)[55]. The RRSA-h uses multiple choice and true/false questions to assess participants' declarative knowledge of online health information seeking, as well as some interactive problem-based exercises to assess elements of their procedural knowledge. Ivanitskaya et al.[33,55] as well as Hanik and Stellefson[53] used this measure to assess eHealth literacy skills in undergraduate and graduate students. The RRSA takes approximately 30 minutes on average to complete.

In contrast to this relatively long measure, Hanna et al.[54] used just one item to gauge participants' ability to recognize high-quality online information by asking them to circle online health information quality seals that they recognized from a set of nineteen images. Additionally, participants were asked to explain the purpose of one of the images they circled. Researchers analyzed whether participants were able to identify one or more real quality seals, as well as whether they could identify that the image was used to signify credibility. Van Der Vaart and Drossaert[57] used seven performance-based multiple choice quiz items to gauge seven dimensions of participants' eHealth literacy skills, which were added to supplement a subjective measure of eHealth literacy. Finally, in this category, St Jean. et al.[56] devised a written assignment where children advised a fictional peer about using the internet to find information about Type 1 diabetes through 13 open-ended questions. The researchers did not use an evident scoring system to rate eHealth literacy skills of this population, but rather applied thematic analysis to characterize the eHealth literacy skills of the participant group as a whole.

Quizzing participants on their knowledge related to eHealth literacy does not require recording or observing participants' online activity, nor necessarily providing participants with internet access, making it more accessible for some research settings in terms of resources and complexity than other tools mentioned previously. As participants are not actively carrying out online health information-seeking tasks with these measurement tools, they may not carry the same degree of ecological validity as measurement tools mentioned previously. However, basing eHealth literacy assessment on participants' knowledge of proficient online information-seeking skills still avoids many of the pitfalls related to subjective self-report measures of eHealth literacy.

Health-Related Knowledge

We identified two measurement tools that examined participants' baseline knowledge of health and their ability to apply that knowledge as an indicator of eHealth literacy. The most prominent tool is the eHealth literacy assessment toolkit (eHLA) devised by Karnoe et al.[31], which is composed of seven distinct measurement tools. Tools 1 and 4 within this set are performance-based measures that assess functional health literacy and participant knowledge of health and disease, respectively. The performance-based aspects of this tool (as well as its subjective tools) have also been used by Holt et al.[58,59] to measure eHealth literacy in medical outpatients and nursing students.

Liu et al.[60] also created a performance-based eHealth literacy measurement tool that assesses participants' health knowledge. In their study, the authors generated a 310-item bank of examples of online health information, which included labels of "easy," "moderate," and "difficult" items. Participants were randomly assigned five items (two easy, two moderate, one difficult) and were asked to rate the information as correct, incorrect, or unsure. Participants were given one point for accurately identifying information as correct or incorrect, and zero points otherwise, for a score out of five representing their eHealth literacy.

In these two eHealth literacy measurement tools, there are no components that directly assess computer literacy in a performance-based manner, nor do they contain performance-based components related to actively seeking health information (e.g., forming a query, selecting a source). We have included them in this scoping review since the authors themselves define these as measures of eHealth literacy (and it should be noted that the eHLA includes subjective measurements that touch upon computer-related components of eHealth literacy). However, judging solely their performance-based components by Norman and Skinner's[7] definition of eHealth literacy, these measures may be more accurately characterized as partial measures of the construct.

Prevalence of Performance-Based eHealth Literacy Measurement Tools

Of the 313 studies included in this scoping review, we identified 33 which used a performance-based measurement tool, representing 10.5% of our sample of the literature. We identified 280 additional studies that utilized measures of eHealth literacy that only incorporated subjective or self-rating aspects, representing 89.5% of our sample of the literature. Additionally, it is notable that 210 of the 313 studies reported using eHEALS in either its original form or translated to another language. Our findings indicate that research conducted on eHealth literacy presently has a strong tendency to rely on self-rated perceptions of eHealth literacy rather than assessing actual ability.

Discussion

The primary purpose of this scoping review was to identify and describe tools that measure eHealth literacy based on objective performance (as opposed to subjective self-rating). We identified 29 such measurement tools, of which only two had been used in more than one peer-reviewed study as of the date of our search. These measurement tools were the RRSA-h[33], which is an online quiz measuring declarative and procedural knowledge related to online health information-seeking, and the eHLA toolkit[31], which assesses eHealth literacy through seven distinct tools, of which two are performance-based. It is noteworthy that the two performance-based tools within the eHLA do not touch upon computer- or internet-specific skills or knowledge, and as such not all aspects of eHealth literacy are measured in a performance-based fashion. The same critique may be applied to the measurement tool created by Liu et al.[60] who similarly do not directly address computer literacy or media literacy in their performance-based assessment tool.

The second purpose of this scoping review was to characterize the prevalence of performance-based eHealth literacy measurement tools amongst the literature in contrast to subjective measurement tools. Our findings indicate that the vast majority of research conducted on eHealth literacy currently relies on self-rated perceptions of eHealth literacy rather than assessing actual ability. This is concerning considering the limited utility for this short self-report measure to predict performed eHealth literacy, as indicated by a significant body of literature (e.g., Maitz et al.[22]; Neter & Brainin[24]; Quinn et al.[25]; Stellefson et al.[21]; Van Der Vaart et al.[26]). If researchers are interested in gauging participants' true ability to locate, evaluate, and use online health information, more efforts should be made to incorporate performance-based measurement tools of eHealth literacy, such as those identified in this scoping review.

Another notable finding of this scoping review is that of the 29 unique eHealth literacy measurement tools with performance-based components identified, only two had been used in more than one peer-reviewed study at the time of this research. This comes in stark contrast to the prevalence of eHEALS, which we found at least 210 studies having used in various contexts and languages. This could be due in part to several of the articles not including full versions of their performance-based instruments, making it challenging for other researchers to replicate these measures in other projects. Another implicit challenge to creating a performance-based eHealth literacy measure which may be adopted for widespread use is the changing state of scientific consensus on health-related topics, meaning that ‘correct’ answers to health-related questions may need to be updated over time. For example, dietary guidelines have changed substantially in the past few decades as they have been updated based on our growing scientific knowledge[61,62]. As well, health-related topics can differ substantially in relevancy or saliency between different populations, meaning a performance-based eHealth literacy measure effective for one population may not be as useful for another. For example, Loda et al.[39] designed a performance-based measure for use by medical students where they needed to produce a histamine intolerance diagnosis on par with a clinical expert using the internet for research; a task that is likely beyond the abilities of typical users without comparable existing medical knowledge.

Judging these performance-based measurement tools by the definition of eHealth literacy proposed by Norman and Skinner[7], the tools with the greatest perceived ecological validity include those having participants answer health-related questions using the internet and those having participants engage in simulated online health-related tasks. These measurement tools evaluate participants’ online health information-seeking abilities in settings similar to those they encounter when seeking information on their own computers. The time-consuming nature (for both participants and researchers) and the equipment needs of these measures present significant barriers to their usage. Efforts to streamline some of these measurement tools to strictly necessary components could assist with broader usage. One example of a concise measure is offered by Witry et al.[47] who created a set of simple eHealth simulation tasks that could be completed in under one minute, however it should be noted that this measure assesses one’s ability to navigate an eHealth platform more so than to actively seek health information online. While considering the challenges to using performance-based eHealth literacy measures, researchers should also weigh the major advantages of these tools in producing a more accurate depiction of performed eHealth literacy as compared to short self-report measures.

One glaring absence across most performance-based measures of eHealth literacy is any mention of social media. In discussing the modern utility of eHEALS, Norman[63] noted that the shifting nature of the internet towards everyday users routinely contributing information online, as opposed to only accessing it, necessitates modifications to existing measurement tools to maintain validity. Consumers are more frequently turning to social media platforms with health-related queries, where they stand to gain social and emotional support from peers whilst gaining crowdsourced wisdom related to their health problem[64]. The validity and trustworthiness of information quality on these platforms has been flagged as a major concern[65]; however, public health organizations have also utilized these engaging platforms to distribute high quality and up-to-date information[66,67]. Acknowledging that users are able to gain useful and accessible health information using social media, more eHealth literacy measurement tools should incorporate these platforms into their assessment. One example of an assessment tool with a social online component is by Van Der Vaart et al.[46], where participants were asked to demonstrate interacting with a health care rating website and peer support forum, for which their proficiency was assessed based on independent task completion and overall task performance. Given the prominence of social media in today's online informational landscape, future performance-based measures of eHealth literacy should consider assessing participants' abilities to identify credible health information on social media platforms.

Limitations

This study presents with a few notable limitations. This scoping review only considered peer-reviewed journal articles published in English, which may present bias into our findings. As well, it is possible that we missed including studies that evaluated skills under the umbrella of eHealth literacy, but that did not describe this using any of the terminology in our search protocol. We did locate studies using terms such as “Health information evaluation skills” [48] and “Online searching behaviour” [39] through our search protocol, indicating some ability to detect studies deviating from our search terms. Finally, it should be noted that the evidence of validity provided in Table 1 provides only a limited surface-level judgment of three types of validity (criterion, construct, and ecological validity) based on the evidence presented in each article. It could very well be the case that the authors have additional evidence of validity that we did not recognize as falling within these types of validity, or that did not make it into their published articles.

Conclusions

This is the first literature review that specifically identifies objective performance-based measurement tools of eHealth literacy, in contrast to subjective self-report measurement tools. We identified 29 unique measurement tools of eHealth literacy with performance-based components, used in various populations and covering various health-related topics. In order to better establish the utility and validity of performance-based measurement tools of eHealth literacy, scholars looking to incorporate performance-based measurement of eHealth literacy into their research should look to utilize and build from some of these existing measurement techniques rather than producing their own. In contexts where research participants can be provided a computer with internet access, measures from the ‘Health-related questions using the internet’, ‘Simulated internet tasks’, or ‘website evaluation tasks’ categories of this scoping review may offer ecologically valid options for assessing eHealth literacy. In contexts where providing such equipment may not be feasible, measures from the ‘Knowledge of the online health information-seeking process' category may offer a simpler performance-based eHealth literacy assessment tool that still alleviates strict reliance on participants' ability to gauge their own skill level.

Additionally, to the best of our knowledge, this is the first literature review that quantifies the approximate prevalence of performance-based versus subjective measurement of eHealth literacy amongst the literature broadly. Amongst peer-reviewed scholarship, eHealth literacy assessment is predominantly conducted using subjective self-report measurement techniques. Performance-based measures of eHealth literacy are likely to provide a far better picture of how proficiently people find, evaluate, and utilize online health information. As such, researchers should consider using more objective measures of eHealth literacy such as those identified in this scoping review.

Conflicts of Interest

None declared.

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Bridging Text II

Study 1 described a systematic scoping review that identified 29 unique existing performance-based eHealth literacy measurement tools and summarized common characteristics of such tools. The table contained within this manuscript provides a useful roadmap to direct researchers toward existing eHealth literacy measurement tools based on testing demonstrable skills or related knowledge. Additionally, in the analysis of 313 articles that measured eHealth literacy, I found only 33 (10.5%) made use of a performance-based measure of eHealth literacy. With the internet representing a dominant driver of health discourse amongst the public, this is a key finding to highlight that current scholarship in the area may be falling short by relying on convenient self-report measures to assess online health information-seeking skill. Given the large proportion of existing eHealth literacy research that has made use of self-report measures, I thought it especially prudent to investigate the elements of online health information-seeking behaviour that may be reasonably predicted by self-report. This leads to the purpose of Study 2, which was to examine the relationship between perceived eHealth literacy and online health information-seeking behaviour during an unrestricted internet search task. I conceptualized the methodological approach of this study with the desire to leverage the affordances of eye-tracking technology to analyze online information-seeking behaviour (given this was a research instrument made newly accessible to me by Dr. Lindsay Duncan's Healthy Living Lab).

Study 2

What Does Self-Reported eHealth Literacy Tell us About Online Health Information-Seeking Behaviour?: An Eye-Tracking Study.

Bradley Crocker, Emily V. Pike, Lindsay R. Duncan

Department of Kinesiology and Physical Education, McGill University, Montreal, Canada

*Corresponding author
Bradley Crocker
Department of Kinesiology and Physical Education
475 Pine Avenue West, Montreal, QC, H2W 1S4
bradley.crocker@mail.mcgill.ca

Manuscript currently in preparation to be submitted for publication.

Abstract

Ideas and beliefs about health-related topics are shaped from various sources, but above all the internet continues to play an increasingly prominent role in people's health information-seeking process. eHealth literacy refers to one's capacity to locate, comprehend, and evaluate online health information; an important skill for those using the internet to inform health-related decisions. The vast majority of eHealth literacy literature has used self-report assessment techniques, which rely on participants' awareness and accurate assessment of their own abilities. The purpose of this study was to observe relationships between self-reported eHealth literacy and online health information-seeking behaviour in young adults during an unrestricted internet search task. We conducted a mixed-methods comparative analysis with screen-recording, eye-tracking, and retrospective think-aloud interview data collection methods to quantify 21 aspects of participants' health information-seeking behaviour while they searched the internet unrestricted for 15 minutes to learn about 'immune boosting'. Regression analyses were conducted to detect correlations between eHEALS scores and behaviour variables. Overall, perceived eHealth literacy did not significantly predict key behaviours such as time spent in any information-seeking stages (query formulation, source selection, content navigation, verification), time spent evaluating sources, or average reliability of websites accessed. Our findings did reveal significant differences in source preference, with those reporting higher eHealth literacy preferring to access and spend more time reading scientific research articles, and those reporting lower eHealth literacy preferring to access and spend more time reading health organization and government websites. These findings suggest that perceived eHealth literacy may not be a strong indicator of actual online health information-seeking proficiency. Future research should strongly consider performance-based measures of eHealth literacy that may

provide more accurate insights into users' ability to identify and evaluate trustworthy health information online.

Introduction

Individuals form beliefs, make decisions, and enact behaviour based on what they perceive to be high-quality and relevant information (Fishbein & Ajzen, 2010). When it comes to health and wellness-related topics, research indicates the internet is a popular source of information; especially for educated young adults (Adamski et al., 2020; Jacobs et al., 2017; Smith, 2011). The internet provides affordances that are effectively irreplicable by other health information resources (such as physician visits), including 24-hour access from the comfort of one's own home, immediate response to queries, the ability to inquire anonymously, and potentially at no cost (Lee & Lin, 2020). Some research has shown cases where online information is deemed more credible by patients than physician diagnoses, which can lead to seeking second opinions, nonadherence with treatment plans, and self-medication (Gualtieri, 2009; Sood et al., 2019; Tan & Goonawardene, 2017)). While the internet has the potential to benefit public health through widespread access to up-to-date health information, it may prove concerning in many instances given the prevalence of misleading, inaccurate, and unsubstantiated health information permeating online spaces (Daraz et al., 2019; Kitchens et al., 2014). Among the most concerning examples is online misinformation related to alternative cancer therapies (Delgado-López & Corrales-García, 2018), which has been suggested to contribute to a statistically significant decrease in survival among patients with curable cancers (Johnson et al., 2023). Online anti-vaccine rhetoric, which exploded during the recent COVID-19 pandemic but existed before and has persisted since (Carpiano et al., 2023), has also been suggested to contribute to hesitance towards life-saving vaccines (Moran et al., 2016).

Online health misinformation is not isolated to medical treatments; preventive medicine and wellness-related topics are also known for especially high prevalence of online sources featuring pseudoscientific theories and scientific claims lacking rigorous evidence. Distinct from medical information that generally pertains to explaining and solving an acute symptom or condition, wellness culture is largely centered around the constant pursuit of self-optimization or self-mastery through holistic approaches, such as nutrition, fitness, and lifestyle regimens (Baker, 2022). Large contingents of the wellness industry position maintaining good health as an individual responsibility which can be enhanced through marketable, but often unfounded, solutions like supplements, superfoods, cleanses, or detoxes (Baker, 2022). One example of this is 'immune boosting', which describes methods by which one can enhance or fortify their immune system against pathogens in their environment. Although research investigating how lifestyle factors may improve immune system function is an interesting and emerging field, to date vaccination is the only rigorously evidence-based approach endorsed by medical organizations (Cassa Macedo et al., 2019). Despite this, other 'immune boosting' techniques and supplements, such as supplementing one's diet with garlic, ginger, or mushrooms, are frequently portrayed online as beneficial (Cassa Macedo et al., 2019; Rachul et al., 2020), clouding search engine results for 'immune boosting' with sources of highly variable quality (Wagner et al., 2020).

Given that so many people use the internet as a primary source of health information, and yet many arrive at very different understandings of what constitutes healthy choices, the online health information-seeking process is evidently not identical between users. Researchers have employed a variety of models to conceptualize the discrete actions involved in the health information-seeking process. In a seminal review of health information-seeking behaviour research by Lambert and Loiselle (2007), the authors note models have arisen since the mid-1990s. In their summary of models they differentiate between those focusing on the information dimension (characteristics of information sought by individuals), or the method dimension (discretionary actions individuals use to obtain health-related information) (Lambert & Loiselle, 2007). When applying this lens to current models of internet-based health information-seeking behaviour, it is clear that most have focused on the information dimension, as well as broad determinants of online health information-seeking (Jia et al., 2021; Marton & Choo, 2012; Wang et al., 2021). Of the few online information-seeking behaviour models in the literature focusing on the method dimension, Marchionini's Information Seeking in Electronic Environments Model (Marchionini, 1995) is among the most descriptive with eight behaviours occurring in a relatively linear process: 1. Recognizing an information problem, 2. defining an information problem, 3. selecting a search engine, 4. formulating a query, 5. executing the search, 6. examining results, 7. extracting information, and 8. reflecting. Later models generally reinforce these basic stages of online information-seeking, but put more emphasis on the non-linear nature with which they often occur (Choo et al., 1999; Foster, 2004; Knight & Spink, 2008; Spink, 1997). For example, Foster (2004) described fluid transitions occurring between three core processes: Opening (e.g., keyword searching and browsing), orientation (e.g., information review), and consolidation (e.g., verifying information). For the purposes of this study, we have consolidated components from these theories into categories of query formulation (a user's decision of which search engine to use and which keywords to input), source selection (a user's strategy of selecting a source from a search engine results page), content navigation (a user's behaviours related to consuming information from a source), and verification (a user's tactics to gauge the relevance and trustworthiness of sources and content). Search engines may be considered an appropriate starting point to study online health information-seeking, as they are the most common means by which users actively seek health information on the internet (Jia et al., 2021; Maon et al., 2017; Sbaffi & Zhao, 2020).

In recognizing the significance of users' ability to retrieve high-quality health information online, Norman and Skinner (2006b) introduced the construct of eHealth literacy defined as "the ability to seek, find, understand, and appraise health information from electronic sources and apply the knowledge gained to addressing or solving a health problem" (p. 2). Concurrent with their publication coining eHealth literacy, Norman and Skinner (2006a) published the eHealth Literacy Scale (eHEALS), an 8-item questionnaire wherein each item is rated using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating a higher perceived eHealth literacy. In a systematic review of eHealth Literacy measurement tools, Karnoe and Kayser (2015) noted that this was the only tool used in multiple studies at the time of publication, and it remains by far the most widely-used instrument across the literature to assess eHealth literacy (Crocker et al., 2023; Griebel et al., 2018).

As a short self-report assessment, the eHEALS is attractive to healthcare providers looking to optimize clinical efficiency, and is convenient for researchers to minimize burden on participants. However, the brevity and self-report nature of this measure limits its usefulness at giving an accurate depiction of how well people critically engage with health information amidst a vast online environment of variable information quality. Ample literature indicates people have a tendency to overestimate their skill with computers (Merritt et al., 2005; Palczyńska & Rynko, 2020) as well as their abilities for locating and understanding information online (Eysenbach & Köhler, 2002; Mahmood, 2016). It is perhaps due in part to these limitations that studies have noted little association between eHEALS scores and demonstrated eHealth skills (Neter & Brainin, 2017; Quinn et al., 2017; Van Der Vaart et al., 2011). That is not to say perceived eHealth literacy is a meaningless construct; a systematic review and meta-analysis by Kim and colleagues (2023) indicated self-assessed eHealth literacy has a moderate correlation with healthy behaviour, and other studies have demonstrated correlations with higher rates of internet use for health information-seeking (Heiman et al., 2018; Tennant et al., 2015). Still, measures of eHealth literacy involving objective measurement of eHealth skills and abilities may be more promising at assessing how people behave online, but such measures seem to be seldom used among researchers to date (Crocker et al., 2023; Griebel et al., 2018).

Given the complex nature of the online information-seeking process, research methods that provide a more nuanced understanding of objective search behaviour are needed. In this study, we opted to record online health information-seeking behaviour using screen-recording and eye-tracking technology. Screen-recording allows researchers to observe what participants are visually exposed to throughout their search, while eye-tracking records participants' precise visual attention. The ability to measure participants' gaze on the screen may be pivotal to conceptualizing information-seeking behaviour, as it is well-established individuals often attend to only parts of the information they are presented (Petty & Cacioppo, 1986; Reyna & Brainerd, 1995), including in health-related contexts (see Schumann et al. (2012) for a review). Recording visual attention allows for a relatively objective (compared to self-report) understanding of what users notice and engage with throughout their search, providing a clearer picture of their information-seeking process than can be achieved with screen-recording alone. In the context of health information-seeking, most research has focused on search results page behaviour with particular focus on how the digital environment, such as a source's position on a search results page, impacts behaviour. For example, Eysenbach and Köhler (2002) used eye-tracking to demonstrate that users pay more attention and are more likely to click sources based on early positioning on a search results page, than on perceived trustworthiness of the source. In more recent eye-tracking work, it has been noted that contemporary users, who generally have more internet experience, tend to select more objective information over subjective or commercial sources (Kammerer & Gerjets, 2012), and consider relevance more important than search results page position when deciding what to click on (Schultheiß et al., 2018). Lopes and Ramos (2020) also applied eye-tracking methods along with performance-based measurement of health literacy to establish that those with superior health literacy are generally more attentive to search results pages and author information during online health information-seeking.

While measuring visual attention via eye-tracking can provide considerable insight into the information-seeking process, combining the method with qualitative data, such as verbal protocols, can improve external validity (Lewandowski & Kammerer, 2021; Orquin & Holmqvist, 2018). Muntinga and Taylor (2018) supplemented eye-tracking with gaze-cued retrospective think-aloud interviews, helping them establish that paying attention to URL addresses on a search results page resulted in better success identifying licensed (versus unlicensed) pharmacy websites, and this strategy was employed more consistently by users who reported having more internet experience. Chang and colleagues (2021) applied similar methods to study the indicators people use to evaluate health-related webpages and find that content-related indicators were consistently used more often than source-related indicators. These studies, and indeed all eye-tracking studies mentioned thus far, have utilized a purposefully designed internet-like simulation for participants to navigate rather than observing behaviour in an authentic online environment. While a controlled environment facilitates comparisons between participants' behaviour, limiting their decisions to a few webpages instead of the effectively endless expanse of the internet comes at the expense of ecological validity

(Lewandowski & Kammerer, 2021). This limitation was addressed in recent work by Chang (2022), who utilized eye-tracking in an open-internet environment to study associations between self-assessed eHealth literacy and online health information-seeking behaviour during four fact-finding internet tasks. Their findings demonstrate relatively minor differences in strategies employed by low- and high-eHealth literacy groups, however the author notes this may have been due to the relatively simplicity of the search task. In this way, Chang (2022)'s study provides a setting to meaningfully analyze information-seeking behaviour related to locating straightforward medical facts, but may have limited applicability for nuanced health and wellness topics for which there exist multiple perspectives and highly variable information quality online.

Purpose and Hypothesis

The internet is playing an increasingly influential role in how people inform their health-related decisions, and whether this benefits people depends largely on their ability to identify, evaluate, and apply trustworthy online health information. Research that has explored people's ability to do so has relied largely on self-report measurement, which may not be a strong predictor of actual ability in this domain. Quantitative methods, such as eye-tracking, may provide greater insight into the relationship between perceived eHealth literacy and performed behaviour; however, the majority of research in this domain has focused on the role of environmental factors rather than individual proficiencies. Just one study has examined relationships between perceived eHealth literacy and online health information-seeking behaviour using eye-tracking, which was in-part limited by using a series of simple fact-finding tasks. Therefore, the purpose of this study was to observe relationships between perceived eHealth literacy and online health information-seeking behaviour during an unrestricted internet search task exploring a complex and nuanced health topic. We hypothesized that perceived eHealth literacy would not correlate significantly with any aspects of observed online health information-seeking behaviour.

Methods

General Approach

This study is a mixed-methods comparative analysis to observe individual's online health information-seeking behaviour while searching for information on 'immune boosting', with the goal of comparing self-reported eHealth literacy to quantifiable behavioural outcomes.

Participants

We recruited 40 young adult participants (ages 18-35 years) from a Canadian university, which is a sample size consistent with studies employing eye-tracking in a non-randomized design (Kessler & Zillich, 2019; Mou & Shin, 2018). We purposefully recruited 10 men and 10 women with at least two years of post-secondary education completed in a health-related field, as well as 10 men and 10 women with at least two years of post-secondary education completed in a non-health-related field.

Data Collection

After providing consent for the study, participants first filled out a questionnaire to collect demographic information and to measure their perceived eHealth literacy. Demographic information collected from participants included their age, gender, race/ethnicity, socioeconomic status, years of post-secondary education, and subject studied in postsecondary education. Perceived eHealth literacy was measured using the aforementioned eHEALS questionnaire (Norman & Skinner, 2006a). We then provided participants with an 'immune boosting' prompt describing a friend getting frequent colds, and wanting to know about foods, supplements, and behaviours that might help them get sick less often. Based on their pre-existing beliefs, the participants wrote an initial answer to the prompt. Then, participants were sat in front of a laptop computer fitted with eye-tracking equipment and software and led through a brief calibration procedure. Participants were then given 15 minutes to navigate the internet to gather information to respond to the prompt. We decided this amount of time for each participant based on pilot participants reporting a reasonable level of information satisfaction within 15 minutes, and with consideration to our available resources to analyze all data generated in this study. Participants were asked to use Google as their only search engine, but otherwise could navigate the internet freely. Participants were permitted to write notes as they searched, if that was their preference, and were encouraged to actively gather information for the full 15 minutes. Throughout their search, eye-tracking and screen recording were used to collect data, and the researcher exited the room to prevent participants modifying their behaviour due to perceived surveillance. Following this 15-minute period, participants were permitted to add-to or modify their answer to the prompt.

After providing their answer, participants engaged in a retrospective, gaze-cued think-aloud interview with the first author. Participants were asked to talk through their thoughts, intentions, and experiences while reviewing a replay of their own eye-tracking data overlaying a screen recording of their search. The first author facilitated this process by asking probing questions and pausing the replay if needed for participants to adequately clarify their behaviour. These interviews were both audio- and screen-recorded, such that the resultant file consisted of the participants' speech overlaying a video of their eye-tracking behaviour. The qualitative data generated from these interviews was used to make sense of quantitative gaze patterns, leveraging the mixed methods nature of this study to arrive at a rich understanding of participants' actions and cognitions during the information-seeking process (Kuusela & Paul, 2000; Salmerón et al., 2017). Participants were not informed of the retrospective interview prior to their information-seeking session, to avoid this knowledge influencing their behaviour.

Data Processing

The data collected in this study included questionnaire data, textual prompt answer data, screen recording data, eye-tracking data, and gaze-cued retrospective think-aloud interview data.

Textual prompt answer data (including participants' responses before and after their searches) were initially processed by uploading photos of each handwritten response into text recognition software. A team of researchers then read through each handwritten response to ensure the text output matched what was physically written. After this process, the responses were coded for the presence of food-related, supplement-related, or behaviour-related recommendations, and assigned a score from 0-3 in each of these categories (0 representing no mention, 1 representing brief mention, 2 indicating that multiple modalities and/or specific brands or substances were mentioned, 3 indicating that specific dosages or routines were mentioned in addition to the requirements of scoring 2). Responses were additionally coded for the mention of vaccines (0 representing no mention, 1 representing any mention) and for mention of advice to seek professional medical advice (0 representing no mention, 1 representing any mention).

From screen-recording data, we output the time participants spent with each webpage on the screen and the URL addresses of each website visited. These URL addresses were then used by two researchers to independently rate the reliability of each website as a health information source using Section 1 of the DISCERN tool, a validated instrument for judging the quality of health resources (Charnock et al., 1999). Possible scores using this instrument ranged from 8 to

40; in instances where researchers scored four or more points apart, the researchers met to discuss and arrive at a consensus score. Otherwise, if within three points, the mean between the two researchers score was used to represent the website's reliability as a health information source. Concurrently, both researchers noted whether a source came from a reputed health organization or government website, a scientific research article, or a commercial website, and similarly met to arrive at a consensus judgment in instances where they disagreed.

From screen-recording and eye-tracking data, we output the time participants spent actively focused on each webpage and each source preview throughout their 15-minute search. A researcher reviewed each eye-tracking replay and made note of the first and last fixation indicated by the eye-tracker on every source preview and information source visually attended to by each participant. In instances where elements were revisited multiple times in a session, time periods were summed to generate total time spent viewing each element. If participants focused on a webpage prior to its content actually rendering on the screen, this time was not included. Cross-referencing these data with the website reliability ratings allowed for the generation of total time spent on low-reliability sources (those in the bottom third of all sources rated in this study) and total time spent on high-reliability sources (those in the top third of all sources rated in this study).

From gaze-cued retrospective think-aloud interview data, we output the time participants engaged in query formulation, source selection, content navigation, and verification behaviours during their 15-minute search. A researcher watched each interview recording, both video and audio components, and noted start and end times indicating periods of engagement in each behaviour type. Verification behaviours were further coded as either source verification (confirming the identity or qualifications of the author or website owner) or information verification (confirming the accuracy of claims by checking references or purposely cross-referencing claims with other sources). In a few instances participants were deemed to be engaging in multiple behaviours at once; for example, when attentively reading health information within a source preview on a search results page a participant could be said to be engaging in both source selection and content navigation behaviour. All time periods of each behaviour were summed to produce a total time spent in each behaviour type, with the exception of verification behaviour. Since the number of sources accessed was highly variable amongst participants (ranging from 1-26), we opted to calculate the proportion of verification behaviour instances to the number of sources accessed. For example, if six instances of verification behaviour were noted during the participants' search, and they accessed eight sources in total, the proportion would be six divided by eight, or 0.75.

Using the processed data described above, we also created variables to represent the proportion of each type of source (health organization / government agency webpage, academic research article, or commercial webpage) accessed by each participant by dividing the instances of visiting each type of source by the total number of sources accessed. For example, if participants accessed three health organization sources, and ten sources in total, the calculated proportion would be 0.3. We also created variables to represent the total amount of time participants spent on high- and low-reliability websites, which were deemed to be the top third and bottom third ranking reliability scores (respectively) of all sources assessed in this study. In this sample, this meant that high-reliability sources were those whose DISCERN reliability score was over 31 (on a scale of 8-40), and low-reliability sources were those less than 27.5.

Table 1
Summary of Online Information-Seeking Behaviour Variables by Data Collection Method

	Variable	Description
Screen Recording	Time spent on webpage	Seconds webpage is displayed on the screen.
	Searches conducted	Queries made with search engine.
	Source reliability	Mean score of two researchers rating the trustworthiness of each webpage.
Eye-Tracking and Screen Recording	Time spent engaging with each webpage	Seconds participants actively looking at the screen while the webpage is displayed.
	Time spent engaging with each source preview	Seconds participants actively looking at source preview on a search results page.
	Source preview component viewing	Whether participants fixated on URL, title, or description in each source preview.
Retrospective Interviews, Eye-Tracking, and Screen-Recording	Time spent on query formulation	Seconds participants spent considering and inputting search terms.
	Time spent on source selection	Seconds participants spent deciding what to click on a search results page.
	Time spent on content navigation	Seconds participants spent actively engaging with health information websites.
	Instances of verification behaviour	Number of times participants checked trustworthiness of a

	website's author or the information on it.

Data Analysis

All variables were initially tested for normality using the Shapiro-Wilk Test to determine the appropriate correlation analysis to perform on each. Pearson correlation coefficients are reported for normally distributed variables, whereas Kendall's Tau correlation coefficients are reported for non-normally distributed variables. All statistical analyses were performed using SPSS software.

Results

Our participants included 20 women and 20 men who ranged from 20 to 34 years of age, with a mean of 23.6 years (SD = 3.3) and had completed a mean of 3.9 (SD = 1.7) years of postsecondary education. Participants reported perceived eHealth literacy scores ranging from 20 to 40 (on a scale of 8 to 40) with a mean score of 29.6 (SD = 4.1); representing comparable but relatively high levels of confidence in their online health information-seeking proficiency compared to other adult populations (Chang, 2022; Quinn et al., 2017). In their 15-minute (900-second) allotted search time, participants spent a mean of 63.12 seconds (SD = 34.83) on query formulation behaviour, 98.53 seconds (SD=43.08) on source selection behaviour, and 468.32 seconds (SD = 119.66) on content navigation behaviour. Time not represented within these three categories of behaviour generally consisted of writing down information they had retrieved or just taking breaks from the task. During their sessions participants conducted an average of 6.15 searches (SD = 3.71) and spent an average of 1.93 seconds (SD = 0.66) viewing each source preview they considered, including an average of 2.94 seconds (SD = 1.41) viewing each source preview they ultimately clicked on. When it came to the components of each source preview, participants viewed URLs 65.6% of the time (75.1% for source previews they clicked on), viewed titles 82.3% of the time (98.3% for source previews they clicked on), and viewed source descriptions 34.0% of the time (44.7% for source previews they clicked on). Participants visited an average of 10.17 sources (SD = 4.91) throughout the 15 minutes, of which health organization or government agency websites made up 45.5%, scientific research articles made up 28.3%, and commercial websites made up just 1.2%. Websites that did not fall under any of these categories mostly consisted of encyclopedia websites and blogs. In their written responses to the 'immune boosting' prompt after 15 minutes of online information-seeking, participants put the greatest emphasis on behaviours (mean score of 1.95 out of 3), then foods (mean score of 1.65 out of 3), then supplements (mean score of 1.33 out of 3). Additionally, 35% of participants mentioned vaccination as a means of improving one's immune system, and 40% of participants recommended seeking professional medical advice.

Correlation analyses indicated very few statistically significant relationships between eHEALS scores and the online health information-seeking variables quantified in this study. Of the 21 behaviour-related variables tested, only 4 significantly correlated with levels of perceived eHealth literacy. Those who rated themselves as more eHealth literate spent significantly more time reading scientific research articles during the search task (0.335, $p = 0.004$) and scientific research articles made up a larger proportion of the sources they accessed (0.338, $p = 0.004$). Conversely, those who rated themselves as more eHealth literate spent significantly less time engaging with government or health organization websites (-0.321, $p = 0.005$) and these sources made up a smaller proportion of the sources they accessed (-0.379, $p = 0.016$). Rounding out the significant relationships, we unsurprisingly found those with two or more years of postsecondary education in a health-related topic rated themselves as being more eHealth literate (0.401, $p = 0.003$). No significant correlations were noted between eHEALS scores and time spent on query formulation, source selection, or content navigation behaviours, nor was any significant correlation found with average source reliability or time spent on reliable health information websites. We also did not find any significant correlations between eHealth literacy and broad emphasis on food, supplements, behaviours, vaccines, or seeking medical advice in participants' responses to the 'immune boosting' prompt.

Table 2

Correlations Between Observed Information-Seeking Behaviour and eHEALS

Variable	Correlation Coefficient	Significance (2-tailed)
Number of Searches	0.025	0.832
Number of Websites Visited	0.135*	0.407
Average Source Reliability	0.067	0.558
Low Reliability Source Screen Time	-0.149	0.195
Low Reliability Source Engagement Time	-0.178	0.124
High Reliability Source Screen Time	0.098*	0.546
High Reliability Source Engagement Time	0.032	0.779
Mean Preview Consideration Time	-0.048	0.673
Mean Clicked Preview Consideration Time	-0.074	0.512
URL-Checking Proportion	-0.048*	0.767
Title-Checking Proportion	0.019	0.870
Desc.-Checking Proportion	-0.045	0.690
URL-Checking Proportion When Clicked	-0.006	0.962
Title-Checking Proportion When Clicked	0.145	0.271
Desc.-Checking Proportion When Clicked	-0.116*	0.476
Query Formulation Time	0.018*	0.913
Source Selection Time	-0.064*	0.695
Content Navigation Time	-0.078*	0.633
Source Verification Behaviour	-0.141	0.222
Information Verification Behaviour	-0.060	0.633
All Verification Behaviour	-0.138	0.231
Proportion of Commercial Websites	-0.014	0.918
Commercial Website Engagement Time	0.015	0.977
Health Org. Website Engagement Time	-0.321	0.005**
Research Article Engagement Time	0.335	0.004**
Proportion of Commercial Websites	-0.014	0.918
Proportion of Health Org. Websites	-0.379*	0.016**
Proportion of Research Articles	0.338	0.004**

*Pearson Correlation Coefficient (otherwise Kendall's Tau Correlation Coefficient)
**$p < 0.05$
Desc.: Description; Org.: Organization

Table 3

Correlations between eHEALS and topics emphasized in participants' responses to the prompt.

Final Response Element	Kendall's Tau Correlation Coefficient	Significance (2-tailed)
Food	-0.003	0.979
Supplements	0.068	0.598
Behaviour	-0.189	0.152
Vaccines	0.015	0.909
Seek Medical Advice	0.011	0.934

Discussion

The purpose of this study was to observe relationships between perceived eHealth literacy, measured via the eHEALS questionnaire, and online health information-seeking behaviour, measured via screen-recording and eye-tracking technology. Generally, perceived eHealth literacy had very few statistically significant correlations with any of the behaviours quantified in this study, indicating little procedural difference in online health information-seeking between those with differing levels of confidence in their eHealth literacy. A substantial number of studies have indicated weak or nonsignificant relationships between eHEALS scores and demonstrated health information-seeking proficiency measured objectively (Neter & Brainin, 2017; Quinn et al., 2017; Van Der Vaart et al., 2011); this study extends upon this body of literature to deepen our understanding of this trend, demonstrating that users seemingly exhibit little behavioural difference in their online health information-seeking process according to self-perceptions of eHealth skills. As nearly 90% of studies measuring eHealth literacy utilize exclusively self-rating tools (Crocker et al., 2023), the evidence presented in this study supports calls to action for researchers to incorporate performance-based measurement tools of eHealth literacy into their work if they seek a reasonable estimation of participants' ability to locate relevant and trustworthy online health information.

The general lack of significant correlations aligns with a similar study conducted by Chang (2022) which involved fact-finding health information tasks, in that self-rated eHealth literacy did not have a significant relationship with query formulation behaviour, time spent on source selection, or verification behaviour. One notable difference in our findings relates to source preview components used by participants; Chang (2022) noted that both high- and low-eHealth literacy groups used source descriptions most, then low-eHealth literacy participants used URLs the second most while high-eHealth literacy participants used URLs the least of all components. Contrastingly, Muntinga and Taylor (2018) found that those who paid more attention to URLs on search results pages demonstrated the highest performance on an eHealth task, seemingly indicating higher eHealth literacy should align with increased focus on URLs. Amongst our participants, source descriptions were viewed the least of all components, and we found no difference in the frequency that certain source preview components were viewed based on eHealth literacy. This may be due to differences in assigned tasks; previous studies used tasks with distinct 'correct' answers which could potentially be located in sources' descriptions, whereas the question we posed our participants elicited a broader range of possible answers that motivated them to extract information from actual webpages rather than source previews. Another notable finding from Chang (2022) was that low eHealth literacy individuals tended to fixate more on search results pages whereas high eHealth literacy individuals tended to have more fixations on health information webpages. These findings somewhat conflict with earlier eye-tracking research that found those with higher health literacy were more attentive to search results pages (Lopes & Ramos, 2020). Using participants' total gaze time, we did not find significant differences in content navigation or source selection behaviours aligning with either of these previous trends, however this may be due primarily to differing methods of data processing.

We found a statistically significant positive relationship between eHealth literacy and time spent reading scientific research articles, as well as the proportion of scientific research articles to all sources accessed. Conversely, those with higher self-rated eHealth literacy spent significantly less time engaging with health organization or government health agency webpages, and these sources represented a significantly smaller proportion of all sources they accessed. Taken together, these results indicate that participants with more confidence in their eHealth literacy skills choose to access and read academic publications to obtain health information, while those with less confidence tend to lean more on webpages published by health organizations or government health agencies. This comes in contrast to findings from Chang (2022), who did not find significant difference in the types of sources accessed in adults with high and low perceived eHealth literacy, and comes in contrast to findings from MacKert and colleagues (2009) who noted that individuals with low health literacy tend to avoid government sources. It should be noted that the online health information source preferences noted in this study may be primarily a result of those with higher perceived eHealth literacy also tending to be those with postsecondary education in a health-related field, meaning they likely had formal training in understanding complex health-and research-related language used in scientific research articles. Additionally, it should be noted that this research was physically conducted within an academic institution, potentially biasing participants with high perceived eHealth literacy towards research articles to a greater extent than they would when information-seeking for their own purposes.

Limitations

This study presents with a few notable limitations. This highly educated population rated themselves as highly eHealth literate, and many received specific training in research methods and academic writing such that their information-seeking may not reflect that of the general population. In addition, though providing participants unrestricted internet access improved the ecological validity of this study, it also produced a less controlled, and thus less easily comparable information environment by which to compare the information-seeking behaviour of participants. Although many participants used similar search terms and there was significant overlap among sources accessed, no two participants went through identical journeys in their information-seeking process. Ample research has demonstrated that the information environment affects the information-seeking process irrespective of user-related skill (Kammerer & Gerjets, 2012; Lewandowski & Kammerer, 2021; Schultheiß et al., 2018), and so we cannot be certain the extent to which the changing environment between participants affected the outcome of this study.

We selected ‘immune boosting’ purposefully because it is a nuanced topic for which there is considerable variance in the quality of online health information that displays in most search results pages (Cassa Macedo et al., 2019; Rachul et al., 2020), allowing us to observe information-seeking behaviour within a somewhat tumultuous information environment. This deviates from Chang’s (2022) study exploring a similar research question with fact-finding tasks, and deviates from those utilized in performance-based eHealth literacy measures that have distinct correct answers (Crocker et al., 2023). This made it challenging to objectively assess the "correctness" of participants' answers to the prompt, but we deemed this acceptable since the focus of this study was on participants' information-seeking process rather than the end result. We still coded participants' responses to the prompt to determine whether there was differential emphasis on particular themes based on perceived eHealth literacy and found no significant correlations.

Conclusions

This study is the first to examine correlations between perceived eHealth literacy and online health information-seeking behaviour during a complex search task. Our findings indicate that the most frequently used measure of eHealth literacy – the eHEALS questionnaire – has limited utility as a proxy for observable online health information-seeking behaviour, particularly for topics with varied discourse online.

Future research should apply similar eye-tracking and retrospective think-aloud interview protocols to other health-related topics, and in populations with less postsecondary education to see whether self-assessed eHealth literacy provides a clearer picture of actual behaviour in these groups. We also encourage researchers to use these methods to test new or existing performance-based measures of eHealth literacy for correlative strength with observable online information-seeking behaviour, to firmly establish whether these more involved measurement tools provide worthwhile insight.

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Bridging Text III

In Study 2, I conducted a mixed-methods comparative analysis to investigate the relationship between self-reported eHealth literacy and observable online health information-seeking behaviour during a search task related to ‘immune boosting’. I employed screen-recording, eye-tracking, and retrospective think-aloud interviews to collect detailed data throughout each participant’s 15-minute search. I used an elaborate, multistep data analysis procedure, performed by a team of researchers, to produce 21 outcome variables relevant to online health information-seeking behaviour. Of the 21 variables, only 4 significantly correlated with levels of perceived eHealth literacy, and these 4 pertained to source preference rather than procedural information-seeking differences. In combination with the finding from Study 1 that a large majority of research assessing eHealth literacy has used exclusively self-report measurement tools, findings from Study 2 add urgency to the need for researchers to develop, or make use of existing, performance-based eHealth literacy measurement tools. To push forward our understanding of how personal factors or interventions might influence proficiency in online health information-seeking, eHealth literacy skills must be assessed with reasonable proxies for real-world behaviour.

It has been rigorously and plentifully demonstrated that inoculation messages have the potential to enhance participants’ ability to identify misinformation and to resist persuasion by it (Compton, 2024). It follows that inoculation messages could play a positive role in affecting participants’ online health information-seeking behaviour, especially relating to the process of identifying and selecting reliable sources. To the best of my knowledge, no research to date has investigated this relationship. So, to leverage the rigorous data and analysis methods applied in Study 2, I decided to add a second data collection for each participant to perform a randomized controlled trial of an inoculation message as described in Study 3. The purpose of Study 3 was to investigate how an inoculation message might alter online health information-seeking behaviour, when compared to those not exposed to an inoculation message.

Study 3

A Randomized Controlled Trial Examining the Effects of Inoculation Message Exposure on Online Health Information-Seeking Behaviour.

Bradley Crocker, Emily V. Pike, & Lindsay R. Duncan

Department of Kinesiology and Physical Education, McGill University, Montreal, Canada

*Corresponding author
Bradley Crocker
Department of Kinesiology and Physical Education
475 Pine Avenue West, Montreal, QC, H2W 1S4
bradley.crocker@mail.mcgill.ca

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Abstract

The internet is a popular means people use to inform themselves on health- and wellness-related topics due its accessibility and convenience. However, search engine results on these topics are often clouded with an abundance of misleading and unsubstantiated content. To benefit from the internet as a health information source, users must be proficient at identifying reliable websites and resisting persuasion by health misinformation. Inoculation message research has demonstrated that exposing users to contextualized forms of misinformation can improve their abilities to discern information veracity, even on topics unrelated to those covered in the intervention. However, there remains a significant gap in the literature concerning how inoculation message exposure might impact online information-seeking behaviour. The purpose of this study was to investigate how an inoculation message alters online health information-seeking behaviour in young adults. We conducted a randomized controlled trial with 40 university-educated young adult participants. Participants engaged in two 15-minute internet searches, on two different days, to answer prompts on wellness-related topics ('immune boosting' and 'cognitive enhancement'). A randomly selected half of participants was exposed to a 5-minute video inoculation message immediately prior to their second search. Online health information-seeking behaviour was recorded with screen-recording, eye-tracking, and retrospective think-aloud interviews. An elaborate data analysis method was applied to quantify 19 aspects of behaviour. As hypothesized, participants exposed to the inoculation message significantly increased their amount of time spent deciding which source(s) to select from search results pages, and their total time spent on source selection behaviour, as compared to the control group. Contradictory to our hypotheses, inoculation message exposure did not result in participants selecting sources with significantly higher average reliability ratings, nor did they

demonstrate significantly more instances of verification behaviour while reading webpages, as compared to the control group. This study is the first to observe significant changes in online health information-seeking behaviour in response to inoculation message exposure, carrying important implications towards future inoculation theory scholarship.

Introduction

The internet is becoming increasingly popular as a primary source for people seeking information on health- and wellness-related topics (Gualtieri, 2009). The internet offers many affordances making it more favourable than acquiring information from physicians or peers; online health information can be accessed 24 hours a day at little to no cost to the consumer, queries can be made anonymously, multiple viewpoints can be considered and compared, and all of this can occur from the comfort of one's own home (Lee & Lin, 2020). While such affordances position the internet to considerably benefit public knowledge and decision-making related to health and wellness, this may be complicated by a high prevalence of misleading and false information online (Kitchens et al., 2014). Given the tumultuous landscape of online health and wellness information, those venturing online must be vigilant in distinguishing trustworthy sources from websites offering unfounded advice, products, or services.

Most research relating to online health misinformation has thus far focused on medical misinformation (Krishna & Thompson, 2021; Wang et al., 2019), such as that relating to alternative cancer therapies (Delgado-López & Corrales-García, 2018) and anti-vaccine rhetoric (Carpiano et al., 2023). Less online misinformation research has focused on wellness-related topics, despite studies suggesting they are at least as commonly searched for (Jia et al., 2021), if not more commonly searched for (Xiong et al., 2021), than information pertaining to specific medical treatments or concerns online. Distinct from medical information that generally pertains to explaining and solving an acute symptom or condition, wellness information is largely centered around the constant pursuit of self-optimization or self-mastery through holistic approaches, such as nutrition, fitness, and lifestyle regimens (Baker, 2022). Large contingents of the wellness industry position maintaining good health as an individual responsibility, which can be enhanced through marketable, but often unfounded, solutions like supplements, superfoods, or detoxes (Baker, 2022). Rapid growth in the popularity of trends with scant clinical evidence to support their effectiveness, such as ‘detox cleanses’ or ‘essential oils’, has been largely attributed to campaigns of online health misinformation (Bossalini & Neiner, 2020; de Regt et al., 2020; Klein & Kiat, 2015). Dietary supplements represent an especially potent global market based on false or misleading claims largely focusing on preventing disease and “optimizing” the performance of the human body (Hys, 2020; Temple, 2010). In contrast to medicine, dietary supplements are also largely unregulated in terms of quality or efficacy assurance (Lam et al., 2022), and numerous studies have found incongruencies between ingredients listed on labels and those actually found within the product (Cohen et al., 2021, 2023; Crawford et al., 2020). Still, commercial entities in this sector are known to leverage celebrity sponsorship (Caulfield, 2017) and to use powerful narrative messaging techniques (Caulfield et al., 2019) to disseminate misinformation widely online where research indicates lies often spread faster than truth (Vosoughi et al., 2018). Wellness-related topics known for prevalence of false and misleading content online, driven in part by commercial interests and low regulatory barriers (Temple, 2010), provide fertile ground to study how people resist or uptake online health misinformation.

Since information on the internet can be effectively published by anyone, it falls upon users to determine whether the content they choose to access is relevant and reliable. In their systematic review of quality indicators for online health information, Sun and colleagues (2019) noted three broad categories: Source (type of website and identity of its owner), content (the information itself and how it’s framed), and design (appearance of the website and interactivity it affords). Past research has shown that source credibility plays a minimal role in how people rate the quality of online health information (Bates et al., 2006), despite it likely being a pivotal factor by which laypersons can hope to establish the reliability of online health information (Chi et al., 2020; Johnson, 2014). A large body of work by Pennycook and colleagues has demonstrated nudging users towards thinking about the accuracy of online content can profoundly reduce their willingness to share or engage with misinformation (Pennycook et al., 2020, 2021; Pennycook & Rand, 2019). This literature implies people have some innate ability to evaluate the validity of what they read online, and likely succumb to believing false and misleading information due more to inattention to credibility than lacking any necessary expertise (Pennycook & Rand, 2021). Increasing attention to trustworthiness during source selection as a means of improving resistance to online misinformation also presents the advantage of utility, irrespective of the specific topic of the false or misleading information at hand, in contrast to interventions that build resistance to specific claims or a specific topic. It has been firmly established within the literature that changing misinformed beliefs is a far more difficult task than fortifying users against misinformation before they get exposed (Chan & Albarracín, 2023; Ecker et al., 2022). Such interventions have largely been explored through the lens of Inoculation Theory.

Inoculation Theory, initially posited by (McGuire & Papageorgis, 1961), is based on an analogy between resistance to attitude change and resistance to contagious disease. In a similar way that bodies with little exposure to foreign contaminants develop minimal immunity, those with little exposure to counterarguments develop minimal resistance to attitude change (McGuire & Papageorgis, 1961). Just as one may protect their health by avoiding exposure to pathogens, one may protect their beliefs by avoiding exposure to argumentation; however, in the modern context where people are bombarded constantly with information, this is not a feasible strategy. Instead, akin to vaccination, a more promising approach to harden people against persuasive messaging may be to inoculate them through exposure to “weakened, defense stimulating forms of the counterarguments” (McGuire & Papegorgis, 1961, p. 327). The inoculation process involves two major components: a threat (participants are made aware that counter-attitudinal parties exist), and refutational pre-emption (participants are exposed to counter-attitudinal message and provided counterarguments and to help resist persuasion attempts) (WMcGuire, 1964a). A large volume of literature has found inoculation messages to be more effective at conferring resistance to persuasion than pro-attitudinal messaging in a variety of contexts, including for health-related topics (Banas & Rains, 2010; Compton et al., 2016). For example, Parker and colleagues (2012) found that reading an inoculation message featuring common persuasive techniques to engage in unprotected sex hardened the resolve of young adults against counter-attitudinal pressures to do so. Relating more specifically to deceptive misinformation, Mason and Miller (2013) found that having undergraduate students read an inoculation message made them more resistant to deceptive health claims used by some commercial food and supplement advertisers. The use of inoculation messages specifically to increase resistance against online misinformation is a relatively young field of research, and findings have been promising. (Wong & Harrison, 2014) found that exposing parents to inoculation messages related to human papillomavirus (HPV) vaccination improved their perceptions of vaccine safety and efficacy, and improved their self-efficacy to refute anti-vaccine messaging based on misinformation. In a similar study related to climate change science, van der Linden and colleagues (2017) found that inoculation messaging was effective at protecting attitudes against some of the most persuasive real-world forms of climate change misinformation identified by their participants.

While these studies are promising, scholars have pointed out that such interventions are limited in part by providing only topic-specific protection against misinformation, which is only marginally useful as they engage in online information-seeking on other topics (Roozenbeek & van der Linden, 2019). This may be attributed to inoculation interventions primarily utilizing passive refutation (participants being provided written passages summarizing counterarguments) rather than active refutation (participants developing their own counterarguments) (Banas & Rains, 2010; Compton et al., 2021). Roozenbeek and van der Linden (2019) utilized more active refutation techniques in a gamified version of inoculation messaging targeting 'fake news' relating to a salient topic at the time (the European refugee crisis). In this game, participants played the role of misinformation-spreader in which they actively select strategies and produce content to mislead the masses, receiving informational prompts throughout the game that note common misinformation cues. Through active engagement in the inoculation messaging this intervention was successful at reducing perceived credibility and persuasiveness of fake news articles related to the refugee crisis, and later the authors found the intervention to be effective at protecting individuals against a broader range of misinformation (published in a separate study) (Maertens et al., 2020). The exact mechanism by which inoculation messages improve broad resistance to misinformation have not been rigorously established, though scholars have posited that bolstered critical thinking directed towards information quality and source credibility stimulated by inoculation messages may contribute (Compton et al., 2021). Researchers have also suggested the "blanket of protection" against misinformation afforded by inoculation message exposure may be due to practicing the skill of counterarguing and familiarization with common logical fallacies (Cook et al., 2017, 2022; Ecker et al., 2022; Parker et al., 2012, 2016). Research methods with the capacity to examine precise changes in users' information-seeking behaviour stimulated by exposure to inoculation messages, in contrast to simply testing users' ability to distinguish true and false headlines or statements, may help to clarify the nuances of the inoculation process (Banas & Rains, 2010; Compton, 2024).

In order for any presented information to make an impact on users' beliefs, attitudes, or preferences, it is generally held that this information must first capture the users' attention, as attention to information is a primary step in decision-making (Orquin & Mueller Loose, 2013; Van Loo et al., 2018). Acknowledging the importance of attention on how users interpret information, eye-tracking research has generated recent interest because of its potential to provide precise and reliable insight into users' visual attention, perceptions, and decision-making processes, beyond what can be achieved by observation or self-report methods (Gwizdka et al., 2019; Lorigo et al., 2008). For example, Lopes and Ramos (2020) employed eye-tracking methods to establish that those with higher health literacy are generally more attentive to search results pages and author information during online health information-seeking. Combining eye-tracking with qualitative data, such as verbal think-aloud protocols, can improve the validity of eye-tracking research even further (Lewandowski & Kammerer, 2021; Orquin & Holmqvist, 2018). Muntinga and Taylor (2018) supplemented eye-tracking with gaze-cued retrospective think-aloud interviews, helping them establish that paying attention to URL addresses on a search results page resulted in better success identifying licensed (versus unlicensed) pharmacy websites, and this strategy was employed more consistently by users who reported having more internet experience. Using similar methods, Chang and colleagues (2021) found that people used content-related indicators more often than source-related indicators when evaluating health-related webpages. In the context of searching the internet for information on 'immune boosting', Crocker and colleagues (2024) used eye-tracking and think-aloud interviews to establish that the extent to which users consider themselves capable of finding and evaluating online health information exhibited very little correlation with time spent on any component of online information-seeking behaviour categories, including query formulation, content navigation, source selection, or information verification. In the present study, we codify online information-seeking behaviour using the same four categories, which overlap conceptually with other models of online information-seeking (Crocker et al., 2024). To date, inoculation message research has yet to make use of eye-tracking methods to capture nuance in how users' information-seeking behaviour may be altered after exposure.

Purpose

The purpose of this study was to compare how an inoculation message changes online health information-seeking behaviour of young adults compared to those not exposed to that inoculation message. Specifically, we sought to identify if the group exposed to the inoculation message demonstrated favourable behaviour changes related to evaluating the reliability of health information during online information-seeking, evidenced by higher attention given to source selection and verification behaviours while engaging in an online health information-seeking task.

Hypothesis

We hypothesized that individuals exposed to the inoculation message (compared to the control group) would spend more time on source selection behaviour (H1a); more time viewing each source preview they considered (H1b), and more time viewing each source preview they considered and ultimately clicked (H1c). We also hypothesized we would observe more instances of verification behaviour per webpage visited in individuals exposed to the inoculation message (compared to the control group) (H2a), particularly related to the identity and trustworthiness of a webpage's author (H2b). Finally, we hypothesized individuals exposed to the inoculation message (compared to the control group) would select sources with higher average reliability ratings (H3a), would spend more time engaging with high quality sources (H3b), and would spend less time engaging with low quality sources (H3c) during their online information-seeking session.

Methods

General Approach

This study is a randomized controlled trial to study whether participants' online health information-seeking behaviour could be modified by exposure to a video inoculation message. Participation in this study involved two sessions; the first to get baseline data of participants' online health information-seeking behaviour, and the second to apply the intervention (unless assigned to the control group) and reassess participants' online health information-seeking behaviour. The first visit described in this study consists of what has already been described in Study 2 of this dissertation.

Participants

We recruited 40 young adult participants (ages 18-35 years) from a Canadian university; a sample size roughly consistent with other published research employing eye-tracking to study information-seeking (Kessler & Zillich, 2019; Muntinga & Taylor, 2018; Tsai & Wu, 2021). We purposefully recruited 10 men and 10 women with at least two years of post-secondary education completed in a health-related field, as well as 10 men and 10 women with at least two years of post-secondary education completed in a non-health-related field. Within these four blocks of 10, participants were randomly assigned to either the intervention or control group (five in each), with the sequence determined by random number generator.

Materials

To create an information-need as a stimulus for online information-seeking, we created two prompts (one for each visit) for participants to read and provide a written response to. Each prompt described a friend wanting to enhance their health/wellness in a specific domain, and seeking advice regarding foods, behaviours, and/or supplements that would help them do so. We designed these prompts around two topics of interest for this study: ‘immune boosting’ and ‘cognitive enhancement’. ‘Immune boosting’ describes methods by which one can enhance or fortify their immune system against pathogens in their environment. Although research investigating how lifestyle factors may improve immune system function is an interesting and emerging field, to date vaccination is the only rigorously evidence-based approach endorsed by medical organizations (Cassa Macedo et al., 2019). Despite this, other ‘immune boosting’ techniques and supplements, such as supplementing one’s diet with garlic, ginger, or mushrooms, are frequently portrayed online as beneficial (Cassa Macedo et al., 2019; Rachul et al., 2020), clouding search engine results for ‘immune boosting’ with sources of highly variable quality (Wagner et al., 2020). ’Cognitive enhancement’ refers to methods by which one can improve the quality of their thinking, memory, or focus. While research in this area has largely focused on the prevention or mitigation of cognitive health decline (including dementia) with aging, there remains a sizable presence of marketing that targets younger populations hoping to optimize their cognitive performance (Crawford et al., 2020; Hamilton, 2018). Apart from following general principles of healthy living like regular sleep and physical activity to prevent decrements in cognitive function (Sewell et al., 2021), there is little scientific support for methods to heighten the brain’s abilities. Through its blocking of adenosine receptors, consuming caffeine has been shown to have a small but significant effect on measures of alertness and reaction time, particularly in sleep-deprived individuals (McLellan et al., 2016). However, research demonstrates mixed results on whether caffeine ingestion improves or inhibits working memory, long-term memory, or executive brain function (McLellan et al., 2016; Nehlig, 2010). Ginkgo biloba, a botanical extract, is among the most popular ingredients in cognitive enhancement supplements (Block et al., 2021; Crawford et al., 2021), but there remains scant scientific evidence that its consumption confers any meaningful benefit to brain health or performance (Crawford et al., 2021).

The inoculation message used in this study consisted of two components: a 5-minute video and two written questions. The video acted as a passive component, and the participants answering the written questions formed the active inoculative component. The design of our inoculation message was ultimately intended to forewarn participants of the existence of online health misinformation, to introduce them briefly to common contributors to the online health information ecosystem, and to educate them on common rhetorical techniques and inherent biases that tend to accompany false and misleading health information online. We selected relevant content for our logic-based inoculation message drawing from past literature related to online health misinformation (Iles et al., 2021) and wellness misinformation (Baker, 2022) techniques. Using the framework of four information-seeking behaviours necessary to acquire health information online (query formulation, content navigation, source selection, and verification), we opted to focus primarily on the source selection stage since this represents a pivotal decision point as to whether users will decide to invest time and attention on reliable or unreliable sources. Specifically, we chose to focus the inoculation message on features of search results pages since this is the most common starting point for people see(Jia et al., 2021; Sbaffi & Zhao, 2020).

The inoculation message video began with dialogue explaining that health information on the internet can be highly variable, particularly so for wellness-related topics like ‘immune boosting’ (the topic inquired into during Visit 1). The video then walks participants through six screenshots of source previews identical in style to what they encountered on a Google search results page, representing news, commercial, academic, blog, health organization, and social media-based health information sources. Overlaying these screenshots, participants were shown dialogue describing the nature of each source type, including advantages and challenges to average users, the likely motivation of their authors, and how these features may be signified to users on a search results page. For example, blogs were described to typically profit through driving attention towards advertisers or through directly sponsored content, and to regularly post engaging and accessible content with language to hype and intrigue, sometimes at the expense of accuracy. For this source type, participants were encouraged to consider the recognizability and reputation of the blog’s owner and author(s) when deciding whether to trust information found on it. The video concludes by reminding users to stay vigilant in identifying the trustworthiness and relevance of the online information they use to inform decisions related to their health and well-being. After the video, participants in the intervention arm of the study were given a printed handout with a short 2-question quiz to reinforce learning. The questions involved deciding which of two source previews appeared “more trustworthy” and briefly providing their reasoning.

Data Collection

Visit 1

After consenting to the study, participants filled in questionnaires to report demographic information and perceived eHealth literacy before reading and responding to the ‘immune boosting' prompt. After providing a response based on their pre-existing beliefs, the participants were seated in front of a laptop computer fitted for eye-tracking before being led through a brief calibration procedure. The researcher then opened a web browser and navigated to Google.ca, after which participants were given 15 minutes to browse the internet to inform their response to the 'immune boosting' prompt. Participants were asked to use Google as their only search engine, but otherwise could navigate the internet freely. Participants were encouraged to actively gather information for the full time, and were permitted to write notes as they searched. The researcher exited the room during their search to prevent participants from modifying their behaviour due to perceived surveillance. Their eye-tracking and screen recording data were collected throughout the search. Once finished their 15-minue search, participants were permitted extra time to add to, edit, or subtract from their initial answer to the prompt. Participants then engaged in a retrospective, gaze-cued think-aloud interview with the first author. While viewing a replay of their own eye-tracking data overlaying a screen recording of their search, participants were asked to verbalize their thoughts and intentions throughout. These interviews were both audio- and screen-recorded, such that the resultant file consisted of the participants' speech overlaying a video of their eye-tracking behaviour. Participants were not informed of the retrospective interview prior to their information-seeking session to avoid influencing their behaviour.

Visit 2

The second visit largely mimicked the first visit, but with the key addition that participants were randomly assigned to exposure (or not) to an inoculation message. This visit occurred a minimum of 24 hours following the first, and participants started by again reporting their perceived eHealth literacy. Participants were then seated in front of a laptop computer fitted for eye-tracking, and at this point those in the intervention arm were provided the inoculation message, while participants in the control group proceeded directly to the next step. All participants were then asked to answer a prompt related to ‘cognitive enhancement’. Then in identical fashion to Visit 1, participants were given 15 minutes to browse the internet to inform their response. They were then permitted to add to, edit, or subtract from their answer to the prompt, and finally engaged in the same retrospective gaze-cued think-aloud interview protocol with the first author.

Measures and Data Processing

The data collected in this study include questionnaire data, textual prompt answer data, screen recording data, eye-tracking data, and gaze-cued retrospective think-aloud interview data. Questionnaires and Prompt Answers. The questionnaires included demographic information (age, gender, race/ethnicity, socioeconomic status, years of post-secondary education, and subject studied in postsecondary education) and the eHealth Literacy Scale (Norman & Skinner, 2006) to measure perceived eHealth literacy. Textual prompt response data (before and after searches) were initially processed by uploading photos of each handwritten response into text recognition software, and the output was verified by a human researcher. Responses were then coded for the presence of food-related, supplement-related, or behaviour-related recommendations, and assigned a score from 0-3 in each of these categories (0 = no mention, 1 = brief mention, 2 = multiple modalities and/or specific brands or substances were mentioned, 3 = specific dosages or routines were mentioned in addition to the requirements of scoring 2). Responses were additionally coded for the mention of vaccines (Visit 1) or medication (Visit 2), as well as for mention of advice to seek professional medical advice (0 representing no mention, 1 representing any mention). Finally, we also asked participants to rate the personal importance they place on each prompt topic on a scale of 1 (very unimportant) to 5 (very important).

Time Spent on Webpages, Source Type, and Source Reliability.

We used screen-recording data to process the time participants had each webpage open on the screen, and to output the URL addresses of each website visited. These URL addresses were used by two researchers to independently rate the reliability of each website as a health information source using Section 1 of the DISCERN tool, a validated instrument for judging the quality of health resources (Charnock et al., 1999). Possible scores using this instrument ranged from 8 to 40; in instances where researchers scored four or more points apart, the researchers met to discuss and arrive at a consensus score. Otherwise, if within three points, the mean between the two researchers score was used to represent the website's reliability as a health information source. Concurrently, both researchers noted whether a source came from a reputed health organization or government website, a scientific research article, or a commercial website, and similarly met to arrive at a consensus judgment in instances where they disagreed.

Cross-referencing these data with the website reliability ratings allowed for the generation of total time spent with low-reliability sources displayed on the screen (those in the bottom third of all sources accessed in the study) and total time spent with high-reliability sources displayed on the screen (those in the top third of all sources accessed in this study). In Visit 1, high-reliability sources were those whose DISCERN reliability score was over 31 (on a scale of 8-40), and low-reliability sources were those less than 27.5. In Visit 2, high-reliability sources were those whose DISCERN reliability score was over 30, and low-reliability were those less than 27. Average source reliability for each participant was calculated by taking the mean reliability score of each website they accessed. We also created variables to represent the proportion of each type of source (health organization / government agency webpage, academic research article, or commercial webpage) accessed by each participant by dividing the instances of visiting each type of source by the total number of sources accessed. For example, if participants accessed three health organization sources, and ten sources in total, the calculated proportion would be 0.3.

Source Preview Consideration and Source Engagement Time.

From screen-recording and eye-tracking data, we processed the time participants spent actively engaging with each webpage and source preview throughout their 15-minute search. A researcher reviewed each eye-tracking replay and made note of the first and last fixation indicated by the eye-tracker on every source preview and information source visually attended to by each participant. In instances where elements were revisited multiple times in a session, time periods were summed to generate total time spent viewing each element. If participants focused on a webpage prior to its content actually rendering on the screen, this time was not included. Cross-referencing these data with the website reliability ratings allowed for the generation of total time engaging with low- and high-reliability sources.

Information-Seeking Behaviour.

From gaze-cued retrospective think-aloud interview data, we processed the time participants engaged in query formulation, source selection, content navigation, and verification behaviours during their 15-minute search. A researcher, who was blinded to whether each participant was a member of the intervention or control group, observed the video and audio components of each interview recording and noted start and end times where participants exhibited each behaviour type. Verification behaviours were further coded as either source verification (confirming the identity or qualifications of the author or website owner) or information verification (confirming the accuracy of claims by checking references or purposely cross-referencing claims with other sources). In a few instances participants were deemed to be engaging in multiple behaviours at once; for example, when attentively reading health information within a source preview on a search results page a participant could be said to be engaging in both source selection and content navigation behaviour. All time periods of each behaviour were summed to produce a total time spent in each behaviour type, with the exception of verification behaviour. Since the number of sources accessed was highly variable amongst participants (ranging from 1-26), we opted to calculate the proportion of verification behaviour instances to the number of sources accessed. For example, if six instances of verification behaviour were noted during the participants' search, and they accessed eight sources in total, the proportion would be six divided by eight, or 0.75.

Data Analysis

All dependent variables were initially tested for normality using the Shapiro-Wilk Test to determine the appropriate statistical test for comparing the extent of behaviour change in the intervention versus the control group. In cases where non-normally distributed data were generated from either Visit 1 or Visit 2, the Mann-Whitney U Test was used to compare differences in the distributions of change between visits in the intervention and control groups. The r value of each Mann-Whitney U result was calculated to estimate effect size, which were interpreted as small ($r = 0.1$), moderate ($r = 0.3$), or large ($r = 0.5$) (Coolican, 2017, p. 484). In cases where normally distributed data were generated from both visits, a repeated measures ANOVA was used to compare differences in how the intervention and control groups changed between visits. The partial eta squared value of each repeated measures ANOVA was calculated to estimate effect size, which were interpreted as small ($\eta p2 = 0.01$), medium ($\eta p2 = 0.06$), or large ($\eta p2 = 0.14$) (Cohen, 1988, p. 287). All statistical analyses were performed using SPSS software.

Results

General Information-Seeking Behaviour

Participants of this study consisted of 20 women and 20 men ranging from 20 to 34 years of age, with a mean of 23.6 years (SD = 3.3) and who had completed a mean of 3.9 (SD = 1.7) years of postsecondary education. Participants reported perceived eHealth literacy scores ranging from 20 to 40 (on a scale of 8 to 40) with a mean score of 29.6 (SD = 4.1); representing comparable but relatively high levels of confidence in their online health information-seeking proficiency compared to other adult populations (Chang, 2022; Quinn et al., 2017). Throughout all 80 15-minute (900-second) online search sessions, participants spent a mean of 66.30 seconds (SD = 37.48) on query formulation behaviour, 113.28 seconds (SD = 55.74) on source selection behaviour, and 464.91 seconds (SD = 118.57) on content navigation behaviour. Time not represented within these behaviour categories generally consisted of writing down information they had retrieved or taking breaks from the task. Participants conducted an average of 6.28 searches (SD = 3.71) during each session, and spent an average of 2.09 seconds (SD = 0.76) viewing each source preview they considered, including an average of 3.29 seconds (SD = 1.40) viewing each source preview they ultimately clicked on. When it came to the components of each source preview, participants viewed URLs 74.4% of the time (82.0% for source previews they clicked on), viewed titles 81.6% of the time (98.5% for source previews they clicked on), and viewed source descriptions 34.1% of the time (49.1% for source previews they clicked on). Participants visited an average of 9.20 sources (SD = 4.07) in each 15-minute session, of which health organization or government agency websites made up 38.4%, scientific research articles made up 31.7%, and commercial websites made up just 1.7%. Websites that did not fall under any of these categories mostly consisted of encyclopedia websites and blogs. In their written responses to the 'immune boosting' prompt after 15 minutes of online information-seeking, participants put the greatest emphasis on behaviours (mean score of 1.95 out of 3), then foods (mean score of 1.65 out of 3), then supplements (mean score of 1.33 out of 3). Additionally, 35% of participants mentioned vaccination as a means of improving one's immune system, and 40% of participants recommended seeking professional medical advice. In their written responses to the 'cognitive enhancement' prompt, participants also put the greatest emphasis on behaviours (mean score of 1.90 out of 3), then foods (mean score of 1.67 out of 3), then supplements (mean score of 1.00 out of 3). For this prompt, just 5% of participants recommended trying medication, and 18% recommended seeking professional medical advice.

Differences Between Visits

Taking into account the full 40-participant sample in this study, there were a few significant differences between visit 1 and visit 2 concerning participants' search behaviour. During the 15-minute (900-second) online information-seeking tasks, participants spent a mean of 98.53 ($SD = 43.08$) seconds on source selection behaviour in visit 1, which increased to a mean of 128.04 ($SD = 68.40$) seconds in visit 2. A Wilcoxon Signed-Rank Test indicated the median difference between visits to be significant ($Z = 2.500$, $p = 0.012$). In visit 1, participants spent a mean of 309.29 ($SD = 174.02$) seconds engaging with sources ranked in the top third of reliability ratings (of all sources accessed in that visit), which dropped significantly ($Z = -2.823$, $p = 0.005$) to a mean of 214.92 ($SD = 144.46$) seconds in visit 2. Conversely, in visit 1 participants spent a mean of 53.44 ($SD = 75.99$) seconds engaging with sources ranked in the bottom third of reliability ratings, which increased significantly ($Z = 3.977$, $p < 0.001$) to a mean of 139.97 (SD = 122.02) seconds in visit 2. While considering whether to click sources on search results pages, participants spent a mean of 1.93 (SD = 0.66) seconds viewing each source preview in visit 1, which increased significantly (Z = 2.070, p = 0.038) to a mean of 2.26 (SD = 0.86) seconds in visit 2. When isolating this to only source previews that participants eventually clicked on, participants spent a mean of 2.94 (SD = 1.41) seconds viewing before clicking during visit 1, which increased significantly (Z = 2.903, p = 0.004) to a mean of 3.64 (SD = 1.40) seconds during visit 2.

A few other notable differences between visit 1 and visit 2 related to participants' relationship to the prompt topics, and their online health information-seeking self-efficacy. Participants rated the importance of 'immune boosting' strategies to them with a mean of 3.72 (SD = 0.99) out of 5, which was significantly higher (z = -1.921, p = 0.055) than their importance rating of cognitive enhancement strategies for which they reported a mean of 3.35 (SD = 1.051). The higher relevance of 'immune boosting' as compared to 'cognitive enhancement' to our participants was also evidenced by the mean pre-search wordcount of participants' response to the prompt being significantly higher (Z = -1.921, p = 0.055) in visit 1 (mean = 76.50 words, SD = 43.01) than in visit 2 (mean = 61.95 words, SD = 50.55). Finally, it should be noted that prior to the search task in each visit, participants rated themselves as significantly more eHealth literate (z = 2.151, p = 0.032) during visit 2 (mean = 3.84 out of 5, SD = 0.53) than during visit 1 (mean = 3.70 out of 5, SD = 0.51).

Inoculation Message Effects

Source Selection Behaviour (H1a – H1c)

The group exposed to the inoculation message had a mean increase of 57.42 seconds (a 71% increase) spent on source selection behaviour between visits, compared to the control group having a mean increase of just 1.60 seconds (a 1.4% increase). A Mann-Whitney U test indicated the median change was significantly different between groups ($U = 300$, $p = 0.006$). The effect size was medium ($r = 0.43$), suggesting a moderate increase in the amount of time spent considering search results pages as a result of the intervention, meaning H1a is supported. The intervention group also had a mean increase of 0.66 seconds (a 33% increase) in time spent considering each source preview on search results pages between visits, while the control group showed no increase. A Mann-Whitney U test indicated the median change was significantly different between groups ($U = 314$, $p = 0.001$). The effect size was large ($r = 0.49$), suggesting a moderate increase in the amount of time spent viewing source previews during participants' search task, meaning H1b is supported. Finally, the intervention group also had a mean increase of 1.47 seconds (a 50% increase) between visits in time spent viewing source previews that they ultimately clicked on, compared to a decrease of 0.06 seconds in the control group. A Mann-Whitney U test indicated the median change between groups was significantly different ($U = 341$, $p < 0.001$). The effect size was large ($r = 0.60$), suggesting that the intervention group had a substantial increase in time spent considering sources before clicking on them as compared to the control group, meaning H1c is also supported. Exposure to the inoculation message in this study demonstrably increased the amount of time participants used to evaluate sources on search results pages during the 15-minute search task.

We additionally looked at whether there were any significant differences in the frequency of participants viewing the title, description, or URL components per source preview considered. There was no significant difference in the frequency of viewing the title of a source preview ($p = 0.495$), even when limiting this to only source previews participants actually clicked on ($p = 0.640$), in either the intervention or control group. Similarly, there was no significant difference in the frequency of viewing the description of source previews when considering them, however when limiting to only clicked source previews it can be noted that the intervention group increased the frequency of viewing source preview descriptions from 79.3% to 98.8% (+19.5%) while the control group increased from 70.9% to 79.0% (+8.1%). A repeated-measures ANOVA indicated the inter-group differences in this case were not significant ($F = 0.517$, $p = 0.476$). The frequency of participants viewing the URL in all considered source previews increased between visits from 68.2% to 92.0% (+23.8%) in the intervention group, while increasing from 63.0% to 74.5% (+11.5%) in the control group. A Mann-Whitney U test indicated the median change between groups was not significantly different ($U = 261.5$, $p = 0.096$). When limiting the analysis to the frequency that participants viewed URLs in just the source previews they clicked on, smaller increases are seen in the intervention group (+19.5%) and the control group (+8.1%), and similarly a Mann-Whitney U test indicated the median change between groups was not significantly different ($U = 233$, $p = 0.383$).

Verification Behaviour (H2a and H2b)

The proportion of observed instances of verification behaviour to the number of websites visited by participants in the intervention group marginally decreased from 0.405 to 0.328 (-0.077) between visits, while decreasing from 0.410 to 0.355 (-0.55) in the control group. A Mann-Whitney U test indicated the median change was not significantly different between groups ($U = 192.5$, $p = 0.841$), meaning H2a is not supported. When considering the average proportion of solely source-related verification behaviour instances to the number of websites visited, the intervention group decreased from 0.346 to 0.243 (-0.123) between visits while the control group decreased from 0.338 to 0.255 (-0.083). A Mann-Whitney U test indicated the median change was not significantly different between groups ($U = 212.5$, $p = 0.738$), meaning

H2b is not supported. Exposure to the inoculation message in this study did not result in a significant observable difference in verification behaviour during the 15-minute search task.

Source Quality (H3a – H3c)

The average source reliability rating of webpages accessed by participants in the intervention group decreased by 0.57 (on a 32-point scale) between visits, while the average reliability in the control group decreased by 0.47. A Mann-Whitney U test indicated the median change was not significantly different between groups ($U = 204$, $p = 0.925$), meaning H3a is not supported. The average time users spent engaging with high-reliability sources in the intervention group decreased by 128.17 seconds (a 36.6% decrease), while the control group decreased by 60.56 seconds (a 22.6% decrease). A Mann-Whitney U test indicated no significant difference in the median change between groups ($U = 161$, $p = 0.301$). A Mann-Whitney U test looking at the median change in time that high reliability sources were on the screen (not factoring in whether participants were actively reading them) similarly indicated no significant difference between groups ($U = 184$, $p = 0.678$). As such, H3b is not supported. The average time users spent engaging with low-reliability sources in the intervention group increased by 57.84 seconds (a 112.5% increase) while the control group increased by 115.22 seconds (a 208.6% increase). A Mann-Whitney U test indicated no significant difference in the median change between groups ($U = 133$, $p = 0.142$). A Mann-Whitney U test looking at the median change in time that low reliability sources were on the screen similarly indicated no significant difference between groups ($U = 133$, $p = 0.072$). As such, H3c is not supported.

Other Observed Effects

In addition to the intervention group spending more time on source selection behaviour, they also saw an average decrease of 47.17 seconds in time spent on content navigation behaviour. This comes in stark contrast to the control group, which had an average increase of 33.55 seconds spent on content navigation behaviour during their search. A repeated measures ANOVA indicated the means between the two groups were significantly different ($F = 5.314$, $p = 0.027$). The effect size of this change was large ($\eta p2 = 0.123$), indicating after the intervention, participants in the inoculation message group spent less time on content navigation behaviour. The intervention group increased their time spent on query formulation behaviour between visits by an average of 18.99 seconds, while the control group had an average decrease of 6.27 seconds. A Mann-Whitney U test indicated no significant difference in the median change between groups ($U = 300$, $p = 0.091$).

Table 1

Changes in Observed Information-Seeking Behaviour Between Study Visits

Variable	Visit 1 Mean (SD)	Visit 2 Mean (SD)	Mean Difference
eHealth Literacy			
Intervention	3.68 (0.445)	3.77 (0.492)	0.09
Control	3.72 (0.575)	3.91 (0.527)	0.21
Query Formulation			
Intervention	58.10 (31.41)	77.09 (47.70)	18.99
Control	68.15 (38.09)	61.88 (30.15)	-6.27
Source Selection**			
Intervention	80.86 (37.83)	138.28 (66.53)	57.42
Control	116.19 (41.48)	117.79 (70.40)	1.60
Content Navigation*			
Intervention	497.86 (137.71)	450.69 (126.69)	-47.17
Control	438.77 (92.67)	472.32 (109.72)	33.55

Variable	Visit 1 Mean (SD)	Visit 2 Mean (SD)	Mean Difference
Screen Time on High-Reliability Sources			
Intervention	466.81 (255.47)	319.63 (155.09)	-147.18
Control	411.89 (171.31)	287.04 (215.93)	-124.85
Engagement Time on High-Reliability Sources			
Intervention	350.05 (213.85)	221.88 (118.73)	-128.17
Control	268.53 (113.71)	207.97 (169.22)	-60.56
Screen Time on Low-Reliability Sources			
Intervention	83.82 (131.36)	150.02 (114.16)	66.20
Control	77.94 (87.13)	246.98 (177.98)	169.04
Engagement Time on Low-Reliability Sources			
Intervention	51.37 (76.29)	109.21 (107.36)	57.84
Control	55.51 (77.60)	170.73 (130.55)	115.22
Average Time Considering Source Previews**			
Intervention	2.00 (0.81)	2.66 (0.83)	0.66
Control	1.85 (0.47)	1.85 (0.68)	0.00
Average Time Considering Clicked Source Previews**			
Intervention	2.94 (1.54)	4.41 (1.33)	1.47
Control	2.93 (1.31)	2.87 (1.00)	-0.06
Average Source Reliability			
Intervention	30.51 (1.98)	29.94 (1.21)	-0.57
Control	29.85 (2.40)	29.38 (2.06)	-0.47
Verification Instances per Website Visited			
Intervention	0.405 (0.367)	0.328 (0.301)	-0.077
Control	0.410 (0.243)	0.355 (0.270)	-0.055
Source Verification Instances per Website Visited			
Intervention	0.346 (0.329)	0.243 (0.282)	-0.123
Control	0.338 (0.199)	0.255 (0.244)	-0.083
Proportion of URL-Checking Source Previews			
Intervention	0.682 (0.202)	0.920 (0.117)	0.238
Control	0.630 (0.269)	0.745 (0.170)	0.115

Variable	Visit 1 Mean (SD)	Visit 2 Mean (SD)	Mean Difference
Proportion of URL-Checking Clicked Source Previews			
Intervention	0.793 (0.238)	0.988 (0.040)	0.195
Control	0.709 (0.315)	0.790 (0.277)	0.081
Proportion of Description-Checking Source Previews			
Intervention	0.380 (0.211)	0.368 (0.130)	-0.012
Control	0.301 (0.136)	0.317 (0.165)	0.016
Proportion of Description-Checking Clicked Source Previews			
Intervention	0.477 (0.263)	0.594 (0.208)	0.117
Control	0.416 (0.224)	0.475 (0.222)	0.059
Proportion of Title-Checking Source Previews			
Intervention	0.810 (0.183)	0.820 (0.165)	0.010
Control	0.836 (0.122)	0.797 (0.156)	-0.039
Proportion of Title-Checking Clicked Source Previews			
Intervention	0.987 (0.032)	0.989 (0.028)	0.002
Control	0.978 (0.051)	0.987 (0.039)	0.009
Websites Visited			
Intervention	9.10 (4.47)	7.45 (3.43)	-1.65
Control	11.25 (5.20)	9.00 (2.90)	-2.25

*$p < 0.05$ for effect of intervention.
**$p < 0.01$ for effect of intervention.

Discussion

The purpose of this study was to compare how an inoculation message changes individuals' online health information-seeking behaviour compared to those not exposed to that inoculation message. Our findings demonstrated a significantly larger increase in time spent evaluating sources on search results pages before selecting which website to consult for health information in the inoculation message group compared to the control group. However, inoculation message exposure in this study did not lead to significantly more verification behaviour or to choosing sources with a higher average reliability rating. This study is the first to provide evidence with eye-tracking that inoculation message exposure can measurably change online information-seeking behaviour; causing participants to slow down when considering which webpages to inform themselves with.

We found that exposure to the inoculation message in this study, with source preview examples related to 'immune boosting', significantly increased the amount of time participants spent (compared to the control group) considering what search results to click during a search related to 'cognitive enhancement'. This was demonstrated by the intervention group having a significantly greater increase in total time spent on the source selection process, as well as a significantly greater increase in time spent evaluating each individual source preview they considered on search results pages. These findings align with other literature demonstrating inoculation effectiveness concerning tangentially-related topics (Parker et al., 2012, 2016), and additionally provide support for the theory that broad resistance to misinformation may occur through the mechanism of heightened saliency and increased scrutiny of information reliability (Compton et al., 2021; Ecker et al., 2022). This augments past literature by suggesting more thoughtful source evaluation as a likely contributor to logic-based inoculation messages focusing on one context enhancing misinformation resistance in another context (Roozenbeek et al., 2022).

We predicted the intervention group would demonstrate more verification behaviour on the webpages themselves due to the inoculation message drawing attention to source reliability; however, no significant differences were noted. This may be a result of the inoculation message video used in this study focusing only on source-related cues featured on search results pages, which seemingly did not transfer to the intervention group being significantly more diligent in evaluating the veracity of webpages after selecting them. This finding suggests that the capacity of an inoculation message to stimulate change in information-seeking behaviour may be relatively specific to the cues emphasized in the message itself. So, though this study reiterates past literature demonstrating that a logic-based inoculation message covering one topic can have positive effects related to another topic (Parker et al., 2012, 2016), our data suggest this may be due to training or reinforcing specific information evaluation skills rather than simply heightening critical thinking in general.

It is notable that despite the intervention group allocating more time to deciding which sources were worth clicking to inform their answer to the prompt, this did not result in higher average source reliability according to the rubric we applied. This may be partly explained by differing informational landscapes for the topics of ‘immune boosting’ and ‘cognitive enhancement’ online, evidenced by the entire sample having a lower average source reliability score for the second visit. Other research has noted that being more attentive to search results pages during online health information-seeking correlates with higher health literacy (Lopes & Ramos, 2020), and that increasing individuals’ attention to accuracy can reduce engagement with misinformation (Pennycook et al., 2021). So, although we did not capture significant changes in the reliability of information accessed by participants as a result of the intervention, we did observe behaviour changes that past literature has demonstrated to be generally favourable. Although not statistically significant, we found greater increases in the frequency of viewing URLs of source previews in the intervention group compared to the control group (characterized by a small-to-moderate effect size). Past literature similarly indicates this to be a favourable behaviour shift in evaluating source reliability (Muntinga & Taylor, 2018). Looking at the amount of time participants allotted to engaging sources based on their reliability, we did not find significant differences in the amount of time participants spent engaging with either high- or low-reliability sources. It is somewhat notable the intervention group spent less time than the control group with low-reliability sources present on their screen to a degree that approached significance with a moderate effect size, but ultimately our findings did not reflect significant improvement in the reliability of sources that participants accessed.

Our findings also indicated significant trends in information-seeking behaviour for which we did not form hypotheses. In response to the inoculation message, the intervention group had a significant reduction in time spent on content navigation behaviour compared to the control group, who conversely had an average increase in time spent on this behaviour. Given the fixed amount of time allotted for the search task and the primary focus of the inoculation message on source selection behaviour, we expect the significant differences in content navigation behaviour to be a byproduct of the intervention group spending significantly more time on source selection behaviour; In order to spend more time deciding what to click on, they had to take time from somewhere else. Though non-significant, the intervention group also had an increase in average time spent on query formulation behaviour compared to the control group, characterized by a moderate effect size, coming despite them also spending more time on source selection behaviour. This may indicate exposure to the inoculation message minorly motivated participants to spend more time considering specific search terms to use during the task. These findings provide a preliminary picture of how online information-seeking behaviour may shift in response to a logic-based inoculation message focused on selecting reliable sources.

Limitations

This study presents with a few notable limitations. Perhaps the most profound limitation of this study that should be considered when interpreting its findings is due to the search topics differing between visit 1 and visit 2. Though there is evidence that both 'immune boosting' and 'cognitive enhancement' have high variability in the quality of information that can be found online about them, the overall informational landscape for each cannot be said to be definitively equivalent, which is demonstrated by significance differences occurring in several elements of behaviour between visits within the control group and entire sample. Additionally, participants reported higher interest in the visit 1 prompt topic compared to visit 2, evidenced by rating 'immune boosting' as significantly more important to them than 'cognitive enhancement', and significantly higher wordcounts in their pre-search response to the prompt in visit 1.

Giving participants unrestricted internet access in this study improved its ecological validity, but at the expense of making each participants' search behaviour easily comparable. Although many participants used similar search terms and there was significant overlap among sources accessed, no two participants went through identical journeys in their information-seeking process. Ample research has demonstrated that information environment affects the information-seeking process irrespective of user-related skill (Kammerer & Gerjets, 2012; Lewandowski & Kammerer, 2021; Schultheiß et al., 2018), and so we cannot be certain the extent to which the changing environment between participants affected the outcome of this study. We also cannot be certain to the extent that the 15-minute time limit of the information-seeking task used in this study may have differently impacted participants' behaviour. We decided this amount of time for each participant based on pilot participants reporting a reasonable level of information satisfaction within 15 minutes, and with consideration to our available resources to analyze all data generated in this study. It is also possible some behavioural elements differed between visits due in part to participants' awareness of the full nature of the think-aloud interview component in Visit 2, whereas in Visit 1 this was left intentionally vague as to not impact their search behaviour. The knowledge that they would need to explain their behaviour immediately following their search to a researcher may have led to more mindful and purposeful information-seeking behaviour in Visit 2 as compared to Visit 1; this is why we decided a control group was necessary for meaningful evaluation of the inoculation message effects in this study.

As with many other health information-seeking studies, it should also be noted that the information need in this research was manufactured by being provided to participants, which is likely not a perfect replication of someone's day-to-day self-motivated information-seeking behaviour. The prompts used in this study asked participants to find information on behalf of a friend with a health concern to promote them feeling some degree of realism, as has been done in past studies (Lopes & Ramos, 2020).

Conclusions

Inoculation messaging research, particularly in the domain of health, has largely assessed effectiveness by testing participants' ability to discern false or misleading information presented to them, or by measuring the degree to which they are persuaded by 'attack' messages. This study is the first to apply eye-tracking methods to observe how online information-seeking behaviour can be altered by an inoculation message, answering calls for inoculation messaging research that "pushes forward our understanding of persuasion and has applied value as a health messaging strategy to help combat serious threats to healthy living" (Compton et al., 2016, p. 1). Our findings indicate that the inoculation message we designed and used led participants to spend more time evaluating sources before clicking on them, but this did not lead to significant differences in the average reliability of the webpages participants accessed, nor did it significantly influence what was emphasized in their response to the prompt. The information-seeking behaviour changes observed in this study present a unique contribution to inoculation theory literature, which has largely evaluated intervention effectiveness by measuring participants' ability to distinguish the veracity of headlines, statements, or social media posts. As such, this study provides mechanistic insight as to how inoculation messages may confer resistance to a broad range of misinformation topics (Parker et al., 2016), supporting the theory that inoculation message exposure leads to heightened attention and effort to evaluating information reliability (Compton et al., 2021).

Future research in this area should employ research designs that can parse apart the effects that specific features of inoculation messages have on online information-seeking behaviour. In this study we utilized an inoculation message related to source types and source evaluation strategies on search results pages, which incorporated both passive (watching the video) and active (answering two questions) components. A study testing the impact of inoculation messages with differing characteristics, such as with only passive or active components, or with fact- versus logic-based inoculation strategies, may provide deeper insight as to how specific components of inoculation messaging can impact information behaviour. Future studies should also consider testing the impact of inoculation messages on online information-seeking behaviour for other topics (e.g., climate change misinformation, political misinformation) and using other populations, such as those with less formal education. It may also be prudent for researchers to study whether the inoculation message effect on information behaviour persists weeks or months following intervention, as some scholars have suggested “booster doses” may be necessary to maintain resistance to misinformation (Maertens et al., 2020).

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General Discussion

Summary of Findings

The overall purpose of my dissertation was to conceptualize what existing measures of eHealth literacy tell us about people's demonstrable online health information-seeking behaviour, and to use this mechanistic understanding of health information-seeking to test whether an inoculation message can favourably alter the process. In tackling this goal, I first conducted a scoping review to identify and describe tools measuring eHealth literacy based on objective performance (in contrast to self-report measures), while characterizing the prevalence of such tools within the literature more broadly. A total of 313 research articles were ultimately included in the review, of which 33 utilized a performance-based measurement of eHealth literacy. The basic structure of the 29 measurement tools used across the 33 studies were arranged into five categories: 1) health-related questions using the internet, 2) simulated online health information-seeking tasks, 3) website evaluation tasks, 4) knowledge of the online health information-seeking process, and 5) health-related knowledge. The scoping review also established that an overwhelming majority of published studies have measured eHealth literacy using only self-report measurement, and of the roughly 10% of studies that used some form of objective measurement only two tools were used in more than one study. Given the potential limitations inherent to self-assessing one's own ability, particularly in this domain, I contend that future scholarship seeking to quantify online health information-seeking ability should make greater effort to do so using new or existing performance-based eHealth literacy measurement tools. Acknowledging the overwhelming popularity of self-report measurement in the existing body of eHealth literacy research, I then conducted a mixed-methods comparative analysis using eye-tracking technology to observe how the most popular self-report eHealth literacy measure, eHEALS (Norman & Skinner, 2006a), correlates with observed online health information-seeking behaviour in a convenience sample of university-educated young adults. I had 40 young adults with different levels of health-related education search the internet for 15 minutes each to inform themselves about 'immune boosting' methods; a topic known for variable information quality online. I used eye-tracking, screen recording, retrospective think-aloud interviews, and an intricate data coding and analysis scheme involving multiple researchers to quantify several aspects of their online health information-seeking behaviour, generating a total of 21 behaviour-related variables. Ultimately, I found the participants' eHEALS scores correlated significantly with only four behavioural outcomes, which pertained only to their source preferences. Those who rated themselves as more eHealth literate favored selecting scientific research articles and spent significantly more time actively reading them, while government or health organization websites made up a significantly smaller proportion of their accessed websites. Those who rated themselves as more eHealth literate also spent significantly less time actively reading government or health organization websites than those who rated themselves as less eHealth literate. The general lack of significant correlations found in this study provides robust evidence to demonstrate the limitations of self-report eHealth literacy measurement to predict actual behaviour when seeking online health information, particularly for topics known for a meaningful presence of online misinformation.

In the final study, I leveraged my existing dataset from study 2 and conducted a randomized controlled trial to test the effects of an inoculation message video on online health information-seeking behaviour. I had the same 40 young adult participants return for a second visit, where half were randomly assigned to see an inoculation message video highlighting source evaluation techniques on search results pages using examples related to 'immune boosting’. Participants then conducted another 15-minute search to inform themselves about ‘cognitive enhancement’ methods; another topic purposefully selected as it is known to have a meaningful presence of unfounded claims online. My findings showed that the group exposed to the inoculation message spent significantly more time evaluating sources on search results pages before selecting websites than the control group. However, this did not lead to significant differences in average reliability of the sources they selected, nor in the frequency of verification behaviour when reading sources. The notion that an inoculation message emphasizing source reliability cues within search results pages caused participants to slow down their source selection process, but did not cause significant differences to other elements of their information-seeking process, may indicate that behavioural changes from inoculation message exposure tend to be process-specific, though not topic-specific. In other words, the findings of Study 3 indicate that behaviour modifications produced by inoculation message exposure tend to be in specific response to behavioural components emphasized within the message.

Contributions to the Literature

Overall, the findings of my dissertation, empowered by novel methodological approaches, contribute to a stronger holistic understanding of the relationship between eHealth literacy measurement and the online health information-seeking process. Specifically, my findings have contributed to furthering our academic understanding of how eHealth literacy is currently measured, how well these measures correlate with online health information-seeking behaviour, and how inoculation messages impact online health information-seeking behaviour.

While there have been other literature reviews published related to eHealth literacy measurement (Karnoe & Kayser, 2015; Lee et al., 2021), my scoping review was the first to specifically identify existing objective performance-based measurement tools. The utility of self-report measures in research has been called into question across several constructs where the average person may lack the metacognitive capacity to differentiate between self-confidence and true skill. eHealth literacy is a particularly strong candidate for being challenging to accurately self-assess, as effective online health information-seeking requires a set of complex health-related and internet-related knowledge and skill (Norgaard et al., 2015; Norman & Skinner, 2006b). Given the importance of performance-based measurement to form an accurate assessment of this construct, the table within my scoping review can act as a useful tool to direct researchers towards existing eHealth literacy measurement tools based on demonstrated behaviour or relevant knowledge. Additionally, my scoping review is the first to quantify the approximate prevalence of performance-based versus self-report measurement tools of eHealth literacy amongst the literature broadly. With the internet representing a dominant driver of health discourse amongst the public, this is a key finding to highlight that current scholarship in the area may be falling short by relying on convenient self-report measures to assess online health information-seeking skill.

Findings from Study 2 supplement this contribution further by examining the existence (or more often non-existence) of significant correlations between self-reported eHealth literacy measures and observable online health information-seeking behaviour. These findings contribute yet further evidence that perceived eHealth literacy has little bearing on performed eHealth literacy (Maitz et al., 2020; Neter & Brainin, 2017; Quinn et al., 2017; Stellefson et al., 2012; Van Der Vaart et al., 2011), and deepens our understanding of the extent of this trend through its use of eye-tracking and novel data processing techniques. Findings from Study 2 largely align with the only other study employing eye-tracking to study the relationship between self-reported eHealth literacy and observed online health information-seeking behaviour, conducted by

(Chang, 2022), though there are notable differences in our approaches. In their research, Chang (2022) had participants conduct factual medical search tasks; four multi-step tasks with precise answers available on the Centre for Disease Control and Prevention (CDC) website. While undoubtably relevant to those seeking information related to a specific medical condition or diagnosis, I contend that the prompts used in my research act as better proxies to the health information needs of everyday users looking to improve their mental or physical health, to inform themselves on healthy lifestyle practices, or to locate solutions to relatively minor decrements to their body's function. In this way my research contributes findings relevant to searching in information environments that feature several relevant sources with highly variable reliability, which I contend lends to higher ecological validity relative to many of the most popular health-related topics in our modern online health information ecosystem.

Inoculation message research has primarily evaluated the effectiveness of inoculation messages on participants' ability to discern false or misleading information presented to them, or by measuring the degree to which they are persuaded by 'attack' messages. Study 3 makes a novel contribution to this literature by examining how the process of selecting relevant and reliable sources to inform oneself can be altered by exposure to an inoculation message; a pivotal skill in resisting persuasion by online misinformation, particularly for non-experts in the topic at hand. Our finding that inoculation message exposure can lead to significantly more time spent on source evaluation (prior to source selection) highlights a potential mechanism by which inoculation messages can enhance resistance to misinformation across topics. Heightened attention to information trustworthiness and an increased general level of scrutiny to information reliability have been previously suggested as mechanisms for broad misinformation resistance in response to inoculation messages (Compton et al., 2021; Ecker et al., 2022; Roozenbeek et al., 2022). To the best of our knowledge, findings from Study 3 represent the first quantitative evidence of these mechanisms taking place during an information-seeking task. In addition to this mechanistic insight into how inoculation messages may confer misinformation resistance to a broad range of topics, findings from Study 3 also highlight that information-seeking behaviour changes resulting from inoculation message exposure may be highly specific to that message's content. Though I hypothesized that there would additionally be changes to verification behaviour while reading sources due to a generally heightened attention to reliability, only the hypotheses related to the source selection phase of information-seeking were supported, directly in line with what was emphasized in the inoculation message presented. I also consider this a valuable instructive finding to researchers designing inoculation message interventions.

Limitations

The limitations of each study included in my dissertation have been described to some extent earlier in this document; here I will briefly discuss some that I believe merit further elaboration. First, I will discuss the limitations associated with providing participants with unrestricted internet access during their search tasks, in contrast to alternatives like designing an internet-mimicking environment for participants to navigate or limiting them to accessing a specific list of select websites. When designing these studies, I decided to allow participants free reign of the internet (with the exception of limiting them to only Google as a search engine option) in the interest of maximizing ecological validity of our study. After conducting pilot testing with six individuals for the Study 2 protocol (three of which returned for a second visit to test the Study 3 protocol), there were general similarities across all participants in their information-seeking behaviour such that I felt assured that the bulk of data collected relevant to our research questions could be effectively quantified and fairly compared between participants.

In my judgment, the greatest challenge the unrestricted environment posed to data analysis was quantifying and thereby comparing the trustworthiness or quality of the roughly 300 unique sources participants selected to access over the course their 20 collective hours of information-seeking. Had I designed a virtual environment for participants as the majority of other eye-tracking researchers have done before (Lewandowski & Kammerer, 2021), I could have deliberately created a set of websites whose content and cues made them fit neatly into categories of ‘low’, ‘moderate’’, and ‘high’ quality sources. In the real world, health information sources can be difficult to objectively evaluate in such terms. For example, one participant clicked on a YouTube.com link that brought them to a video clip from the Huberbman Lab podcast discussing supplements that may boost one’s immune system performance. The host of this show, Dr. Andrew Huberman, is a professor at the Stanford University School of Medicine who generally cites the information he provides with links to peer-reviewed scientific studies. Conversely, Dr. Huberman’s show could be said to be considerably commercially biased in the topic of this video due to the show being sponsored by a billion-dollar nutrition supplement company as well Dr. Huberman’s personal financial stake held in several health supplement brands and products. Should this be considered a low, moderate, or high-quality source of health information on ‘immune boosting’? To put forward my best effort to address this limitation, I rated each website using the reliability component of a validated health website rating rubric (DISCERN; Charnock et al., 1999), and had a second researcher do the same to create a mean reliability rating (or to discuss and reach consensus when our ratings considerably differed). By no means do I consider this a perfect proxy for the trustworthiness of each source, nor the correctness of the information presented by each source, but I believe it provides a reasonable estimation of source reliability worthy of inclusion in this research.

Another limitation of this research pertains to the health-related, or perhaps more aptly described as wellness-related, topics selected to guide participants' searches. I purposefully selected 'immune boosting' and 'cognitive enhancement' among a shortlist of potential topics after conducting test searches for each to see the types of sources participants would likely encounter in search results pages. I chose these two topics because common related search terms seemed to consistently deliver sources of variable type and quality within the first search results page (important as past research indicates very few online information-seekers venture onto page 2 or beyond when dissecting Google search results; Jansen & Spink, 2006). Data generated by our six pilot participants further confirmed this to be the case. This comes in contrast to search results pages generated by queries with more medical terms, which predictably tend to include only rigorous scientific sources on the first page. Also, in contrast to many queries involving medical terms, these wellness-related topics do not lend themselves well to an objective evaluation of participants' correctness in their response to the prompts. I included very brief summaries of current scientific consensus on 'immune boosting' and 'cognitive enhancement' methods in the Materials section of my Study 3 manuscript, broadly implying that research indicates general principles of healthy living (such as regular sleep, physical activity, and a varied diet) as the most worthwhile answer to the prompt, apart from vaccination for 'immune boosting' and caffeine ingestion for some aspects of 'cognitive enhancement'. This is based on my reading of some expert opinion pieces and relevant literature reviews in these topic areas, but it is important to note that I do not consider myself to have adequate expertise to definitively state whether participants' responses to these prompts are firmly right or wrong in relation to scientific consensus. Furthermore, the very reason search results pages generated by queries for these topics contain varied types and quality of relevant sources likely stems from a lack of firm scientific consensus. Recognizing the challenges in objectively assessing the accuracy of participants' responses, I instead opted to create a rubric to quantify what participants touched upon thematically in their responses based on the three components specifically mentioned in both prompts (food, behaviour, and supplements). This allowed me to factor participants' responses to the prompt into data analysis in some capacity, but not with specific regard to whether their information-seeking session was successful in listing only evidence-based strategies to their fictional friend in need.

Future Directions

As discussed in Study 1 and Study 2, one of the biggest takeaways I would like researchers to glean from my dissertation is the limited utility for self-report measurement tools to accurately predict online health information-seeking behaviour. Promoting peoples' ability to locate, identify, and use reliable online health information will be pivotal to weathering the threats of increased misinformation proliferation through continuously advancing artificial intelligence capabilities and declining trust in public institutions. In order to accurately evaluate the effectiveness of interventions that may help to bolster eHealth literacy, researchers must develop and make use of performance-based eHealth literacy measurement tools. My findings from Study 1 indicate many such tools already exist, but there are very few instances of the same tool being used across studies, making intervention effectiveness difficult to contrast and compare amongst the literature. One challenge to creating a broadly applicable performance-based measurement tool for eHealth literacy could be the need for health information to be continuously updated as scientific consensus evolves; what may have been the best answer to a health-related question at one given time may no longer be considered a good answer in just a few years. I would thus challenge researchers to develop or make use of existing performance-based eHealth literacy tools that emphasize information-seeking processes (e.g., source evaluation skills, verification behaviour) rather than the simple correctness in fact-finding tasks. As I have demonstrated in Study 2 and Study 3, eye-tracking online health information-seeking behaviour could be a helpful method of validating such measurement tools.

In Study 3, I demonstrated that a logic-based inoculation message, focused on source evaluation techniques within search results pages, involving both active and passive learning components, can significantly impact information-seeking behaviour immediately following exposure. The qualifiers in the previous sentence are indicative of the numerous features of an inoculation message intervention that should be investigated individually to better understand their importance to impacting online information-seeking behaviour. The findings of Study 3 act as a proof-of-concept that inoculation messages can change the way people go about informing themselves online, but the study design gives little insight into the extent specific features of our inoculation message played a meaningful role in this change. I opted to use a logic-based inoculation message focused on rhetorical techniques and signifiers common to many low-reliability health information sources; informed by literature noting this strategy has been more effective at conferring broad misinformation resistance than fact-based inoculation messages (which focus on pre-bunking specific false and misleading statements) in some contexts (Cook et al., 2017; Vraga et al., 2020). However, no research has established whether this trend holds regarding changes to online information-seeking behaviour, which future studies should address. I decided to use both passive (watching a video) and active (answering follow-up questions) components in this inoculation message intervention as past research has demonstrated advantages to both approaches in combination (Trecek-King & Cook, 2024). In their meta-analysis of inoculation message interventions, Lu and colleagues (2023) found that passive interventions generally produced better results, though research shows active inoculation to be slightly more promising when directly comparing the two methods (Green et al., 2022). Further research remains needed to examine how well active and passive inoculation message techniques, separately and in combination, improve resistance to misinformation; no study to date has examined how these techniques may differently impact online information-seeking behaviour. Past research has also noted that resistance to misinformation can decay within months or even weeks following inoculation message exposure, unless ‘booster dose’ interventions are applied (Maertens et al., 2020; Maertens, 2022); something my dissertation does not address when it comes to online information-seeking behaviour changes that should be examined in future research. Finally, future inoculation message research focused on online information-seeking behaviour outcomes should also examine whether behaviour changes occur differently in the context of other topics and information-seeking tasks. For example, asking participants to locate health information with a definitively correct answer (e.g., What differentiates ischemic and hemorrhagic strokes?) or asking participants to investigate the veracity of specific health claims. In the case of the latter, a recent publication in Nature found consistent evidence that users instructed to use the internet to evaluate the veracity of a fake news article were more likely to have elevated confidence in its validity than to become more critical of it (Aslett et al., 2024). Future research should examine whether inoculation message interventions focused on internet source evaluation could blunt this problematic outcome, and methods such as eye-tracking could prove useful to understand the precise information-seeking behaviour mechanisms that contribute.

In Study 2 and Study 3, I collected data as participants engaged in an active search process wherein they sought health information via search engine relevant to a manufactured information need. Although research indicates that processes starting with search engines represent a fairly large proportion of how people use the internet to inform themselves on health-related topics, this by no means paints an all-encompassing picture of how the internet influences health-related attitudes, beliefs, and behaviour. Of the roughly 5.45 billion internet users worldwide, about 5.17 billion are also social media users (Statista, 2024), making social media platforms a major contributor to discourse on every conceivable topic, including health. While active information-seeking processes can still be conducted on these platforms, modern social media interfaces like Instagram and TikTok increasingly drive information exposure through recommendation algorithms rather than users thoughtfully selecting sources (as I examined in Study 2 and Study 3). Furthermore, verifying source reliability on these platforms involves a range of critical information literacy and domain-specific literacy skills currently unaccounted for in eHealth literacy scholarship. As I discussed in the Study 1 discussion section, there is continued need for future research to meaningfully incorporate users' abilities to evaluate health information presented on social media platforms into methods of assessing eHealth literacy. This may first require further research elaborating on relevant credibility and authenticity cues for health information on prominent social media platforms, as this work remains in relative infancy especially for platforms popular amongst young adults like Instagram and TikTok (Jenkins et al., 2020; Kirkpatrick & Lawrie, 2024). Additionally, future research should examine whether inoculation message exposure alters information processing behaviour when viewing health information within social media environments, potentially using eye-tracking methods.

Finally, I believe it's worth re-emphasizing that Study 2 and Study 3 were conducted using a convenience sample of university-educated young adults, a decision made largely in the interest of completing my doctoral degree within a reasonable amount of time. Future research should apply similar methods to these studies in less educated and potentially less internet-savvy populations to establish whether the trends I report in this dissertation carry over.

Conclusion

The internet presents an exciting and unparalleled tool by which public health advocates can share detailed, relevant, and up-to-date health information to the public effectively and efficiently. The internet concurrently presents a challenge to public health advocates by platforming a plethora of false and misleading health information that can lead to widespread useless and sometimes dangerous behaviour. The extent to which we can empower citizens to locate, evaluate, and utilize high-quality online health information effectively will undoubtably have a profound impact on public health outcomes presently and in the future. Research in the domains of eHealth literacy and inoculation message interventions can inform critically important solutions to this societal problem. Seeking to make meaningful contributions to these fields of study, the overall goal of my dissertation was twofold. First, I sought to conceptualize what existing measures of eHealth literacy tell us about people's online health information-seeking behaviour, with particular emphasis on performance-based measurement techniques. Second, I sought to apply this understanding to test whether an inoculation message intervention could favourably change online health information-seeking behaviour. I conducted a series of three studies, each guided by a specific research question, that in combination addressed the goal of my dissertation. Overall, the findings of my dissertation, empowered by novel methodological approaches, contribute to a stronger holistic understanding of the relationship between eHealth literacy measurement and the online health information-seeking process. Additionally, my research provides support for inoculation messages promoting favourable procedural differences in the online health information-seeking process. More research is needed to clarify key features of inoculation messages that can affect changes in online health information-seeking behaviour. Future research should additionally incorporate health information found on social media platforms into eHealth literacy assessment and into the design and evaluation of health-related inoculation message interventions.

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