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# Giving to Get Well: Patients' Willingness to Manage and Share Health Information on AI-Driven Platforms

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## Abstract:

The digitalization of healthcare makes for the widespread availability of patient-provided data. Artificial Intelligence (AI) relies on this data. In this information-intensive environment, it is imperative to understand the contributing factors of an individual's willingness to manage and share personal health information (PHI). Drawing from the health belief model, we identify the factors that motivate individuals to manage and share their PHI in an AI-driven health platform to obtain its intended benefits. We recognize security risks and present the use of a blockchain database as a representative means of securely managing and controlling an individual's PHI. Data collected from a nationally representative sample of allergy sufferers indicate that the health belief model strongly predicts willingness to share PHI on a personalized AI-supported platform. Our study makes significant contributions by investigating the factors that motivate patients to use an AI-driven health platform to manage their health.

**Keywords:** Artificial Intelligence (AI)-Driven Health Platforms, Health Belief Model (HBM), Willingness To Share, Managing Personal Health Information, Blockchain.

# 1    Introduction

Artificial intelligence (AI) advances are taking shape and promising to transform the healthcare industry. According to a study by Accenture, AI in the U.S. healthcare industry is expected to have a compound annual growth rate of 46.1% and reach $95.65 billion by 2028 (Vantage Market Research, 2022). AI can offer a more personalized healthcare experience that optimizes the time it takes to gather information for more efficient decision-making, ultimately allowing better patient care. AI is making its presence known across the medical profession, and medical professionals, researchers, patients, and healthcare providers that do not embrace this technology could be left behind.

Ultimately, the success of AI-based platforms for medical purposes depends heavily on individual willingness to use the technology.[1] AI can collect, combine, and analyze large amounts of data from various sources, increasing information-gathering and processing capabilities tremendously (Deane, 2018). This capability offers numerous benefits but also potential risks. For example, according to Rocher, Hendrickx, and de Montjoye (2019), AI can profile, identify, and track individuals by de-anonymizing once anonymized information. Some AI only needs 15 data points about an individual to identify the person. Because of security risks, people may be reluctant to share their personal health information (PHI) with AI-based platforms (Deane, 2018).

Achieving the potential benefits of AI from patient platforms will depend on (1) the development of intelligent systems that can collect and analyze vast datasets and (2) the willingness of data owners to share and manage their data with these intelligent systems (Agarwal & Khuntia, 2009). Within healthcare, these conditions are (1) the development of systems that can collect and process PHI and provide or augment diagnostics as/more efficiently and effectively than a traditional doctor-patient profile and (2) patients' ability and willingness to manage and share their own PHI. AI developers work to satisfy the first condition but often take the second condition for granted with the attitude, "If we build it, they will come." However, the first condition is certainly not sufficient to satisfy the second. Without convincing many individuals to share their PHI, an AI-driven health platform cannot serve its purpose. As a result, the question arises as to how to increase individuals' willingness and ability to manage and share their PHI with AI-powered health platforms. Thus, the purpose of our investigation is to discover how to begin to satisfy this second condition by addressing the following questions:

> **Are patients willing to share their PHI with AI-driven health platforms despite security risks?**

> **Are patients empowered and ready to manage their PHI, thus, in large part, bringing the control of information to the individual?**

While numerous studies focus on the design aspects of AI-based predictive models, a significant lack of studies investigate the behavioral aspects pertaining to the usability of these models by patients and clinicians. We adapt Rosenstock's (1974) health belief model (HBM) and expand it to identify the determinants of our test subjects' willingness to share PHI with an AI-driven health platform that uses a blockchain-based database. We apply the HBM to a patient profile in which patients do not solely rely on traditional healthcare provider information channels to get diagnostic and treatment information. Instead, they are empowered to use their PHI to get diagnostic and treatment information from an AI platform. As a result, our application of the HBM moves beyond a patient's willingness to follow a proactive health behavior to considering how patients might proactively use (manage and share) their personal health information to help them receive health-related guidance and insights. This patient information management and information sharing behavior represent a future path of the healthcare industry, and we wish to determine whether this well-regarded health-centered model explains behavior under this new "informationally empowered" patient health profile.

Because we care about the practical usability of AI-driven health platforms rather than purely hypothetical usability, we model our research instrument on an actual AI-driven health platform (i.e., doc.ai).[2] This platform uses AI for diagnostic and treatment information and a blockchain-based database to store PHI in

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[1] We define an AI-based healthcare platform as a software application that (1) collects and stores data for analysis by artificial intelligence (e.g., machine learning) and (2) makes the results of that data analysis available to patients and healthcare professionals in order to guide diagnostic and treatment decisions. We base this definition on an actual AI-based healthcare platform (doc.ai) that we describe in section 2.

[2] We provide more specific information regarding this health platform in sections 2 and 3.

a manner that promotes privacy. [3] The blockchain's decentralized storage model and encryption techniques minimize the risks associated with unauthorized access, allowing blockchain technology to enhance healthcare and individual ownership of PHI (Bean, 2018). By combining both of these technologies (AI and blockchain) into our study, we not only increase the practicality of our findings but also increase the dimensionality of our investigation by beginning to identify health AI use factors and the privacy benefits that blockchain can provide in this context, motivating a willingness to share PHI.

## 2    Background and Prior Research

While numerous applications for patient data management exist, most of these applications focus on patient administrative functions such as bill payment, appointment scheduling, and access to patient records (Burke, 2017). Even though these applications might enhance some of the functionality associated with the traditional doctor-patient relationship, this conventional approach to healthcare has begun to erode with the emergence of newly engaged patients who prefer more efficient routes to obtain diagnostic and treatment information, sometimes in real-time (Butler, 2014).

With a growing emphasis on health IT, instead of the doctor being the sole provider of diagnostic and treatment information to the patient, patients are beginning to manage various aspects of their healthcare experience through a wide variety of tools and technologies (Agarwal & Khuntia, 2009). Consequently, the healthcare industry is leveraging the power of health informatics with the goal of "patient empowerment," where patients are given sufficient knowledge and information to make their own health decisions (USF Health Online, 2018). However, this empowerment primarily depends on the development of intelligent systems that can collect PHI and provide diagnostics more efficiently and effectively than would be possible through a traditional doctor-patient profile, as well as on patients' ability to collect, manage, and share their own PHI (Agarwal & Khuntia, 2009).

### 2.1    AI in Healthcare

Artificial intelligence in healthcare uses various technologies to replicate human cognition in analyzing a wide variety of medical data. According to the International Data Corporation, compared to all other sectors, the healthcare industry will experience the highest compound annual growth rate in health-related data by 36% by 2025 (Kent, 2018). AI can learn from a large volume of data and correct acquired information to provide accurate feedback for decision-making (Davenport, 2013).

AI in healthcare can take multiple forms, such as machine learning and deep learning. Machine learning is a branch of AI that uses complex algorithms to provide predictive analytics and treatment recommendations by learning from existing data and identifying patterns with minimal human intervention (Sas, 2019). Deep learning, a subset of machine learning, uses computer system algorithms designed to mimic the human brain. Deep learning allows machines to use massive amounts of structured and unstructured data to solve complex problems (Marr, 2018). Natural Language Processing and AI-driven chatbots offer the possibility of highly personalized patient PHI interfaces and healthcare recommendations.

Specific health-related data, such as high-quality biomedical data, can be highly disparate and require complex data analysis techniques (Mamoshina et al., 2018). This level of complexity, paired with high growth rates in healthcare data, renders AI particularly beneficial to the healthcare industry, allowing healthcare providers to leverage AI's ability to incorporate better intelligence into various health-related devices and applications to provide patients with real-time diagnostic and treatment information. According to PwC Global (2017), "One of AI's biggest potential benefits is to help people stay healthy so they 'don't need a doctor, or at least not as often.'" Agarwal and Dhar (2014) observe that healthcare is an industry that can benefit the most from AI's power of predictive analytics, where the traditional approach of delaying treatment until the construction and testing of a suitable explanatory model could result in lost lives.

Recently developed AI-powered health applications include, for example, the AI system designed by DeepMind for Google, which has proven successful in interpreting eye scans and providing recommendations on more than 50 sight-threatening eye diseases with the precision and expertise of a world-renowned eye surgeon (Fauw et al., 2018; Suleyman, 2018). Another breakthrough by Mayo Clinic

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[3] We further discuss doc.ai's blockchain storage solution in section 2.

Ventures and AlivCor is developing a bloodless blood test that uses AI to analyze electrocardiogram signals to screen for increased blood potassium levels to prevent the life-threatening condition hyperkalemia (Farr, 2018). Arterys, Inc. has used AI's deep learning and cloud computing to create a medical imaging and clinical diagnosis platform that can examine breast, heart, liver, and lung images with precision, making it easier for physicians to diagnose tumors and heart disease (Arterys Inc., 2018).

While the technical advances in AI-driven health platforms for diagnostics are tremendous, physicians' actual use of these platforms is often limited (Lin et al., 2017). Additionally, a considerable amount of research focusing on designing and testing AI-based predictive models (Bardhan et al., 2014; Lin et al., 2017; Meyer et al., 2014) suffers from limited adoption by patients and clinicians.

A medical trial by doc.ai and Anthem Blue Cross uses an AI-driven health platform to predict when an individual will experience environmental allergies or allergy symptoms. Participants join the trial by downloading a mobile application to their smartphone and entering data on personal "omics," including phenomics (biometrics), exposome (environmental health risks), genomics (family- and gene-related conditions), and pharmacomics (medications). Additionally, trial participants record specific information about past allergies and current allergy symptoms. doc.ai's cloud systems store the data in a blockchain-based database in an anonymizing manner and analyze the pharmacomics and allergy symptoms on a large scale using machine learning to provide each participant with an individual report through the same mobile application with information regarding allergy triggers and time of day they are most likely to experience symptoms. Based on this doc.ai tool, we define an AI-based healthcare platform as a software application that (1) collects, stores, and processes data analyzed by artificial intelligence (e.g., machine learning) and (2) makes the results of that data analysis available to patients and healthcare professionals to guide diagnostic and treatment decisions. The data needs of this medical trial highlight the importance of understanding how to target participants motivated to share their PHI to enable AI-based analysis.

Thus far, the existing patient medical information within electronic health records has been entered by providers such as hospitals, physicians, and pharmacies with the assumption that a patient's privacy is protected by HIPAA under the patient agreement to disclose information. This assumption is based on the premise that the providers enter the information into the electronic health records. However, the patient health information disclosure and the applicability of HIPAA differ when sharing information with health applications not governed by a provider, health plan, or healthcare clearinghouse (Wharton Business Daily, 2018).

The Office for Civil Rights (OCR) within the U.S. Department of Health and Human Services (HHS) has released guidance on HIPAA and information sharing with health applications—specifically how HIPAA applies in situations where the patient uses health applications to create, manage, and share health information. According to the OCR guidance, if health application developers are collecting health information from consumers to provide a service directly to the consumers without their information being collected on behalf of a healthcare provider, healthcare clearinghouse, or health plan, consumers and developers are likely not subject to HIPAA regulations. Similarly, mobile healthcare application developers independently using consumer-generated personal health information to develop AI-based health applications are not subject to HIPAA requirements (Litten & Burland, 2021).

The use of large amounts of PHI can create privacy and security concerns. According to a Forrester Research report, "AI requires a ton of data, so the privacy implications are bigger" (Dashevsky, 2018). Moreover, "there is potential for a lot more personally identifiable data being collected. IT definitely needs to pay attention to masking that data" (Botelho, 2017). According to an *MIT Technology Review* survey, most Americans overwhelmingly agree that AI needs some regulation in light of increased data security issues and cyber-attack sophistication. Both are ranked as the respondents' highest specific concerns (Hao, 2019). Moreover, numerous European countries are ahead of the U.S. in adopting safeguards with, for example, the implementation of the General Data Protection Regulation (GDPR), which the European Parliament enacted in May 2018 to address data protection and privacy of personal information of European citizens (Grojean, 2018; Kurtz et al., 2018).

## 2.2 Willingness to Share Personal Health Information

Data has become one of the driving forces behind the successful digital transformation toward the Internet of Things (IoT), with a significant portion of the world-generated data being from the healthcare industry (Bresnick, 2017). For AI-based models and tools to be effective in healthcare, patients must be willing to share their PHI. Information sharing is "a person's willingness to distribute information in a collaborative

fashion," which depends on an individual's perceived level of reliance on the internal and external entities associated with the information exchange (Hwang et al., 2014).

Findings from a study conducted by GfK Global of over 22,000 Internet users across 17 countries indicate that more than 27 percent of the population surveyed are willing to share their personal information in exchange for various benefits such as personalized services and lower costs (GfK, 2017). This study also points to a large portion of the population that is leery of sharing their personal information. Individuals and governments recognize the need to maintain the utmost security concerning PHI (Mamoshina et al., 2018), as evidenced by the establishment of the Health Insurance Portability and Accountability Act (HIPAA) of 1996, which mandates the protection of personally identifiable information maintained by the U.S. healthcare industry (U.S. Department of Health and Human Services, 2017).

While HIPPA attempts to ensure the proper use of PHI, a general aversion to disclosing PHI can act as a barrier hindering new technological developments that heavily rely on the use and exchange of patient information (Mamoshina et al., 2018). Some research has investigated drivers of willingness to share personal information, and their findings help identify potential methods for overcoming constraints and motivating sharing. Liang, Xue, and Zhang (2017) investigate online health information use behavior among individuals with physical disabilities. Their findings indicate that outcome-based beliefs such as perceived benefits increase online health information use behavior, while perceived risks minimize it. Furthermore, they found that information quality and system quality increase perceived benefits and reduce perceived risks. Similarly, Raban and Rafaeli (2007) explore the impact of information ownership on the willingness to share information online. These authors find a higher propensity to share privately owned information than organizationally owned content. They infer that ownership plays a major role in an individual's information-sharing decisions and should be given special consideration in the application design process.

## 2.3    Readiness to Manage Personal Health Information on Blockchain-Based Applications

Over the past several years, the proper collection and storage of PHI have become core issues among policymakers striving to implement appropriate security measures and policies to protect patient data. One guiding principle within this issue is consumer empowerment, which hinges on passing the control and ownership of data from the healthcare provider to the patient (Anderson & Agarwal, 2011). Raban and Rafaeli (2007) indicate that this form of individual data ownership may be necessary for data sharing, especially with non-traditional healthcare providers. Therefore, some AI-driven health platforms may require individual PHI ownership and management when sharing PHI with the platform.

Blockchain provides the healthcare industry with a solution to issues concerning the collection and storage of PHI by implementing effective security measures for storing and managing PHI. According to *Blockchain in Healthcare Today*, "Blockchain technology can elevate care excellence, and enhance the participation of owning one's health and data" (Bean, 2018). Blockchain's decentralized storage model allows users to migrate away from storing PHI on a centralized server, which is often susceptible to security vulnerabilities (FinTech Network, 2017), and blockchain also offers healthcare providers the ability to anonymize or mask PHI with encryption technology, minimizing the risks associated with unauthorized access. According to an *MIT Technology Review* survey, most Americans overwhelmingly agree that AI needs to be regulated in light of increased data privacy issues and cyber-attack sophistication; both are ranked as their highest specific concerns (Hao, 2019). Thus, it is imperative to raise individuals' awareness about the implications of AI and its potential impact on privacy and security.

The IT community increasingly offers advanced technical solutions promising greater security, data integrity, accessibility, and interoperability.  Blockchain technology is a promising technology that provides the healthcare industry solutions to many privacy and security issues associated with AI-driven applications. The blockchain is a decentralized database of transactions with changes to the transactions added as blocks within the database. Thus, the blockchain provides the integrity of information through hash links among the blocks offering the user a tamper-resistance system of transactions. Hence, blockchain is evolving as a critical technology addressing a wide variety of privacy and security issues within the healthcare space. Blockchain technology further passes data ownership to individuals while allowing them to manage their own PHI. Even though it is enticing for an individual to use an AI-based health application that incorporates blockchain to store health information and obtain real-time decisions, individuals might still be reluctant to take control of their own data due to the added responsibility of managing their personal health information by themselves. Thus, our study also attempts to answer the

question—are individuals ready to manage their PHI, thus, in large part, bringing the control of information to the individual?

The AI-driven health platform created by doc.ai for their allergy medical trial with Anthem utilizes blockchain technology to allow individuals to manage their own PHI securely and anonymously (doc.ai, 2018). doc.ai's PHI storage solution is "a first-of-its-kind blockchain environment for healthcare that will be open to consumers, data scientists, and healthcare providers. This ecosystem is built on the Ethereum blockchain to leverage smart contracts, enabling both user privacy and ownership of data, as well as the integrity and the provenance of the data for the predictive models" (PR Newswire, 2018)

While a blockchain environment can promote secure ownership of PHI, one potential remaining is that patients may not want to own their own data (Lichtenwald, 2017), indicating that security measures on their own are not sufficient to persuade individuals to manage their PHI. Other internal or external motivators may be necessary to promote individual data management that can facilitate data sharing, enabling AI-driven health platforms to provide valuable diagnostic and treatment information.

## 3 Theoretical Framework and Hypothesis Development

Building upon the foundational literature presented in the preceding sections, in our effort to understand the factors that contribute to an individual's intention to use an AI-driven health platform, we draw on the health belief model (HBM) and explore the possible antecedents to a patient's readiness to manage and willingness to share PHI on such a platform (Refer to Figure 1 for the conceptual model). In reference to our conceptual model (Figure 1), the following sub-sections discuss the HBM and its application to our setting, including extensions to information management and security in the AI-health platform context.
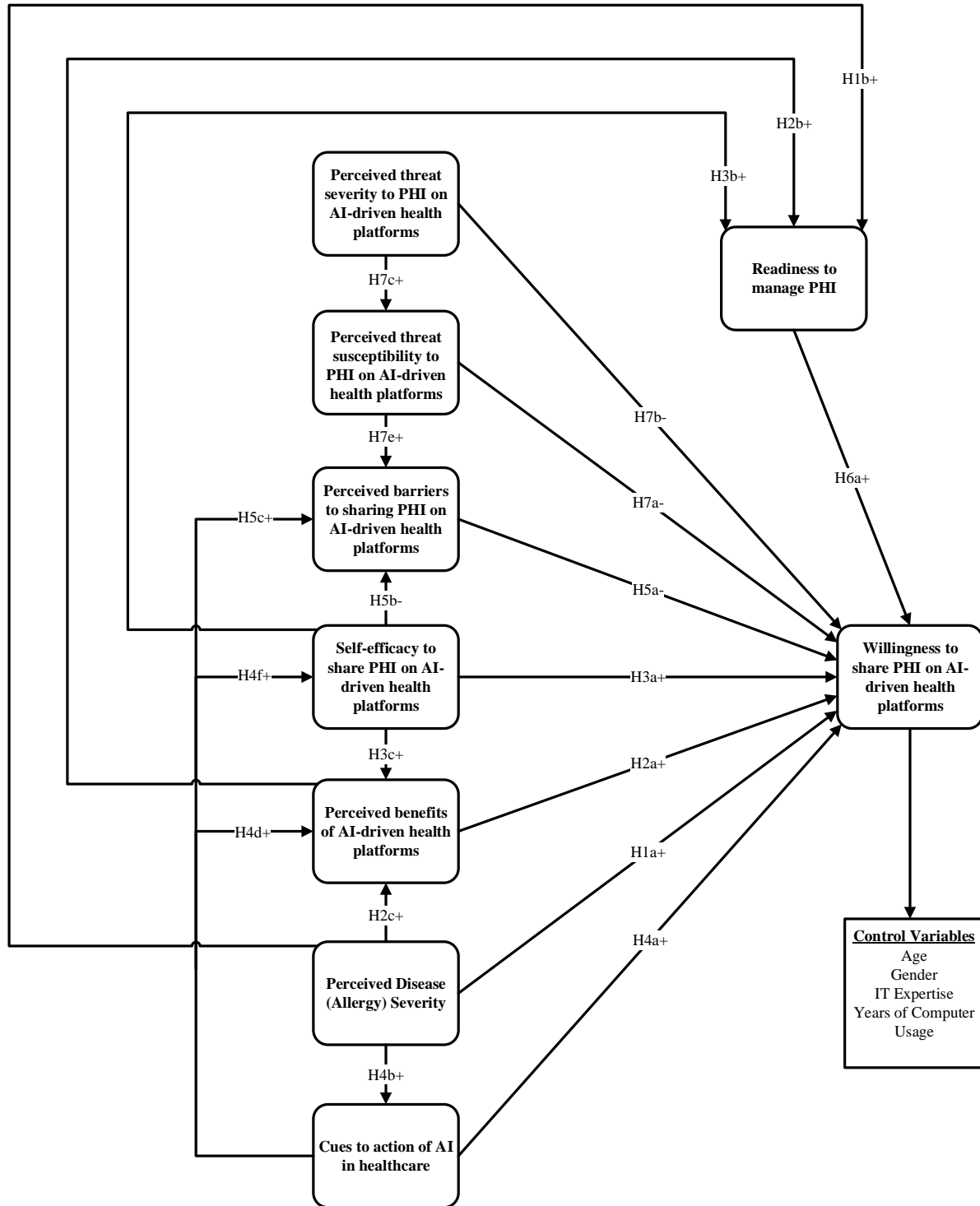
**Figure 1: Conceptual Model (Adapted from Janz and Becker (1984))**

## 3.1    Health Belief Model

The HBM was initially developed to explain the health-related behaviors of individuals while attempting to predict their adoption of specific preventive measures (Rosenstock, 1974). According to the theory, health-related behaviors have two key determinants: "(1) the value placed by an individual on a particular goal; and (2) the individual's estimate of the likelihood that a given action will achieve that goal" (Janz & Becker, 1984, p. 2). The HBM decomposes these determinants of patient propensity to adopt healthy

behaviors into multiple constructs. In this model, healthy behavior is a positive function of the perceived severity of and susceptibility to an adverse health condition, perceived benefits of the proffered solution, and self-efficacy and cues to adopt the solution. In contrast, healthy behavior is a negative function of the perceived barriers to adoption. Since its inception, this model has successfully predicted behaviors such as seat belt use, health screenings, medical compliance, and the use of vaccinations (Janz & Becker, 1984).

While extant research has used the traditional Technology Acceptance Model (TAM) and its constructs, such as "usefulness" and "ease of use," in explaining technology acceptance/adoption and intention to use (Davis, 1989; Venkatesh et al., 2003; Venkatesh, 2000), these factors do not necessarily explain individuals' information management and sharing decisions related to health applications. Furthermore, TAM-related constructs may be irrelevant until the patient decides to share their health information with the particular application. Since these applications require patients to manage and share their sensitive information in receiving a diagnosis, patients are more likely to conduct a cost-benefit analysis by evaluating the barriers and benefits of sharing information, which are key intermediate constructs of HBM. Thus, while we recognize the importance of TAM and its extended unified model with numerous antecedents that have been verified in the workplace and eCommerce contexts, we believe that key intermediate constructs in HBM can better explain what drives patients' information management and sharing decisions in a healthcare context, where the HBM is well established.

The HBM also considers the "medical procedure" patient profile. In the context of the medical procedure profile, diagnostic and treatment information is readily available from healthcare providers, and the theorized action is compliance with prescribed medical procedures. However, a parallel "informational participation" profile has emerged with additional benefits for medical data ownership, sharing, and analysis. In the context of the informational participation profile, the patient has the opportunity to receive diagnostic and treatment information that is not readily available from traditional healthcare providers but is available from other sources, such as online communities or digital technologies. For this profile, the theorized action is the patient's willingness to acquire, store, and share healthcare data to identify prescribed medical procedures. Applying the HBM to this profile extends beyond the aspects of patient compliance to investigate a more proactive form of patient behavior.

Recently, AI-driven health applications have emerged as a digital technology that can analyze PHI to provide diagnostic and treatment information efficiently or effectively. However, both the readiness to manage PHI and the willingness to share PHI on AI-driven health platforms are necessary conditions to reap the benefits of AI-driven health platforms. The willingness to share is necessary to receive AI-driven diagnostic and treatment information for two reasons. First, AI needs a large dataset to conduct the analysis required to learn answers to medical questions. Second, the same AI system needs access to the individual patient's PHI to provide customized medical information, just as a traditional healthcare provider would need PHI to prescribe personalized medical procedures.

Additionally, sharing PHI requires a readiness to manage that information because patients can only share information they store and access with a digital system. A readiness to manage one's information assumes a level of responsibility and effort. We predict that the HBM constructs of perceived disease severity, perceived benefits of AI-driven health platforms, and self-efficacy to share PHI affect readiness to manage PHI, and these factors, plus cues to action and perceived barriers to sharing PHI on AI-driven health platforms are drivers of a willingness to share PHI on AI-driven health platforms.[4]

### 3.1.1 Perceived Disease Severity

Perceived severity is an individual's belief in the seriousness or magnitude of a threat. When individuals perceive an illness to be severe, they are more likely to adopt a behavioral response to mitigate the risk of developing the condition (Rosenstock, 1974). In other words, disease severity motivates compliance with medical procedures by increasing the disutility of an illness. According to Anderson and Agarwal (2011), an individual's current medical state is an important precursor to their willingness to provide access to PHI on digital platforms. We similarly predict that disease severity will motivate the sharing of PHI to obtain unique insights regarding triggers and treatments. Unlike the traditional medical procedure patient profile in which the healthcare provider stores and manages patient health information to provide diagnosis and

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[4] We do not hypothesize an effect of perceived disease susceptibility despite its role in the HBM because our sample is of individuals who are already all susceptible to our selected disease (i.e., allergies), so we cannot observe the effect of susceptibility.

treatment, the informational participation profile includes ownership of PHI as a precursor to sharing that information. We hypothesize:

**H1a: Perceived allergy severity is positively associated with willingness to share PHI on AI-driven health platforms.**

**H1b: Perceived allergy severity is positively associated with readiness to manage PHI.**

### 3.1.2 Perceived Benefits

A driving factor in compliance with medical procedures is a belief that the prescribed procedure will produce sufficiently desirable marginal benefits to equal or exceed the marginal cost of paying for and following the procedure (Rosenstock, 1974). Thus, we predict that AI-driven health platforms' perceived benefits of access to medical knowledge toward identifying medical procedures will positively influence a willingness to bear the personal cost of sharing personal information on such platforms. Individual data management is an added cost and can dissuade patients from wanting to assume the informational participation profile and receive the associated medical knowledge. However, the greater the marginal benefits of the medical knowledge available on AI-driven health platforms, the more willing patients will be to bear the added cost of data management necessary for data sharing. We hypothesize:

**H2a: Perceived benefits of AI-driven health platforms are positively associated with willingness to share PHI on AI-driven health platforms.**

**H2b: Perceived benefits of AI-driven health platforms are positively associated with readiness to manage PHI.**

The end goal for a patient is to realize perceived, attainable, valuable benefits from following a medical procedure, and the greater the suffering from the medical condition, the greater the procedure's perceived benefit. Individuals suffering from an adverse health condition may more readily perceive the benefits of increased medical care or new research related to that condition (Anderson & Agarwal, 2011). If additional information beyond what is available from a traditional healthcare provider is necessary to pursue a procedure that can resolve a medical condition, and if that information is attainable from an AI-driven health platform, then disease severity may increase the perceived benefits of AI-driven health platforms. We further conceptualize that when the severity of a health condition increases, individuals are more likely to perceive greater benefits from AI-driven health platforms, thereby sharing PHI. An individual's feelings of the seriousness or severity of an illness or a health condition may vary depending on their consideration of the medical consequences (e.g., disability, death) or social consequences (e.g., family, friends, social relationships) of the illness. When considering the medical or social consequences increases, individuals are more likely to seek out healthcare providers or external tools that can resolve, relieve, or manage the disease or health condition. When tools such as AI-based health platforms are available to such individuals, they are more likely to perceive higher benefits from such tools due to the seriousness of the experienced health condition and their need to eliminate or mitigate the adverse effects of the illness. Consequently, individuals are more willing to share their PHI to experience the inherent benefits of such tools. In the context of our study, allergy sufferers who experience severe symptoms are more likely to perceive greater benefits and thus are more willing to share their PHI with such AI-based health platforms specifically designed to manage allergies. We predict that perceived benefits will also mediate the relationship between allergy severity and willingness to share PHI on AI-driven health platforms because allergy relief is the end-goal of the information participation patient profile. We hypothesize:

**H2c: Perceived allergy severity is positively associated with the perceived benefits of AI-driven health platforms.**

**H2d: Perceived benefits of AI-driven health platforms partially mediate the relationship between perceived allergy severity and willingness to share PHI on AI-driven health platforms.**

### 3.1.3 Self-efficacy

Self-efficacy refers to individuals' beliefs in their ability to engage in specific behaviors. According to Bandura (1986), self-efficacy "is concerned not with the skills one has but with judgments of what one can do with whatever skills one possesses" (391). Individuals are more likely to engage in a behavior when they feel confident in their ability to perform the behavior (Ajzen 1991; Herath & Rao, 2009) successfully.

Studies have shown self-efficacy as an antecedent to behavioral choice (Lee & Larsen, 2009; Milne et al., 2000).

In the HBM, the construct of self-efficacy captures a patient's ability to follow a prescribed medical procedure. Under the medical procedure profile, receiving information regarding the prescribed procedure from traditional healthcare providers is straightforward for many patients. However, the informational participation profile adds a layer of difficulty by requiring patient proactivity in sharing PHI with AI platforms to obtain medical information. This added difficulty necessitates additional self-efficacy to share PHI. We predict that patients with this form of self-efficacy will be more willing to share PHI on AI-driven health platforms. We also expect self-efficacy to share PHI on AI-driven health platforms will increase patient readiness to manage PHI. Without this self-efficacy to share, patients would not perceive the ability to obtain benefits from sharing and would not choose to bear the added cost of managing health information without expecting added benefits. We hypothesize:

> **H3a: Self-efficacy to share PHI on AI-driven health platforms is positively associated with willingness to share PHI on AI-driven health platforms.**

> **H3b: Self-efficacy to share PHI on AI-driven health platforms is positively associated with readiness to manage PHI.**

Patients' perceptions of the benefits of following prescribed medical procedures are affected by a belief in their ability to take advantage of those benefits. In other words, patients are less likely to perceive benefits from a treatment they feel incapable of pursuing. This may be especially true in the informational participation patient profile because of the higher level of personal responsibility to receive any benefits. We predict that increased self-efficacy to share information on AI-driven health platforms will increase the perception of benefits. Furthermore, the ability to share information is not sufficient to do so without an expectation of realized benefits from sharing. Thus, when individuals' perceived capability to use such systems increases, it may reduce barriers to using such platforms while increasing their confidence and willingness to share PHI. As a result, we also predict that perceived benefits will mediate the relationship between self-efficacy and the willingness to share PHI on AI-driven health platforms. We hypothesize:

> **H3c: Self-efficacy to share PHI on AI-driven health platforms is positively associated with the perceived benefits of AI-driven health platforms.**

> **H3d: Perceived benefits of AI-driven health platforms partially mediate the relationship between self-efficacy to share PHI on AI-driven health platforms and willingness to share PHI on AI-driven health platforms.**

### 3.1.4    Cues to Action

Perceived severity, perceived benefits, and self-efficacy alone may not lead a patient to comply with medical procedures (Rosenstock, 1974). An additional trigger or external cue (e.g., a reminder from a medical professional or automated system to take medication) may be necessary. Prior research has shown that these cues increase compliance with prescribed medical procedures (Janz & Becker, 1984). Similarly, for the informational participation profile, online content that builds awareness of health information-sharing systems, such as AI-driven health platforms enabling the acquisition of medical diagnoses and treatments, can provide external cues to encourage information sharing. We predict that the external signals from increased awareness of AI-driven health platforms will increase the willingness to share PHI on these platforms. We hypothesize:

> **H4a: Cues to action are positively associated with willingness to share PHI on AI-driven health platforms.**

In addition to increasing willingness to share PHI, cues to action likely mediate the relationship between allergy severity and willingness to share. The onus is greater on the patient in the informational participation profile to discover outlets for acquiring medical information than on the patient in the medical procedure profile, who can often receive sufficient diagnostic and treatment information from a primary healthcare provider. Even in situations of severe illness, external cues through increased awareness of AI-driven health platforms can promote the willingness to share health information with these platforms to find much-needed relief. Furthermore, the more severe an illness is, the more motivated the patient may be to discover potential remedies. Under the medical procedure profile, this may involve more frequent visits to primary care providers or specialists. Under the informational participation profile, this likely involves researching technology-driven healthcare solutions to gain information beyond what primary care

providers offer. Based on these two premises, we predict that allergy severity will increase the frequency with which a patient receives external cues to action by motivating patients to research and learn about technology in healthcare. In turn, for some patients, these external cues may act as a driver for sharing PHI with AI-based health platforms compared to patients who do not receive such external cues. Thus, we also predict that these cues will mediate the relationship between allergy severity and willingness to share PHI on these health platforms. We hypothesize:

> **H4b: Perceived allergy severity is positively associated with cues to action.**

> **H4c: Cues to action partially mediate the relationship between perceived allergy severity and willingness      to      share      PHI      on      AI-driven      health      platforms.**

As individuals become more aware of AI technologies, they increasingly perceive their value. As external sources extol the added opportunities for positive health outcomes that AI can provide, patients become increasingly aware of the health benefits of AI-driven platforms. As individuals become more aware of AI technologies, they become increasingly comfortable with them. For example, the more individuals hear about personal assistants, such as Siri or Alexa, the more capable these individuals feel about interacting with them. As a result, we make three predictions regarding the effects of external cues on individuals' desire, ability, and willingness to share PHI on AI-driven health platforms. First, we predict that more frequent cues will increase the perceived benefits of AI-driven health platforms. Second, we predict that the perceived benefits will increase an individual's willingness to share PHI with AI-based health platforms to receive the benefits. Thus, perceived benefits will mediate the relationship between cues to action and willingness to share. The willingness comes from the desire for the benefits themselves, not merely the increased awareness that external cues provide. Third, we predict that more frequent external cues will increase patients' self-efficacy to share. We hypothesize:

> **H4d: Cues to action are positively associated with the perceived benefits of AI-driven health platforms.**

> **H4e: Perceived benefits of AI-driven health platforms partially mediate the relationship between cues to action and willingness to share PHI on AI-driven health platforms.**

> **H4f: Cues to action are positively associated with self-efficacy to share PHI on AI-driven health platforms.**

### 3.1.5   Perceived Barriers

According to the HBM, for the medical procedure patient profile, disease severity, susceptibility, perceived benefits of the prescribed treatment, self-efficacy to follow the treatment, and awareness of the need for the treatment by internal and external cues increase patient willingness to adhere to that treatment. One additional HBM construct is the existence of barriers preventing patient compliance with prescribed medical procedures. Perceived barriers can include inconvenience, difficulty, danger, unpleasantness, and discomfort when engaging in a medical procedure (Janz & Becker, 1984). Within HBM, perceived barriers refer to an individual's perception of the costs of engaging in a recommended health behavior. Extant literature indicates that an individual will engage in a cost-benefit analysis prior to sharing information online or with third parties. The Antecedents–Privacy Concerns–Outcomes Model (APCO) (Dinev & Hart, 2006; Smith et al., 2011) posits that individuals will consider the potential benefits received by disclosing information in conjunction with the risks prior to information disclosure. Similarly, within HBM, perceived barriers refer to an individual's perception of the costs of engaging in a recommended health behavior. Similarly, within HBM, perceived barriers refer to an individual's perception of the costs of engaging in a recommended health behavior. According to HBM, individuals are more likely to engage in a recommended health action if they perceive a high risk from the threat of a disease or health condition, if they feel susceptible to the disease, and if the benefits outweigh the costs (barriers) (Rosenstock, 1974). We predict that barriers to sharing PHI will negatively affect patients' willingness to share under the informational participation profile. We hypothesize:

> **H5a: Perceived barriers to sharing PHI on AI-driven health platforms are negatively associated with willingness to share PHI on AI-driven health platforms.**

We also predict that other HBM constructs will influence patients' perceptions of barriers to sharing PHI on AI-driven health platforms. First, as patients' belief in their ability to adhere to prescribed medical procedures increases, their perceptions of barriers preventing compliance with those procedures decrease. It follows, then, that increased ability to share PHI on AI-driven health platforms will decrease perceived hurdles to do so. Second, more frequent external cues can increase awareness of both benefits from a chosen course of action and limitations preventing successful action. Although we predict that cues will positively affect the perception of benefits from such platforms, we also expect that cues will have another contravening effect, namely a positive effect on the perception of barriers. We hypothesize:

**H5b: Self-efficacy to share PHI on AI-driven health platforms is negatively associated with perceived barriers to sharing PHI on AI-driven health platforms.**

**H5c: Cues to action are positively associated with perceived barriers to sharing PHI on AI-driven health platforms.**

### 3.1.6    Readiness to Manage Personal Health Information

Patients traditionally rely on healthcare providers to store and manage their health information, assuming that their current healthcare providers are the primary and sometimes the sole users of that information. Inherent to the desire to share PHI with AI-driven health platforms is the understanding that other, nontraditional healthcare agents may also be important users of a patient's health information. Under the information participation profile, patients must be willing to store and manage their own health information to be able to share it, when necessary, with AI-driven health platforms. Patient empowerment becomes an important issue when managing one's PHI, which relies on passing the control and ownership of PHI from the healthcare provider to the patient. AI-platforms incorporating blockchain technology can facilitate patient data ownership and management by eliminating the issues surrounding the collection and storage of PHI by implementing appropriate security measures to protect patient data. Extant literature indicates that an individual's readiness to accept and manage a technology will increase their willingness to participate as a member of the technological platform (Melas et al., 2014). Furthermore, the increased privacy and security preserving mechanisms surrounding blockchain technology can reduce patient concerns about sharing data with AI-based health platforms, thus increasing patient willingness to share PHI on such platforms. As a result, we predict that a readiness to manage PHI and gain greater control of their PHI will increase the willingness to share that information as AI-platform participants. We hypothesize:

**H6a: Readiness to manage PHI is positively associated with willingness to share PHI on AI-driven health platforms.**

An individual's readiness to manage their PHI is a necessary condition for sharing PHI because patients can only share information that they control and willingly process (Raban & Rafaeli, 2007; Hwang et al., 2013, 2014). Without the ability to manage PHI, the desire to share, motivated by either the negative effects of an illness, the positive effects of a health solution, or the self-efficacy to pursue those benefits, may seem less feasible or essential. Also, because managing PHI comes with an added cost in effort and responsibility (Lichtenwald, 2017), those who are the most motivated to share their PHI will also be the most motivated to bear the cost of managing their PHI (Hwang et al., 2013, 2014).

Both allergy severity and perceived benefits increase patient willingness to comply with medical procedures in an attempt to either enjoy the solution's utility or, at least, avoid the disutility of the problem (Rosenstock, 1974). The cost of compliance simultaneously presents a hurdle (Janz & Becker, 1984). Since the management of PHI is a precursor to sharing PHI, the cost of management (the necessary condition) becomes an added cost of sharing (compliance with the procedure). The cost of information management can reduce the desired benefits leading to a willingness to share, but conversely, the desire for benefits or relief can increase the willingness to bear these costs. As a result, we predict that readiness to manage PHI may mediate the relationship between perceived allergy severity and the willingness to share PHI with AI-driven health platforms, as well as the perceived benefits and willingness to share PHI. We hypothesize:

**H6b: Readiness to manage PHI partially mediates the relationship between perceived allergy severity and willingness to share PHI on AI-driven health platforms.**

**H6c: Readiness to manage PHI partially mediates the relationship between perceived benefits of AI-driven health platforms and willingness to share PHI on AI-driven health platforms.**

Readiness to manage PHI as a precursor to and necessary condition for sharing PHI also influences the consequences of self-efficacy. Self-efficacy in each of these arenas can increase participation in the management and sharing tasks (Lee & Larsen, 2009; Milne et al., 2000), but the perceived ability to share information does not immediately imply an ability to manage that information if management and sharing rely on different tasks, skillsets, or technologies (Compeau & Higgins, 1995). Any lack of perceived ability to manage PHI can reduce, or even remove, the ability of patients' self-efficacy to promote a willingness to share that PHI.[5] Thus, we also predict that readiness to manage PHI may mediate the relationship between self-efficacy to share and the willingness to share PHI with AI-driven health platforms. We hypothesize:

**H6d: Readiness to manage PHI partially mediates the relationship between self-efficacy to share PHI on AI-driven health platforms and willingness to share PHI on AI-driven health platforms.**

### 3.1.7   Perceived PHI Threat Severity and Susceptibility

Within HBM, perceived threat susceptibility is defined as an individual's subjective perception of the risk of contracting a disease or health condition. In contrast, threat severity is the perceived seriousness of contracting an illness or disease (Janz & Becker, 1984). Prior literature has successfully applied the perceived threat severity and susceptibility constructs to information-security-related behaviors (Koloseni et al., 2019; Ng et al., 2009; Raddatz et al., 2021; Silic et al., 2018) where "parallels can be drawn between preventive healthcare behavior (such as observing a healthy diet to avoid heart diseases) and information protective behaviors (such as using a strong password to prevent unauthorized use of one's account)" (Ng et al., 2009, p. 817). While threat severity and susceptibility of a disease or illness motivate individuals to engage in preventative health behavior, information security threats motivate individuals to engage in protective computer security-related behavior. Individuals are more likely to adopt security-related behaviors to protect their personal information when they consider themselves more susceptible to a cyber-incident or when they perceive the loss from unauthorized access to their personal information to be severe (Boss et al., 2015; Johnston et al., 2016). We likewise hypothesize the relevance of this information security application of the HBM in determining behavior under the informational participation patient profile. Whereas the severity of and susceptibility to a disease would increase patient willingness to comply with prescribed medical procedures, the threat severity of and susceptibility of PHI on AI-driven health platforms would decrease patient willingness to share this information because of concerns about preserving data security. We hypothesize:

**H7a: Perceived threat susceptibility to PHI on AI-driven health platforms is negatively associated with willingness to share PHI on AI-driven health platforms.**

**H7b: Perceived threat severity to PHI on AI-driven health platforms is negatively associated with willingness to share PHI on AI-driven health platforms.**

We also predict that the perceived severity of threats to personal information indirectly determines willingness to share in combination with perceived threat susceptibility for two reasons. First, according to previous literature, individuals' perception of their susceptibility to a negative event increases the more severe that event becomes. Second, expected loss from a cyber-incident is the product of likelihood (i.e., susceptibility) and exposure (i.e., severity). Individuals are less motivated to protect against extremely unlikely events, regardless of their consequences, but as the likelihood of a negative outcome increases, individuals are more likely to respond to the severity of the consequences. Based on these two principles, we predict that (1) the perceived severity of threats surrounding the security of PHI shared on AI-driven health platforms will increase perceived susceptibility to these threats, and (2) perceived susceptibility to these threats will mediate the relationship between perceived severity and patient willingness to share PHI on such platforms. We hypothesize:

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[5] Blockchain technology's security and privacy-preserving mechanisms may add to individuals' perceived ability to successfully manage their PHI by lowering the bar for maintaining information security and privacy (PR Newswire, 2018).

**H7c: Perceived threat severity to PHI on AI-driven health platforms is positively associated with perceived threat susceptibility to PHI on AI-driven health platforms.**

**H7d: Perceived threat susceptibility to PHI on AI-driven health platforms fully mediates the relationship between perceived threat severity to PHI on AI-driven health platforms and willingness to share PHI on AI-driven health platforms.**

Finally, by expanding the HBM for the data security aspect of the informational participation patient profile, we also introduce an additional potential hurdle to sharing PHI, specifically the inability to ensure data security after sharing. We predict that the perception of susceptibility to threats to the security of PHI shared with AI-driven health platforms will increase the perception of barriers to sharing that information. We hypothesize:

**H7e: Perceived threat susceptibility to PHI on AI-driven health platforms is positively associated with perceived barriers to sharing PHI on AI-driven health platforms.**

## 4 Methodology

We use a survey for data collection to test the relationships depicted in our model and research hypotheses. We conducted a comprehensive literature review to identify the determinants of an individual's willingness to share personal health information on AI-driven health platforms consistent with the constructs in the HBM. The survey instrument introduced a health platform and associated AI-driven medical trial that could predict patients' allergy risks and identify allergy triggers. We selected environmental allergies as the illness for our survey to ensure realism (Nagin & Pogarsky, 2001) and internal validity (Harrington, 1996). Our setting is based on an AI-driven health platform designed by doc.ai and Anthem Blue Shield to predict individuals' risk of allergies (doc.ai, 2018). Additionally, we chose environmental allergies as a suitable disease condition for testing the usability of AI-driven health platforms because allergies are identified as the sixth leading cause of chronic illness in the United States, affecting approximately 50 million individuals annually (CDC, 2017) with environmental allergies being the most common of all types (doc.ai 2018).

Appendix A includes our survey instrument, which is comprised of two parts. The first part of the survey captures perceived allergy severity (ASEV), as well as the following HBM constructs as they pertain to sharing personal health information on AI-driven health platforms: perceived benefits (PBEN), cues to action (CUES), self-efficacy (SEFF), and perceived barriers (PBAR) as determinants of willingness to share (WILL) personal health information on AI-driven health platforms. The first part of our survey instrument also captures the expanded HBM constructs of perceived severity (PSEV) and perceived susceptibility (PSUS) to threats against personal health information shared with AI-driven health platforms.

The second part of the survey measures readiness to manage (READ) personal health information using a blockchain technical solution. The IT community increasingly offers advanced technological solutions promising greater security, data integrity, accessibility, and interoperability. Blockchain technology is a promising technology that provides the healthcare industry solutions to many security issues associated with AI-driven applications. Blockchain is evolving as a critical technology addressing a wide variety of security issues within the healthcare space. Blockchain technology further passes the data ownership to individuals, allowing them to manage their own PHI. Even though it is enticing for an individual to use an AI-based health application that incorporates blockchain as a means of storing health information and obtaining real-time decisions, individuals might still be reluctant to take control of their data due to the added responsibility of storing and protecting their personal health information by themselves. Thus, our study also addresses the question of whether individuals are ready to take control and manage their own personal health information with AI.

We constructed this second survey part for three reasons. First, we hypothesize that managing personal health information is a necessary precursor to sharing personal health information. Second, in addition to focusing on allergies as the specific illness in our study, modeling the personally managed storage solution for health information as a blockchain-based database again increases the real-world applicability of our findings by mirroring the storage solution of an actual AI-driven health platform (doc.ai, 2018). Finally, blockchain and AI are both prevalent technologies set to revolutionize the healthcare industry (Mamoshina et al., 2018). By including blockchain in our investigation, we can increase the contribution of our study and the relevance of our findings to academics and practitioners.

## 4.1    Measures and Instrumentation

To improve the reliability and validity of our measures, we employed multi-item scales adapted from existing scales in extant literature (Straub, 1989) and contextualized them to fit an AI-driven healthcare setting. All measures in our study were modeled reflectively and assessed using a 7-point Likert scale anchored from 'strongly disagree' to 'strongly agree.' We derived the items measuring cues to action and willingness to share personal health information on an AI-driven platform from Dinev and Hart (2006). We adapted all other HBM construct items from Ng et al. (2009), Johnston and Warkentin (2010), and Kwahk and Lee (2008). Refer to Table 1 for the constructs, measure type, source, and number of items retained for primary data analysis. To ensure survey efficiency and eliminate low-effort responses (Krosnick, 1999), we embedded attention checks throughout the survey. Our survey also captures relevant demographic variables of gender, age, highest level of education, level of IT and computer expertise, and years of computer usage.

### Table 1. Sources of Measurement Items

| Construct | Type | Source | Number of Items |
|---|---|---|---|
| Perceived Disease (Allergy) Severity | Reflective | Ng et al., (2009) | 3 |
| Willingness to share personal health information on AI-driven health platforms | Reflective | Dinev & Hart (2006) | 3 |
| Perceived threat severity of personal health information on AI-driven health platforms | Reflective | Ng et al. (2009); Johnston & Warkentin (2010) | 4 |
| Perceived threat susceptibility of personal health information on AI-driven health platforms | Reflective | Ng et al. (2009); Johnston & Warkentin (2010) | 4 |
| Perceived barriers of AI-driven health platforms | Reflective | Ng et al. (2009) | 3 |
| Self-efficacy to share personal health information on AI-driven health platforms | Reflective | Johnston & Warkentin (2010) | 3 |
| Perceived benefits of AI-driven health platforms | Reflective | Ng et al. (2009) | 7 |
| Cues to action to use AI in healthcare | Reflective | Dinev & Hu (2007); Ng et al. (2009) | 3 |
| Readiness to manage personal health information | Reflective | Kwahk & Lee (2008) | 5 |

## 4.2    Sample Population and Procedure

We tested our proposed model depicted in Figure 1 by administering a Qualtrics survey through Amazon Mechanical Turk (MTurk) to individuals in the United States who are experiencing or have experienced environmental allergies or environmental allergy symptoms. We believe that a web-based survey is the most appropriate data collection method for this study because our target population comprises individuals throughout the United States who suffer from allergies. We selected MTurk as a suitable method for collecting data since we needed to reach a diverse range of allergy sufferers from all over the United States without restricting ourselves to individuals from a specific area or region. Recent literature suggests that data collected from MTurk compared to other research settings, such as target survey panels, render similar results (Berinsky et al., 2012; Steelman et al., 2014). Furthermore, according to recent research, MTurk respondents provide higher or equal quality data with minimal bias compared to data obtained through survey panels primarily because of the ease in rejecting an MTurk respondent's results if they provide low-quality data such as patterned responses with low variance. Moreover, providing low-quality responses will decrease an MTurker's overall statistics about how accurately they have completed an assigned task, affecting their ability to participate in future projects (Buhrmester et al., 2011; Casler et al., 2013; Goodman et al., 2013). The subjects received monetary compensation for their participation in the study. Before respondent selection, we provided the respondents with a definition of allergies from CDC.gov.

Before the primary data collection, we conducted a pilot test using 145 respondents from MTurk who have suffered or currently suffer from environmental allergies. We retained all 145 responses as no respondent failed an attention check, and no responses contained any missing values. Based on the pilot study results, we concluded that our instrument was appropriate for data collection without modifying the survey items.

We determined the appropriate sample size for the main investigation by conducting a power analysis for structural equation models. With a power level of 0.8, an anticipated effect size of 0.3, and an alpha level

of 0.05, a minimum sample of 200 respondents was necessary to ensure sufficient power. In addition to the 145 responses from the pilot study, we collected data from another 108 respondents, yielding 253 respondents for our primary analysis. We do not report the response rate because participants self-selected their participation in the study once the survey was posted on MTurk.

Of the 253 participants included in the final sample, 56.5 percent are male. The average age of the participants is 34.7. 51.3 percent of the participants report that they have a high or very high level of computer and IT expertise, with an average of 20.9 years of computer usage experience. Based on evidence from extant literature, we model gender, age, IT and computer expertise, and years of computer usage as control variables due to their potential influence on willingness to share information (Anderson & Agarwal 2011; Dinev & Hart 2006).

# 5    Data Analyses and Results

## 5.1    Measurement Model Validation

To assess the internal consistency and reliability of the measurement model, we conducted a confirmatory factor analysis using AMOS 25 (Hair et al., 2017). The measurement model examines the relationships between the measured and latent variables in the model. We assessed our measurement model by examining convergent validity, item reliability, and discriminant validity. We report our validation statistics in Table 2.

We assessed the convergent validity of the measures by examining the item loadings and the average variance extracted (AVE) values. As suggested by Straub, Boudreau, and Gefen (2004), we also ensured that our measures did not cross-load on other constructs. Except for one cue to action item, all survey items load on their respective constructs with loadings exceeding the recommended threshold of 0.7 (Nunnally, 1978). All AVE values are greater than the minimum recommended value of 0.5 (Gefen & Straub, 2005), indicating that each construct successfully explains more than 50% of the variance of the measures associated with that construct (Hair, 2017).

**Table 2. Summary Results for the Measurement Model**

| Construct | Indicator | Mean | Std. Dev. | Est. >0.7 | AVE >0.5 | CA >0.7 | CR >0.7 | $R^2$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 ASEV | ASEV1 | 5.08 | 1.39 | 0.78 | 0.59 | 0.81 | 0.81 | – | 0.77 | | | | | | | | |
| | ASEV2 | 5.21 | 1.37 | 0.74 | | | | | | | | | | | | | |
| | ASEV3 | 5.07 | 1.44 | 0.79 | | | | | | | | | | | | | |
| 2 WILL | WILL1 | 5.11 | 1.36 | 0.85 | 0.63 | 0.84 | 0.84 | 0.61 | 0.46 | 0.80 | | | | | | | |
| | WILL2 | 4.74 | 1.44 | 0.78 | | | | | | | | | | | | | |
| | WILL3 | 4.87 | 1.45 | 0.75 | | | | | | | | | | | | | |
| 3 PSEV | PSEV1 | 5.14 | 1.67 | 0.86 | 0.77 | 0.93 | 0.93 | – | 0.32 | 0.01 | 0.87 | | | | | | |
| | PSEV2 | 5.32 | 1.59 | 0.87 | | | | | | | | | | | | | |
| | PSEV3 | 5.18 | 1.67 | 0.88 | | | | | | | | | | | | | |
| | PSEV4 | 5.08 | 1.74 | 0.89 | | | | | | | | | | | | | |
| 4 PSUS | PSUS1 | 4.78 | 1.60 | 0.79 | 0.65 | 0.88 | 0.88 | 0.22 | 0.27 | -0.23 | 0.52 | 0.80 | | | | | |
| | PSUS2 | 4.65 | 1.56 | 0.84 | | | | | | | | | | | | | |
| | PSUS3 | 4.27 | 1.60 | 0.73 | | | | | | | | | | | | | |
| | PSUS4 | 4.66 | 1.56 | 0.85 | | | | | | | | | | | | | |
| 5 PBAR | PBAR1 | 3.91 | 1.70 | 0.75 | 0.60 | 0.82 | 0.82 | 0.35 | 0.04 | -0.27 | 0.23 | 0.57 | 0.77 | | | | |
| | PBAR1 | 3.71 | 1.68 | 0.74 | | | | | | | | | | | | | |
| | PBAR1 | 3.60 | 1.62 | 0.83 | | | | | | | | | | | | | |
| 6 SEFF | SEFF1 | 5.2 | 1.40 | 0.77 | 0.59 | 0.81 | 0.81 | 0.03 | 0.33 | 0.66 | 0.27 | 0.07 | -0.27 | 0.77 | | | |
| | SEFF2 | 5.50 | 1.31 | 0.74 | | | | | | | | | | | | | |
| | SEFF3 | 5.46 | 1.31 | 0.79 | | | | | | | | | | | | | |
| 7 PBEN | PBEN1 | 5.21 | 1.30 | 0.76 | 0.57 | 0.90 | 0.90 | 0.46 | 0.41 | 0.79 | 0.24 | 0.04 | -0.20 | 0.77 | 0.75 | | |
| | PBEN2 | 5.14 | 1.24 | 0.79 | | | | | | | | | | | | | |
| | PBEN3 | 5.19 | 1.30 | 0.77 | | | | | | | | | | | | | |
| | PBEN4 | 5.17 | 1.31 | 0.73 | | | | | | | | | | | | | |
| | PBEN5 | 5.16 | 1.18 | 0.73 | | | | | | | | | | | | | |
| | PBEN6 | 5.40 | 1.25 | 0.73 | | | | | | | | | | | | | |
| | PBEN7 | 5.46 | 1.23 | 0.76 | | | | | | | | | | | | | |
| 8 CUES | CUES1 | 3.63 | 1.79 | 0.86 | 0.63 | 0.83 | 0.83 | 0.06 | 0.28 | 0.35 | 0.13 | 0.12 | 0.33 | 0.19 | 0.33 | 0.79 | |
| | CUES2 | 2.93 | 1.87 | 0.68 | | | | | | | | | | | | | |
| | CUES3 | 3.91 | 1.90 | 0.83 | | | | | | | | | | | | | |
| 9 READ | READ1 | 5.20 | 1.46 | 0.90 | 0.71 | 0.92 | 0.93 | 0.26 | 0.44 | 0.56 | 0.14 | 0.05 | -0.05 | 0.51 | 0.51 | 0.34 | 0.84 |
| | READ2 | 5.34 | 1.41 | 0.84 | | | | | | | | | | | | | |
| | READ3 | 5.39 | 1.47 | 0.78 | | | | | | | | | | | | | |
| | READ4 | 5.15 | 1.54 | 0.85 | | | | | | | | | | | | | |
| | READ5 | 5.32 | 1.44 | 0.84 | | | | | | | | | | | | | |

Note: n = 253 Item min = 1; Item max = 7; AVE = Average variance extracted; CA = Cronbach's alpha; CR = Composite (Rho) reliability. 1 ASEV = Perceived disease (allergy) Severity; 2 WILL = Willingness to share; 3 PSEV = Perceived threat severity to personal health information; 4 PSUS = Perceived threat susceptibility to personal health information; 5 PBAR = Perceived barriers to use AI-driven health platforms; 6 SEFF = Self-efficacy to use AI-driven health platforms; 7 PBEN = Perceived benefits of using AI-driven health platforms; 8 CUES = Cues to action to use AI in healthcare; 9 READ = Readiness to manage personal health information. The square-root of AVE values is highlighted in the diagonal value.

To ensure the reliability of our measures, we examined composite (Rho) reliability and Cronbach's Alpha values. Composite (Rho) reliability and Cronbach's Alpha values for all constructs are above 0.7, which is the minimum acceptable level of reliability of the measurement items (Cronbach, 1951; Fornell & Larcker, 1981; Gefen & Straub, 2005; Nunnally & Bernstein, 1994). To ensure discriminant validity, we compared latent variable correlations with the square root of the AVE values according to the Fornell-Larcker criterion (Fornell & Larcker, 1981). The square root of AVE values for each construct is greater than the highest correlation with other constructs except for the square root of the AVE for self-efficacy, which is less than the absolute value of the correlations with benefits. Since self-efficacy and benefits depict an acceptable level of reliability, we retained all items for further analysis.

We assessed the measurement model fit by examining a variety of goodness-of-fit statistics: 1) Chi-square ($\chi^2$), 2) Incremental Fit Index (IFI), 3) Tucker Lewis Index (TLI), and 4) Comparative Fit Index (CFI). The $\chi^2$ index for the model is below the recommended threshold of ≤ 5 (p < 0.0001). However, prior research has identified $\chi^2$ statistic to have limitations due to its sensitivity to large sample sizes (Joreskog & Sorbom, 1989), so we pair this $\chi^2$ analysis with other measures of goodness-of-fit. IFI, TLI, and CFI range from 0 to 1, with values closer to 1 indicating a good model fit (Byrne, 2016; Joreskog & Sorbom, 1989). All these values are above the recommended threshold (IFI=0.914; TLI=0.901; CFI=0.913;

$\chi^2$=1017.372; degrees of freedom (df)=524). Additionally, standardized root mean square residual (RMR) and root mean square error of approximation (RMSEA) are below the recommended threshold of ≤ 0.08 (RMR=0.049; RMSEA=0.061).

With self-reported data where independent and dependent variables are not measured in different contexts, there is a potential threat of common method variance (CMV) (Podsakoff et al., 2003). We implemented the necessary steps prior to data collection recommended by those authors to minimize the threat of CMV. These steps include item randomization, the anonymity of study participants, and random selection of the study participants. We also provided definitions of constructs and terms within the instrument to our study participants whenever necessary.

## 5.2 Structural Model Testing

We measured the structural model and its associated hypotheses using AMOS 25. AMOS is a covariance-based statistical tool that utilizes structural equation modeling (SEM) to assess the proposed theoretical relationships (Byrne, 2016). We assessed the structural model fit before analyzing the relationships depicted in the research model.

All goodness-of-fit statistics are above or very close to the threshold values (IFI=0.935; TLI=0.864; CFI=0.932: $\chi^2$=93.974; df=39). The RMR and RMSEA are also below the suggested threshold of ≤ 0.08 (RMR=0.073; RMSEA=0.075). Table 3 displays structural model test results, including standardized path coefficients and path significance based on one-tailed tests. $R^2$ values are shown below. Standardized path coefficients measure the hypothesized relationship strength between the independent and dependent variables. In contrast, the $R^2$ value measures the combined effects of the exogenous variables on each endogenous latent variable (Hair, 2017).

Our results support all hypothesized relationships at $p < 0.05$ or better, except for the relationship between perceived barriers and willingness to share, which is still directionally consistent with H5a as hypothesized ($\beta$ =-0.019). Approximately 61.2% of the variance in willingness to share is explained by its exogenous determinants. Threat susceptibility accounts for 21.8% of the variance explained, perceived barriers account for 34.5%, self-efficacy accounts for 2.5%, perceived benefits account for 46.2%, and cues for 6%. None of the controls included in the model significantly impact willingness to share. Table 4 presents the results of our hypothesized mediation relationships. We draw on guidelines from Baron and Kenny (1986) to analyze mediation effects using the Gaskin and Lim (2018) indirect effect plugin for AMOS 25.

### Table 3. Significance Analysis of the Direct Effects

| Hypothesis | Path (Predicted Sign) | Path Coefficient | t Value | Significance (one-tailed) | Supported at $p < 0.05$ |
|---|---|---|---|---|---|
| H1a | Perceived Allergy Severity → Willingness to Share PHI (+) | 0.180 | 3.981 | p < 0.001 | Supported |
| H1b | Perceived Allergy Severity → Readiness to Manage PHI (+) | 0.415 | 4.234 | p < 0.001 | Supported |
| H2a | Perceived Benefits → Willingness to Share PHI (+) | 0.241 | 8.317 | p < 0.001 | Supported |
| H2b | Perceived Benefits → Readiness to Manage PHI (+) | 0.203 | 3.036 | p < 0.01 | Supported |
| H2c | Perceived Allergy Severity → Perceived Benefits (+) | 0.297 | 3.271 | p < 0.01 | Supported |
| H3a | Self-efficacy → Willingness to Share PHI (+) | 0.166 | 2.921 | p < 0.01 | Supported |
| H3b | Self-efficacy → Readiness to Manage PHI (+) | 0.428 | 3.323 | p < 0.01 | Supported |
| H3c | Self-efficacy → Perceived Benefits (+) | 1.202 | 13.024 | p < 0.001 | Supported |
| H4a | Cues to Action → Willingness to Share PHI (+) | 0.089 | 2.721 | p < 0.01 | Supported |
| H4b | Perceived Allergy Severity → Cues to Action (+) | 0.329 | 4.028 | p < 0.001 | Supported |
| H4d | Cues to Action → Perceived Benefits (+) | 0.203 | 2.961 | p < 0.01 | Supported |
| H4f | Cues to Action → Self-efficacy (+) | 0.114 | 2.535 | p < 0.01 | Supported |
| H5a | Perceived Barriers → Willingness to Share PHI (-) | -0.019 | -0.466 | n.s. | Not Supported |
| H5b | Self-efficacy → Perceived Barriers (-) | -0.338 | -5.344 | p < 0.001 | Supported |
| H5c | Cues to Action → Perceived Barriers (+) | 0.191 | 4.185 | p < 0.001 | Supported |

| H6a | Readiness to Manage PHI → Willingness to Share PHI (+) | 0.073 | 2.746 | p < 0.01 | Supported |
|---|---|---|---|---|---|
| H7a | Perceived PHI Threat Susceptibility → Willingness to Share PHI (-) | -0.169 | -4.996 | p < 0.001 | Supported |
| H7b | Perceived PHI Threat Severity → Willingness to Share PHI (-) | -0.049 | -1.788 | p < 0.05 | Supported |
| H7c | Perceived PHI Threat Severity → Perceived PHI Threat Susceptibility (+) | 0.417 | 8.379 | p < 0.001 | Supported |
| H7e | Perceived PHI Threat Susceptibility → Perceived Barriers (+) | 0.382 | 9.519 | p < 0.001 | Supported |
| Control Variables | Age → Willingness to Share PHI | -0.023 | -1.499 | n.s. | - |
| | Gender → Willingness to Share PHI | 0.343 | 1.153 | n.s. | - |
| | IT Expertise → Willingness to Share PHI | -0.104 | -0.594 | n.s. | - |
| | Years of Computer Usage → Willingness to Share PHI | -0.040 | -0.171 | n.s. | - |

The results indicate that readiness to manage information partially mediates the relationships between allergy severity, self-efficacy, perceived benefits, and willingness to share; perceived benefits partially mediate the relationships between allergy severity, self-efficacy, cues to action and willingness to share; cues partially mediate the relationship between allergy severity and willingness to share, and threat susceptibility partially mediates the relationship between threat severity and willingness to share health information. Hence, we find partial support for our hypotheses regarding mediation effects. No mediators fully mediate any relationships, but all hypothesized mediators partially mediate hypothesized relationships.

**Table 4: Significance Analysis of the Indirect Effects/Mediation Testing**

| Hypothesis | Relationship | Indirect Effects | | | | Conclusion |
|---|---|---|---|---|---|---|
| | | Path Coefficient | Confidence Interval | | p Value | |
| | | | Lower | Upper | | |
| H2d | Perceived Allergy Severity → Perceived Benefits → Willingness to Share PHI | 0.072 | 0.031 | 0.124 | p < 0.01 | Partial Mediation |
| H3d | Self-efficacy → Perceived Benefits → Willingness to Share PHI | 0.290 | 0.201 | 0.417 | p < 0.001 | Partial Mediation |
| H4c | Perceived Allergy Severity → Cues to Action → Willingness to Share PHI | 0.029 | 0.010 | 0.058 | p < 0.05 | Partial Mediation |
| H4e | Cues to Action → Perceived Benefits → Willingness to Share PHI | 0.049 | 0.021 | 0.091 | p < 0.01 | Partial Mediation |
| H6b | Perceived Allergy Severity → Readiness to Manage PHI → Willingness to Share PHI | 0.030 | 0.013 | 0.060 | p < 0.01 | Partial Mediation |
| H6c | Perceived Benefits → Readiness to Manage PHI → Willingness to Share PHI | 0.015 | 0.004 | 0.036 | p < 0.05 | Partial Mediation |
| H6d | Self-efficacy → Readiness to Manage PHI → Willingness to Share PHI | 0.031 | 0.008 | 0.068 | p < 0.05 | Partial Mediation |
| H7d | Perceived PHI Threat Severity → Perceived PHI Threat Susceptibility → Willingness to Share PHI | -0.071 | -0.105 | -0.042 | p < 0.001 | Partial Mediation |

## 6   Post hoc Analysis

While conducting our main analysis, we believed it would be compelling to explore a subset in our dataset of individuals who perceived that their PHI was susceptible yet who were still willing to share their PHI. In conducting this analysis, we only included respondents who selected 5 or higher (7-point Likert scale) for both threat susceptibility and willingness, which included 67 respondents. Results can be found in table 5. Notably, even though susceptibility and severity had higher mean values (5.567 and 5.769, respectively) than our main analysis, they had no significant effect on willingness (H7a and H7b), and severity had no significant effect on susceptibility (H7c). Moreover, only benefits (H2a), self-efficacy (H3a), and readiness (H6a) had a significant direct relationship to willingness. This finding suggests that this subset of individuals, converse to our main analysis, do not respond to the seriousness of consequences as the likelihood of the negative outcome increases. Additionally, the results indicate that these individuals

potentially care only about the benefits offered by the AI-driven health platform and their ability to use the platform to manage their PHI. In essence, benefits outweigh any associated risks to their PHI. An alternative explanation might be that these respondents did not possess the capabilities to properly evaluate the magnitude or severity of the possible threats and consequences of unauthorized individuals accessing their PHI.

**Table 5. Post hoc Analysis of High Susceptibility/High Willingness Respondents**

| Path (Predicted Sign) | | β | t Value | Significance |
|---|---|---|---|---|
| H1a | Perceived Allergy Severity → Willingness to Share PHI (+) | -0.020 | -0.420 | n.s. |
| H1b | Perceived Allergy Severity → Readiness to Manage PHI (+) | 0.312 | 1.749 | *p* < .05 |
| H2a | Perceived Benefits → Willingness to Share PHI (+) | 0.103 | 2.693 | *p* < .01 |
| H2b | Perceived Benefits → Readiness to Manage PHI (+) | 0.173 | 1.129 | n.s. |
| H2c | Perceived Allergy Severity → Perceived Benefits (+) | 0.080 | 0.545 | n.s. |
| H3a | Self-efficacy → Willingness to Share PHI (+) | 0.192 | 2.750 | *p* < .01 |
| H3b | Self-efficacy → Readiness to Manage PHI (+) | 0.404 | 1.530 | n.s. |
| H3c | Self-efficacy → Perceived Benefits (+) | 0.740 | 3.874 | *p* < .001 |
| H4a | Cues to Action → Willingness to Share PHI (+) | -0.007 | -0.194 | n.s. |
| H4b | Perceived Allergy Severity → Cues to Action (+) | 0.429 | 2.150 | *p* < .05 |
| H4d | Cues to Action → Perceived Benefits (+) | 0.107 | 1.208 | n.s. |
| H4f | Cues to Action → Self-efficacy (+) | 0.093 | 1.723 | *p* < .05 |
| H5a | Perceived Barriers → Willingness to Share PHI (-) | -0.005 | -0.306 | n.s. |
| H5b | Self-efficacy → Perceived Barriers (-) | -0.472 | -2.818 | *p* < .01 |
| H5c | Cues to Action → Perceived Barriers (+) | 0.443 | 5.867 | *p* < .001 |
| H6a | Readiness to Manage PHI → Willingness to Share PHI (+) | 0.060 | 1.965 | *p* < .05 |
| H7a | Perceived PHI Threat Susceptibility → Willingness to Share PHI (-) | -0.063 | -0.959 | n.s. |
| H7b | Perceived PHI Threat Severity → Willingness to Share PHI (-) | -0.003 | -0.074 | n.s. |
| H7c | Perceived PHI Threat Severity → Perceived PHI Threat Susceptibility (+) | 0.068 | 1.060 | n.s. |
| H7e | Perceived PHI Threat Susceptibility → Perceived Barriers (+) | 0.139 | 0.758 | n.s |
| Control Variables | Age → Willingness to Share PHI | -0.005 | -0.306 | n.s. |
| | Gender → Willingness to Share PHI | 0.307 | 1.115 | n.s. |
| | IT Expertise → Willingness to Share PHI | 0.281 | 1.607 | n.s. |
| | Years of Computer Usage → Willingness to Share PHI | -0.018 | -1.109 | n.s. |
| Note: n = 67 | | | | |

# 7 Discussion, Implications, and Future Research

Our study aims to explore the factors that motivate a specific target audience's (i.e., environmental allergy sufferers) willingness to share PHI on an AI-driven health platform as a means for the platform to serve its intended purpose of providing healthcare information. As a study in the medical context, we hypothesize that the constructs of the HBM, paired with several constructs designed to extend the HBM based on our research questions, can predict willingness to manage and share PHI.

Based on data collected from 253 allergy sufferers across the United States, our overall results indicate strong empirical support for our theorized research model. While controlling for age, gender, IT expertise, and years of computer usage, study results suggest that perceived disease (allergy) severity, perceived benefits, self-efficacy, cues to action, readiness to manage, perceived PHI threat severity, perceived PHI threat susceptibility all have a direct influence on willingness to share. We also find multiple indirect effects: perceived disease severity influences willingness to share indirectly through perceived benefits, cues to action, and readiness to manage; self-efficacy influences willingness through perceived benefits and readiness to manage information; cues to action influences willingness through perceived benefits; perceived data severity influences willingness through perceived data susceptibility; and perceived benefits influences willingness through readiness to work.

We find no effect of one HBM proposed construct, namely, perceived barriers on willingness to share. One explanation for the insignificance of the link between perceived barriers and willingness to share is that some other constructs, specifically self-efficacy and susceptibility to threats to personal health information, may simultaneously capture respondents' perceptions of barriers. For example, respondents

may consider a lack of self-efficacy a barrier, or vice versa; they may consider self-efficacy an ability to overcome barriers. Furthermore, respondents may view the difficulty of addressing security threats to health information once shared as a barrier to sharing that information. The negative association between self-efficacy and perceived barriers (H5b) and the positive association between threat susceptibility and perceived barriers (H7e) support this conclusion. Furthermore, Liang et al. (2017) find that perceived benefits enhance a patient's use of online health information while perceived risks reduce it. Those authors additionally find that an individual's physical disability mitigates the negative relationship between perceived risk and online information use. Thus, individuals with more debilitating conditions are more likely to ignore the potential risks associated with online health information use (Liang et al., 2017).

Regarding the control variables used in our study, we find no significant impact of age, gender, IT expertise, and years of computer usage on an individual's willingness to share PHI on an AI-driven health platform. While individuals who consider themselves to have a high or very high level of computer and IT expertise could have a higher tendency to use various digital devices to manage their health, our results do not support this assumption within our context. We conclude that the primary factors depicted in our research model are better determinants of an individual's willingness to share PHI than our control variables.

## 7.1    Theoretical Implications

Our study makes important contributions to the current stream of research in the healthcare information systems field by investigating the behavioral aspects of health IT— particularly the use of an AI-driven health platform to manage individual health. In a closely related study, Anderson and Agarwal (2011) explore the impact of privacy and the role of emotion on an individual's willingness to share digitized PHI by using a sample of hypothetical patients. However, this type of sample might not necessarily reveal the true information disclosure intentions of the patients. Thus, to fill this gap, we have used a sample of individuals suffering from a particular disease condition in testing their willingness to share information on an AI-driven health platform which we believe to be one of the strengths of our study.

We also contribute to a nascent stream of literature that applies the HBM to explain and predict individuals' health-related behavior related to health IT adoption.  In the past, Ahadzadeh, Sharif, Ong, and Khong (2015) and Walrave, Waeterloos, and Ponnet (2020) applied the HBM to health-related internet use and the adoption of a COVID contact tracing app, respectively. We build on this literature by applying the HBM to the innovative and potentially disruptive field of AI-based, patient-centric healthcare technologies in a way that highlights the motivators and hurdles to promoting an informationally empowered patient profile.

Our study also contributes significantly to the stream of AI research in the information systems field. While many studies focus on the design aspects of AI-based predictive models, a significant lack of studies investigate the behavioral aspects pertaining to the usability of these models by patients and clinicians. To our best knowledge, our study is the first to investigate the determinants of a patient's willingness to share PHI on an AI-driven health platform. Furthermore, in exploring these determinants, we look at both positive (perceived benefits, self-efficacy, and cues to action) and negative (perceived PHI threat severity, perceived PHI threat susceptibility, and perceived barriers) internal motivators as intended by the HBM.

Finally, our study extends the HBM by including the construct—readiness to manage personal health information. When exploring the factors that motivate an individual to share PHI, it is imperative to pay special attention to the control and ownership of PHI. While many believe that the ownership and control of PHI should be passed to the patient, it has been a topic for debate over the past several years (Anderson & Agarwal, 2011) due to the issue of whether patients are ready to manage their own data. We attempt to shed light on this topic and inform changes to policy through the investigation of circumstances where individuals are willing to take managerial control of their PHI. We present the use of a blockchain database as a means of securely managing an individual's own PHI as implemented by the platform designed by doc.ai and Anthem to predict individuals' risk of allergies (doc.ai, 2018). Our study results indicate that individuals are more willing and ready to manage their PHI in a scenario where an AI-based health platform incorporates a blockchain-based database.

## 7.2    Practical Implications

The results of our study also offer practical implications. There has been rapid growth in the development and use of AI-driven health applications in the healthcare industry for medical diagnostics as well as

personal health management by both clinicians and patients. While several FDA-approved AI-based health applications are at work in the market, many of these applications have usability limitations for physicians and patients (Lin et al., 2017). Thus, the creators of these applications must understand the right conditions under which patients will use these applications for their intended purpose. Our study contributes to practice by investigating the conditions motivating individuals to share their PHI on healthcare platforms.

Our study findings indicate that perceived threat severity and perceived threat susceptibility significantly influence an individual's willingness to share PHI on an AI-driven platform. Our results further indicate that readiness to manage PHI has a significant positive influence on willingness to share. These results imply that individuals are less willing to share their PHI through applications that pose more significant risks to their personal information. Moreover, information security and privacy concerns have become a significant issue within AI-based health applications due to their use of large amounts of individual health data for diagnostic and predictive purposes.

Blockchain technology could provide a potential solution to mitigating some of these concerns associated with the AI-driven health platforms by allowing patients to maintain a distributed ledger of their PHI, where the patients can manage and control their own data while monitoring their data access privileges. Our results provide further support for this notion. Going forward, a continuation of the positive momentum of AI in healthcare very much depends on a high level of security. Thus, designers of AI-driven platforms need to pay close attention to implementing features that allow patients to manage their PHI securely on such platforms while attempting to minimize the inherent security and privacy risks to personal health information.

Our study also indicates that cues to action significantly influence an individual's willingness to use and share PHI on AI-driven health platforms, which is noteworthy for practitioners and system developers. Increasing the awareness of the potential benefits of AI in healthcare may help alleviate negative feelings about AI that individuals may harbor. When developing such applications, as shown in our results, practitioners should prompt patients about the use of AI in healthcare, which in turn, can help the AI-driven health application to be more successful—physicians can get the valuable data they need to fight a disease condition due to more patients using the application and submitting their PHI.

Thus far, extant health IT literature has primarily focused on the security and privacy of PHI in the hands of third parties such as healthcare providers. However, new HIPAA guidelines specify that consumers and developers are likely not subject to HIPAA regulations if the health information is never shared with healthcare providers or other intermediaries. Thus, this lack of HIPAA guidelines has to be carefully considered for the creation and development of future policies, especially since the rising healthcare costs have resulted in patients taking to self-diagnosing themselves and further demanding control of their own health data to make the best suitable healthcare decisions by themselves (Kushner & Verma, 2018). Even though healthcare technology is advancing rapidly, individuals still lack control and authority over their most valuable personal health information. Empowering individuals to take control and manage their own health information will result in individuals making their own healthcare decisions and deciding how their healthcare information will be used (Whitehouse.gov, 2018). This study provides a baseline for future studies to consider creating policies that govern consumer health privacy in situations where HIPAA is noticeably absent.

## 7.3    Limitations and Avenues for Future Research

Our study suffers from several limitations. First, while the respondents were representative of the population and consisted of the intended sample of individuals suffering from various environmental allergies, the participants could still self-select into the study, introducing potential bias to the results. Furthermore, while using a survey increases generalizability regarding the results obtained, the study could still fail to maximize precision and realism (McGrath, 1982). Future studies can use other data collection methods, such as experiments, interviews, and field studies to understand whether these methods capture the willingness perceptions of individuals in a similar manner as an online survey.

Using a paid sample through MTurk could introduce potential bias to the results obtained. Participants may self-select into the study for the sole purpose of obtaining incentives. Furthermore, our study focuses on the willingness to share information with AI-based platforms. Thus, compared to the general public, MTurk respondents may be more familiar and have more experience in using advanced technologies and, therefore, more comfortable providing personal information online, which may bring biases in the

estimation. On the other hand, studies have demonstrated that the results obtained through data collected from sources such as survey panels or directly from employees without any incentives are similar to the results obtained from data collected through MTurk (Berinsky et al., 2012; Mason & Suri, 2012; Paolacci et al., 2010). While we attempt to eliminate such biases by controlling for IT expertise and years of computer usage, future studies can try to overcome this limitation by obtaining data directly from individuals using AI-driven health platforms to manage their health.

Another limitation pertains to the measurement of willingness to share PHI rather than the respondent's actual sharing behavior. Measuring an individual's actual behavior is challenging due to information accessibility limitations. Regulations such as HIPAA prevent researchers from promptly gaining access to patients' information-sharing behavior on health platforms. While behavioral intention has served as a good proxy for actual behavior (Sheeran, 2002; Venkatesh et al., 2003), there is no guarantee that a respondent will behave in the same manner as indicated in the survey. Thus, if plausible, future studies should investigate realized sharing behavior within the healthcare setting using an AI-based health platform to provide disease diagnostics and predictive analytics.

We modeled our study based on doc.ai, which uses de-identification, encryption, and edge computing (ensures that the consumer health information shared with the AI-based application stays within the mobile device without leaving the device at any point). The application uses "federated learning," a distributed machine learning approach utilizing differential privacy that allows consumers to train new health algorithms on their mobile devices, where the AI health application only shares model learnings with external entities without sharing PHI. While it may appear that the promise of AI could create a future healthcare system where external entities never need access to personal PHI, we believe that it is entirely dependent on how the AI system receives the PHI in the first place. This paper sheds light on this potential issue. In this sense, we note the growing popularity of personal medical devices that provide remote patient monitoring and objective reporting of PHI, eliminating the need for patients to collect and self-report their health information subjectively. The interconnected network of sensors, devices, and applications that collect individual health information while enabling machine-to-machine interaction in real-time is known as the Internet of Medical Things (IoMT). Thus, we consider the possibility that many patients will feed AI systems PHI through the IoMT and call for future studies to investigate whether patients' PHI is even more vulnerable due to the security vulnerabilities in these medical devices.

Finally, while our study provides excellent insight into the information-sharing behavior of individuals with a particular disease condition within an AI-driven platform, it does not reveal the sharing behavior intentions of all possible disease conditions. Moreover, information-sharing behaviors could vary among individuals depending on the perceived benefits associated with a particular AI-driven health platform. Furthermore, our sample frame is generalizable to the extent that the disease is severe enough yet manageable (e.g., allergies, diabetes, high blood pressure, epilepsy, myasthenia gravis) by the patient without constantly visiting a healthcare provider. Future studies should attempt to replicate our analysis with other diseases to understand whether the factors motivating individuals to share their PHI differ depending on the disease. Moreover, future studies should attempt to capture individual information-sharing behavior within AI-driven health platforms with other target audiences.

## 7.4    Conclusion

Artificial intelligence has begun to take a leading role in the healthcare industry. A combination of AI-based technologies and access to a vast pool of patient health information has empowered clinicians and patients to work toward a future of better healthcare delivery. However, the question remains whether patients are willing and ready to take on the responsibility and risks of self-care technologies. Our study makes significant contributions toward answering this question by explaining the determinants of individuals' willingness to share and readiness to manage their personal health information on an AI-driven health platform to reap the many benefits offered to manage health proactively. Drawing upon the health belief model, we present a research model to explain various contextual factors influencing an individual's PHI disclosure intentions. Data collected from a nationally representative sample of 253 individuals who are currently suffering from environmental allergies indicate that perceived disease (allergy) severity, perceived benefits, self-efficacy, cues to action, perceived threat severity to PHI, and perceived threat susceptibility to PHI are all contributing factors of an individual's willingness to disclose PHI in an AI-driven health platform in providing predictive analytics and diagnostics for a medical condition. Thus, our study can serve as a foundation for the implementation, design, and adoption of AI-driven platforms for future research.

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## Appendix A: Survey

| Filter Question |
| --- |
| Have you experienced or are you currently experiencing any environmental allergies or environmental allergy                                                                                                      symptoms? ("Allergies are an overreaction of the immune system to substances that generally do not affect other individuals. These substances, or allergens, can cause sneezing, coughing, and itching." CDC.gov) Yes No Not                                                                                                          Sure *(Individuals who answer "Yes" to this question will be selected to participate in the study)* |
| **First Part of Scenario** |
| Imagine that you have been invited to participate in an environmental allergy data research study conducted by a group of well-regarded clinicians and allergists. The purpose of the study is to have artificial intelligence (AI) analyze your personal health information to learn about your susceptibility to allergies    and    identify    allergy    triggers    and    treatments    for    various    allergies. *Please describe the extent to which you agree or disagree with the following statements pertaining to the above scenario based on your experience with allergies and their related symptoms.* |

| Construct | Questions<br>Scale: 1 = *Strongly Disagree* — *7 = Strongly Agree* |
| --- | --- |
| **Willingness to share personal health information on AI-driven health platforms** | WILL1: I am willing to share my personal health information with AI-driven health platforms to better predict my risks of allergies and identify allergy triggers.<br><br>WILL2: I am happy to share my share my personal health information on AI-driven health platforms to predict my risks of allergies and identify allergy triggers.<br><br>WILL3: It is likely that I would share my personal health information on AI-driven health platforms to predict my risks of allergies and identify allergy triggers. |
| **Perceived Disease (Allergy) Severity** | ASEV1: Allergies and their associated symptoms are a serious problem for me.<br><br>ASEV2: Allergies and allergy symptoms negatively affect my daily life.<br><br>ASEV3: In general, allergies and their associated symptoms are a significant problem for me. |
| **Perceived benefits of using AI-driven health platforms** | PBEN1: AI-driven health platforms can be effective in predicting an individual's allergy triggers by using patient data. |

| | PBEN2: AI-driven health platforms can be effective in providing real-time health diagnostics to predict an individual's allergy risks. |
|---|---|
| | PBEN3: AI-driven health platforms can be effective in providing personalized preliminary diagnostics about allergies and allergy triggers. |
| | PBEN4: AI-driven health platforms can be effective in monitoring a patient's allergy medication to reduce dosage error. |
| | PBEN5: AI-driven health platforms can be effective in reducing the likelihood of an individual's susceptibility to allergic reactions by analyzing the individual's health data. |
| | PBEN6: AI-driven health platforms can be effective for allergists and clinicians to stay in touch, conduct virtual "check-ins," and monitor patients who are susceptible to allergies. |
| | PBEN7: AI-driven health platforms are effective for public health officials to better track allergy symptoms and their causes by using patient data. |
| **Cues to action to use AI in healthcare** | CUES1: I have followed news and developments about the use of AI in healthcare. |
| | CUES2: I have discussed with friends and people around me about the use of AI in healthcare. |
| | CUES3: I read about the use of AI in healthcare in newsletters or articles. |
| **Perceived barriers to use AI-driven health platforms** | PBAR1: Sharing my personal health information on AI-driven health platforms is time-consuming. |
| | PBAR2: Sharing my personal health information on AI-driven health platforms would require starting a new habit, which is difficult. |
| | PBAR3: Sharing my personal health information on AI-driven health platforms requires a considerable investment of effort other than time. |
| **Self-efficacy to use AI-driven health platforms** | SEFF1: I could use AI-driven health platforms to share my personal health information even if I had never used such a platform before. |

| | SEFF2: I could use AI-driven health platforms to share my personal health information even if I had only online help for reference. |
| | SEFF3: I could use AI-driven health platforms to share my personal health information even if no one is around to help me. |
| **Perceived threat severity to personal health information on AI-driven health platforms** | SEV1: If the personal health information I share on AI-driven health platforms were accessed by unauthorized entities, it would be significant. |
| | SEV2: If the personal health information I share on AI-driven health platforms were accessed by unauthorized entities, it would be serious. |
| | SEV3: If the personal health information I share on AI-driven health platforms were compromised, it would be serious. |
| | SEV4: If the personal health information I share on AI-driven health platforms were accessed by unauthorized entities, it would be severe. |
| **Perceived threat susceptibility to personal health information on AI-driven health platforms** | SUS1: It is a real possibility that the personal health information I share on AI-driven health platforms will be accessed by unauthorized individuals. |
| | SUS2: My personal health information that I share on AI-driven health platforms is at risk of being accessed by unauthorized entities. |
| | SUS3: It is likely that the personal health information I share on AI-driven health platforms will be accessed by unauthorized individuals. |
| | SUS4: My personal health information that I share on AI-driven health platforms is vulnerable to unauthorized access. |

| **Second Part of Scenario** |
| --- |
| Now imagine that the environmental allergy data research study is considering incorporating a blockchain database to the AI-driven platform. In a blockchain database, individuals are responsible for keeping their own personal information private. Individuals store their personal health information on their own devices that are only accessible by the device owner. The blockchain database anonymizes their personal health information by replacing personally identifiable information with unique IDs through the use of encryption technology.

*Please describe the extent to which you agree or disagree with the following statements pertaining to the above scenario.* |

| **Readiness to manage personal health information** | READ1 I look forward to personally taking control of my own health information. |

| | READ2 I am ready to take control of my personal health information. |
| | READ3 I am happy to manage my personal health information myself. |
| | READ4 I look forward to personably managing my own health information. |
| | READ5 I am ready to manage my own personal healthcare information. |
| **Demographics** | Gender:<br>Male<br>Female<br><br>Age:<br>0-100<br><br>What is your knowledge of computers and IT?<br>*Low-Very high*<br><br>Years of Computer Usage:<br>0-50 |

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