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Public Health Practitioners’ Adoption of Artificial Intelligence: The Role of Health Equity Perceptions and Technology Readiness

Angela Hernandez

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Public Health Practitioners' Adoption of Artificial Intelligence: The Role of Health Equity Perceptions and Technology Readiness

by

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A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

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ACCEPTANCE

This dissertation was prepared under the direction of the *ANGELA LEE HERNANDEZ* Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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DEDICATION

I dedicate this dissertation to everyone in my family. Javier, your love, support, and encouragement have been my light in this journey. Isa, thank you for cheering me on and sharing your academic journey with me. Dani, thank you for helping me stay motivated and on track. Forest, thank you for celebrating my victories. Sebastian and Marina, your curiosity to learn and explore inspired me. Mami y Papi, thank you for your unconditional love. Los amo! Gracias!

I also dedicate this work to my dear friend, the late Dr. Casey Goodman; your memory lives on these pages.

I hope this work contributes to ensuring that all individuals and communities have the best opportunity to achieve the best health possible.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ASTHO	Association of State and Territorial Health Officials
BI	Behavioral Intention to Use AI
BU	Behavioral Usage of AI
CDC	Centers for Disease Control and Prevention
EE	Effort Expectancy
FC	Facilitating Conditions
IF	Institutional Factors
ML	Machine Learning
NACCHO	National Association of County and City Health Officials
PE	Performance Expectancy
SI	Social Influence
TAM	Technology Acceptance Model
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action
TRI	Technology Readiness Index
UTAUT	Unified Theory of Acceptance and Use of Technology
WHO	World Health Organization

ABSTRACT

Public Health Practitioners' Adoption of Artificial Intelligence: The Role of Health Equity Perceptions and Technology Readiness

By

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Artificial Intelligence (AI) applications are expanding to many industries and sectors, including public health. An increased interest in AI has resulted in research on user acceptance; the existing acceptance models still need to be expanded to understand user acceptance of AI technologies. This empirical investigation uses the Unified Theory of Acceptance and Use of Technology (UTAUT) to test the relationships between UTAUT constructs and extended factors that may impact public health practitioners' intention to adopt AI-driven applications. The results suggest that facilitating conditions, effort expectancy, social influence, and health equity perceptions represent predictors of a positive intention to use AI technology, which denotes a positive influence on technology adoption. Technology readiness moderates the relationship between performance expectancy and intention to use AI; health equity did not moderate any UTAUT constructs. Institutional factors moderate the relationship between intention to use AI and usage behavior. These results contribute to research by extending the framework of the UTAUT to the adoption of AI in a public health context. The results also provide public officials, practitioners, and policymakers insight into the mechanisms supporting AI adoption and decision-making.

INDEX WORDS: Unified Theory of Acceptance and Use of Technology, UTAUT, public health, artificial intelligence, health equity

I CHAPTER 1: INTRODUCTION

Increased availability, access, and ease of use of the tools that enable AI techniques are accelerating the development of applications in various industries, including the health sector (Lavigne et al., 2019). The tools that facilitate AI techniques are more accessible, less expensive, and easier to use, increasing the potential to assist clinicians, health system managers, policymakers, and public health practitioners in making more precise and effective decisions (Chiolero & Buckeridge, 2020; Gunasekeran et al., 2021; Lavigne et al., 2019; Marcus et al., 2020; Mooney & Pejaver, 2018; Odone et al., 2019). Applying concepts from precision medicine to precision population health can enhance public health's ability to deliver the right public health interventions to the right population at the right time in the context of social and environmental health determinants (Dowell et al., 2016; Khoury et al., 2020).

The coronavirus disease 2019 (COVID-19) pandemic posed significant challenges to people, communities, and society, displaying health inequalities broadly, impacting economies, and stressing public health and healthcare systems (Laurencin & McClinton, 2020; Nicola et al., 2020). It exposed the strengths and limitations of public health systems, bringing the value and need of public health to the forefront. The public health response to COVID-19 worldwide leveraged technological advances to support population surveillance, case identification, contact tracing, and evaluation of interventions (Budd et al., 2020; Dananjayan & Raj, 2020; Hickok, 2020; Smidt & Jokonya, 2021).

Advances in information technology infrastructure and computing power, availability of large data sets, and AI-driven health technologies can support essential public health functions (*CDC - 10 Essential Public Health Services - CSTLTS*, 2021) by increasing efficiency, accuracy, and scale (Cossin & Thiébaut, 2020). These methods could improve the current understanding of population health, expand opportunities for interventions at a larger scale, and lower costs that extend beyond past capabilities.

In 2019, the World Health Organization (WHO) released guidelines on digital health interventions for health-system strengthening (*WHO | New Ethical Challenges of Digital Technologies, Machine Learning and Artificial Intelligence in Public Health*, n.d.). Despite the potential, the public health sector has been slower in adopting digital innovations than other sectors. With the increasing development of AI applications, their integration into health care, and their extension into public health practice, the factors influencing public health practitioner acceptance of AI remain an open discussion area (Bauer & Lizotte, 2021; Benke & Benke, 2018; Flaxman & Vos, 2018; Ksantini et al., 2020; Morgenstern et al., 2021; Schwalbe & Wahl, 2020).

I.1 Research Purpose

This research examines United States public health practitioners' intention to adopt AI to support public health functions using the Unified Theory of Acceptance and Use of Technology (UTAUT) model by Venkatesh et al. (2003). The unified theory of acceptance UTAUT is a technology acceptance model that explains how users accept and use technology. Venkatesh et al. (2003) formulated UTAUT by integrating the constructs of several models used to explain behavior in information systems usage. The UTAUT model describes four fundamental constructs as predictors of usage behavior: 1) performance expectancy, 2) effort expectancy, 3) social influence, and 4) facilitating conditions (Venkatesh et al., 2003). Performance and effort expectancy and social influence are determinants of usage intention and behavior, and facilitating conditions directly determine user behavior. Gender, age, experience, and voluntariness of use moderate the four UTAUT constructs' impact on usage intention and behavior (Venkatesh et al., 2003).

The literature on AI applications and technology adoption models discusses opportunities, risks, and barriers to implementing AI in different sectors, including public health. Researchers have applied the UTAUT to various technologies to measure acceptance and have demonstrated the UTAUT's continued validity and relevance. However, according to Venkatesh (2022), the adoption and benefits of AI are still not well understood. Building on UTAUT, Venkatesh (2022) proposes a research agenda to assess individual, technology, and environmental characteristics, as well as interventions to inform research and organizations' decisions related to AI adoption.

The area of concern of this study is the intersection of artificial intelligence, public health, and technology adoption. This research aims to identify and examine factors that influence the adoption of AI by public health practitioners by extending Venkatesh et al.'s 2003 version of the UTAUT model to include constructs inherent to the nature of public health practice, such as health equity perceptions and technology readiness. The primary research question that guides the research objective is: What factors influence the adoption of emerging AI technology by practitioners in the public health field?

This study assesses if the UTAUT model provides a robust theoretical basis for examining public health practitioners' adoption of AI technology and adds to the body of knowledge.

This research aims to contribute to gaps in theory and practice:

1. The technology acceptance model developed by Venkatesh is the basis for exploring the external and contextual factors, including the effect of health equity perceptions and technology readiness, that could influence public health practitioners' adoption of AI technology. This expansion will determine if UTAUT applies in the context of

public health practice, if health equity perceptions predict the intention and use of AI, and whether health equity perceptions and technology readiness are factors for consideration as moderators for usage.

2. From a practice perspective, it aims to assist public officials, health practitioners, developers, and policymakers in understanding barriers and enablers for the acceptance of AI for public health functions. Determining the factors influencing public health practitioners' adoption of AI will help understand the mechanisms to support decision-making.
3. In general, this study helps to contribute to the knowledge of technology adoption by answering the research question: What factors influence public health practitioners' adoption of emerging artificial intelligence technology to support public health functions?

In summary, the results contribute to research by extending the framework of the UTAUT to the adoption of AI in a public health context. The results also provide public officials, practitioners, and policymakers insight into the mechanisms supporting AI adoption and public health decision-making.

II CHAPTER 2: LITERATURE REVIEW

Improvements in information technology infrastructure and computing power allow artificial intelligence (AI) to support data integration and synthesis by increasing efficiency, accuracy, and scale (Cossin & Thiébaut, 2020). The tools that enable AI techniques evolved significantly during the study period, becoming more accessible, less expensive, and easier to use, increasing the potential to assist clinicians, health system managers, policymakers, and public health practitioners in improving the accuracy, preciseness, and effectiveness of their decisions (Chiolero & Buckeridge, 2020; Gunasekeran et al., 2021; Lavigne et al., 2019; Marcus et al., 2020; Mooney & Pejaver, 2018; Odone et al., 2019). Advances in the information technology infrastructure and computing power, availability of large datasets, and AI-driven technologies may support essential public health functions (CDC - 10 Essential Public Health Services - CSTLTS, 2021).

The COVID-19 pandemic expedited the uptake of AI approaches to inform public health decision-making and accelerated public health data modernization initiatives (CDC DMI, 2021). The extent of AI's contributions to inform the COVID-19 pandemic is broad and several functions rapidly became operational during the pandemic and post-pandemic phase, including disease tracking and prediction (Akhtar et al., 2019; Allan et al., 2022; Dong et al., 2020); diagnosis and prognosis (Naude et al., 2020), treatment and vaccines (Fleming, 2018; Segler et al., 2018), and social control interventions (Naude et al., 2020). However, these applications also exposed potential, limitations, constraints, and pitfalls. With the increasing development of AI applications and their integration into health care and public health, the factors that influence public health practitioners’ use of AI remain an open area of discussion (Bauer & Lizotte, 2021; Benke & Benke, 2018; Flaxman & Vos, 2018; Ksantini et al., 2020; Morgenstern et al., 2021; Schwalbe & Wahl, 2020).

The literature review aimed to answer the following question: What factors influence public health practitioners' adoption of artificial intelligence technology to support public health functions? The literature review explored AI approaches in public health, their risks and benefits, theoretical approaches to predicting a person's attitude toward using an information system, and the relevance of this matter.

A structured approach identified relevant publications for addressing the question. Search on the keywords (i.e., AI; health or population health or public health or health equity; technology acceptance or technology acceptance model or TAM) in 4 international online bibliographic databases (i.e., Business Source Complete (28 publications), Web of Science (71 publications), ProQuest (79 publications) and PubMed (59 publications) databases) led to 237 publications with a matching criterion. A scan of the identified publications by reading their titles and abstracts led to the selection of 64 publications relevant to the research question. The selected publications identified opportunities for contribution to research and practices concerning applying a technology acceptance model for using AI technologies in a public health context.

II.1 Artificial Intelligence Approaches in Public Health

Artificial intelligence relates to intelligent agents in coded algorithms designed and constructed to perform tasks like a human brain. Public health applications have used natural language processing (NLP), knowledge representation, automated reasoning, and machine learning approaches. NLP tools extract data from medical records, publications, or social media. Knowledge representation uses software ontologies that describe relations, properties, and categories of concepts and entities (e.g., ICD-11). Automated reasoning studies decision-making under constraints and provides a foundation for decision-support systems. These methods support learning public health systems for precision population health (Lavigne et al., 2019). Machine learning (ML) continuously and automatically refines algorithms using large amounts of data to improve precision. Public health research often includes machine learning, signal processing, or combining several machine learning methods. A common machine learning and signal processing approach includes convolutional neural networks (Schwalbe, 2020) for feature extraction and support vector machines for classification (Lavigne et al., 2019). Machine learning approaches to modeling epidemiologic data are becoming increasingly prevalent in the literature (Dey et al., 2018; Flaxman & Vos, 2018; Glymour & Bibbins-Domingo, 2019; Haneef et al., 2020; Hung et al., 2020; Lavigne et al., 2019; Mema & McGinty, 2020; Morgenstern et al., 2021; Pollett & Blazes, 2019; Wong et al., 2019).

However, more studies are needed to research theoretical models that assess the factors that influence the adoption of AI for public health practice. The upward trend in AI for public health is promising. It can support public health goals, improve screening and diagnosis, mortality and morbidity assessments, disease outbreak investigation and surveillance, health policy, and public health practice. The application of concepts from precision medicine using AI to precision population health can enhance public health's ability to deliver the right public health interventions to the right population at the right time in the context of social and environmental health determinants (Dowell et al., 2016; Khoury et al., 2020).

The COVID-19 pandemic posed significant challenges to people, communities, and society, displaying health inequalities broadly, impacting economies, and stressing public health and healthcare systems (Laurencin & McClinton, 2020; Nicola et al., 2020). It challenged public health systems, exposed the strengths and limitations, and brought the value and need of public health to the forefront. The public health response to COVID-19 worldwide rapidly built on advances in technology to support population surveillance, case identification, contact tracing, and evaluation of interventions; for example, using mobile data and communication with the public to notify exposures (Budd et al., 2020; Dananjayan & Raj, 2020; Hickok, 2020; Smidt & Jokonya, 2021). These methods could improve the current understanding of population health, expand opportunities for intervention at a larger scale, and lower costs that extend beyond past capabilities.

According to Morgenstern (2020), the top domains for opportunities for AI applications for public health are disease surveillance and improving public health interventions. Traditional disease surveillance could benefit from the ability to use novel data sources for extracting meaningful public health information from unstructured data sources (Chiolero & Buckeridge, 2020), and public health interventions can identify actionable public health insights by leveraging real-time insights from big data, facilitating personalized health promotion and social networking models (Morgenstern et al., 2021).

With these possibilities, the field is cautiously optimistic (Wiemken & Kelley, 2020) about the impact of AI on public practice and has raised concerns about AI tools and methods, infrastructure, workforce capabilities, confidentiality, and data protection (Schwalbe & Wahl, 2020), as well as ethical, regulatory, and practical factors as factors that could deter the adoption and support to such technologies (Cossin & Thiébaut, 2020; Dowell et al., 2016; Flahault et al., 2017; Lavigne et al., 2019; Morgenstern et al., 2021; Rajkomar et al., 2018; Sampson et al., 2019; Smith et al., 2020). Most notably, applying AI approaches to decision-making or predictions at a population level may risk increasing health inequities, either through the use of non-representative data or through unequal access to the technology (Arcaya & Figueroa, 2017;

Azzopardi-Muscat & Sørensen, 2019; Burger, 2020; Gansky & Shafik, 2020; Manjarres, Fernandez-Aller, et al., 2021; Smith et al., 2020; Weiss et al., 2018).

II.2 Risks And Barriers

There is significant attention in the literature to the potential benefits of AI to support public health functions, but the implementation of AI systems at a large scale in public health organizations poses challenges (Morgenstern et al., 2021; Odone et al., 2019; Pollett & Blazes, 2019; Potts & Kastelle, 2010). According to the literature, various factors may present as barriers and risks. These factors include limited infrastructure, workforce capabilities, staff expertise, and leadership, which would require upskilling and cross-training, hiring staff with dedicated AI expertise, and financial support to innovate (Morgenstern et al., 2021). The largely unregulated nature of AI requires the development of rigorous regulation to realize these benefits to public health. Policies are necessary to ensure increased standardization, address confidentiality and privacy concerns, mitigate implications derived from the modeling's complexity, prevent the diversion of limited resources from proven approaches, and warrant that attention focuses on developing advanced methods rather than data generation (Morgenstern et al., 2021). Lower barriers to ease the use of machine learning training models and the relative simplicity of deploying such models are needed to attain the high rewards related to cost savings, which can be substantial.

However, the performance of the AI tools and methods and their applications are unclear (e.g., black box). Most AI approaches center on access to clean, high-quality data, which can be challenging to find for public health applications. Concerns about the lack of quality data may lead to models that replicate the biases present in their training data and lack or limited interpretability (Azzopardi-Muscat & Sørensen, 2019; Brall et al., 2019; Burger, 2020; Glauser, 2020; Johnson, 2019; McCradden et al., 2020; Morley et al., 2020; Smith et al., 2020).

The discussion of AI and ethical considerations is beyond the public health field. There is a general acknowledgment of the potential of AI technologies to contribute to global socio-economic solutions. Discussions highlighting the challenges posed by these technologies in the ethical, moral, legal, humanitarian, and sociopolitical domains are active. Attempts to address these matters are resulting in an abundance of confusing ethical codes, guidelines, and frameworks, many of which lack scientific rigor and subjectiveness and can lead to incoherence, superficiality, and redundancy (Asaro, 2019; Car et al., 2019; Cox, 2020; Huang et al., 2019; Manjarres & Fernandez-Aller et al., 2021; Manjarres & Pickin et al., 2021; Ram, 2019; Turner Lee, 2018; Zarifis et al., 2021).

Morley (2020) categorized ethical issues related to AI in health care into epistemic, related to misguided, inconclusive, or inscrutable evidence; normative, related to unfair outcomes and transformative effectiveness; or traceability. These ethical issues arise at six levels of abstraction: individual, interpersonal, group, institutional, and societal or sectoral (Morley et al., 2020). The variety of burdens or harms that might exist in public health programs may be categorized as risks to privacy and confidentiality, especially in data collection activities; risks to liberty and self-determination, given the power accorded public health to enact almost any measure necessary to contain disease; and risks to justice if public health practitioners propose targeting public health interventions only to certain groups (Kass, 2001). Several ethical elements are in the literature for AI, including the risk of harm and bias due to the potential for selection bias in datasets, errors that could be damaging to humans, and value judgments that can create, sustain, or exacerbate health inequities (Flaxman & Vos, 2018). Fairness, accountability, transparency, respect for data rights, privacy, and risk of unequal access to such technologies, inequalities in the opportunity to benefit from such technologies, and inequity in the burdens generated by such technologies (Schwalbe & Wahl, 2020) are concerning (Glauser, 2020; Hung et al., 2020; Lavigne et al., 2019; McCradden et al., 2020; Morley et al., 2020; Murphy et al., 2021; Weiss et al., 2018). There is significant attention in the literature to the potential benefits of AI in supporting decision-making or prediction and the different factors that may impact adoption. There is an urgent need to understand further how to use these technologies best to enhance public health function and how these factors will affect public health practitioners' adoption of these technologies (Flaxman & Vos, 2018; Morgenstern et al., 2021).

II.3 Health Equity and Artificial Intelligence

Smith et al. (2020), in *Four Equity Considerations for the Use of Artificial Intelligence in Public Health,* highlight the importance of understanding the connection between health inequities and AI as a priority when considering deploying the technology for public health. Since public health functions focus on populations rather than persons and require collective intervention, implementing AI technology in this context has a higher positive or negative influence on health inequities than at the individual level (Smith et al., 2020).

Unequal access: There is a risk of unequal access to such technologies, inequalities in the opportunity to benefit from such technologies, and inequity in the burdens generated by such technologies. This dimension poses the question: How does using artificial intelligence in public health reinforce or remediate the gap between those who may benefit from public health (including its data and interventions) and those who do not?

Algorithmic bias and values: AI systems must be programmed or trained with specific data that might be biased and will invariably reflect value judgments that can create, sustain, or exacerbate health inequities. This dimension poses the question: What conscious or unconscious biases and value judgments exist or may be introduced in AI systems, including how systems are trained?

Plurality of values across systems: Depending on cultural or societal norms and values, different values will likely manifest in AI technologies across health systems, such as local, provincial, territorial, state, national, and international systems. These norms could lead to adopting technologies, interventions, or systems that produce unique outputs or outcomes according to those values or assumptions. This result may, in turn, create differences in outcomes between health systems that are attributable, at least in part, to the many values and assumptions within the artificial intelligence technologies used within those systems – which may constitute a source of health inequities. This dimension poses the questions: To what extent do the explicit or implicit values and assumptions that inform artificial intelligence technologies in public health cohere across technologies, interventions, and systems? Where different values and assumptions lead to health inequalities, should this be considered inequitable?

Fair decision-making procedures: Reaching a consensus about those values and assumptions might be unlikely. However, reaching a consensus on equitable outcomes from artificial intelligence in public health might also be challenging. This dimension poses the question: What should fair processes for developing and implementing AI technologies and approaches look like, and how should diverse populations design them?

Equity considerations and challenges in public health are contextual and experienced differently by populations or communities. Smith et al. recommend understanding these equity considerations and mapping the varying perspectives of diverse populations and stakeholders. In addition, it is important to consider who will be positively or negatively impacted by implementing AI approaches in public health surveillance, interventions, decision-making, policy, or research.

II.4 Theoretical Framework

Several theories can frame the study of technology acceptance. Research concerning the behavioral intention and use of new technologies primarily uses the Unified Theory of Acceptance and Use of Technology (UTAUT) and the underlying Technology Acceptance Model (TAM). The TAM, first introduced by Fred Davis, has been extensively used to investigate factors affecting user's acceptance of technology (Davis, 1989). Since then, the TAM has further developed and extended to incorporate additional factors and variables into the model to explain the predictors of TAM core elements. The TAM has been used in studies of the acceptance of various types of information technology and industries and is recognized as a sound acceptance theory (Dwivedi et al., 2020; Marangunić & Granić, 2015; Sohn & Kwon, 2020; Tamilmani et al., 2021; Venkatesh et al., 2003).

The origins of TAM stem from the theory of reasoned action (TRA) and the theory of planned behavior (TPB). TPB aims to predict and explain a person's behaviors through that person's behavioral intentions. The theory has several assumptions: people tend to behave rationally and use available information to decide whether to act or not; people guide their actions by conscious motives only; people consider the consequences of their actions before they act or not. Factors that predict the intention to perform that behavior include (1) a person's attitude toward the behavior (i.e., favorable or unfavorable appraisal) and (2) subjective norms regarding the behavior (i.e., expect social approval/disapproval of others and what others are doing). The TRA looks at behavioral intentions rather than attitudes as the main predictors of behaviors. Limitations include not considering personality, demographic variables, and assumptions that perceived behavior control predicts actual behavior control (Marangunić & Granić, 2015; Miles, 2012).

Fred Davis (1989) adapted the TRA and TPB theories and proposed the TAM to explain how users accept and use technology. The TAM explains technology acceptance in a three-stage process. First, external factors, such as system design features, trigger cognitive responses, such as perceived ease of use and perceived usefulness, which form an attitude towards technology, consequently influencing behavior. The outcome of this process is predicted by perceived ease of use, perceived usefulness, and behavioral intention. Perceived usefulness refers to "the degree to which a person believes that using a system would improve their performance," and perceived ease of use is "the degree a person believes that using a system would be free from effort." External variables influence attitudes toward the use of technology (Davis, 1989).

The TAM has been developing through years of research and has experienced various extensions. Additional factors and variables suggested by the authors were incorporated into the model to explain the predictors of TAM core elements (Tamilmani et al., 2021; Venkatesh et al., 2003). According to Marangunić and Granić (2014), these modifications fall into four major categories:

- *External predictors* of perceived usefulness and perceived ease of use include prior usage and experience, self-efficiency, and confidence in technology.
- Factors from other technology acceptance theories for the increasing predictive validity of the TAM include subjective norms, expectations, user participation, risk, and trust.
- *Contextual factors* that could have a moderating effect include gender, cultural diversity, and technology characteristics.

- *Usage measures* for operationalizing system usage include attitude toward technology, perception, and actual technology usage.

There is limited research on TAM frameworks regarding technology adoption by public health practitioners for public health practices. In the studies focused on healthcare, the TAM was used to investigate the adoption of electronic health records systems (Terrizzi et al., n.d.) and trust and personal information privacy concerns barriers to using health insurance that explicitly utilizes AI (Zarifis et al., 2021).

The unified theory of acceptance and use of technology (UTAUT) explains how users accept and use technology. Venkatesh et al. (2003) formulated UTAUT by integrating the constructs of several models used to explain behavior in information systems usage. The UTAUT model describes four fundamental constructs as predictors of usage behavior: 1) performance expectancy, 2) effort expectancy, 3) social influence, and 4) facilitating conditions (Venkatesh et al., 2003). Performance and effort expectancy and social influence are determinants of usage intention and behavior, and facilitating conditions directly determine user behavior. Gender, age, experience, and voluntariness of use are moderators of the four constructs' impact on usage intention and behavior (Venkatesh et al., 2003).

Venkatesh et al. (2003) defined performance expectancy (PE) as "the degree to which users believe using the system will help them to attain gains in job performance." PE includes five constructs from different models:

- perceived usefulness (TAM/TAM2 and Combined TAM and TPB - C-TAM-TPB),
- extrinsic motivation (Motivational Model - MM),
- job-fit (Model of PC Utilization - MPCU),

- relative advantage (Innovation Diffusion Theory – IDT), and
- outcome expectations (Social Cognitive Theory - SCT).

Effort expectancy (EE) is defined as "the degree to which ease is associated with the use of the system" (Venkatesh et al., 2003). Three constructs from other theories are captured in the concept of effort expectancy:

- perceived ease of use (TAM/TAM2),
- ease of use (IDT), and
- complexity (MPCU).

Social influence (SI) is defined as "the degree to which an individual perceives that important others believe they should use the new system" (Venkatesh et al., 2003). SI represents:

- subjective norms (TRA, TAM2, TPB/DTPB, C-TAM-TPB),
- social factors (MPCU), and
- images (IDT).

Facilitating conditions (FC) is defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of a system" (Venkatesh et al., 2003). FC captures from 3 different constructs:

- perceived behavioral control (TPB/DTPB and C-TAM-TPB),
- facilitating conditions (MPCU), and
- compatibility (IDT).

Venkatesh’s (2003) UTAUT model examines the influence of the constructs of performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and behavioral intention on the use and actual use of technology. The factors described by Venkatesh (2003) may influence public health practitioners' decision to adopt technology in public health practice at government agencies or publicly funded settings.

Facilitating conditions (Venkatesh et al., 2003) may include the resources, assistance, and compatibility with existing systems. Therefore, facilitating conditions could influence technology adoption, including AI. Performance expectancy (Venkatesh et al., 2003) is defined as the “degree to which users believe using technology will help them attain gains in job performance.” Public health practitioners have experienced improvements in job performance facilitated by technology, such as improvements in records management (e.g., death, birth, vaccination records, and integrated disease surveillance systems.). Performance improvement could influence public health practitioners' adoption of technology. However, at the time of the study, the incorporation of AI into routine procedures was limited. Effort expectancy (Venkatesh et al., 2003) is defined as “the degree of ease associated with using technology.” In general, public health practitioners perform a broad range of activities often linked to time constraints and technologies that are easily adaptable could influence the adoption of AI technology. Social influence (Venkatesh et al., 2003) is defined as “the degree to which an individual perceives that important people believe they should use a given technology.” Most people, including public health practitioners, are influenced by the opinions of those who are important to them when deciding whether to perform a behavior or not (Ajzen & Fishbein, 1975). Social influence and norms could influence the adoption of technology by public health practitioners. These four critical components of UTAUT demonstrate significant evidence of behavioral use via intention to use. The UTAUT framework has an instrument that measures the determinants of behavioral intention; the framework has been extended by adding and testing additional factors.

The adoption and benefits of AI are still not well understood (Venkatesh, 2022). Building on UTAUT, Venkatesh proposes a research agenda to assess individual, technology, and environmental characteristics, as well as interventions to inform research and organizations' decisions related to AI adoption.

This research agenda provides a setting to explore contextual factors inherent to the adoption of AI in the context of public health practice, such as health equity concerns, technology readiness, and institutional factors. The Centers for Disease Control and Prevention (CDC) defines health equity as "the state in which everyone has a fair and just opportunity to attain their highest level of health. Achieving this requires focused and ongoing societal efforts to address historical and contemporary injustices, overcome economic, social, and other obstacles to health and healthcare, and eliminate preventable health disparities (CDC, 2022)." CDC states that "despite prevention efforts, some groups of people are affected by disease more than other groups of people. The occurrence of these diseases at greater levels among certain population groups more than among others is often referred to as a health disparity." Public health goals often included implementing efforts to help reduce health disparities and promote health equity. Public health functions typically focus on populations rather than persons and require collective intervention. Therefore, implementing AI technology in this context has a higher positive or negative influence on health inequities than at the individual level (Smith et al., 2020).

Technology readiness (Parasuraman, 2000) is defined as "the propensity to embrace and use new technologies to accomplish goals in home life and at work. It has been validated as a predictor of the adoption of innovative technologies." The technology readiness index is a multidimensional construct with four dimensions: optimism, innovativeness, discomfort, and insecurity. This construct helps segment public health practitioners based on their underlying positive and negative technology beliefs.

Institutional factors (Lavigne et al., 2019) are new constructs defined as environmental and economic factors supported by the employee that facilitate the adoption of technology. Public health services are often funded and delivered by governmental organizations or publicly funded agencies, for which updates to technical infrastructure are subject to ongoing support, policies, or extensive procedures that are often prone to delays. Institutional factors may influence the adoption of AI by public health practitioners positively or negatively.

II.5 Theoretical Importance

The literature review highlights the need to enhance the understanding of users' adoption and use of AI tools to improve work performance. UTAUT (Venkatesh, 2022) has been used broadly to explain the intention and use of technology and provides a theoretical basis to explore contextual factors inherent to the adoption of AI in the context of public health practice. A theoretical explanation of independent variables on dependent variables is proposed to validate the applicability of UTAUT constructs in the context of this study or to establish a suitable model for answering our research question. The considered independent variables on behavioral intention are 1) facilitating conditions, 2) performance expectancy, 3) effort expectancy, 4) social influence, 5) health equity perceptions, 6) technology readiness, 7) institutional factors, and 8) behavioral intention. The final dependent variable (use behavior) represents the use of AI by public health practitioners to perform their functions. Understanding acceptance at this stage is critical because AI tools and techniques can provide substantial benefits in providing in-depth knowledge of individuals' health and predicting population health risks.

III CHAPTER 3: RESEARCH DESIGN

This study uses quantitative research methods to determine the intention to use AI technology in public health by adapting the Venkatesh et al. (2003) UTAUT model. This research uses a survey instrument that includes the constructs developed by Venkatesh et al. (2003) adapted to AI technology by Sohn et al. (2020), and relevant public health constructs, including a newly developed construct to assess health equity perceptions based on Smith (2020), technology readiness constructs based on Parasuraman (2000), and institutional factors constructs based on Lavigne (2019). A survey instrument was developed using Qualtrics software, Version Jan 2023 (Qualtrics, Provo, UT), to collect information from a sample of public health practitioners. The instrument used a five-point Likert scale to measure the study constructs. Using the UTAUT model, the constructs that potentially influence public health practitioners' intention to use AI were measured to determine correlations between these factors and the subsequent adoption of AI. This research extends the base UTAUT model by assessing health equity perceptions, technology readiness, and institutional factors to examine their influence on public health practitioners' intention and use of AI. Variable definitions of the constructs and roles for use in the extended UTAUT model are:

Performance expectancy (PE)	"The degree to which users believe using the system will help them to attain gains in job performance" (Venkatesh et al., 2003)
Effort expectancy (EE)	"The degree of ease associated with the use of the system" (Venkatesh et al., 2003)
Social influence (SI)	"The degree to which an individual perceives that important others believe they should use the new system" (Venkatesh et al., 2003)
Facilitating conditions (FC)	"The degree to which an individual believes that an organizational and technical infrastructure exist to support use of a system" (Venkatesh et al., 2003)

Health equity (HE)	"The degree to which an individual believes inequities might manifest when AI is implemented or used in public health" (Adapted from Smith et al., 2020)
Technology readiness (TRI)	"People's propensity to embrace and use new technologies for accomplishing goals in home life and at work" (Parasuraman 2000)
Institutional factors (IF)	"Environmental and economic institutional factors" (Adapted from Lavigne et al., 2019)
Behavioral intention (BI)	"The degree to which an individual is willing to use a system" (Venkatesh et al., 2003)
Behavioral usage (BU)	"Current usage of system" (Venkatesh et al., 2003)

This research examined the influence of *performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC),* and the *intention (BI)* and *use (BU)* of AI by public health practitioners. The model was expanded by:

1. adding a health equity construct based on Smith et al. (2020) to examine its influence on behavioral intention and use of AI by public health practitioners,
2. exploring the moderating effect of health equity on performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions on intention to use AI,
3. examining the moderating effect of technology readiness on performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions on intention to use AI,
4. testing the moderating effect of institutional factors on the intention and use of AI,
5. using the UTAUT model to explore the adoption of AI in a public health context.

The technology acceptance model developed by Venkatesh served as the basis for exploring external and contextual factors, including the effect of health equity on public health practitioners' adoption of AI technology. This expansion aimed to determine if UTAUT applies in the context of public health practice and if health equity perceptions are a factor that influences the intention and use of AI. In addition, the expanded model explores if health equity perceptions and technology readiness have a moderating effect on the UTAUT constructs and the intention to use AI and if institutional factors have a moderating effect on the intention and use of AI. From a practice perspective, it aimed to assist public officials and policymakers with a better understanding of barriers and enablers for accepting AI to support public health functions. In addition, determining the factors that influence the adoption of AI by public health practitioners will help developers create applications that are more suitable for adoption. The proposed framework (Figure 1) was called UTAUT-HE/TRI.

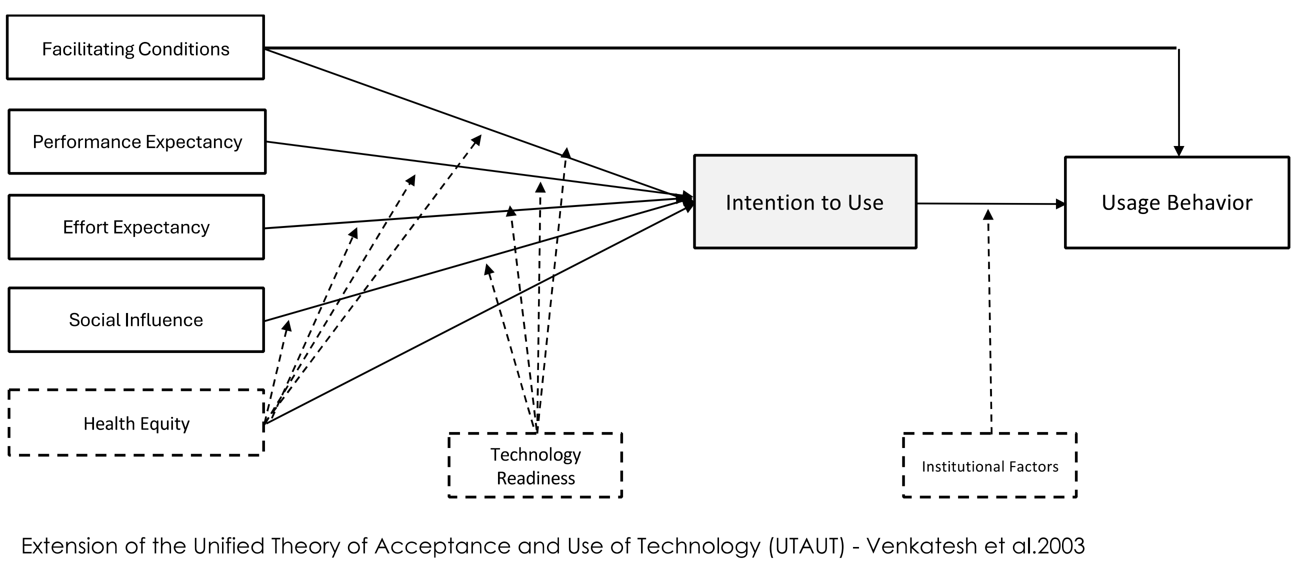


Figure 1: Proposed UTAUT-HE/TRI Framework Model

Note. The proposed UTAUT-HE/TRI model for AI adoption by public health practitioners is based on the UTAUT model by Venkatesh et al. (2003), with added factors of health equity perceptions, technology readiness, and institutional factors.

III.1 Research Questions and Hypothesis Testing

Research Question 1: What factors influence the adoption of emerging AI technology by practitioners in the public health field?

III.2 Hypotheses And Rationale

There is extensive evidence of using the UTAUT constructs, such as facilitating conditions, performance expectancy, effort expectancy, and social influence to assess the intention and use of technology. However, more research is needed into its use in public health practice, particularly regarding technological developments using artificial intelligence. UTAUT constructs are expected to have positive relationships similar to those observed in other information technology research. The UTAUT model will be feasible for assessing public health practitioners' adoption of AI technology. One of the public health goals is to help reduce health disparities and promote health equity. Public health practitioners' perceptions about implementing AI technology for public health practice could potentially influence, positively or negatively, health inequities at a population level (Smith et al., 2020). Despite sufficient evidence of concerns related to the potential effect of AI on health equity, this unique construct in the public health field has not been explored. The readiness of technology can help to categorize public health workers according to their beliefs about technology, whether they are positive or negative. Positive beliefs can potentially impact their intention to use AI. Public health practitioners' perceptions of their particular context concerning institutional factors may have a positive or negative effect on the adoption of AI.

Research Question 1: To what extent do the factors of facilitating conditions, performance expectancy, effort expectancy, and social influence, influence public health practitioners' behavioral intention to use AI technology?

H1: Facilitating Conditions (FC) have a direct positive effect on the behavioral intention (BI) to use AI.

H2: Performance expectancy (PE) has a direct positive effect on the behavioral intention (BI) to use AI.

H3: Effort expectancy (EE) has a direct positive direct effect on the behavioral intention (BI) to use AI.

H4: Social influence (SI) has a direct positive effect on the behavioral intention (BI) to use AI.

Research Question 2: To what extent do health equity perceptions influence public health practitioners' behavioral intention to use AI technology?

H5: Health equity (HE) perceptions have a direct positive effect on the behavioral intention (BI) to use AI.

Research Question 3: To what extent do facilitating conditions influence public health practitioners' behavioral usage of AI technology?

H6: Facilitating conditions (FC) have a direct positive effect on AI usage behavior (BU).

Research Question 4: To what extent does behavioral intention influence public health practitioners' behavioral usage of AI technology?

H7: Behavioral intention (BI) has a direct positive effect on AI usage behavior (BU).

Research Question 5: To what extent do health equity perceptions moderate the relationship between facilitating conditions, performance expectancy, effort expectancy, social influence, and behavioral intention to use AI technology?

H8a: Health equity perceptions moderate the relationship between facilitating conditions and behavioral intention to use AI.

H8b: Health equity perceptions moderate the relationship between performance expectancy and behavioral intention to use AI.

H8c: Health equity perceptions moderate the relationship between effort expectancy and behavioral intention to use AI.

H8d: Health equity perceptions moderate the relationship between social influence and behavioral intention to use AI.

Research Question 6: To what extent does technology readiness moderate the relationship between facilitating conditions, performance expectancy, effort expectancy, social influence, and behavioral intention to use AI technology?

H9a: Technology Readiness moderates the relationship between facilitating conditions and behavioral intention to use AI.

H9b: Technology Readiness moderates the relationship between performance expectancy and behavioral intention to use AI.

H9c: Technology Readiness moderates the relationship between effort expectancy and behavioral intention to use AI.

H9d: Technology Readiness moderates the relationship between social influence and behavioral intention to use AI.

Research Question 7: To what extent do institutional factors moderate the relationship between behavioral intention and behavioral usage of AI technology?

H10: Institutional Factors moderate the relationship between behavioral intention and behavioral usage of AI.

This study proposes testing the hypotheses using the Partial Least Squares (PLS) – Structural Equation (SEM) model as described in the proposed research model for AI adoption by public health practitioners (Figure 1).

This study adhered to all ethical guidelines established by Georgia State University (GSU), and all participants were treated fairly and ethically. No personal or identifiable information was collected during this research study, and consent was obtained before participation. Data were collected after approval from the GSU Institutional Review Board (IRB).

IV CHAPTER 4: METHODOLOGY

IV.1 Data Collection and Sampling

This research examines the factors influencing public health practitioners' adoption of emerging artificial intelligence technology for public health. *Public health* is a broad field that includes many professionals, such as epidemiologists, biostatisticians, health educators, environmental health specialists, and more (APHA, 2024).

According to the Association of State and Territorial Health Officials, in 2017, state health departments in the United States had an estimated 97,000 staff members (ASTHO, 2017). In 2019, local health departments had an estimated 158,000 workers, according to the National Profile of Local Health Departments conducted by the National Association of County and City Health Officials (NACCHO, 2019). Therefore, before the COVID-19 pandemic, the total number of public health workers in the United States may have been around 255,000 at state and local health departments. Data from the U.S. Public Health Service Commissioned Corps, a United States uniformed service, indicates that about 6,000 public health professionals are delivering public health promotion services, disease prevention programs, and moving forward public health science (USPHS, n.d.).

These numbers do not include other public health professionals who work for federal agencies within the Department of Health and Human Services, such as the Centers for Disease Control (CDC) and Prevention, the Food and Drug Administration (FDA), the National Institutes of Health (NIH), Indian Health Service (IHS), and the Department of Veterans Affairs (VA) or the public health workforce employed by academic institutions, non-governmental organizations, and other sectors including the health care sector. Estimating the number of public health practitioners working in the United States is challenging as the counts may vary depending on how public health is defined and measured.

This study used a sampling approach relying on the availability and accessibility of data sources. First, the study used Microsoft Bing Chat (GPT- 4 [Chat Generative Pre-Trained Transformer]) to select a random sample of 1% of the estimated 255,000 public health workers. The processes included identifying all health departments within a state, selecting the health departments serving the most populated counties, and then determining a representative sample of the workforce with each county with publicly available email.

The process included the following steps:

1. Identifying all health departments within a state using the prompt "List of health departments in [state name],"
2. Ranking the health departments within each state by the population served and selecting the most populous in the state by using the prompt "select health departments in [state name] serving most of the population,"
3. Selecting a sample health department staff with an available email from the selected health departments by using the prompt "select a representative sample of the workers with available email in the following format, FirstName, LastName, Email, Title, Department, City, County, State, Source."

The sample included deduplicated contacts from all state health departments and selected county and city health departments. Second, contacts from public health officials and state epidemiologists from each state were included; the list was supplemented with contacts from professional public health associations and interest public health groups.

Qualtrics software Version Jan 2023 was utilized to distribute and collect a survey instrument for primary data collection. The study aimed to achieve 300 completed surveys, equating to a 12% response rate, from approximately 2,500 identified public health practitioners.

Various strategies to reach out to public health practitioners were used: First, the compiled email list was distributed via Qualtrics software, inviting public health practitioners to complete the survey via link. Qualtrics sent four automated weekly reminders over a month, re-distributing the survey link. Second, the email invited public health practitioners to forward the link to their networks and colleagues. Third, flyers with a quick response code option (QR) were distributed among public health practitioners to post at selected public health workplaces and shared within their networks and colleagues. The fourth activity included recruiting via email invitation to complete the survey to individual public health practitioner contacts via LinkedIn, including the American Public Health Association and Women in Public Health group. A fifth recruitment activity involved public health practitioner participants at the 2023 American Public Health Association conference in Atlanta, Georgia. The meeting had several artificial intelligence-related sessions where the survey instrument flyers were distributed.

After deduplicating the initial sample, 2,327 unique emails were distributed between November 10 and December 31, 2023. Approximately 847 emails did not reach the recipient, resulting in 1,480 public health practitioners being emailed. This could have resulted from several potential reasons: the email address didn't exist, the receiving server had a high-security firewall, the receiving mailbox was full, or the recipient server was offline, among others. As a result, the study received 119 complete surveys; 21 were excluded due to quality or bot response, resulting in 98 surveys available for analysis, representing an effective response rate of 6.6%. The datasets were extracted from the Qualtrics software, cleaned, and prepared for analysis in SPSS.

IV.2 Measures

The scales for the theoretical constructs for measures of performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), behavioral intention (BI), and behavioral use (BU) were adapted from Venkatesh (2003). The measurements for institutional factors (IF) were adapted from Lavigne (2019) and technology readiness (TRI) from Parasuraman (2000). Two scales were developed for health equity; the first was designed to determine a baseline health equity measure, and the second was to assess specific AI-related health equity perceptions. The items were adjusted to fit the focus and relevance of this study. The complete list of questions and their associated constructs can be found in Appendix A.

IV.3 Reliability

Reliability refers to the consistency of a measure and whether the results can be reproduced under the same conditions. The study measured the internal consistency of the items within each construct using Cronbach's alpha. The constructs were found to have internal consistency reliability coefficients greater than 0.70, as per Venkatesh and Davis (2000). Table 1 shows the Cronbach's alpha coefficient for each scale. The initial testing of the constructs of facilitating conditions (FC) (Cronbach's alpha of 0.534) and health equity (HE-Base) (Cronbach's alpha of 0.136) revealed lower internal consistency. For facilitating conditions, by removing question 4, "Artificial intelligence systems are not compatible with other systems I use at work," Cronbach's alpha improved to 0.706. For health equity, by reversing the scale of question 1, "I don't think there are health inequities in the United States (rev)," and removing question 4, "Current health inequities are acceptable, but I don't want it to increase. (removed)," Cronbach's alpha improved to 0.96. The second scale of the health equity construct (AI-specific) resulted in a Cronbach's alpha of 0.809. Due to better specificity, only the AI-specific health equity construct was used in the model.

Table 1: Source of Constructs

Construct	Source Reliability	α
Performance Expectancy*	0.88 – 0.94	0.890
Effort Expectancy*	0.87 – 0.94	0.821
Social influence*	0.81 – 0.94	0.779
Facilitating Conditions*	0.81 – 0.89	0.706
Health Equity	-	0.809
Technology Readiness**	0.80 – 0.95	0.785
Institutional Factors***	-	0.76
Behavioral Intention*	0.90– 0.92	0.872
Behavioral Use*	0.82 – 0.91	0.875

*Source: *Venkatesh (2003); ** Parasuraman (2000); ***Lavigne (2019)*

IV.4 Validity

Based on expert reviews, the questionnaire demonstrated good content validity. Several items were modified based on their feedback to ensure clarity and adequate length for maintaining engagement, with an estimated completion time of 10-12 minutes. The survey questions and scale were adjusted based on the input, and the flow and mechanics of the survey were rearranged for ease of response on mobile and computer screens.

To measure the constructs' validity, the study analyzed convergent validity within the measures. The resultant correlation coefficients were significant at the 0.1 and 0.05 levels, confirming validity as described in Appendix C. The Cronbach's alpha for the entire questionnaire was .852, indicating good internal consistency.

IV.5 Data Analysis

The data analysis processes involved a series of systematic steps, including preparing survey data for analysis, performing statistical calculations on these data using SPSS, and testing the proposed hypothesis using regression analysis.

The survey was coded in the Qualtrics System using a five-point Likert scale, ranging from strongly disagree to strongly agree, which was used to measure the survey responses. The survey items were categorized by assigning a numerical value to the responses on the scale, and a variable name was assigned to each variable. Each anonymous response was assigned a unique identifier. Datasets were downloaded from Qualtrics as Excel files and then exported as .sav datasets for analysis in IBM SPSS Statistics.

The data cleaning process included checking the coded data for errors or inconsistencies and correcting or removing any found to ensure the data were accurate, reliable, and ready for analysis. The final dataset didn't include missing data because the survey required a response for each question before moving to the next question, and the codes were verified to ensure the proper measurement.

Statistical analysis included the following:

1. Reviewing Descriptive Statistics: The first step in the analysis was to review the descriptive statistics. This involved summarizing the main features of the data set, such as the mean, median, mode, and standard deviation, to attain a general understanding of the data distribution.
2. Calculating Overall Scores: The overall scores for each factor were averaged from the scores from individual items. This step helped to condense the data into a more manageable form and provided a summary measure for each factor.
3. Performing Pearson's Correlation: Pearson's correlation was conducted to determine

the relationship between the independent and dependent variables. This statistical method measures the strength and direction of the linear relationship between two variables.

4. Performing Linear Regression: Linear regression is a statistical technique that assesses the relationship between a dependent variable and one or more independent variables using the testing procedures defined by Pallant (2020).
5. Screening for Outliers: The data were first screened for outliers by standardizing the participants' residuals.
6. Assessing for Collinearity and Homoscedasticity: The study used tolerance and the variance inflation factor (VIF) measures for evaluation and visually examining a plot of standard residuals.
7. Testing the Hypothesized Model: The study used regression analysis to examine the hypothesized model. This involved reviewing the relationships between the constructs.

V CHAPTER 5: RESULTS

V.1 Descriptive Statistics

A total of 119 subjects participated in the study. Of those, 98 completed the survey. Of the 98 public health practitioners' respondents, the majority were female (72.4%), most were within the age range of 45-54 years (28.6%), followed by 25-34 years (24.5%), White or Caucasian was the predominant race or ethnicity (42.9%) followed by Black or African American (21.4) and Hispanic or Latinos (19.4). The work areas varied; however, epidemiology/disease surveillance represented 26.5%, followed by public health practitioners working in public health programs/service delivery. Most of the respondents had >20 years of experience (29.6%), followed by 11-20 years of experience (24.5%). Most served urban populations (27.6%) and were affiliated with state/local government (38.8%) or federal government (28.9%)—Table 2.

The study participants completed a 34-item questionnaire for technology adoption UTAUT-HE/TRI model that used Likert-scale format responses for the UTAUT constructs including [performance expectancy (4 items), effort expectancy (4 items), social influence (4 items), facilitating conditions (4 items), intention to use (2 items), usage behavior (1 item)], technology readiness (9 items), health equity perceptions (3 items) and institutional factors (4 items) as described in Appendix A.

The descriptive statistics for the UTAUT-HE/TRI are listed in Appendix B. The overall scores for each construct were averaged from the scores of individual items. Table 3 includes the descriptive statistics for the UTAUT-HE subscales, including the UTAUT variables performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC); it highlights that effort expectancy had the highest average value with a mean of 3.77 (*SD* = 0.78). Technology readiness had the highest average value among the extended variables

(HE, TRI, IF), with a mean of 3.53 (*SD* = 0.62).

Table 2: Public Health Practitioners Demographic and Experience

Variable	*n*	%
Gender Identity		
Male	25	25.5
Female	71	72.4
Other	2	2.00
Age (yrs.)		
18 - 24	4	4.10
25 - 34	24	24.5
35 - 44	21	21.4
45 - 54	28	28.6
55 - 64	19	19.4
≥65	2	2.0
Race/Ethnicity		
White or Caucasian	42	42.9
Black or African American	21	21.4
American Indian/Native American or Alaska Native	2	2.0
Asian	6	6.10
Hispanic or Latino	19	19.4
Multiple Race	8	8.0
Area of Work		
Community Health	5	5.1
Epidemiology/Disease Surveillance	26	26.5
Environmental Health	4	4.1
Health Education and Promotion	12	12.2
Health Policy/Management	9	9.2
Public Health Programs/Service Delivery	19	19.4
Social/Behavioral Health	5	5.1
Other	18	18.4
Experience (yrs)		
0-2	8	8.2
3-5	16	16.3
6-10	21	21.4
11-20	24	24.5
>20	29	29.6
Population Served		
Urban	27	27.6
Suburban	11	11.2
Rural	13	13.3
Other	34	34.7
N/A	13	13.3
Affiliation		

Academia	11	11.2
Community Based Organization or Other Non-Governmental Organization	11	11.2
Federal Government	28	28.6
Local/County/City Government	19	19.4
State Government	19	19.4
Other	10	10.2

Table 3: Descriptive Statistics for UTAUT-HE/TRI Subscales

Subscale		***n***	**Min**	**Max**	***M***	**SD**
Facilitating Conditions	FC	98	1.00	5	2.79	0.93
Performance Expectancy	PE	98	1.00	5	3.77	0.78
Effort Expectancy	EE	98	1.25	5	3.54	0.79
Social Influence	SI	98	1.75	5	3.28	0.74
Health Equity Perceptions	HE	98	1.33	5	3.13	0.73
Technology Readiness Index	TRI	98	2.00	5	3.53	0.62
Institutional Factors	IF	98	1.00	5	2.81	1.02
Intention to Use AI	BI	98	1.00	5	3.40	1.07
Actual Adoption	BU	98	1.00	5	2.67	1.22

V.2 Correlation Analysis

A correlation analysis was performed to assess the strength and direction of the linear relationships between the variables. This analysis was conducted using IBM SPSS, a statistical software package. The study involved a bivariate calculation, a statistical method used to determine the relationship between two variables. This calculation provided two critical pieces of information:

Direction of the Relationship (Pearson Correlation): The Pearson correlation coefficient was used to determine the direction of the relationship between the variables. This coefficient ranges from -1 to 1. A value of -1 indicates a total negative linear correlation, meaning as one variable increases, the other decreases. A value of 0 indicates no correlation, meaning the variables do not move together. A value of +1 indicates a total positive correlation, meaning as one variable increases, the other also increases.

Strength of the Relationship: The strength of the relationship was determined by the size of the Pearson correlation coefficient. A coefficient close to 0 indicates no relationship, a coefficient close to 1 indicates a strong positive relationship, and a coefficient close to -1 indicates a strong negative relationship.

The correlation analysis indicates that all variables were correlated at varying significance levels and did not report negative relationships. The results of this analysis are presented in Table 4.

Table 4: Correlation Analysis

Scale		FC	PE	EE	SI	HE	TRI	IF	BI	BU
Facilitating Conditions	**FC**	1								
Performance Expectancy	**PE**	$.513^{**}$	1							
Effort Expectancy	**EE**	$.483^{**}$	$.487^{**}$	1						
Social Influence	**SI**	$.365^{**}$	$.609^{**}$	$.362^{**}$	1					
Health Equity Perceptions	**HE**	$.309^{**}$	$.494^{**}$	$.418^{**}$	$.523^{**}$	1				
Technology Readiness Index	**TRI**	$.537^{**}$	$.345^{**}$	$.544^{**}$	$.352^{**}$	$.327^{**}$	1			
Institutional Factors	**IF**	$.433^{**}$	$.256^{**}$	$.316^{**}$	$.276^{**}$	$.324^{**}$	$.275^{**}$	1		
Intention to Use	**BI**	$.481^{**}$	$.541^{**}$	$.536^{**}$	$.508^{**}$	$.542^{**}$	$.505^{**}$	$.389^{**}$	1	
Usage Behavior	**BU**	$.523^{**}$	$.371^{**}$	$.304^{**}$	$.247^{*}$	$.323^{**}$	$.214^{*}$	$.368^{**}$	$.447^{**}$	1

***. Correlation is significant at the 0.01 level (2-tailed).*

**. Correlation is significant at the 0.05 level (2-tailed).*

V.3 Multicollinearity

A multicollinearity test was conducted to ensure the validity of the model. This test is crucial to confirm that the model's independent variables do not significantly overlap in their effects. Two measures assessed collinearity: tolerance and the variance inflation factor (VIF). Tolerance quantifies the proportion of an independent variable's variability that is not explained by the other variables in the model. VIF, the reciprocal of tolerance, measures how much the variance of the estimated regression coefficients is increased due to multicollinearity.

According to Pallant (2020), if the tolerance value is small (less than 0.10), it indicates high multicollinearity due to strong correlations among the variables. Similarly, if the VIF values are greater than 10, it suggests the presence of collinearity, and those variables should be removed from the model. In this analysis, all the tolerance values were significantly higher than 0.10, and all the VIF values were below 2.2. These results, as shown in Table 5, indicate that multicollinearity is not a concern in the model. Consequently, the independent variables in the model provide unique and valuable insights into the dependent variable.

Table 5: Multicollinearity

Factor	Collinearity Statistics	
	Tolerance	VIF
Facilitating Conditions (FC)	.521	1.919
Performance Expectancy (PE)	.457	2.188
Effort Expectancy (EE)	.553	1.810
Social Influence (SI)	.536	1.864
Health Equity (HE)	.541	1.848
Technology Readiness Index (TRI)	.563	1.775
Institutional Factors (IF)	.742	1.347
Intention to Use (BI)	.472	2.117

a. Dependent Variable: BU

V.4 Regression Model Analysis

The original proposal intended to test UTAUT-HE/TRI with a Structural Equation Model (SEM) to analyze structural relationships between the measured variables and latent constructs. In particular, the intention was to use the Partial Least Squares SEM (PLS-SEM) due to the complexity of the model structures. However, due to limitations in the sample size, the power of the model was potentially compromised, and the analysis approach was modified to examine the linear regression effect of each of the model pathways via SPSS by analyzing the independent variables (V) interaction with the dependent variables (DV) in several data runs. The level of statistical significance used was p-value < 0.1.

V.5 Intention to Use & UTAUT Constructs Model

The first analysis involved testing the original UTAUT independent variables facilitating conditions (FC), performance expectancy (PE), effort expectancy (EE), and social influence (SI) for the dependent variable intention to use (BI). The analysis examined the effect of the model on the independent variable intention to use (BI) and assessed the regression coefficients to determine the effects of the predictors [BI = f (FC, PE, EE, SI)]. The results are shown in Tables 6 – 8:

Table 6: Intention to Use and UTAUT Constructs Model Summary

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	.669[a]	.448	.424	.813

a. Predictors: (Constant), FC, PE, EE, SI

Table 7: Intention to Use and UTUAT Constructs ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	p
1	Regression	49.827	4	12.457	18.837	<.001[b]
	Residual	61.502	93	.661		
	Total	111.329	97			

a. Dependent Variable: BI

b. Predictors: (Constant), FC, PE, EE, SI

Table 8: Intention to Use and UTAUT Constructs Coefficients[a]

Model		B	SE	Beta	*t*	p
1	(Constant)	-.530	.475	-	-1.115	.268
	FC	.194	.109	.169	1.783	.078
	PE	.231	.149	.169	1.551	.124
	EE	.390	.127	.286	3.073	.003
	SI	.348	.142	.240	2.455	.016

a. Dependent Variable: BI
p-value < 0.1

The model explains 45% of the variance in the dependent variable ($R^2 = 0.45$). The adjusted R^2, which adjusts for the number of predictors in the model, is 0.424. This indicates a moderate fit of the model. The overall model was found to be statistically significant ($F(4, 93) = 18.84$, $p < 0.001$). This suggests that at least one of the predictors contributes to the prediction of the dependent variable. The regression coefficients indicate the following relationships:

- The intercept is -.530, the expected mean value of Y when all X=0.
- For variable FC, the regression coefficient is 0.194 ($t(93) = 1.783$, $p = 0.078$). The p-value is statistically significant ($p < 0.1$). This suggests that for each unit increase in FC, we expect an average increase of 0.194 units in the intention to use, assuming all other variables are held constant.
- For variable EE, the regression coefficient is 0.390 ($t(93) = 3.073$, $p = 0.003$). The p-value is statistically significant ($p < 0.1$). This suggests that for each unit increase in EE, we expect an average increase of 0.39 units in the intention to use, assuming all other variables are held constant.
- For variable SI, the regression coefficient is 0.348 ($t(93) = 2.455$, $p = 0.016$). The p-value is statistically significant ($p < 0.1$). This suggests that for each unit increase in SI,

we expect an average increase of 0.348 units in the intention to use, assuming all other variables are held constant.

- For variable performance expectancy (PE), the regression coefficient is 0.231 (t (93) = 1.551, p = 0.124). The p-value is above 0.1, and a statistically significant relationship cannot be claimed.

V.6 Intention to Use and UTAUT Constructs with Health Equity Model

The second analysis involved testing the original UTAUT independent variables facilitating conditions (FC), performance expectancy (PE), effort expectancy (EE), social influence (SI), and health equity (HE) for the dependent variable intention to use (BI).

The analysis examined the effect of the model on the independent variable intention to use (BI) and assessed the regression coefficients to determine the effects of the predictors [BI = f (FC, PE, EE, SI, HE)]. The results are shown below in Tables 9 – 12:

Table 9: Intention to Use and UTAUT Constructs with Health Equity Model Summary

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	.698[a]	.488	.460	.787

a. Predictors: (Constant), FC, PE, EE, SI, HE

Table 10: Intention to Use and UTUAT Constructs with Health Equity ANOVAa

Model		Sum of Squares	df	Mean Square	F	p
1	Regression	54.302	5	10.860	17.8521	<.001[b]
	Residual	57.027	92	.620		
	Total	111.329	97			

a. Dependent Variable: BI

b. Predictors: (Constant), FC, PE, EE, SI, HE

Table 11: Intention to Use and UTAUT Constructs with Health Equity Coefficientsa

Model		B	SE	Beta	*t*	p
1	(Constant)	-.793	.471	-	-1.684	.096
	FC	.199	.106	.172	1.883	.063
	PE	.164	.147	.120	1.119	.266
	EE	.319	.126	.234	2.536	.013
	SI	.228	.145	.157	1.573	.116
	HE	.368	.137	.250	2.687	.009

a. Dependent Variable: BI
p-value < 0.1

The model explains 49% of the variance in the dependent variable ($R^2 = 0.488$). The adjusted R^2, which adjusts for the number of predictors in the model, is 0.460. This indicates a moderate fit of the model. The overall model was found to be statistically significant ($F (5, 92) = 17.85$, $p < 0.001$). This suggests that at least one of the predictors contributes to the prediction of the dependent variable. The regression coefficients indicate the following relationships:

- The intercept is -.793, which is the expected mean value of Y when all X=0.
- For variable FC, the regression coefficient is 0.199 ($t (92) = 1.883$, $p = 0.063$). The p-value is statistically significant ($p < 0.1$). This suggests that for each unit increase in FC, we expect an average increase of 0.199 units in the intention to use, assuming all other variables are held constant.
- For variable EE, the regression coefficient is 0.319 ($t (92) = 2.536$, $p = 0.013$). The p-value is statistically significant ($p < 0.1$). This suggests that for each unit increase in EE, we expect an average increase of 0.319 units in the intention to use, assuming all other variables are held constant.
- For variable HE, the regression coefficient is 0.368 ($t (92) = 2.687$, $p = 0.009$). The p-value is statistically significant ($p < 0.1$). This suggests that for each unit increase in SI,

we expect an average increase of 0.368 units in the intention to use, assuming all other variables are held constant.

- For variable performance expectancy (PE), the regression coefficient is 0.164 (t (92) = 1.119, p = 0.266). The p-value is above 0.1, and a statistically significant relationship cannot be claimed.
- In this model for variable social influence (SI), the regression coefficient is 0.228 (t (92) = 1.573, p = 0.119). The p-value is above 0.1, and a statistically significant relationship cannot be claimed.

V.7 Usage Behavior and Behavioral Intention Model

The third analysis tested the independent variable intention to use (BI) for the dependent variable usage behavior (BU). The analysis examined the model effect on the independent variable intention to use and assessed the regression coefficients to determine the effects of the predictors [BU = f (BI)]. The results are shown in Tables 9 – 11:

Table 12: Usage Behavior and Behavioral Intention Model Summary

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	.447[a]	.200	.191	1.101

a. Predictors: (Constant), BI

Table 13: Usage Behavior and Behavioral Intention ANOVAa

Model		Sum of Squares	df	Mean Square	F	P
1	Regression	29.079	3	29.079	23.968	<.001[b]
	Residual	116.472	96	1.213		
	Total	145.551	97			

a. Dependent Variable: BU

a. Predictors: (Constant), BI,

Table 14: Usage Behavior & Behavioral Intention Coefficientsa

Model		B	SE	Beta	t	P
1	(Constant)	.934	.372	-	2.510	.215
	BI	.511	.104	.447	4.896	<.001

a. Dependent Variable: BU

The model explains 20% of the variance in the dependent variable ($R^2 = 0.200$). The adjusted R^2, which adjusts for the number of predictors in the model, is 0.191. The difference between the R^2 and the adjusted R^2 is not large, suggesting that the predictors are relevant. However, since the values are not close to 1, the model may not explain a large proportion of the variability in the outcome. The overall model was found to be statistically significant ($F(1, 96) = 23.968$, $p < 0.001$), suggesting that at least one of the predictors contributes to the prediction of the dependent variable. The regression coefficients indicate the following relationships:

- The intercept is 0.934, which is the expected mean value of Y when all X=0.
- For variable BI, the regression coefficient is 0.511 ($t(96) = 4.896$, $p = <0.001$). The p-value is statistically significant ($p < 0.1$). This suggests that for each unit increase in BI, we expect an average increase of 0.511 units in the intention to use, assuming all other variables are held constant.

V.8 Usage Behavior Model & Behavioral Intention with Facilitating Conditions

The fourth analysis involved testing the independent variables of intention to use (BI) and facilitating conditions (FC) for the dependent variable usage behavior (BU). The analysis examined the original UTAUT model effect on the independent variable intention to use and assessed the regression coefficients to determine the effects of the predictors [BU = f (BI, FC)]. The results are shown in Tables 15 – 17:

Table 15: Usage Behavior & Behavioral Intention with Facilitating Conditions Summary Model

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	.569[a]	.323	.309	1.018

a. Predictors: (Constant), BI, FC

Table 16: Usage Behavior & Behavioral Intention with Facilitating Conditions ANOVAa

Model		Sum of Squares	df	Mean Square	F	p
1	Regression	47.084	2	23.542	22.713	<.001[b]
	Residual	98.467	95	1.036		
	Total	145.551	97			

a. Dependent Variable: BU

a. Predictors: (Constant), BI, FC

Table 17: Usage Behavior & Behavioral Intention with Facilitating Conditions Coefficientsa

Model		B	SE	Beta	t	p
1	(Constant)	.212	.385	-	.552	.582
	BI	.290	.110	.254	2.639	.010
	FC	.529	.127	.401	4.168	<.001

a. Dependent Variable: BU

The model explains 32% of the variance in the dependent variable ($R^2 = 0.323$). The adjusted R^2, which adjusts for the number of predictors in the model, is 0.309. The difference between the R^2 and the adjusted R^2 is not large, suggesting that the predictors are relevant. However, since the values are not close to 1, the model may not explain a large proportion of the variability in the outcome. The overall model was found to be statistically significant ($F(2, 95) = 22.713$, $p < 0.001$), suggesting that at least one of the predictors contributes to the prediction of the dependent variable. The regression coefficients indicate the following relationships:

- The intercept is 0.212, which is the expected mean value of Y when all X=0.
- For variable BI, the regression coefficient is 0.290 ($t(95) = 2.639$, $p = 0.010$). The p-value is statistically significant ($p < 0.1$). This suggests that for each unit increase in BI, we expect an average increase of 0.212 units in the intention to use, assuming all other variables are held constant.
- For variable FC, the regression coefficient is 0.529 ($t(95) = 4.168$, $p = <0.001$). The p-value is statistically significant ($p < 0.1$). This suggests that for each unit increase in FC, we expect an average increase of 0.529 units in the intention to use, assuming all other variables are held constant.

V.9 Moderation Analysis

The subsequent analysis involved testing to assess the moderation effects of the variables health equity (HE), technology readiness (TRI), and institutional factors (IF). The following tables present a series of process analyses using Process Analysis v4.2, created by Andrew Hayes (2012). This logistic regression path analysis modeling tool measures moderator effects on the models.

The first moderation model, *BI (Y: BI, X: FC, W: HE)*, examined changes in the relationship between facilitating conditions (FC) and intention to use (BI) at different levels of health equity perceptions (HE). The results are shown in Table 18.

Table 18: Moderation Analysis of Health Equity on Facilitating Conditions and Intention to Use

R	R^2	MSE	F	df1	df2	p
0.635	0.403	0.707	21.156	3.00	94.00	0.00

Model of Outcome Variable BI

Variable	Coefficient	SE	*t*	p	LLCI	ULCI
Constant	-.065	1.070	-.608	.952	-2.188	2.058
FC	.515	.341	1.51	.134	-.162	1.192
HE	.752	.339	2.216	.029	.078	1.425
FC*HE	.034	.102	-.352	.726	-.239	.167

Test(s) of highest order unconditional interaction(s)

Variable	R^2 Change	F	df1	df2	p
FC*HE	.00	.124	1.00	94.0	.726

The moderation analysis examined the effect of facilitating conditions (X) on intention to use (Y) and how this relationship is moderated by health equity perceptions (W). The dependent variable in this model was intention to use (BI), the independent variable was facilitating conditions (FC), and the moderating variable was health equity perceptions (HE). The results suggest that health equity does not moderate the relationship between facilitating conditions and intention to use.

The second moderation model, *BI (Y: BI, X: PE, W: HE)*, examined changes in the relationship between performance expectancy (PE) and intention to use (BI) at different levels of health equity perceptions (HE). The results are shown in Table 19.

Table 19: Moderation Analysis of Health Equity on Performance Expectancy and Intention to Use

R	R^2	MSE	F	df1	df2	p
0.623	0.393	0.719	20.290	3.00	94.0	0.00

Model of Outcome Variable BI

Variable	Coefficient	SE	*t*	p	LLCI	ULCI
Constant	.511	1.711	.291	.766	-2.881	3.907
PE	.329	.441	.745	.458	-.547	1.204
HE	.308	.593	.519	.605	-.870	1.486
PE*HE	.057	.145	.394	.694	-.231	.346

Test(s) of highest order unconditional interaction(s)

Variable	R^2 Change	F	df1	df2	p
PE*HE	0.01	1.556	1.00	94.0	.694

The moderation analysis examined the effect of performance expectancy (X) on intention to use (Y) and how this relationship is moderated by health equity perceptions (W). The dependent variable in this model was intention to use (BI), the independent variable was performance expectancy (PE), and the moderating variable was health equity (HE). The results suggest that health equity does not moderate the relationship between performance expectancy and intention to use.

The third moderation model, *BI (Y: BI, X: EE, W: HE),* examined changes in the relationship between effort expectancy (EE) and intention to use (BI) at different levels of health equity perceptions (HE). The results are shown in Table 20.

Table 20: Moderation Analysis of Health Equity on Effort Expectancy and Intention to Use

R	R^2	MSE	F	df1	df2	p
0.641	0.410	0.699	21.798	3.00	94.0	0.00

Model of Outcome Variable BI

Variable	Coefficient	SE	*t*	p	LLCI	ULCI
Constant	-.663	1.760	-.377	.707	-4.157	2.831
EE	.642	.476	1.349	.181	.303	1.588
HE	.719	.555	1.298	.198	-.382	1.821
EE*HE	-.041	.143	-.284	.777	-.325	.244

Test(s) of highest order unconditional interaction(s)

Variable	R^2 Change	F	df1	df2	p
EE*HE	0.0005	.0804	1.00	94.0	.777

The moderation analysis examined the effect of effort expectancy (X) on intention to use (Y) and how this relationship is moderated by health equity perceptions (W). The dependent variable in this model was intention to use (BI), the independent variable was effort expectancy (EE), and the moderating variable was health equity (HE). The results suggest that health equity does not moderate the relationship between effort expectancy and intention to use.

The fourth moderation model, *BI (Y: BI, X: SI, W: HE)*, examined changes in the relationship between social influence (SI) and intention to use (BI) at different levels of health equity perceptions (HE). The results are shown in Table 21.

Table 21: Moderation Analysis of Health Equity on Social Influence and Intention to Use

R	R^2	MSE	F	df1	df2	p
0.602	.361	.755	17.846	3.00	94.0	0.00

Model of Outcome Variable BI

Variable	Coefficient	SE	*t*	p	LLCI	ULCI
Constant	-.1570	1.635	-.097	.924	-3.401	3.090
SI	.550	.494	1.111	.270	-.431	1.532
HE	.666	.512	1.300	.197	-.352	1.682
SI*HE	-.0310	.145	-.213	.831	-.318	.256

Test(s) of highest order unconditional interaction(s)

Variable	R^2 Change	F	df1	df2	p
SI*HE	.0003	.0456	1.00	94.0	.831

The moderation analysis examined the effect of social influence (X) on intention to use (Y) and how this relationship is moderated by health equity perceptions (W). The dependent variable in this model was intention to use (BI), the independent variable was social influence (SI), and the moderating variable was health equity (HE). The results suggest that health equity does not moderate the relationship between social influence and intention to use.

The fifth moderation model, *BI (Y: BI, X: FC, W: TRI),* examined changes in the relationship between facilitating conditions (FC) and intention to use (BI) at different levels of technology readiness (TRI). The results are shown in Table 22.

Table 22: Moderation Analysis of Technology Readiness on Facilitating Conditions and Intention to Use

R	R^2	MSE	F	df1	df2	p
0.567	.321	.804	14.841	3.00	94.00	0.00

Model of Outcome Variable BI

Variable	Coefficient	SE	*t*	p	LLCI	ULCI
Constant	-.5317	1.236	-.430	.668	-2.986	1.922
FC	.683	.456	1.498	.137	-.222	1.589
TRI	.851	.366	2.322	.022	.123	1.578
FC*TRI	.096	.123	-.780	.438	-.340	.149

Test(s) of highest order unconditional interaction(s)

Variable	R^2 Change	F	df1	df2	p
FC*TRI	.004	.608	1.00	94.00	.438

The moderation analysis examined the effect of facilitating conditions (X) on intention to use (Y) and how this relationship is moderated by technology readiness (W). The dependent variable in this model was intention to use (BI), the independent variable was facilitating conditions (FC), and the moderating variable was technology readiness (TRI). The results suggest that technology readiness does not moderate the relationship between facilitating conditions and intention to use.

The sixth moderation model, *BI (Y: BI, X: PE, W: TRI),* examined changes in the relationship between performance expectancy (PE) and intention to use (BI) at different levels of technology readiness (TRI). The results are shown in Table 23.

Table 23: Moderation Analysis of Technology Readiness on Performance Expectancy and Intention to Use

R	R^2	MSE	F	df1	df2	p
0.656	.430	.674	23.615	3.00	94.0	0.00

Model of Outcome Variable BI

Variable	Coefficient	SE	*t*	p	LLCI	ULCI
Constant	2.342	1.807	1.296	.198	-1.246	5.930
PE	-.331	.485	-.682	.497	-1.293	.632
TRI	-.365	.537	-.679	.499	-1.432	.702
PE*TRI	.267	.140	1.912	.059	-.0103	.544

Test(s) of highest order unconditional interaction(s)

Variable	R^2 Change	F	df1	df2	p
PE*TRI	.022	3.656	1.00	94.0	.059

The moderation analysis examined the effect of performance expectancy (X) on intention to use (Y) and how this relationship is moderated by technology readiness (W). The dependent variable in the model was intention to use (BI), the independent variable was performance expectancy (PE), and the moderating variable was technology readiness (TR). The results suggest that technology readiness moderates the relationship between performance expectancy and intention to use.

The seventh moderation model, *BI (Y: BI, X: EE, W: TRI),* examined changes in the relationship between effort expectancy (EE) and intention to use (BI) at different levels of technology readiness (TRI). The results are shown in Table 24.

Table 24: Moderation Analysis of Technology Readiness on Effort Expectancy and Intention to Use

R	R^2	MSE	F	df1	df2	p
0.594	.353	.767	17.073	3.00	94.0	0.00

Model of Outcome Variable BI

Variable	Coefficient	SE	*t*	p	LLCI	ULCI
Constant	.1873	1.878	.010	.921	-3.541	3.915
EE	.382	.547	.698	.487	.704	1.468
TRI	.401	.550	.730	.467	-.690	1.492
EE*TRI	-.035	.151	.235	.815	-.264	.334

Test(s) of highest order unconditional interaction(s)

Variable	R^2 Change	F	df1	df2	p
EE*TRI	.0004	.055	1.00	94.0	.82

The moderation analysis examined the effect of effort expectancy (X) on intention to use (Y) and how this relationship is moderated by technology readiness (W). The dependent variable in the model was intention to use (BI), the independent variable was effort expectancy (EE), and the moderating variable was technology readiness (TRI). The results suggest that technology readiness does not moderate the relationship between effort expectancy and intention to use.

The eight moderation model, *BI (Y: BI, X: SI, W: TRI)* examined changes in the relationship between social influence (SI) and intention to use (BI) at different levels of technology readiness (TRI). The results are shown in Table 25.

Table 25: Moderation Analysis of Technology Readiness on Social Influence and Intention to Use

R	R^2	MSE	F	df1	df2	p
.620	.384	.730	19.523	3.00	94.0	0.00

Model of Outcome Variable BI

Variable	Coefficient	SE	*t*	p	LLCI	ULCI
Constant	.8664	1.905	.455	.650	-2.915	4.648
SI	.077	.574	.135	.893	-1.062	1.217
TRI	.212	.536	.395	.694	-.853	1.277
SI*TRI	.131	.156	.839	.404	-.179	.440

Test(s) of highest order unconditional interaction(s)

Variable	R^2 Change	F	df1	df2	p
SI*TRI	.046	.704	1.00	94.0	.404

The moderation analysis examined the effect of social influence (X) on intention to use (Y) and how this relationship is moderated by technology readiness (W). The dependent variable in the model was intention to use (BI), the independent variable was social influence (SI), and the moderating variable was technology readiness (TRI). The results suggest that technology readiness does not moderate the relationship between social influence and intention to use.

The ninth moderation model, *BU (Y: BU, X: BI, W: IF),* examined changes in the relationship between intention to use (BI) and usage behavior (BU) at different levels of institutional factors. The results are shown in Table 26.

Table 26: Moderation Analysis of Institutional Factors on Intention to Use and Usage Behavior

R	R^2	MSE	F	df1	df2	p
.516	.267	1.136	11.382	3.00	94.0	0.00

Model of Outcome Variable BU

Variable	Coefficient	SE	*t*	p	LLCI	ULCI
Constant	2.1047	1.026	2.052	.043	0.068	4.142
BI	-.056	.296	.189	.850	-0.644	0.532
IF	-.349	.386	-.904	.368	-1.116	0.418
BI*IF	.174	.103	1.693	.092	-0.030	0.379

Test(s) of highest order unconditional interaction(s)

Variable	R^2 Change	F	df1	df2	p
BI*IF	.022	2.865	1.00	94.0	0.09

The moderation analysis examined the effect of intention to use (X) on usage behavior (Y) and how this relationship is moderated by institutional factors (W). The dependent variable in the model was usage behavior (BU), the independent variable was intention to use (BI), and the moderating variable was institutional factors (IF). The regression analysis results showed a significant interaction effect between intention to use and institutional factors on usage behavior was statistically significant ($\beta = .17$, $p < .09$). The results suggest that institutional factors moderate the relationship between intention to use and usage behavior.

V.10 Hypothesis Findings

H1. Public health practitioners' perceived facilitating conditions influence the intention to use AI for public health practice.

The standardized coefficient for facilitating conditions on intention to use is $\beta = 0.19$, reporting a statistically significant p-value of 0.08. Therefore, the hypothesis is supported.

H2. Public health practitioners' perceived performance expectancy positively influences the intention to use AI for public health practice.

The standardized coefficient for performance expectancy on intention to use is β = 0.23, reporting a non-statistically significant p-value of 0.12. Therefore, the hypothesis is not supported.

H3. Public health practitioners' effort expectancy positively influences the intention to use AI for public health practice.

The standardized coefficient for effort expectancy on intention to use is β = 0.39, reporting a statistically significant p-value 0.003. Therefore, the hypothesis is supported.

H4. Public health practitioners' social influence positively influences the intention to use AI for public health practice.

The standardized coefficient for social influence on intention to use is β = 0.35, reporting a statistically significant p-value of 0.01. Therefore, the hypothesis is supported.

H5. Public health practitioners' health equity perceptions positively influence the intention to use AI for public health practice.

The standardized coefficient for health equity perceptions on intention to use is β = 0.37, reporting a statistically significant p-value of 0.09. Therefore, the hypothesis is supported.

H6. Public health practitioners' perceptions of facilitating conditions positively influence usage behavior.

The standardized coefficient for facilitating conditions on intention to use is β = 0.53, reporting a statistically significant p-value of <0.001. Therefore, the hypothesis is supported.

H7. Public health practitioners' intention to use positively influences usage behavior.

The standardized coefficient for intention to use on usage behavior is β = 0.30, reporting a statistically significant p-value of 0.01. Therefore, the hypothesis is supported.

H8a Public health practitioners' health equity perceptions moderate the relationship between facilitating conditions and intention to use AI.

The standardized coefficient for health equity perceptions on the relationship between effort expectancy and intention to use AI is β = 0.34, with a p-value of 0.73. The results suggest that health equity perceptions do not moderate the relationship between facilitating conditions and intention to use. Therefore, the hypothesis is rejected.

H8b Public health practitioners' health equity perceptions moderate the relationship between performance expectancy and intention to use AI.

The standardized coefficient for health equity perceptions on the relationship between performance expectancy and intention to use AI is β = 0.57, with a p-value of 0.69. The results suggest that health equity perceptions do not moderate the relationship between performance expectancy and intention to use. Therefore, the hypothesis is rejected.

H8c Public health practitioners' health equity perceptions moderate the relationship between effort expectancy and intention to use AI.

The standardized coefficient for health equity perceptions on the relationship between effort expectancy and intention to use AI is β = -0.041, with a p-value of 0.78. The results suggest that health equity perceptions do not moderate the relationship between effort expectancy and intention to use. Therefore, the hypothesis is rejected.

H8d Public health practitioners' health equity perceptions moderate the relationship between social influence and intention to use AI.

The standardized coefficient for health equity perceptions on the relationship between social influence and intention to use AI is β = -0.31, with a p-value of 0.83. The results suggest that health equity perceptions do not moderate the relationship between social influence and intention to use. Therefore, the hypothesis is rejected.

H9a Public health practitioners' technology readiness moderates the relationship between facilitating conditions and intention to use AI.

The standardized coefficient for technology readiness on the relationship between effort expectancy and intention to use AI is β = 0.10, with a p-value of 0.44. The results suggest that technology readiness does not moderate the relationship between facilitating conditions and intention to use. Therefore, the hypothesis is rejected.

H9b Public health practitioners' technology readiness moderates the relationship between performance expectancy and intention to use AI.

The standardized coefficient for technology readiness on the relationship between performance expectancy and intention to use AI is β = 0.27, with a p-value of 0.06. The results suggest that technology readiness moderates the relationship between performance expectancy and intention to use. Therefore, the hypothesis is supported.

H9c Public health practitioners' technology readiness moderates the relationship between effort expectancy and intention to use AI.

The standardized coefficient for technology readiness on the relationship between effort expectancy and intention to use AI is β = -0.04, with a p-value of 0.82. The results suggest that technology readiness does not moderate the relationship between effort expectancy and intention to use. Therefore, the hypothesis is rejected.

H9d Public health practitioners' technology readiness moderates the relationship between social influence and intention to use AI.

The standardized coefficient for technology readiness on the relationship between social influence and intention to use AI is β = 0.13, with a p-value of 0.40. The results suggest that technology readiness does not moderate the relationship between social influence and intention to use. Therefore, the hypothesis is rejected.

H10 Public health practitioners' institutional factors moderate the relationship between intention to use and usage behavior.

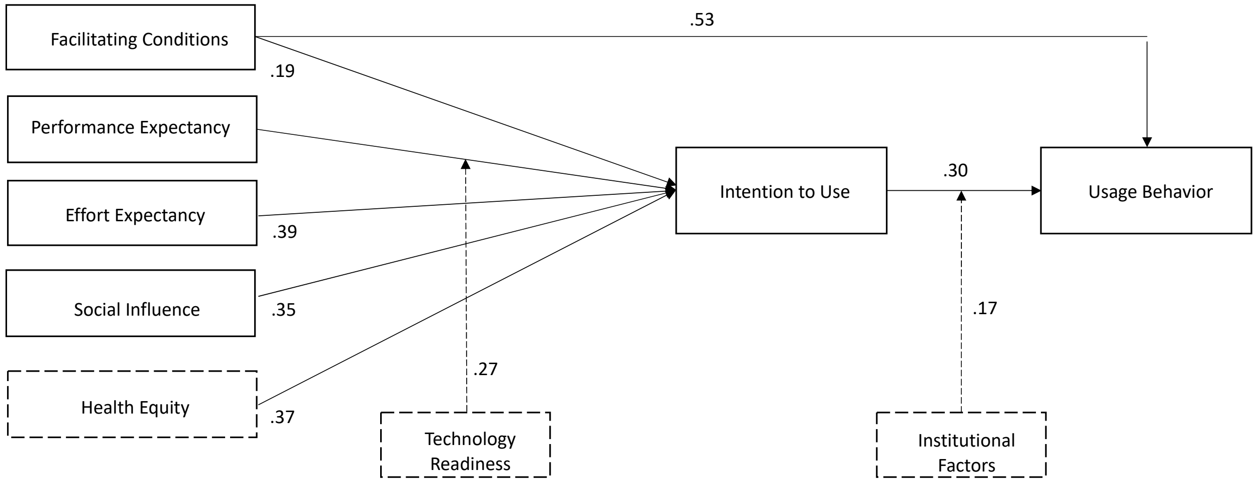
The standardized coefficient for institutional factors on the relationship between intention to use and actual use is β = 0.17, with a p-value of 0.09. The results suggest that institutional factors moderate the relationship between intention to use and actual use. Therefore, the hypothesis is supported.

Table 27: Hypothesis Support Summary

No.	Hypothesis	DV	IV	Mod	β	p	Supported
H1	*Public health practitioners' perceived facilitating conditions positively influences the intention to use AI for public health practice.*	FC	BI	-	.19	0.08	Y
H2	*Public health practitioners' perceived performance expectancy positively influences the intention to use AI for public health practice.*	PE	BI	-	.23	0.12	N
H3	*Public health practitioners' effort expectancy positively influences the intention to use AI for public health practice.*	EE	BI	-	.39	0.00	Y
H4	*Public health practitioners' social influence positively influences the intention to use AI for public health practice.*	SI	BI	-	.35	0.01	Y
H5	*Public health practitioners' health equity perceptions positively influence the intention to use AI for public health practice.*	HE	BI	-	.37	0.09	Y
H6	*Public health practitioners' perceptions facilitating conditions positively influences usage behavior.*	FC	BU	-	.53	<.001	Y
H7	*Public health practitioners' intention to use positively influence usage behavior.*	BI	BU	-	.30	0.01	Y
H8a	*Public health practitioners' health equity perceptions and moderates the relationship*	FC	BI	HE	.34	0.73	N

	between facilitating conditions and intention to use.						
H8b	*Public health practitioners' health equity perceptions and moderates the relationship between performance expectancy and intention to use.*	PE	BI	HE	.57	0.69	N
H8c	*Public health practitioners' health equity perceptions and moderates the relationship between effort expectancy and intention to use.*	EE	BI	HE	-.04	0.78	N
H8d	*Public health practitioners' health equity perceptions and moderates the relationship between social influence and intention to use.*	SI	BI	HE	-.31	0.83	N
H9a	*Public health practitioners' technology readiness and moderates the relationship between facilitating conditions and intention to use.*	FC	BI	TRI	.10	0.44	N
H9b	*Public health practitioners' technology readiness and moderates the relationship between performance expectancy and intention to use.*	PE	BI	TRI	.27	0.06	Y
H9c	*Public health practitioners' technology readiness and moderates the relationship between effort expectancy and intention to use.*	EE	BI	TRI	-.04	0.82	N
H9d	*Public health practitioners' technology readiness and moderates the relationship between social influence and intention to use.*	SI	BI	TRI	.13	0.40	N
H10	*Public health practitioners' institutional factors' moderate the relationship between intention to use and usage behavior.*	BI	BU	IF	0.17	0.09	Y

p-value < 0.1



Extension of the Unified Theory of Acceptance and Use Technology (UTAUT) – Venkatesh et al. 2003

Figure 2: Supported Model Summary

VI CHAPTER 6: DISCUSSION

This study examines factors influencing public health practitioners' adoption of artificial intelligence technology by extending Venkatesh's (2003) UTAUT model to explore the effects of health equity perceptions, technology readiness, and institutional factors. The proposes a model that considers the independent variables facilitating conditions, performance expectancy, effort expectancy, social influence, and health equity perceptions to assess public health practitioners' intention to use AI. The analysis explored the moderation effect of health equity perceptions and technology readiness on the original UTAUT constructs and intention to use AI, as well as facilitating conditions on intention to use AI and usage behavior. The model represents the use of AI by public health practitioners to perform their functions. During the study, generative AI experienced rapid uptake, and public health agencies released policies and procedures for using generative AI (WHO, 2024; HHS, 2022; NIH, 2023; CDC, 2024).

The predictors of the UTAUT model explain approximately 60 –70 % of the variance in behavioral intentions across different domains (Venkatesh et al., 2003; Thomas et al., 2013). However, various factors dependent on the context moderated UTAUT direct relationships (Jadil et al., 2021; Kelly et al., 2022). Context-dependent factors are essential when assessing the acceptance of AI products in different industries (Gansser et al., 2021; Kelly et al., 2022). In health care, constructs such as loss of privacy, bias, perceived substitution, and value have been considered (Dieter, 2021; Fan et al., 2020; Prakash & Das, 2021).

The UTAUT constructs of facilitating conditions, performance expectancy, effort expectancy, and social influence as factors influencing a public health practitioner's intent to use AI were determined to contribute 45% of the variance in the behavioral intent to use AI. Three of the four constructs reflected a statistically significant positive relationship with the public health practitioner's intention to use the technology (FC, EE, SI). Performance expectancy did not reflect such a relationship; possibly, practitioners may not have yet realized how AI can improve their performance.

Social influence predicts the intention to use AI. It is reasonable to assume that other professionals in the field influence public health practitioners' decisions and practices (Ajzen & Fishbein, 1975). Public health practice is an interdisciplinary discipline influenced by adopting interventions, technologies, and practices in other areas within the same field or other fields. In addition, the context of public health practice is broad, providing opportunities to exchange and seek input from other public health practitioners within their subject matter area, attending public health conferences, engaging in evidence-based practice, and assessing the impact of public health interventions. The use of AI is an essential topic of discussion in the literature, in public health conferences, and practitioner panel discussions. However, the findings related to social influence vary across the literature; in some studies, social influence positively predicts intentions across various industries, particularly healthcare (Gursoy et al., 2019; Lin et al., 2021), likely due to high levels of social contact. In contrast, other studies on adopting AI-based systems in the healthcare sector (Fan et al., 2020; Floruss & Vahpahl, 2020) found no influence of social influence on behavioral intention. In many of these studies, trust was the most influential determinant of behavioral intention.

The relationship between effort expectancy and intention to use represents another public health practitioner behavior predictor. Effort expectancy is defined as one's perception of the degree of ease associated with using the technology, such as AI technology, applied to their job (Venkatesh & Davis, 2000). The finding determines that effort expectancy predicts the intention to use AI; the finding reinforces the assumption that less effort positively affects the intention to use AI (Gansser et al., 2021). AI applications increased during the research period, and their use continues to expand. However, AI use in public health is still perceived as very new or potentially even unknown to the public health workforce, as evidenced by the relatively recent release of guidance by national and international public health agencies (WHO, 2024; HHS, 2022; NIH, 2023; CDC, 2024). Effort expectancy continues to be an area of exploration for researchers. Gansser (2021) studied acceptance of technology in three segments, mobility, health, and household, and determined that the role of effort expectancy needed further study as a predictor of technology adoption in these contexts. Furthermore, Fan (2020) found no significant influence of effort expectancy on adopting an AI-based medical diagnosis system.

In our model, facilitating conditions predict the intention and use. Facilitating conditions is defined as one's perception of the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the technology (in this case, AI technology) to perform tasks related to their job relevance. Venkatesh et al. (2003) found that facilitating conditions are significant for older people at late stages of experience. Recent studies argue that facilitating conditions do not predict intention in the presence of performance expectancy and effort expectancy constructs (Gansser et al., 2021; Kelly et al., 2023); the age and experience of the respondents may influence the findings. The relationship between facilitating conditions and AI use was positive, implying that the facilitating conditions could lead to usage behavior.

Performance expectancy does not appear to be a predictor in the original or expanded models, which include health equity. Performance expectancy is defined as one's perception of the degree to which an individual believes that using technology, such as AI, will help attain gains in job performance. This finding is surprising as studies have identified performance expectancy as having a significant effect on the behavioral intention to use AI (Fan et al., 2020;

Gansser et al., 2021). This outcome may be due to the limitations in sample size or the limited availability of the technology for broad use during the study. AI applications are relatively new, and implementing policies and procedures that support AI is relatively recent. Also, respondents may need more explicit examples of how AI could improve their performance. In addition, studies comparing job performance using traditional vs. AI-supported procedures are limited. There may be insufficient studies showing AI technology-specific benefits, and thus, public health practitioners may not have established a firm belief in the technology. Observing whether this result changes with a more extensive sample of public health practitioners would be interesting.

Further exploration of the model included health equity perceptions as a dependent variable of behavioral intention. In this model, the addition of health equity was determined to contribute 49% of the variance in the behavioral intent to use AI, representing a 9% change from the original UTAUT model. Health equity perceptions were defined as the "degree to which an individual believes inequities might manifest when AI is implemented or used in public health." This finding indicates health equity perceptions as a potential positive predictor of public health practitioners' intention to use AI; this outcome is significant as it reflects a unique predictive factor in public health. Health equity concerns are potential barriers to public health practitioners' adoption of AI technology. The literature discussed concerns related to the limitations of the degree of representativeness of all populations in data, varying availability of the technology by public health practitioners, and reported challenges for health care and public health. However, AI could enhance public health by identifying and addressing health disparities. AI applications may provide valuable insights into the social determinants of health. In addition, proper data governance can help ensure that AI applications identify and reduce bias by representing all populations in the data. Moreover, AI tools could help automate specific tasks, freeing up resources for public health professionals to focus on more complex and nuanced issues. Health equity perceptions did not moderate the relationship between UTAUT constructs and intention to use AI.

Technology readiness is defined as an individual's propensity to embrace and use new technologies to accomplish goals at home and work. Technology readiness only positively influences the relationship between performance expectancy and intention to use. The finding in the study indicates a positive moderation effect of performance expectancy on the intention to use. The result could explain the likelihood that a person considered ready to adopt technology will likely believe that using the technology, such as AI, will help attain gains in job performance. Even though there is no literature to support this finding in the context of AI and public health, technology readiness could determine whether technology could surpass the performance of industry experts (accounting and medical experts) (Kelly, 2023).

The relationship between intention to use and facilitating conditions on usage behavior was positive; the model contributed 32% of the variance in the dependent variable. In addition, institutional factors presented a moderating effect on intention to use and usage behavior. These findings must be interpreted cautiously, as the study did not collect evidence of actual use.

The proposed model, UTAUT-HE/TRI, has been empirically supported and identified UTAUT constructs that may impact public health practitioners' adoption of AI technology. These factors include facilitating conditions, effort expectancy, social influence, and health equity perceptions. Technology readiness moderates facilitating conditions on intention to use, and institutional factors moderate behavioral intention and usage of AI. Health equity perceptions enhance the model and represent a unique predictor of AI adoption by public health practitioners.

VII CHAPTER 7: CONTRIBUTIONS, LIMITATIONS, FUTURE RESEARCH AND CONCLUSIONS

VII.1 Implications For Researchers

Artificial Intelligence (AI) applications will likely expand to many industries and sectors, including public health. An increased interest in AI has resulted in research on user acceptance of AI in sector industries. The existing acceptance models are limited to understanding user acceptance of AI technologies. Researchers continue to explore the factors that influence acceptance of AI, including considerations where the need for human contact cannot be replicated or replaced by AI (Kelly, 2023). While the UTUAT model is validated to demonstrate that facilitating conditions, performance expectancy, effort expectancy, and social influence predict the intention to use technology (Venkatesh, 2003), the use of the model applied to AI in public health is limited.

This research suggests that the UTAUT is a valuable model for measuring public health practitioners' behaviors toward adopting AI technology. It is important to note that performance expectancy did not directly affect the intention to use; this relationship should be further investigated and validated. In addition, this research contributes to the UTAUT framework by investigating other predictors not considered in previous studies. Health equity directly influences the intention to use AI; this is a significant finding as the construct is unique within a public health context. Institutional factors show a moderating influence on the relationship between intention to use and adoption. Health equity, technology readiness, and institutional factors should be further validated.

VII.2 Implications For Practitioners

From a practice perspective, this study contributes to assisting public officials and health practitioners, developers, and policymakers with a better understanding of barriers and enablers' acceptance of AI for public health functions. The COVID-19 pandemic allowed AI technology to support several public health functions, including tracking and prediction, diagnosis and prognosis, treatment and vaccines, and social control. However, AI applications will benefit from improvements to reduce constraints and pitfalls. Determining the factors influencing public health practitioners' adoption of AI will help understand the mechanisms to support adoption and decision-making. AI systems for public health use have not reached maturity levels. Therefore, it is essential to consider unique factors such as the effect of health equity considerations relating to 1) inequalities in the opportunity to benefit from AI technologies, 2) bias and values as systems must be programmed or trained with specific data that might be biased and will invariably reflect value judgments that can create, sustain, or exacerbate health inequities, 3) plurality of values across systems depending on cultural or societal norms and values, different values will likely manifest in AI technologies across health systems and 4) fair decision-making procedures as reaching a consensus about those values and assumptions might be unlikely.

Many UTAUT studies have identified performance expectancy as having a significant effect on the behavioral intention to use AI (Fan et al., 2020; Gansser et al., 2021). As AI technology extends its use in public health, public officials, health practitioners, developers, and policymakers must have information comparing traditional vs. AI-supported procedures and enhancements in job performance and public health outcomes.

VII.3 Limitations

This study is subject to several limitations and assumptions that can affect the accuracy of the research results. 1. The sample does not represent the population of public health practitioners in the United States, as no unique source can compile the total population. The study used a sampling frame of public health officials with valid contact information randomly selected per state using generative AI. The approach posed limitations, subject to the training of the generative AI and the accuracy and completeness of the information it pulled, resulting in a convenience sample that may not represent the population. Additional recruitment approaches added subjectivity to the sample selection. 2) Uses and applications of AI technology vary and continuously evolve. The study did not assess adopting a specific AI product; instead, it used a broad concept, and respondents interpreted AI use based on their own experience 3) The measurement of health equity perceptions could have limited validity due to the complexity and multi-dimension of the construct and the effect of AI on health disparities may result as an immediate effect of the use of AI. 4) Participants may not have access to AI applications; therefore, the usage behavior was not evidenced in the survey. 5) The low number of responses to the survey impacted the power, and the original analysis plan had to be adjusted to accommodate this limitation. 6) Due to the voluntary nature of the survey, public health practitioners interested in using or using AI may have been more likely to respond.

VII.4 Future Research

Further research with a larger sample size will validate the constructs of performance expectancy, health equity, and technology readiness. The findings related to health equity perceptions as a predictor of intentions and use of AI provide the opportunity for future research. Studies that expand assessing different health equity dimensions can inform the effect of intention and use of AI. Exploring other predictors, such as trust and privacy concerns, as the literature indicates, these constructs may have a strong influence on adopting AI technology. Finally, future research could also expand the assessment of UTAUT as a model suitable for measuring the adoption of AI in a public health context.

VII.5 Conclusion

The purpose of this research was to study factors that influence public health practitioners’ behavioral intent to adopt AI technology for public health practice using the theoretical framework of the UTAUT model. The findings suggest that the UTAUT model can serve as a model to help determine the predictors that influence public health practitioners’ behavioral intent to adopt AI technology for public health practice. Organizational and technical infrastructure, ease of use of the applications, technology readiness, and social influence are important factors when considering AI adoption.

Perceptions of how AI will manifest in health equity are a predictor of public health practitioners' intention and use of AI. Since public health functions focus on populations rather than persons and require collective intervention, implementing AI technology in this context has a higher positive or negative influence on health inequities than at the individual level.

AI technology will continue to expand, including applications for public health, and public officials and health practitioners, developers, and policymakers will need to understand better the barriers and enablers' acceptance of AI. The UTAUT framework can serve as a model to help determine predictors in the context of AI technology. However, additional research is necessary to refine its use on AI technology and public health. Public health policymakers should be attentive to these developments to ensure resources, policies, and strategies are in place to support the use of AI, given that it helps improve public health outcomes.

APPENDICES

Appendix A. Survey Instrument

Part I. Demographics and Work Experience

Q1 How do you describe yourself?

a. Male
b. Female
c. Non-binary third gender
d. Prefer not to say

Q2 How old are you?

a. 18-24 years old
b. 25-34 years old
c. 35-44 years old
d. 45-54 years old
e. 55-64 years old
f. 65+ years old

Q3 Choose one or more races or ethnicities that you identify with

a. White or Caucasian
b. Black or African American
c. American Indian/Native American or Alaska Native
d. Asian
e. Native Hawaiian or Other Pacific Islander
f. Hispanic or Latino
g. Other

Q4 What is your predominant area of work:

a. Community Health
b. Epidemiology/Disease Surveillance
c. Environmental Health
d. Health Education and Promotion
e. Health Policy/Management
f. Public Health Programs/Service Delivery
g. Social/Behavioral Health
h. Other

Q5 How many years of public health experience do you have?

a. 0-2 years

b. 3-5 years
c. 6-10 years
d. 11-20 years
e. More than 20 years

Q6 What type of population do you serve?

a. Urban
b. Suburban
c. Rural
d. Other
e. Not applicable

Q7 What is your affiliation or the affiliation of your main employer?

a. Federal Government
b. State Government
c. Local/County/City Government
d. Community Based Organization or Other Non-Governmental Organization
e. Academia
f. Other

Part II. Perceptions of Adoption of Artificial Intelligence (AI)

Artificial Intelligence (AI) is the simulation of human intelligence processes by machines, especially computer systems. Specific applications of AI include expert systems, natural language processing, speech recognition, and machine vision.

Machine Learning (ML) is a branch of artificial intelligence (AI) and computer science that uses data and algorithms to imitate how humans learn, gradually improving accuracy. Some examples include smart assistants (Siri, Alexa, Google Assistant), facial detection and recognition, chatbots, text editors, virtual travel booking agents, detecting email spam, predictive analytics like the weather, product recommendations, and healthcare and medical diagnosis.

Level of agreement with each statement**:**

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
1	2	3	4	5
o	o	o	o	o

Q8 Effort Expectancy (EE)

a. Interacting with artificial intelligence/machine learning systems would be clear and understandable. (1)

b. It would be easy for me to become skillful at using artificial intelligence/machine learning systems. (2)
c. I would find artificial intelligence/machine learning systems easy to use in my work. (3)
d. Learning to operate artificial intelligence/machine learning systems would be easy for me. (4)

Q9 Performance Expectancy (PE)
a. Artificial intelligence/machine learning systems would be useful in my work. (1)
b. Artificial intelligence/machine learning systems would improve how I do my work (performance). (2)
c. Artificial intelligence/machine learning systems would increase the number of tasks finished or the number of outcomes in my work (productivity). (3)
d. Artificial intelligence/machine learning systems would improve the quality of my work. (4)

Q10 Social Influence (SI)
a. People who influence my behavior would think that I should use artificial intelligence/machine learning systems. (1)
b. People around me would take a positive view of me using artificial intelligence/machine learning systems for my work. (2)
c. People who are important to me would think that I should use artificial intelligence/machine learning systems for my work. (3)
d. I would use artificial intelligence/machine learning systems if my colleagues used them. (4)

Q11 Facilitating Conditions (FC)
a. I have the resources necessary to use artificial intelligence/machine learning systems. (1)
b. I have the knowledge necessary to use artificial intelligence/machine learning systems. (2)
c. A specific person or technical resource is available to assist with using artificial intelligence/machine learning systems. (3)
d. Artificial intelligence/machine learning systems are not compatible with other systems I use at work. (4)

Health equity is the state in which everyone has a fair and just opportunity to attain their highest level of health. Achieving this requires focused and ongoing societal efforts to address historical and contemporary injustices, overcome economic, social, and other obstacles to health and healthcare, and eliminate preventable health disparities.

Health disparities are preventable differences in the burden of disease, injury, violence, or opportunities to achieve optimal health experienced by populations disadvantaged by their social or economic status, geographic location, and environment. https://www.cdc.gov/healthequity/whatis/

Q12 Health Equity - Baseline (HEBASE)

a. I don't think there are health inequities in the United States (4)

b. I am concerned about health inequities in the United States population. (1)

c. Increased health disparities in the United States are unacceptable. (2)

d. Current health inequities are acceptable, but I don't want it to increase. (5)

Q13 Health Equity Perceptions (HE)

a. Artificial intelligence systems increase health equity in the population. (1)

b. Using artificial intelligence/machine learning systems can help reduce health disparities. (2)

c. Artificial intelligence/machine learning systems can serve as a great equalizer for health equity. (3)

Q14 Technology Readiness Index (TRI)

a. Technology gives people more control over their lives. (1)

b. Products and services that use the newest technologies are much more convenient to use. (2)

c. Technology makes me more efficient in my work. (3)

d. Other people come to me for advice on new technologies. (4)

e. In general, I am among the first in my circle of friends to acquire new technology when it appears. (5)

f. I can usually figure out new high-tech products and services without help from others. (6)

g. I keep up with the latest technological developments in my area. (7)

h. There should be caution in replacing important people-tasks with technology because new technology can break down or get disconnected. (8)

i. Whenever something gets automated, I need to check carefully that the machine or computer is not making mistakes. (9)

Q15 Institutional Factors (IF)

a. My agency/employer has the necessary financial resources to use artificial intelligence/machine learning systems. (1)

b. My agency/employer has skilled staff to use artificial intelligence/machine learning systems. (2)

c. My agency/employer has the systems infrastructure to support the use of artificial intelligence/machine learning systems. (3)

d. My agency/employer has policies in place to support the use of artificial intelligence/machine learning systems. (4)

Part IV: Intention and Use

Q16 Behavioral Intention (BI)

a. If I had access to artificial intelligence/machine learning systems, I would use them at work in the next weeks. (1)

b. Given that I have access to artificial intelligence/machine learning systems, I predict I will use them in the next weeks. (2)

Q17 Actual Adoption of AI (BU)

a. I have access to artificial intelligence/machine learning systems and use them for my work.

Appendix B. Descriptive Statistics

Validity Statistics for Survey Items

Item	*n*	Min	Max	*M*	*SD*
Interacting with artificial intelligence/machine learning systems would be clear and understandable.	98	1	5	3.33	0.993
It would be easy for me to become skillful at using artificial intelligence/machine learning systems.	98	1	5	3.73	0.980
I would find artificial intelligence/machine learning systems easy to use in my work.	98	1	5	3.49	0.933
Learning to operate artificial intelligence/machine learning systems would be easy for me.	98	1	5	3.59	0.993
Artificial intelligence/machine learning systems would be useful in my work.	98	1	5	3.90	0.867
Artificial intelligence/machine learning systems would improve how I do my work (performance).	98	1	5	3.79	0.876
Artificial intelligence/machine learning systems would increase the number of tasks finished or the number of outcomes in my work (productivity).	98	1	5	3.82	0.878
Artificial intelligence/machine learning systems would improve the quality of my work.	98	1	5	3.56	0.985
People who influence my behavior would think that I should use artificial intelligence/machine learning systems.	98	1	5	3.05	0.967
People around me would take a positive view of me using artificial intelligence/machine learning systems for my work.	98	1	5	3.16	0.971
People who are important to me would think that I should use artificial intelligence/machine learning systems for my work.	98	1	5	3.16	0.927
I would use artificial intelligence/machine learning systems if my colleagues used them.	98	1	5	3.73	0.937
I have the resources necessary to use artificial intelligence/machine learning systems.	98	1	5	2.93	1.160
I have the knowledge necessary to use artificial intelligence/machine learning systems.	98	1	5	3.01	1.214
A specific person or technical resource is available to assist with using artificial intelligence/machine learning systems.	98	1	5	2.42	1.139
Artificial intelligence/machine learning systems are not compatible with other systems I use at work.	98	1	5	3.13	0.959
Artificial intelligence systems increase health equity in the population.	98	1	5	2.95	0.817
Using artificial intelligence/machine learning systems can help reduce health disparities.	98	2	5	3.38	0.844
Artificial intelligence/machine learning systems can serve as a great equalizer for health equity.	98	1	5	3.07	0.900
Technology gives people more control over their lives.	98	2	5	3.46	0.954
Products and services that use the newest technologies are much more convenient to use.	98	2	5	3.35	0.964

Technology makes me more efficient in my work.	98	1	5	4.11	0.656
Other people come to me for advice on new technologies.	98	1	5	3.36	1.142
In general, I am among the first in my circle of friends to acquire new technology when it appears.	98	1	5	2.85	1.196
I can usually figure out new high-tech products and services without help from others.	98	1	5	3.51	1.160
I keep up with the latest technological developments in my area.	98	1	5	3.46	1.057
There should be caution in replacing important people-tasks with technology because new technology can break down or get disconnected.	98	1	5	3.87	1.032
Whenever something gets automated, I need to check carefully that the machine or computer is not making mistakes.	98	2	5	3.83	0.931
My agency/employer has the necessary financial resources to use artificial intelligence/machine learning systems.	98	1	5	3.02	1.26
My agency/employer has skilled staff to use artificial intelligence/machine learning systems.	98	1	5	2.87	1.249
My agency/employer has the systems infrastructure to support the use of artificial intelligence/machine learning systems.	98	1	5	2.97	1.239
My agency/employer has policies in place to support the use of artificial intelligence/machine learning systems.	98	1	5	2.40	1.043
If I had access to artificial intelligence/machine learning systems, I would use them at work in the next weeks.	98	1	5	3.55	1.085
Given that I have access to artificial intelligence/machine learning systems, I predict I will use them in the next weeks.	98	1	5	3.26	1.187
I have access to artificial intelligence/machine learning systems and use them for my work.	98	1	5	2.67	1.225

Appendix C. Validity Statistics

Variable	Item	*P-Value*	Validity	Reliability
Effort Expectancy	Interacting with artificial intelligence/machine learning systems would be clear and understandable.	<.001	Valid	0.821
	It would be easy for me to become skillful at using artificial intelligence/machine learning systems.	<.001	Valid	
	I would find artificial intelligence/machine learning systems easy to use in my work.	<.001	Valid	
	Learning to operate artificial intelligence/machine learning systems would be easy for me.	<.001	Valid	
Performance Expectancy	Artificial intelligence/machine learning systems would be useful in my work.	<.001	Valid	0.890
	Artificial intelligence/machine learning systems would improve how I do my work (performance).	<.001	Valid	
	Artificial intelligence/machine learning systems would increase the number of tasks finished or the number of outcomes in my work (productivity).	<.001	Valid	
	Artificial intelligence/machine learning systems would improve the quality of my work.	<.001	Valid	
Social Influence	People who influence my behavior would think that I should use artificial intelligence/machine learning systems.	<.001	Valid	0.779
	People around me would take a positive view of me using artificial intelligence/machine learning systems for my work.	<.001	Valid	
	People who are important to me would think that I should use artificial intelligence/machine learning systems for my work.	<.001	Valid	
	I would use artificial intelligence/machine learning systems if my colleagues used them.	<.001	Valid	
Facilitating Conditions	I have the resources necessary to use artificial intelligence/machine learning systems.	<.001	Valid	0.706
	I have the knowledge necessary to use artificial intelligence/machine learning systems.	<.001	Valid	
	A specific person or technical resource is available to assist with using artificial intelligence/machine learning systems.	<.001	Valid	
Health Equity	Artificial intelligence systems increase health equity in the population.	<.001	Valid	0.809
	Using artificial intelligence/machine learning systems can help reduce health disparities.	<.001	Valid	

	Artificial intelligence/machine learning systems can serve as a great equalizer for health equity.	<.001	Valid	
Technology Readiness	Technology gives people more control over their lives.	<.001	Valid	0.785
	Products and services that use the newest technologies are much more convenient to use.	<.001	Valid	
	Technology makes me more efficient in my work.	<.001	Valid	
	Other people come to me for advice on new technologies.	<.001	Valid	
	In general, I am among the first in my circle of friends to acquire new technology when it appears.	<.001	Valid	
	I can usually figure out new high-tech products and services without help from others.	<.001	Valid	
	I keep up with the latest technological developments in my area.	<.001	Valid	
	There should be caution in replacing important people-tasks with technology because new technology can break down or get disconnected.	0.539	Valid	
	Whenever something gets automated, I need to check carefully that the machine or computer is not making mistakes.	0.004	Valid	
Institutional Factors	My agency/employer has the necessary financial resources to use artificial intelligence/machine learning systems.	<.001	Valid	0.76
	My agency/employer has skilled staff to use artificial intelligence/machine learning systems.	<.001	Valid	
	My agency/employer has the systems infrastructure to support the use of artificial intelligence/machine learning systems.	<.001	Valid	
	My agency/employer has policies in place to support the use of artificial intelligence/machine learning systems.	<.001	Valid	
Behavioral Intentions	If I had access to artificial intelligence/machine learning systems, I would use them at work in the next weeks.	<.001	Valid	0.872
	Given that I have access to artificial intelligence/machine learning systems, I predict I will use them in the next weeks.	<.001	Valid	
Usage Behavior	I have access to artificial intelligence/machine learning systems and use them for my work.	<.001	Valid	0.875

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VITA

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