Understanding the Determinants of Wearable Smart Device Adoption: A Quantitative Analysis

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Abstract

Wearable smart devices offer opportunities to improve patient care and operational efficiency, yet adoption among healthcare professionals remains uneven. This study investigated psychological, social, and contextual factors influencing adoption, guided by the Unified Theory of Acceptance and Use of Technology (UTAUT). A quantitative correlational survey of 270 Oregon healthcare professionals measured seven independent variables (Performance Expectancy, Effort Expectancy, Attitude Toward Using Technology, Social Influence, Facilitating Conditions, Self-Efficacy, and Anxiety) against Behavioral Intention. Multiple linear regression analysis, following verification of statistical assumptions, revealed the model explained 48.1% of the variance in adoption intention. Attitude Toward Using Technology and Social Influence emerged as significant positive predictors, while Anxiety was a significant negative predictor. Performance Expectancy, Effort Expectancy, and Self-Efficacy were not significant, and Facilitating Conditions approached significance. These results suggest that emotional readiness and peer influence outweigh technical or usability considerations in shaping adoption decisions. Effective implementation strategies should focus on reducing technology-related anxiety, strengthening professional support networks, and aligning device use with organizational culture. Future research should examine longitudinal adoption patterns and extend the model to include constructs such as trust and ethical considerations to better support sustainable digital health integration.

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Chapter 1: Introduction

Wearable smart devices have become an increasingly prominent aspect of modern technology, particularly in the realm of health monitoring and fitness tracking (Soh et al., 2015). These devices, such as smartwatches, fitness bands, and heart monitors, offer users the ability to monitor various health metrics such as heart rate, physical activity, and sleep patterns (Scheid et al., 2023). As technology continues to evolve, these devices are playing a crucial role in empowering individuals to take control of their health, providing real-time data that can inform lifestyle changes and improve overall well-being (Kang & Exworthy, 2022). The integration of wearable technology into daily life has significant implications for public health, particularly in encouraging proactive health management and facilitating early detection of potential health issues (Kang & Exworthy, 2022).

The broader context of this study is rooted in the ongoing digital transformation of the healthcare industry. As healthcare systems worldwide grapple with challenges such as rising costs, an aging population, and the increasing prevalence of chronic diseases, there is a growing emphasis on preventive care and managing health outside traditional clinical settings (Greiner, 2003). By enabling continuous monitoring and providing personalized health insights, wearable devices are recognized as a key component of the shift toward more patient-centered care (Lu et al., 2020). However, despite the potential benefits of wearable technology, adoption rates remain inconsistent, particularly among specific populations such as healthcare professionals who are both users and potential advocates of these technologies (Kang & Exworthy, 2022).

Understanding the factors that influence the adoption of wearable smart devices is essential for several reasons. First, healthcare professionals represent a unique user group whose acceptance of wearable technology can significantly impact its broader adoption, both within the healthcare industry and among the general public. Given their role as early adopters and influencers of health-related technologies, understanding what drives or hinders their use of wearable devices can provide valuable insights for developers, marketers, and policymakers. Second, the adoption of wearable devices in healthcare settings can contribute to more efficient and effective patient care, supporting remote monitoring, telemedicine, and data-driven decision-making (Canali et al., 2022). Therefore, exploring the adoption patterns among healthcare professionals was not only relevant but also crucial for the future integration of wearable technology into healthcare practices.

Previous research on the adoption of wearable technology has identified several key factors that influence user acceptance, including perceived usefulness, ease of use, social influence, and concerns about privacy and security (Kumar, 2022; Robertson, 2020). These studies often employ established theoretical frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to analyze the factors that drive adoption. However, much of the existing research has focused on the general population or specific consumer groups, with limited attention to healthcare professionals as a distinct user segment. Furthermore, while cultural and demographic factors have been explored in numerous studies (Ryu, 2023; Taib, 2021), there is a need for more research that considers the unique context of healthcare professionals. This is especially true for healthcare professionals in regions like Oregon, where the integration of technology into healthcare practices is undergoing active evolution.

Empirical studies have demonstrated that healthcare professionals' adoption of technology is influenced by a combination of individual, organizational, and technological factors (Skokin, 2022). However, there was still a gap in understanding how these factors interact, specifically in the context of wearable smart devices. This gap is particularly relevant in light of the increasing emphasis on digital health initiatives and the potential role of wearables in enhancing healthcare delivery (Canali et al., 2022). As such, this study addressed this gap by focusing on healthcare professionals in Oregon, exploring the factors that influence their decision to adopt wearable smart devices and how these factors can be integrated into a unified model of technology acceptance.

The adoption of wearable smart devices among healthcare professionals is a critical area of study with far-reaching implications for both the healthcare industry and the broader public. Understanding the factors that shape adoption decisions in this group can inform strategies for increasing technology uptake, improving efficiency, and enhancing patient engagement. By focusing on this specific population, the research contributes to a deeper understanding of how wearable technology can be effectively integrated into healthcare practices, ultimately supporting improved health outcomes and more personalized models of care. The following sections provide a detailed exploration of the problem, purpose, and methodology of this study, building upon the foundational context established in this introduction.

Statement of the Problem

The problem addressed in this study is the lack of understanding of the factors that influence the decision of healthcare professionals to adopt wearable smart devices in Oregon. While wearable smart devices have gained popularity in consumer markets (Poongodi et al., 2019), their adoption in professional healthcare settings remained uneven and under-researched (Kang & Exworthy, 2022). This difference existed despite the potential benefits these technologies offer to healthcare spaces, such as enhanced health monitoring (Kumar, 2022; Robertson, 2020). This is particularly concerning given that healthcare professionals are not just potential users but also key advocates for these technologies within their patient populations (Taib, 2021). As a result, there was limited understanding of the specific factors that influence the decisions of healthcare professionals to adopt these devices (Cannali et al., 2022).

Existing research primarily focused on adoption among general consumer populations, often neglecting the unique context of healthcare professionals, who may have different motivations and barriers to adoption (Skokin, 2022). For example, while factors such as perceived usefulness, ease of use, and social influence are well-documented in broader studies, there was little insight into how these factors interact in healthcare (Ryu, 2023). Lack of adoption among healthcare professionals can have significant negative consequences, including missed opportunities to improve patient outcomes and advance the integration of technology in clinical practice. If these barriers were not addressed, the potential benefits of wearable devices in healthcare might have remained unrealized, resulting in slower innovation and lower overall healthcare quality. This study filled the gap by examining how performance expectancy, effort expectancy, social influence, and facilitating conditions influenced the intention to use wearable smart devices among healthcare professionals in Oregon, while also exploring additional factors such as attitude toward using technology, self-efficacy, and anxiety that further informed adoption strategies and highlighted potential areas for improvement.

Purpose of the Study

The purpose of this quantitative study was to understand the factors influencing the decision to adopt wearable smart devices among healthcare professionals in Oregon. Guided by the Unified Theory of Acceptance and Use of Technology (UTAUT), the primary goal was to examine how four core independent variables, specifically performance expectancy, effort expectancy, social influence, and facilitating conditions, predict the dependent variable, behavioral intention to adopt wearable technologies. In addition to these core predictors, the study also explored supplementary factors, including attitude toward using technology, self-efficacy, and anxiety, to provide a more comprehensive understanding of adoption behaviors within this population. While the research questions focused on the four UTAUT constructs, the inclusion of these additional variables offered context-specific insights that could inform future research and practice. Data were collected through a structured online survey distributed to 300 healthcare professionals working in various settings across Oregon. The minimum required sample size of 109 was determined using G Power a priori analysis, and the final dataset exceeded this threshold, ensuring adequate statistical power. The survey measured key constructs using validated scales from prior studies, and relationships between variables were analyzed using structural equation modeling (SEM). This approach allowed for a nuanced view of how core and supplementary factors interact to influence adoption. Findings from this study offer valuable implications for developers, marketers, and policymakers aiming to enhance the adoption and sustained use of wearable technologies in healthcare.

Introduction to Theoretical Framework

The guiding framework for this study was the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh, Morris, Davis, and Davis (2003). UTAUT synthesizes constructs from earlier technology acceptance models, including the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), the Diffusion of Innovations theory (DOI), and Social Cognitive Theory (SCT), to provide a comprehensive and empirically supported approach for predicting technology adoption. This consolidation reduces redundancy across models while offering a parsimonious yet powerful framework for analyzing user acceptance. UTAUT identifies four core constructs, Performance Expectancy (PE), Effort

Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), as primary determinants of behavioral intention and use. PE reflects the belief that technology will improve job performance; EE concerns the perceived ease of use; SI represents the influence of important others; and FC captures the extent to which organizational and technical infrastructure support the use. These relationships are moderated by age, gender, experience, and voluntariness of use, highlighting the contextual nature of technology adoption.

In this study, UTAUT guided the development of the problem statement, purpose, and research questions by providing a structure for examining how these four determinants influenced healthcare professionals' intentions to adopt wearable smart devices in Oregon. PE and EE were relevant to professionals' judgments of usefulness and usability, SI aligned with the collaborative and culturally shaped nature of healthcare work, and FC reflected the need for institutional support such as training, technical assistance, and policy alignment. Together, these constructs provided a foundation for understanding adoption patterns in a sector where both individual and organizational factors play critical roles. To broaden the analysis, the study also incorporated three supplementary constructs drawn from extensions of UTAUT and earlier models: Attitude Toward Using Technology (ATUT), Self-Efficacy (SE), and Anxiety (ANX). ATUT captures overall positive or negative dispositions toward technology, SE reflects confidence in one's ability to use it effectively, and ANX measures apprehension or discomfort toward use. While not part of UTAUT's original core determinants, prior studies have found these variables to be influential in technology adoption, and their inclusion offered an opportunity to explore whether attitudinal and affective factors carried particular weight in the healthcare wearable context. Elements of Diffusion of Innovations (DOI) theory were also integrated to provide broader contextual grounding. Concepts such as relative advantage, compatibility, and complexity parallel UTAUT's PE and EE constructs, situating wearable adoption within the larger process of innovation diffusion in healthcare organizations. By linking DOI concepts to UTAUT rather than treating them as separate frameworks, this study emphasized both the individual perceptions measured by UTAUT and the systemic, cultural, and workflow-related considerations captured in DOI. The integrated framework, therefore, combines UTAUT's four primary predictors of behavioral intentions with the supplementary constructs (ATUT, SE, ANX) and aligned DOI elements. This integration guided every stage of the research: the identification of the problem, the articulation of the purpose and research questions, the development of the survey instrument, and the interpretation of findings. As shown in Figure A1 (see Appendix A), the framework positions PE, EE, SI, and FC as the primary drivers of behavioral intention to adopt wearable devices, supplemented by ATUT, SE, and ANX, and contextualized through DOI's emphasis on relative advantage, compatibility, and complexity. This conceptual roadmap provided the theoretical grounding for systematically examining the interplay of individual, social, and organizational influences on wearable device adoption among healthcare professionals.

Introduction to Research Methodology and Design

This study employed a quantitative research methodology with a correlational research design to examine relationships among constructs derived from the Unified Theory of Acceptance and Use of Technology (UTAUT) and supplementary variables. A correlational design was appropriate because it allowed the study to identify the strength and direction of associations among predictors of adoption without experimental manipulation, thereby providing insight into behavioral patterns in a naturalistic healthcare context (Creswell, 2014; Venkatesh et al., 2003). This alignment was critical to addressing the study's problem statement regarding the inconsistent adoption of wearable smart devices and to fulfilling the purpose of identifying which factors most strongly influence behavioral intention to adopt these technologies.

The data were collected through a structured online survey distributed to healthcare professionals in Oregon across varied clinical settings, including hospitals, clinics, and specialty care facilities. The instrument included validated multi-item scales for UTAUT's four core constructs, Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, as well as supplementary constructs of Attitude Toward Using Technology, Self-Efficacy, and Anxiety, adapted from prior technology acceptance models. Demographic data (e.g., role, years of experience, and prior exposure to wearable technologies) were also gathered to explore potential moderating effects, consistent with UTAUT propositions. Data analysis was conducted using statistical modeling techniques suitable for testing complex relationships among multiple independent and dependent variables. These procedures enabled simultaneous examination of direct and indirect effects across constructs, ensuring the analysis remained consistent with the integrated theoretical framework. The design thus supported rigorous testing of the study's hypotheses while also providing exploratory insight into supplementary variables that may inform future refinements to technology adoption models in healthcare.

By grounding the methodology in a well-established theoretical framework and using validated measures, this study ensured that data collection, measurement, and analysis were both theoretically coherent and empirically rigorous. The quantitative correlational design was therefore well aligned with the research problem, purpose, and questions, enabling a systematic exploration of how individual, social, and organizational factors influence healthcare professionals' intentions to adopt wearable smart devices. This design also provided a structure for testing theoretically derived hypotheses while allowing exploratory consideration of supplementary variables, thereby balancing rigor with flexibility. Ultimately, the methodology offered a sound foundation for producing findings that were both meaningful for theory development and practically useful for improving adoption strategies in healthcare settings.

Research Questions

RQ1

To what extent does performance expectancy influence the decision of healthcare professionals to adopt wearable smart devices in Oregon?

RQ2

To what extent does effort expectancy influence the decision of healthcare professionals to adopt wearable smart devices in Oregon?

RQ3

To what extent does social influence impact the decision of healthcare professionals to adopt wearable smart devices in Oregon?

RQ4

To what extent do facilitating conditions influence the decision of healthcare professionals to adopt wearable smart devices in Oregon?

Hypotheses

$H1_0$

Performance expectancy does not significantly influence the decision of healthcare professionals to adopt wearable smart devices in Oregon.

$H1_a$

Performance expectancy significantly influences the decision of healthcare professionals to adopt wearable smart devices in Oregon.

$H2_0$

Effort expectancy does not significantly influence the decision of healthcare professionals to adopt wearable smart devices in Oregon.

$H2_a$

Effort expectancy significantly influences the decision of healthcare professionals to adopt wearable smart devices in Oregon.

$H3_0$

Social influence does not significantly influence the decision of healthcare professionals to adopt wearable smart devices in Oregon.

$H3_a$

Social influence significantly influences the decision of healthcare professionals to adopt wearable smart devices in Oregon.

$H4_0$

Facilitating conditions do not significantly influence the decision of healthcare professionals to adopt wearable smart devices in Oregon.

$H4_a$

Facilitating conditions significantly influence the decision of healthcare professionals to adopt wearable smart devices in Oregon.

Significance of the Study

This study was significant because it played a pivotal role in integrating wearable smart device technology into clinical practices. By addressing a critical gap in understanding the factors that influence the adoption of wearable smart devices among healthcare professionals, this research provided valuable insights that can inform both theoretical advancements and practical applications. Understanding the specific factors that drive healthcare professionals' decisions to adopt these devices enable organizations to tailor their training, support, and communication efforts. This leads to greater integration of wearable technologies in patient care, as well as potentially result in improved patient outcomes, increased efficiency in healthcare delivery, and a more proactive approach to health management.

From an academic perspective, this study contributed to the literature by applying and extending the UTAUT within a healthcare context. By examining how UTAUT constructs influenced technology adoption among healthcare professionals, the study provided empirical evidence that enhances our understanding of technology acceptance in a critical sector. This research also contributed to the ongoing discourse on the digital transformation of healthcare, offering a nuanced understanding of the barriers and facilitators to technology adoption. By identifying the key drivers of wearable technology adoption among healthcare professionals, this study helped bridge the gap between the potential benefits of these technologies and their actual usage in healthcare settings. The outcomes of this research can inform policy and practice, lead to a more technologically integrated and efficient healthcare system, and provide valuable insights for healthcare administrators, technology developers, academic researchers, and policymakers.

Definitions of Key Terms

Adoption of Wearable Smart Devices

Refers to the decision-making process through which healthcare professionals in Oregon choose to incorporate wearable smart devices, such as fitness trackers and health monitors, into their daily practices and routines (Dinh-Le et al., 2019).

Cultural Factors

These are the shared beliefs, values, customs, and behaviors that influence how healthcare professionals in Oregon perceive and interact with wearable smart devices, potentially affecting their willingness to adopt such technologies (Taib, 2021).

Data Privacy

Data privacy concerns involve the protection of personal and patient health information collected by wearable smart devices, including how data is stored, accessed, and shared in compliance with legal and ethical standards (Acquisti et al., 2015).

Data Security

This term refers to the safeguards and protocols implemented to protect information collected by wearable devices from unauthorized access, breaches, or cyberattacks, thereby ensuring the confidentiality and integrity of health data (Denning & Denning, 1979).

Healthcare Technology Integration

Healthcare technology integration refers to the process of embedding wearable smart devices into existing clinical systems, workflows, and electronic health records to support patient monitoring and care delivery (Dinh-Le et al., 2019).

Interoperability

Interoperability refers to the capability of wearable smart devices to connect with and exchange information across various healthcare systems and platforms, enabling seamless data sharing and coordinated patient care (Klecun, 2016).

Patient Engagement

Patient engagement is the active participation of patients in managing their own health, often enhanced by wearable devices that provide real-time feedback, personalized insights, and self-monitoring tools (Martin et al., 2021).

Regional Factors

These are the specific environmental, economic, and policy-related aspects of Oregon that impact the adoption of wearable smart devices among healthcare professionals, including state healthcare regulations and local market dynamics (Kumar, 2022).

Technology Literacy

Technology literacy refers to the ability of healthcare professionals to effectively understand, use, and troubleshoot wearable smart devices, including the skills needed to interpret and act upon device-generated data (Or & Tao, 2012).

User Experience

User experience encompasses the overall perceptions and interactions a user has with a smart home device, including aspects such as usability, satisfaction, and emotional responses (Hassenzahl & Tractinsky, 2006).

Summary

Chapter One introduced the research study focus on understanding the factors influencing the adoption of wearable smart devices among healthcare professionals in Oregon. The chapter began with an overview of the general topic, highlighting the increasing importance of wearable technology in healthcare and the need to address the inconsistent adoption rates among healthcare professionals. The significance of this study was then established, emphasizing its potential contributions to both the practical integration of wearable technologies in healthcare settings and the theoretical advancement of technology acceptance models. The problem statement identified the inconsistent and insufficient adoption of wearable smart devices in the healthcare industry as a critical issue, with potential negative consequences for patient care and healthcare efficiency if not addressed. The purpose of the study was outlined, aiming to investigate the independent variables and factors that influence adoption and to develop a unified model to predict and explain these behaviors.

The chapter introduced the theoretical framework that guided the study, specifically the Unified Theory of Acceptance and Use of Technology (UTAUT), which provided a comprehensive lens for analyzing the factors influencing technology adoption. The research methodology and design were briefly discussed, indicating the use of a quantitative survey approach and structural equation modeling (SEM) to analyze the data. The study highlights the significance of its findings, which can inform both academic research and practical applications in healthcare, ultimately leading to the improved adoption and integration of wearable smart devices in clinical practice. The chapter set the stage for the subsequent sections of the dissertation, which delve deeper into the literature, methodology, and analysis related to the study's objectives.

Chapter 2: Literature Review

The purpose of this study was to explore the factors influencing the decision to adopt wearable smart devices among healthcare professionals in Oregon. The problem addressed was the lack of comprehensive understanding of the factors influencing the adoption of wearable devices within the healthcare industry. Despite the potential benefits of wearable devices for enhancing patient care and improving health outcomes, what influences their adoption and their integration into professional healthcare settings was not understood (Kang & Exworthy, 2022). This chapter presents a detailed literature review aimed at identifying and synthesizing the existing research related to wearable technology adoption by healthcare professionals. The study's significance lies in its insights that inform strategies for increasing the adoption of wearables in healthcare. By identifying the primary facilitators and barriers to adoption, this research contributed to improved patient monitoring, enhanced chronic disease management, and overall better healthcare outcomes. As healthcare systems face mounting pressure to adopt more innovative, data-driven solutions, understanding how healthcare providers receive wearable technologies is essential for enhancing patient care quality and optimizing resource use.

This study was guided by the Unified Theory of Acceptance and Use of Technology (UTAUT), a theoretical framework that offers a comprehensive approach to examining technology adoption. UTAUT is especially relevant in healthcare, where adoption decisions are influenced by various factors, including performance expectancy, effort expectancy, social influence, and facilitating conditions. This framework provided a structured lens for analyzing how these factors interact in healthcare contexts, offering a deeper understanding of the complexities of adoption specific to wearable technology in clinical settings. UTAUT served as the foundation for evaluating adoption behaviors within the study population, focusing on the interactions between individual and organizational influences.

This chapter is organized into key sections that each contribute to understanding the research problem. This study begins with an exploration of the UTAUT framework, highlighting its relevance to technology adoption in healthcare. Following this, a discussion on the perceived benefits and value of wearable technology in healthcare highlights enhanced patient outcomes and other efficiencies. Then, a discussion on the operational integration of wearables in clinical settings analyzes the commonly discussed struggles noted in the literature for adoption. An exploration of the professional versus patient perceptions of wearable technology then highlights how these differences impact adoption. The factors influencing adoption are then analyzed to highlight the gap in understanding amongst factors impacting healthcare professionals. This is followed by an examination of the organizational and policy implications for wearable adoption programs, which have been frequently discussed in recent years. The second is data security and ethical considerations, which round out the literature review to examine how these considerations impact the potential for wearable technology adoption, let alone the adoption itself. The review critically analyzes the strengths, weaknesses, and gaps in the existing literature, particularly as they pertain to healthcare professionals as a unique user group and the specific context of Oregon, thereby establishing the need for further research.

This review is grounded in an extensive search of multiple academic databases, including *PubMed*, *IEEE Xplore*, *Scopus*, *ScienceDirect*, and *ProQuest*. The focus was on peer-reviewed journal articles, dissertations, and conference papers, with search terms such as "wearable technology in healthcare," "UTAUT model in healthcare adoption," "performance expectancy in clinical settings," and "facilitating conditions for technology adoption in healthcare." This literature spans two decades (2000-2023) but emphasizes recent studies to ensure relevancy to current technological advancements. Documentation of the databases accessed, keyword combinations, and search strategies ensures transparency and provides a foundation for replicability in future research. The chapter establishes a robust basis for investigating the factors influencing the adoption of wearable devices in healthcare, paving the way for the research methodology discussed in Chapter 3.

Theoretical Framework

The guiding theoretical framework for this study was the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh, Morris, Davis, and Davis (2003). UTAUT integrates elements from multiple technology acceptance models, such as the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Diffusion of Innovations (DOI) theory. UTAUT's core constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions were well-suited for analyzing technology adoption within healthcare, an industry that involves both individual and organizational influences (Venkatesh et al., 2003; Yusif et al., 2016). By structuring this study around UTAUT, the research provided a nuanced understanding of how these constructs impacted healthcare professionals' decision-making and integration of wearable technologies. The framework also supported the addition of supplemental constructs, including self-efficacy, anxiety, and attitude toward technology, which have been identified in prior studies as potentially significant in explaining adoption behaviors in certain contexts (Venkatesh et al., 2012; Alaiad & Zhou, 2014).

Performance Expectancy

Performance expectancy refers to the perceived effectiveness of a technology in enhancing job performance (Venkatesh et al., 2003). In healthcare, performance expectancy is highly relevant as professionals prioritize technologies that contribute to improved patient care, operational efficiency, and clinical accuracy (Patil et al., 2022; Zhang et al., 2019). For example, wearable devices such as continuous glucose monitors (CGMs) and wearable ECGs support real-time monitoring, which is invaluable for managing chronic diseases and early diagnosis (Jovanov & Milenkovic, 2011; Patel et al., 2015). Studies have indicated that healthcare professionals are more inclined to adopt wearable technology when it offers clear clinical benefits, such as enhanced diagnostic capabilities or streamlined workflows (Piwek et al., 2016). However, certain specialties required a higher level of proof regarding efficacy, and concerns about variability in device data accuracy had created reservations among practitioners (Aggelidis & Chatzoglou, 2009). In Oregon, where healthcare settings ranged from advanced metropolitan hospitals to rural clinics, performance expectancy could vary significantly. Professionals in urban hospitals may have viewed wearables as complementary tools within technologically rich environments, whereas those in smaller or rural facilities may have evaluated them more cautiously due to resource constraints or differing patient needs. This variation underscored the importance of investigating performance expectancy as a driver of adoption decisions in this regional context. This section integrates literature on the importance of performance expectancy in healthcare, demonstrating its critical role as a driver of adoption decisions in clinical contexts.

Effort Expectancy

Effort expectancy refers to the ease of use associated with a new technology, which is particularly crucial in high-pressure healthcare environments (Chau & Hu, 2002; Or & Tao, 2012). In healthcare, where time constraints and patient safety are paramount, wearable devices need to integrate seamlessly with existing workflows and electronic health record (EHR) systems to be effective (Rahimi & Vimarlund, 2007). Devices that require extensive training or additional setup are less likely to be adopted due to the complexity and time investment involved (Wu et al., 2007). Research has demonstrated that healthcare professionals are more likely to adopt wearable technologies that offer user-friendly interfaces and intuitive functionality (Pai & Huang, 2011). However, studies also showed that effort expectancy alone was not always a strong predictor of adoption, as integration issues with legacy systems and inconsistencies in device interfaces could pose significant barriers to consistent usage (Kim & Park, 2012). In Oregon's healthcare landscape, varying levels of IT infrastructure across facilities may have shaped perceptions of effort expectancy. Larger institutions with dedicated IT departments might have been able to mitigate usability concerns, whereas smaller clinics might have faced greater difficulty in accommodating new systems, making perceived ease of use a particularly important consideration for this study. By synthesizing studies on usability, this section illustrates how effort expectancy impacts healthcare adoption, particularly in environments where technology must not disrupt critical clinical routines.

Social Influence

Social influence reflects the impact of peers, colleagues, and institutional leaders on an individual's technology adoption decisions (Chau & Hu, 2002; Karahanna et al., 1999). In healthcare, where collaborative practices and hierarchical structures are prevalent, social influence can significantly impact the adoption of wearable devices. Research indicated that when senior healthcare professionals or respected figures advocate for wearable technology, their support can encourage adoption among peers and junior staff (Legris et al., 2003). Moreover, as patients increasingly used personal health tracking devices, some healthcare providers experienced implicit pressure to integrate wearable technology into their care models to meet patient expectations (Acquisti et al., 2015). In Oregon, where healthcare systems often had strong professional networks, particularly within larger integrated delivery networks, the role of social influence may have been amplified. Adoption decisions could be shaped not only by direct peer recommendations but also by professional associations, training programs, and state-level healthcare initiatives promoting digital health solutions. This section integrates literature on how social influence affects healthcare professionals, demonstrating how professional culture and peer support influence their willingness to adopt new technologies.

Facilitating Conditions

Facilitating conditions involve the availability of resources, technical support, and organizational infrastructure that enable technology use (Venkatesh et al., 2003; Yusif et al., 2016). For healthcare professionals, supportive facilitating conditions were critical as wearable technologies often require integration with other systems and specialized training for effective use. Research showed that institutions providing adequate IT support, professional development opportunities, and seamless EHR integration saw higher rates of wearable adoption among staff (Jovanov & Milenkovic, 2011; Klecun, 2016). Conversely, in under-resourced settings, such as rural areas, limited technical support and infrastructure can hinder technology adoption regardless of perceived usefulness or ease of use (Cresswell & Sheikh, 2013). In Oregon, facilitating conditions likely varied across the urban–rural divide, making this construct particularly relevant in examining regional adoption trends. This section synthesizes literature on the role of facilitating conditions in healthcare, emphasizing that robust organizational support is essential for wearable technology adoption.

Attitude Toward Using Technology

Attitude Toward Using Technology (ATUT) refers to an individual's overall evaluative feeling, whether it be positive or negative, toward engaging with a specific technology (Ajzen & Fishbein, 1980; Davis et al., 1989). While ATUT was not included as one of the four original constructs in the Unified Theory of Acceptance and Use of Technology (UTAUT), it has been incorporated into extended models, such as UTAUT2, and is widely recognized in technology adoption literature as a meaningful predictor of behavioral intention (Venkatesh et al., 2012). ATUT reflects not only a cognitive assessment of a technology's usefulness and ease of use but also the affective responses and predispositions an individual holds toward adopting it (Taylor & Todd, 1995). In the context of healthcare, these attitudes are shaped by a combination of professional experiences, patient care priorities, perceived risks, and alignment with personal values or ethical considerations (Ifinedo, 2012).

In the adoption of healthcare technology, ATUT has been shown to play a mediating role between cognitive perceptions, such as performance expectancy and effort expectancy, and the eventual intention to adopt or continue using a technology (Holden & Karsh, 2010). For example, when healthcare professionals view wearable smart devices positively, they are more likely to explore their capabilities, integrate them into clinical workflows, and recommend their use to colleagues or patients (Rahimi et al., 2018). Conversely, negative attitudes, stemming from skepticism about data accuracy, concerns about increased workload, or apprehension about patient privacy, can hinder adoption even when perceived usefulness and ease of use are high (Alaiad & Zhou, 2014). In wearable technology research, ATUT has been linked to willingness to adopt remote monitoring systems, mobile health applications, and other patient-centered digital tools (Kim & Park, 2012; Kuo et al., 2013).

For this study, ATUT was included as an additional construct to capture the broader affective dimension of technology adoption decisions among healthcare professionals in Oregon. The inclusion of ATUT enabled the examination of whether positive or negative attitudes toward wearable smart devices served as independent predictors of adoption intentions beyond the cognitive and infrastructural factors outlined in UTAUT. This was particularly relevant in a healthcare setting where professional identity, patient interaction, and trust in technology can strongly influence adoption behaviors. By assessing ATUT alongside performance expectancy, effort expectancy, social influence, facilitating conditions, self-efficacy, and anxiety, the study aimed to develop a more complete understanding of the forces, both rational and emotional, that shape the adoption of wearable smart devices in clinical practice.

Self-Efficacy

Self-efficacy, as conceptualized by Bandura (1986) and later applied in technology adoption research (Compeau & Higgins, 1995), referred to an individual's belief in their capability to perform tasks using a particular technology. In healthcare technology studies, self-efficacy has been shown to influence both the likelihood of adoption and the sustained use of digital tools (Holden, 2011). For wearable smart devices, self-efficacy encompassed confidence in tasks such as configuring device settings, interpreting output data, and troubleshooting minor technical issues. Prior studies have indicated that higher self-efficacy reduces the cognitive and emotional barriers to technology adoption, especially in environments where formal training is limited (Chang et al., 2012). In Oregon's healthcare settings, where staff might range from highly tech-savvy to minimally experienced with digital tools, self-efficacy could be a determining factor in adoption. For example, a nurse confident in using mobile health applications might be more willing to pilot a new wearable technology program, whereas one with low technology confidence might resist participation despite recognizing potential clinical benefits.

Anxiety

Technology-related anxiety refers to feelings of apprehension or fear associated with using new digital tools (Venkatesh, 2000). In the context of healthcare, anxiety could stem from concerns about making errors, compromising patient safety, or violating data privacy regulations. Research indicated that anxiety could negatively influence both behavioral intention and actual usage (Meuter et al., 2003). In studies involving healthcare professionals, those with higher technology-related anxiety often required more extensive training and ongoing support to achieve comfort with new systems (Chou & Chou, 2021). For wearable smart devices, anxiety might arise from the need to rely on automated monitoring systems, uncertainty about device accuracy, or concerns about legal liability in interpreting device-generated data. In Oregon, variations in institutional support structures, patient demographics, and exposure to digital health initiatives may have influenced these anxiety levels, making them a meaningful construct for inclusion in this study.

Comparison with Alternative Frameworks

While the Unified Theory of Acceptance and Use of Technology (UTAUT) served as the primary theoretical framework for this study, alternative models, such as the Technology Acceptance Model (TAM) and the Diffusion of Innovations (DOI) theory, offered valuable insights into technology adoption behaviors and were carefully considered. Each of these models brought unique perspectives, yet they were limited in their ability to capture the full scope of factors influencing healthcare professionals' adoption of wearable technology, particularly in the context of organizational and social influences that are integral to UTAUT.

Developed by Davis (1989), the Technology Acceptance Model (TAM) was one of the most widely used frameworks for understanding technology adoption. TAM was grounded in two central constructs of perceived usefulness and perceived ease of use that predict an individual's likelihood of adopting new technology. Perceived usefulness refers to the extent to which a person believes that using a specific technology will enhance their job performance, while perceived ease of use refers to the degree to which an individual expects the technology to be free of effort. TAM's simplicity and focus on user perceptions made it a popular model in various fields, including healthcare, where early-stage adoption studies have often benefited from an accessible and streamlined model (Holden & Karsh, 2010; King & He, 2006). In healthcare, TAM has been effectively applied to examine adoption behaviors related to electronic health records (EHRs), telemedicine, and other digital health tools. For instance, Holden and Karsh (2010) found that perceived usefulness significantly influenced the adoption of EHRs among healthcare professionals, demonstrating the relevance of TAM in understanding how utility shapes technology adoption. Similarly, Aggelidis and Chatzoglou (2009) found that perceived usefulness played a crucial role in healthcare staff's acceptance of hospital information systems, thereby reinforcing the applicability of TAM to healthcare settings.

TAM's limitations in addressing external influences, such as social pressure and organizational support, made it less suitable for this study. While perceived usefulness and ease of use are important, they did not fully capture the complex, multi-layered environment in which healthcare professionals operate (Tung et al., 2008). Adoption decisions in healthcare are often influenced by institutional policies, peer behaviors, and regulatory standards, factors that TAM does not explicitly incorporate. Moreover, TAM's relatively static nature does not address how technology adoption might evolve, which is critical for studying wearables that require ongoing engagement and adaptation to organizational changes (Wu et al., 2007). In comparison, UTAUT integrates these broader influences through constructs like social influence and facilitating conditions, providing a more holistic perspective on adoption behaviors within clinical environments. By encompassing both individual and organizational factors, UTAUT overcomes the limitations of TAM, offering a more robust framework for analyzing wearable device adoption among healthcare professionals.

The Diffusion of Innovations (DOI) theory, proposed by Rogers (1962), examined how innovations spread within social systems over time. DOI identifies five primary attributes: relative advantage, compatibility, complexity, trialability, and observability. These attributes affect the rate at which an innovation is adopted. Relative advantage reflects the perceived improvement over current practices, while compatibility measures the degree to which the technology aligns with existing values and practices. Complexity addresses ease of understanding and use, trialability indicates the extent to which an innovation can be experimented with, and observability reflects the visibility of its results to others (Rogers, 2003).

DOI theory has been widely applied in healthcare to study the diffusion of large-scale technologies, such as electronic health records, telemedicine, and mobile health applications. DOI's focus on social systems and the broader diffusion process makes it particularly useful in public health and organizational studies, where collective adoption trends are a key emphasis. For instance, Greenhalgh et al. (2004) utilized DOI to investigate the diffusion of EHRs across healthcare settings, identifying social networks and communication channels as key factors in the dissemination of technology. Similarly, Cresswell and Sheikh (2013) highlighted how organizational culture and leadership impact the adoption of digital health solutions, aligning with DOI's emphasis on social and institutional influences.

While the DOI's macro-level focus on how innovations spread across populations is insightful, it lacked the micro-level detail needed to understand individual decision-making processes within healthcare. DOI primarily examines how innovations gain traction across a social system, rather than investigating the specific factors that influence an individual's decision to adopt. This focus limits the applicability of DOI to understanding the adoption of wearable devices by individual healthcare professionals, where personal motivations, perceptions, and contextual factors, such as team dynamics and support systems, are significant (Kijsanayotin et al., 2009). Furthermore, DOI does not explicitly address the continuous interaction between users and technology over time, a key factor in healthcare settings where long-term integration and sustained use of wearable devices are essential for achieving meaningful outcomes (Rogers, 2003).

Compared to DOI, UTAUT provides a more precise focus on individual adoption behaviors within an organizational context. The social influence and facilitating conditions constructs in UTAUT align well with the collaborative and structured nature of healthcare environments, where peer dynamics and institutional support are central to technology adoption. By capturing these elements, UTAUT offered a more comprehensive framework for understanding how wearable technologies are integrated into healthcare practice, particularly in clinical settings where both individual and organizational factors significantly impact adoption behaviors.

Both TAM and DOI offered valuable perspectives on technology adoption, but they fell short of addressing the full range of factors relevant to the adoption of wearable technology in healthcare. TAM, while straightforward and focused, lacks the organizational and social dimensions that play a significant role in healthcare, where adoption decisions are influenced by a network of peers, supervisors, and institutional policies. DOI provides insight into how innovations spread at the population level, but does not adequately capture the personal, immediate factors that impact an individual healthcare professional's decision to adopt wearable devices in their daily practice.

In contrast, UTAUT's integration of performance expectancy, effort expectancy, social influence, and facilitating conditions made it particularly well-suited for examining wearable technology adoption in healthcare settings. UTAUT captured both the individual perceptions and organizational factors that influence adoption decisions, providing a balanced framework for exploring the interplay of personal utility, peer dynamics, and institutional support. This comprehensive approach aligned closely with the unique characteristics of the healthcare sector, where wearable devices must not only meet individual expectations for usability and efficacy but also align with broader organizational goals and support systems (Venkatesh et al., 2003; Yusif et al., 2016). By addressing these critical dimensions, UTAUT provided a robust foundation for this study, enabling a nuanced examination of the factors influencing the adoption of wearable technology among healthcare professionals in Oregon.

Perceived Benefits and Value of Wearable Technology in Healthcare

The adoption of wearable technology in healthcare has shown considerable promise, particularly in enhancing patient care, increasing engagement, and improving operational efficiency. Numerous studies have explored the general benefits of wearable devices; however, literature lacks a sufficient analysis of the factors specifically influencing healthcare professionals' decisions to adopt these technologies in a professional context. This section synthesizes the existing research on the perceived benefits and value of wearable technology in healthcare, highlighting areas of consensus and divergence among scholars and identifying key gaps that underscore the importance of studying these factors among healthcare professionals in Oregon.

Adoption Trends and Benefits of Wearable Technology

The adoption of wearable technology in healthcare has been driven primarily by its perceived benefits, including enhanced patient monitoring, improved care delivery, and the potential for increased user engagement and empowerment (Huhn et al., 2022; Piwek et al., 2016). Studies have emphasized how wearable devices facilitate real-time health monitoring, enabling early interventions and more precise treatment decisions (Lee & Lee, 2020). For example, continuous glucose monitors (CGMs) and wearable ECGs provide healthcare providers with actionable data for managing chronic conditions, such as diabetes and cardiovascular disease, demonstrating tangible clinical utility (Patil et al., 2022).

In addition to improving health outcomes, wearables have often been celebrated for promoting patient autonomy. Devices such as fitness trackers allow users to visualize and control their health metrics, fostering proactive behavior and adherence to care plans (Martin et al., 2021). However, much of this research focuses on consumer adoption and behavior change, with limited exploration of how healthcare professionals perceive and adopt these tools for use in their practices (Kang & Exworthy, 2022). Despite the general enthusiasm for wearable technology, gaps remained in understanding its applicability in clinical environments. For instance, Azodo et al. (2020) highlighted the complexity of translating consumer-oriented technologies into professional settings, where factors such as data accuracy, device reliability, and regulatory compliance take precedence. These differences suggested a need for research that specifically examines the adoption patterns and attitudes of healthcare professionals toward wearable devices.

Limited Exploration of Professional Adoption

While the general adoption of wearable devices has been widely studied, the dual role of healthcare professionals as personal users of wearable technology and as medical authorities recommending these devices to patients has remained underexplored. Existing literature on consumer adoption often emphasizes factors such as ease of use, perceived usefulness, and social influence (Venkatesh & Davis, 2000). However, these frameworks did not adequately address the complex considerations healthcare professionals must balance when deciding to adopt wearables in their personal lives versus endorsing them in clinical settings.

their personal lives, healthcare professionals may adopt wearable devices for general health monitoring, fitness tracking, or personal convenience. Studies, such as those by Piwek et al. (2016), have highlighted that consumer-driven adoption often prioritizes usability and lifestyle alignment. Yet, healthcare professionals may hold these devices to a higher standard when evaluating their utility for patient care. Professionals often demand clinical-grade validation of device accuracy, reliability, and data integration capabilities before recommending them to patients (Azodo et al., 2020; Jovanov & Milenkovic, 2011). This dual perspective highlighted a significant gap in understanding how healthcare professionals reconcile their personal experiences with wearables and their professional judgment when recommending them for clinical use. Moreover, healthcare professionals' willingness to recommend wearable devices to patients is influenced by their perceived clinical utility in improving health outcomes. Research by Misra et al. (2023) suggested that professionals were cautious about endorsing wearables due to concerns about data accuracy, patient compliance, and potential legal liabilities. This contrasted with the more casual and personal adoption patterns among professionals who may use wearables for fitness or lifestyle tracking rather than clinical decision-making. The literature failed to adequately explore whether personal usage experiences positively or negatively impact professionals' attitudes toward recommending these devices in medical practice.

Institutional and organizational factors further complicated this dual adoption dynamic. In settings with robust IT infrastructure and administrative support, healthcare professionals may have felt more confident in integrating wearable technology into their clinical recommendations (Cresswell & Sheikh, 2013). Conversely, in resource-limited settings, professionals may have viewed wearables as impractical or burdensome, both for themselves and their patients. The divergence between personal and professional adoption in these contexts underscores the need for research that examines how healthcare professionals navigate these dual roles and how their personal experiences with wearables inform their professional perspectives.

While the literature has broadly addressed wearable adoption from consumer and patient perspectives, it has provided limited insights into the nuanced roles of healthcare professionals. Future research should investigate how professionals' personal experiences with wearables influence their clinical recommendations, as well as how organizational, technological, and cultural factors shape these decisions. Addressing this gap is crucial for understanding the intricate relationship between personal adoption behaviors and professional endorsement practices among healthcare providers.

Divergence Between Consumer and Professional Adoption

The literature revealed a significant divergence in the motivations and barriers to wearable adoption between consumer and professional users. For consumers, the adoption of wearable devices was driven largely by perceived health benefits, convenience, and user-friendly design (Martin et al., 2021). Wearables were often marketed as tools for personal empowerment, emphasizing features like fitness tracking and sleep monitoring (Lu et al., 2022). However, healthcare professionals adopted these technologies based on entirely different criteria, such as clinical accuracy, reliability, and the ability to integrate seamlessly with existing systems (Or & Tao, 2012).

Several studies illustrated this divergence. Kang and Exworthy (2022) reported that while consumers often viewed wearables as empowering tools for self-management, professionals were more concerned with the potential risks of relying on incomplete or inaccurate data. Similarly, Lee and Lee (2020) found that professionals frequently questioned the clinical validity of wearable devices, particularly those developed for the consumer market. These concerns highlighted the need for research that bridges the gap between consumer and professional adoption, ensuring that wearables meet the rigorous standards required in clinical practice.

The lack of research on professional adoption was further compounded by the absence of region-specific studies. Healthcare environments in regions like Oregon present unique challenges, including disparities in infrastructure and resource availability between urban and rural settings (Borges do Nascimento et al., 2023). These contextual factors are likely to influence adoption decisions; however, the literature provides limited insights into how regional variations shape professionals' attitudes toward wearables. Professional roles and specialties also play a critical role in adoption behaviors. For instance, a cardiologist may evaluate a wearable ECG monitor differently than a primary care physician assesses the utility of a fitness tracker in preventive care. However, existing studies often failed to differentiate adoption factors across professional roles, treating healthcare providers as a monolithic group. This oversimplification highlighted a critical need for more nuanced, role-specific research (Gagnon et al., 2012).

Moving Toward a Professional-Centric Research Agenda

The literature underscored the importance of adopting a professional-centric approach to studying wearable technology adoption. While consumer adoption studies provided valuable insights, they did not adequately address the complexities of professional use in clinical settings. To bridge this gap, future research should focus on identifying the specific factors that influence healthcare professionals' decisions, such as clinical validation, workflow integration, and alignment with regulatory standards (Holden & Karsh, 2010). This study addressed these gaps by examining the unique factors that influence wearable adoption among healthcare professionals in Oregon. By examining the interplay of professional roles, regional contexts, and organizational readiness, this research provided a more comprehensive understanding of how wearable technology can be effectively integrated into clinical practice.

Operational Integration of Wearable Technology in Clinical Workflows

Integrating wearable technology into clinical workflows has been widely discussed in healthcare literature, with various studies highlighting both the operational benefits and challenges of wearable devices in practice. The literature suggests that while wearable technology offers promising enhancements for patient care through real-time data monitoring and streamlined operations, practical challenges, including infrastructure, compatibility with existing systems, and data management, remain significant. This section synthesizes the current research on wearable technology integration in clinical settings, identifying common themes, areas of agreement and divergence, and highlighting the operational factors that shape adoption within clinical workflows.

Operational Efficiency

Wearable technology has been widely recognized for its potential to improve operational efficiency in healthcare settings. According to studies by Alami et al. (2021) and Kang and Exworthy (2022), wearables enable healthcare providers to automate routine monitoring tasks, thereby reducing the workload for medical staff and allowing them to prioritize more complex care needs. By facilitating quicker access to real-time health data, wearable devices can streamline workflows, making them especially valuable in high-demand healthcare environments. Wearables integrated with electronic health records (EHRs), for instance, enable healthcare professionals to continuously monitor vital signs and respond quickly to changes, thereby enhancing patient care efficiency and supporting a proactive approach to patient management. For example, Kang and Exworthy (2022) found that wearables, such as heart monitors and oxygen saturation devices, enhanced clinical efficiency by reducing the need for manual checks, allowing clinicians to allocate more time to direct patient care. Similarly, Huhn et al. (2022) reported that wearable technology improved workflow efficiency by providing healthcare teams with constant insights into a patient's vital signs, thereby supporting rapid intervention in acute cases.

While the benefits of real-time monitoring have been well documented, some studies have argued that these improvements are highly dependent on the quality and stability of the technology and infrastructure used. Research by Jovanov and Milenkovic (2011) and Or and Tao (2022) suggests that healthcare facilities with limited resources may struggle to integrate wearable devices into their operations due to technical and financial constraints. Wearables may require additional IT support, data management systems, and training for healthcare providers, which can lead to inefficiencies if these support mechanisms are not in place. Or and Tao (2022) cautioned that although wearable technology has the potential to streamline workflows, the lack of seamless integration between wearables and existing clinical systems, like electronic health records (EHRs), can hinder the full realization of these benefits. This discrepancy indicated a divergence in the literature: while wearable technology is praised for its efficiency, its operational benefits are highly dependent on the availability of adequate infrastructure and support resources. This gap is particularly relevant in regions like Oregon, where healthcare resources and technological infrastructure vary significantly between urban and rural settings.

Compatibility with Existing Systems and Infrastructure

One of the greatest challenges to wearable integration in clinical settings is compatibility with existing healthcare information systems. Several studies have underscored the importance of interoperability between wearable technology and EHRs, a necessity for enabling clinicians to access comprehensive patient data in one system. According to Rahimi and Vimarlund (2020), wearables that can seamlessly integrate with EHRs allow healthcare providers to obtain a holistic view of patient health, which can lead to more cohesive and effective care. This integration minimizes disruptions, allowing clinicians to maintain a streamlined workflow without needing to switch between multiple platforms.

Despite the benefits of integration, many studies have shown that healthcare institutions often lack the necessary technological infrastructure to achieve interoperability. Jovanov and Milenkovic (2011) argued that the technical limitations of current EHR systems frequently prevented successful integration with wearable devices, resulting in data silos where valuable patient information remained isolated. The lack of interoperability not only creates inefficiencies in data management but also raises concerns about the continuity of care when critical patient data cannot be easily shared or accessed. This challenge is compounded in resource-limited settings, where financial constraints may prevent institutions from upgrading to interoperable systems. The literature thus revealed a divide, with well-resourced institutions experiencing fewer integration issues than under-resourced or rural healthcare facilities, such as those found in parts of Oregon.

Training and Workforce Adaptation

Another recurring theme in the literature was the need for adequate training and workforce adaptation when integrating wearable technology into clinical workflows. Studies consistently emphasized that healthcare professionals require structured training on how to use wearable devices effectively, interpret data, and incorporate these insights into patient care. For instance, Lee et al. (2020) found that a lack of training can lead to frustration among healthcare providers, resulting in low adoption rates and misuse of wearable devices. Training not only improves technical competence but also fosters acceptance, as healthcare professionals become more confident in incorporating wearable technology into their daily routines.

The extent and effectiveness of training programs vary widely across institutions. Studies like those of Yusif et al. (2016) indicate that while large hospitals may have the resources to implement comprehensive training sessions, smaller clinics or rural healthcare facilities may not have the budget or personnel to offer the same level of support. This disparity in training resources may have contributed to the inconsistent adoption and effectiveness of wearable technology across different healthcare settings. The literature suggested that a lack of standardized training protocols exacerbates the gap between institutions that can afford extensive support and those that cannot, further complicating the operational integration of wearables.

Data Management and Privacy Concerns

Data management, particularly the secure handling of sensitive patient information, is another critical issue in integrating wearable technology into clinical workflows. As wearables generate vast amounts of patient data, healthcare providers face the dual challenges of managing this information effectively while ensuring patient privacy. Several studies, such as those by Acquisti et al. (2015) and Greenhalgh et al. (2020), have highlighted concerns regarding data storage, access, and security, particularly given the sensitive nature of health data. Efficient data management requires a robust infrastructure capable of handling large data volumes, along with strict adherence to privacy regulations to prevent data breaches.

The literature pointed to significant challenges in achieving this level of data security. According to Alami et al. (2021), many healthcare institutions struggled to keep up with the regulatory requirements and technical demands of managing wearable data. In regions with limited resources, such as rural parts of Oregon, the infrastructure necessary for secure data storage and transmission is often lacking, leaving patient data vulnerable. This divergence highlights a critical gap in the literature: while larger healthcare institutions may have the resources to invest in secure data management systems, smaller or rural facilities often lack these resources, which affects the broader scalability of wearable technology in clinical workflows.

Variability in Organizational Support and Infrastructure Readiness

Organizational support, including financial resources and administrative backing, played a critical role in the successful integration of wearable technology into clinical workflows. Studies emphasized that without institutional commitment, the adoption and effectiveness of wearable devices can be severely limited. For instance, Kang and Exworthy (2022) asserted that hospitals that allocated resources toward IT infrastructure, staff training, and device maintenance experienced smoother integration and greater clinician satisfaction with wearable technology. Variability in organizational support remains a notable challenge, with smaller institutions and rural facilities often lacking the resources to provide necessary infrastructure upgrades and technical support. Studies by Chau and Hu (2021) highlighted that the disparity in resources between urban and rural healthcare facilities led to unequal access to wearable technology. Institutions in resource-limited settings face barriers in achieving the same operational benefits as those in well-funded urban areas, exacerbating disparities in healthcare technology adoption. This pointed to a key gap in the literature. While there was consensus that organizational readiness was essential for successful wearable integration, there was limited research on how to address these disparities in different healthcare environments, particularly in underserved or rural regions.

Organizational and Policy Factors

In addition to infrastructure and workforce considerations, organizational and policy factors also influenced the integration of wearable technology into clinical workflows. Research has indicated that healthcare organizations with clear policies and financial incentives for technology adoption tend to experience higher levels of integration success. For example, policies that prioritized funding for technology infrastructure or reimbursements for wearable use encouraged broader adoption (Lee et al., 2020). However, without adequate policies that explicitly address the integration of wearable technology, many institutions were left with unclear guidelines and insufficient support for successful adoption. Policy inconsistencies are particularly problematic in regions with limited access to technology support or where funding for digital health initiatives is lacking. Studies indicated that national and regional healthcare policies often overlook specific needs for wearable adoption, which can create uncertainty about privacy regulations, reimbursement practices, and data handling protocols. The literature called for more detailed policies that specifically addressed wearable integration, as existing digital health policies tended to focus broadly on telehealth without addressing the unique challenges of wearables (Acquisti et al., 2015; Yusif et al., 2016).

The integration of wearable technology into clinical workflows offers substantial potential to enhance patient care and operational efficiency; however, the literature highlights critical barriers that must be addressed for these benefits to be fully realized. While there was general agreement on the advantages of real-time monitoring and enhanced data accessibility, studies revealed that the successful integration of wearables relied heavily on factors such as system compatibility, organizational support, workforce readiness, and robust data management. Disparities in infrastructure, particularly in rural or resource-limited regions, complicated the adoption of wearable technology, underscoring a significant gap in research on how these challenges vary across healthcare environments. The current literature also suggests that, while organizational readiness was essential, the absence of standardized training, consistent data management protocols, and tailored policy support continued to hinder the widespread adoption of wearable devices. Given these gaps, this study examined the specific factors influencing the adoption of wearable technology among healthcare professionals in Oregon, providing insights into how infrastructure, training, and organizational readiness can be optimized to facilitate the integration of wearable technology in diverse clinical settings.

Professional and Patient Perceptions of Wearable Technology

The growing use of wearable technology in healthcare highlighted a duality of perspectives: those of healthcare professionals and those of patients. Understanding these perceptions is critical, as both parties' attitudes toward wearables impact their effectiveness and adoption in clinical settings. The current literature illustrates several shared views, such as the perceived benefits of health monitoring and patient empowerment, while also identifying significant divergences, particularly in areas like data reliability, clinical utility, and trust in technology. This section synthesizes findings on both professional and patient perspectives on wearable technology, examining key areas of agreement and contention while identifying gaps in the literature that underscore the need for further exploration.

Patient Empowerment and Engagement

One of the most agreed-upon benefits of wearable technology from the patient perspective is its role in enhancing engagement and empowerment in personal health management. Numerous studies, including those by Martin et al. (2021) and Piwek et al. (2016), have highlighted that wearable devices, such as fitness trackers and heart rate monitors, offer patients real-time insights into their health, which fosters a proactive approach to managing chronic conditions and making healthier lifestyle choices. Wearable technology enables patients to visualize their progress and access their health metrics independently, which many studies have identified as a motivator for behavior change and improved health outcomes (Kang & Exworthy, 2022). This level of engagement was associated with improved adherence to treatment plans and more informed interactions with healthcare providers, as patients could track and share their health data over time.

The literature also revealed limitations in the perceived value of wearables from the patient's perspective. Studies by Huhn et al. (2022) and Lee et al. (2020) suggest that while many patients reported feeling empowered by wearable technology, others experienced information overload or anxiety due to continuous health monitoring. These patients may become overly focused on minor health fluctuations, leading to unnecessary stress or the compulsion to seek immediate healthcare intervention for non-critical readings. This indicated a divergence in how different patients interpreted and reacted to wearable data, pointing to the need for personalized support in wearable device use. Despite these variations, there was broad agreement in the literature on the potential of wearable technology to empower patients; however, studies suggested that the benefits were maximized when patients received guidance on accurately interpreting their data.

Enhanced Patient Outcomes

A significant portion of the literature indicated that wearable technology offered substantial benefits for patient outcomes, primarily through real-time health monitoring and data collection. Studies have shown that wearable devices, such as continuous glucose monitors (CGMs) and heart rate monitors, enable healthcare providers to continuously and remotely monitor patients' health metrics, leading to better-informed treatment decisions and proactive interventions (Huhn et al., 2022; Patel et al., 2022). For example, CGMs enabled patients with diabetes to track their glucose levels in real-time, providing data that healthcare professionals could use to make timely adjustments in care, thereby improving the management of chronic conditions (Piwek et al., 2016). These devices also contributed to patient empowerment, as they enabled patients to actively participate in their own health management, which has been linked to improved adherence and better health outcomes (Kang & Exworthy, 2022).

While there was broad agreement on these immediate patient benefits, the literature diverged on the long-term impacts of wearables on chronic disease outcomes. Ryu (2023) noted that many studies have focused on the short-term benefits derived from pilot programs or clinical trials, with limited longitudinal data to assess the sustained effectiveness of these devices. Lee et al. (2020) also highlighted that much of the research was industry-funded, which may have emphasized immediate benefits without addressing potential limitations or long-term effectiveness. This highlighted a critical gap in the literature regarding the sustained impact of wearables on chronic disease management and overall health outcomes over extended periods. Independent, long-term studies are needed to validate these preliminary findings and establish the effectiveness and reliability of wearables as tools for ongoing patient care.

Clinical Utility and Data Reliability: A Professional Perspective

From the healthcare professional perspective, perceptions of wearable technology are shaped by concerns about data reliability, clinical utility, and integration with standard care practices. Studies such as those by Acquisti et al. (2015) and Or and Tao (2022) demonstrated that healthcare providers valued wearable devices primarily for their potential to provide continuous, actionable data on patients, particularly in managing chronic conditions like diabetes and cardiovascular disease. Wearables that provided accurate, real-time health metrics enabled clinicians to make timely decisions and adjust treatment plans based on observed trends, leading to improved patient outcomes (Patil et al., 2022). Nevertheless, many healthcare professionals expressed concerns regarding the clinical accuracy and reliability of wearable data. Lee et al. (2020) highlighted that while some wearables were rigorously tested and FDA-approved, others lacked the precision and validation necessary for clinical reliance. This inconsistency led some professionals to view wearables skeptically, fearing that inaccurate data may result in misdiagnoses or unnecessary interventions. Jovanov and Milenkovic (2011) argued that the medical utility of wearables depended on their technological maturity and compatibility with clinical requirements, yet there remained limited standardization across devices. This inconsistency in data quality and reliability generated a degree of mistrust among healthcare providers, who hesitated to incorporate wearables into their clinical workflows until they could be assured of their accuracy and utility in medical contexts.

Divergence in Perceived Value Between Healthcare Professionals and Patients

While patients often view wearable devices as empowering tools that provide valuable health insights, healthcare professionals tend to approach these technologies with more caution. Several studies have found that patients value wearables for the personalized feedback they provide, which helps them make informed lifestyle changes and engage actively in their health management (Martin et al., 2021). As noted by Chau and Hu (2021), patients often saw wearables as an extension of their self-monitoring practices, contributing to a positive health identity and reinforcing trust in digital health solutions. This aligned with the patient-centered design of many wearables, which offered direct access to health metrics such as heart rate, physical activity, and sleep patterns. Patients' positive perceptions of wearables underscored the demand for accessible, user-friendly health monitoring tools that support personal health accountability.

In contrast, healthcare professionals were primarily concerned with the clinical utility, accuracy, and reliability of wearable devices. While patients may have appreciated the immediate feedback provided by wearables, healthcare professionals appeared to approach them with greater caution for their patients, often requiring evidence of clinical validity before fully endorsing their use. According to Holden and Karsh (2010), professionals were inclined to trust technology that is peer-reviewed, rigorously tested, and validated for medical settings. This disparity was evident in studies, such as those by Aggelidis and Chatzoglou (2009), which showed that while patients may adopt wearables based solely on perceived utility, healthcare professionals are more motivated by empirical validation and regulatory approval. Lee et al.

(2020) discussed that healthcare professionals prioritized accurate, clinically relevant data, as these devices impacted medical diagnoses and treatment plans. Therefore, while patients and healthcare providers both recognized the value of wearable devices, healthcare professionals were cautious due to potential discrepancies in data accuracy, which raised concerns about the reliability of these devices in clinical applications. This divergence in perspectives reflected a fundamental gap in the literature. Although studies acknowledged healthcare professionals' concerns over data reliability, few comprehensively examined how these concerns influenced adoption decisions within clinical environments. Research is needed to explore how professional concerns about data integrity, integration with EHRs, and device validation affect the adoption of wearable technology, specifically among healthcare professionals, especially in states like Oregon, where healthcare infrastructure and patient demographics can significantly impact perceptions of wearable utility.

Biases and Limitations in Existing Research

The existing literature on wearable technology adoption often exhibited bias, particularly in studies funded by technology manufacturers, which may have overemphasized the devices' benefits while underreporting their limitations. Industry-sponsored research frequently highlighted positive patient experiences and immediate health improvements, while independent academic studies with a clinical focus tended to underscore the practical challenges associated with integration and data reliability (Chau & Hu, 2021). This bias underscored the need for balanced, objective research that addressed both the advantages and limitations of wearables from a clinical perspective. Much of the current research was conducted in well-resourced, technologically advanced healthcare settings, which limits the generalizability of the findings across diverse healthcare environments. Studies that emphasized operational efficiency often lacked context on how these devices performed in resource-limited settings, where the technical and financial support necessary for seamless integration may be inadequate. As a result, the literature lacked a detailed analysis of wearable adoption in varied contexts, such as rural healthcare facilities in Oregon, where resource limitations may impact the feasibility and effectiveness of wearable technology. This gap in the literature underscores a critical need for research that examines the adoption of wearable technology in specific healthcare settings and considers the unique challenges faced by healthcare professionals in various regions.

The perceived benefits and value of wearable technology in healthcare have been widely acknowledged; however, the literature reveals significant gaps regarding healthcare professionals' specific perspectives on its adoption. While there was general consensus on the positive impact of wearables on patient engagement and operational efficiency, healthcare providers continued to express reservations about the clinical reliability and data accuracy of these devices. Additionally, the majority of studies focused on immediate outcomes, with limited research on long-term effectiveness and sustained use, particularly in professional healthcare settings. Studies funded by technology companies frequently emphasized the positive impacts of wearable devices, particularly regarding patient empowerment and engagement, which may skew findings toward highlighting benefits while downplaying limitations or challenges (Greenhalgh et al., 2004). Conversely, studies conducted within academic or clinical settings, as reported by Yusif et al. (2016), often focused on the limitations of wearables, particularly regarding data reliability and integration challenges. This split in perspective may have influenced the perceived benefits and drawbacks of wearable technology, underscoring the importance of balancing both patient-centered and clinician-centered research to obtain an objective understanding of wearable adoption and efficacy in healthcare. Moreover, audience bias was also evident, as studies aimed at technology users (patients) often presented wearables as easy-to-use, empowering tools, whereas research targeted at medical professionals took a more cautious approach, emphasizing the limitations of wearables and the need for further validation (Chau & Hu, 2002). This divide suggested a need for more neutral research that addresses the perceptions of both patients and professionals equally, providing a comprehensive understanding of wearable technology's role in healthcare.

Convergence and Divergence in Perceived Benefits and Risks

Across the literature, there was a notable convergence on the shared benefits that both healthcare professionals and patients perceive in wearable technology, particularly its potential to improve patient engagement and support proactive health management. Studies agreed that wearables can enhance patient-provider communication, as patients track their health metrics more regularly and bring relevant data to clinical consultations (Kijsanayotin et al., 2009). However, there was divergence concerning the risks associated with these technologies, with patients often unaware of potential data inaccuracies or the limitations of self-monitoring, while healthcare professionals are acutely aware of these risks and hesitant to rely on wearables without thorough validation. This divergence revealed a gap in understanding how to bridge patient enthusiasm with professional caution. While patients may quickly adopt wearables due to perceived convenience and empowerment, professionals were more measured, balancing enthusiasm with practical considerations about data accuracy and the devices' ability to integrate into existing clinical workflows. Addressing these disparities in perception required further research to determine how wearable technology can be effectively positioned as a reliable and collaborative tool that meets the needs of both patients and professionals.

The literature revealed substantial areas of convergence and divergence in patient and professional perceptions of wearable technology in healthcare. Patients generally viewed wearables as empowering tools that support self-management, while healthcare professionals prioritized data accuracy, reliability, and integration with clinical workflows. These differing perspectives have impacted the adoption and effectiveness of wearable technology, as patients' motivations for adoption are often rooted in personal utility, whereas healthcare professionals focus on empirical validation. Existing biases in the literature, often shaped by funding sources and intended audience, underscore the need for balanced research that equally addresses the perspectives of both patients and healthcare providers.

To foster a shared confidence in the role of wearable technology, the literature suggested the need for research that aligns patient enthusiasm with professional standards, potentially through improved validation of devices and more comprehensive patient education. Addressing these gaps leads to more effective integration of wearable technology into healthcare, creating a collaborative environment where wearables support improved health outcomes without compromising clinical standards. This study examined the specific factors influencing the adoption of wearable technology among healthcare professionals, particularly within Oregon's healthcare landscape, to gain a deeper understanding of how both patient and professional perspectives can shape the role of wearable technology in clinical care.

Factors Influencing Wearable Adoption Decisions Among Healthcare Professionals

The adoption of wearable technology by healthcare professionals is influenced by a range of factors, including perceived usefulness, ease of use, organizational support, social influence, and contextual elements specific to clinical environments. Research in recent years has extensively explored these variables, often revealing shared themes and occasionally highlighting contrasting views. While the literature agreed on several core factors driving adoption, such as clinical utility and ease of integration, it also diverged on certain elements, such as the influence of patient expectations and organizational readiness. This section synthesizes existing research on the primary factors influencing the adoption of wearable devices among healthcare professionals, offering insights into areas of convergence and divergence, and highlighting gaps that underscore the need for further research.

Perceived Usefulness and Clinical Utility

A predominant factor influencing the adoption of wearable technology among healthcare professionals was the perceived usefulness and clinical utility of the technology. Healthcare professionals were more likely to adopt wearables when they perceived these tools as beneficial to patient care, particularly in terms of real-time monitoring, improved diagnostic accuracy, and enhanced treatment decision-making (Jovanov & Milenkovic, 2011; Piwek et al., 2016). Studies by Lee et al. (2020) and Patel et al. (2022) have highlighted that wearables offering tangible improvements to clinical outcomes are generally more favorably received. For example, devices such as continuous glucose monitors and wearable ECGs are widely regarded as beneficial due to their ability to provide continuous data, which can improve chronic disease management and aid in early diagnosis.

Research also revealed limitations in perceived utility due to concerns over data accuracy. Professionals were often skeptical of data generated by consumer-grade wearables, which may lack clinical validation (Huhn et al., 2022). Such concerns highlighted a divergence in the literature: while some studies emphasized the potential of wearables to enhance care, others cautioned against over-reliance on data that may not meet clinical standards. This discrepancy highlighted a research gap in evaluating the performance of wearable devices in real-world healthcare settings, particularly in terms of whether they can provide reliable, actionable data.

Ease of Use and Technological Integration

Ease of use was another critical factor influencing the adoption of wearables. Research consistently shows that healthcare professionals are more likely to adopt wearable devices that are intuitive and require minimal training (Or & Tao, 2012). Complex or unintuitive devices created barriers to adoption, as healthcare professionals already work in high-stress, time-sensitive environments where seamless integration into workflows is essential. Studies by Chau and Hu (2002) and Yusif et al. (2016) emphasized that technologies requiring extensive setup or adjustment disrupted workflows and were less likely to be adopted. The ability of wearable technology to integrate with existing systems, such as electronic health records (EHRs), significantly affected its adoption. Research by Kang and Exworthy (2022) and Rahimi and Vimarlund (2020) suggests that interoperability between wearables and EHRs streamlines patient data management and enhances efficiency. However, in organizations lacking such infrastructure, professionals reported frustration over fragmented systems and data silos, which hindered the integration of wearable devices. This highlighted an area of divergence: while some literature assumed seamless integration as a benefit, other studies revealed the reality that not all healthcare environments were equipped to support wearable technology. This disparity underscored a gap in the literature, as few studies focused specifically on healthcare institutions' readiness to incorporate wearables, particularly in resource-limited settings.

Social Influence and Peer Recommendations

The role of social influence and peer recommendations in the adoption of wearable devices has been well-documented. Healthcare professionals often looked to colleagues and supervisors as guides for adopting new technologies, especially in collaborative, team-based environments (Karahanna et al., 1999; Legris et al., 2003). Research suggests that when respected colleagues endorse wearable devices, adoption rates are likely to increase, as healthcare professionals value the opinions of their peers in validating new technologies (Aggelidis & Chatzoglou, 2009). The strength of social influence appears to vary depending on the organizational culture. In some settings, social influence had a highly impactful effect, while in others, it had a negligible impact on adoption. For instance, Acquisti et al. (2015) found that social influence was a stronger driver in large hospital systems than in smaller clinics or private practices, where individual preferences play a more prominent role. This divergence suggests that social influence may not be uniformly impactful across all healthcare settings, highlighting a gap in understanding how organizational size and structure influence the adoption process.

Organizational Support and Facilitating Conditions

The availability of organizational support and facilitating conditions played a crucial role in the adoption of wearable devices. Research has indicated that healthcare professionals are more likely to adopt wearable technology if they have access to necessary resources, including technical support, training, and sufficient IT infrastructure (Klecun, 2016; Yusif et al., 2016). Facilities that prioritized technology adoption and provided robust support systems encouraged greater adoption, as healthcare professionals felt more confident in using wearables when they knew support was readily available. This factor was often context-dependent. Studies by Greenhalgh et al. (2004) and Jovanov and Milenkovic (2011) suggested that rural or under-resourced facilities frequently faced barriers to providing these support structures, which can limit wearable adoption. In such settings, healthcare professionals reported a lack of technical assistance and training, resulting in lower adoption rates. This variation revealed an important divergence: while some literature assumed that facilitating conditions were a given in healthcare settings, other studies highlighted substantial disparities in organizational support. This gap suggested a need for more region-specific research to understand how organizational resources affect wearable adoption in various healthcare environments, such as rural versus urban settings or well-funded versus under-resourced institutions.

Patient Influence and Expectations

The expectations of patients were also emerging as a factor in wearable adoption, with patients increasingly interested in wearables to monitor their health and track progress (Martin et al., 2021). Research has shown that healthcare professionals often feel pressured to adopt wearable devices, as patients frequently bring their own health data from consumer devices to consultations, expecting it to be interpreted and integrated into their care plans (Lee et al., 2020). This shift reflected a trend toward patient-centered care, where patient preferences shaped clinical decisions and practices (Chau & Hu, 2021). There was divergence on how strongly patient expectations impact professional adoption decisions. Some studies, such as those by Kijsanayotin et al. (2009), have suggested that patient demand for wearable technology significantly influences adoption, particularly in private practices, where patient satisfaction is a key factor. Conversely, others suggested that healthcare professionals remained skeptical of data from consumer wearables and resisted incorporating patient-generated data into clinical decisions (Patel et al., 2022). This variance suggested that while patient expectations were an important consideration, they may not fully drive adoption decisions, especially when healthcare professionals doubt the clinical validity of consumer wearables. Addressing this discrepancy necessitated further research to investigate the extent to which patient demand influences the adoption of wearable devices in clinical settings and how professionals strike a balance between patient expectations and clinical standards.

Divergences in Professional Acceptance

While there was broad agreement on several factors influencing wearable adoption, such as perceived usefulness and ease of integration, the literature revealed some notable divergences. For example, younger healthcare professionals were often more open to adopting wearable technology, viewing it as aligned with digital health trends and personal familiarity with technology (Holden & Karsh, 2010). Older professionals, however, showed resistance, perceiving wearables as unnecessary or lacking clinical rigor (Greenhalgh et al., 2004). This generational divide suggested that attitudes toward wearable adoption may be influenced by prior exposure to technology, professional experience, and comfort with digital health solutions.

Biases within the literature must be considered, as studies funded by technology companies often highlighted the benefits of wearable technology more heavily than those conducted in independent clinical settings. Research by Kim & Park (2012) and Wu et al. (2007) pointed out that studies with commercial backing frequently emphasized potential operational efficiencies, potentially skewing the findings. Conversely, studies from academic or government sources may have emphasized practical challenges, such as data reliability and workflow integration issues, reflecting a more cautious approach. Recognizing these biases was essential to gaining an objective understanding of wearable adoption drivers among healthcare professionals.

The literature on factors influencing the adoption of wearable devices among healthcare professionals presents a complex interplay of individual, organizational, and contextual elements. While there was consensus on the importance of perceived utility, ease of use, and organizational support, divergences arose in areas such as data reliability, patient influence, and professional demographics. These variances underscore gaps in the literature, particularly regarding how patient expectations, organizational readiness, and professional demographics specifically impact adoption within distinct healthcare settings, such as Oregon. This research study addressed these gaps by examining the factors influencing wearable adoption among healthcare professionals, particularly in the unique healthcare landscape of Oregon, providing insights into how wearable technology can be more effectively integrated into clinical practice.

Organizational and Policy Influences on Wearable Technology Adoption

Organizational and policy influences are crucial in determining the adoption of wearable technology in healthcare settings. Research revealed that the readiness, policy frameworks, and overall organizational culture of healthcare institutions significantly affected healthcare professionals' decision-making regarding the integration of wearable technology. This section synthesizes existing research on the role of organizational and policy factors, exploring how organizational support, resource allocation, and regulatory policies influence the adoption of wearable devices. While there was consensus on the importance of these influences, the literature also presented diverse perspectives on the strength of these factors and highlighted gaps in understanding how policies impact wearable technology adoption across different healthcare contexts.

Organizational Support and Resource Allocation

A consistent theme in the literature is that organizational support, including adequate funding, training, and IT resources, is essential for the adoption of wearable technology. Research by Klecun (2016) and Yusif et al. (2016) has underscored that healthcare organizations investing in wearable technology infrastructure, such as dedicated IT support and staff training, are more likely to achieve successful adoption. When organizations provided sufficient resources, healthcare professionals reported greater confidence in integrating wearables into clinical workflows, leading to increased use and higher acceptance rates. Limited resources often constrain healthcare organizations, especially in rural or smaller healthcare facilities, where resource scarcity hinders the integration of wearable technology. Studies have indicated that facilities with budget constraints may have prioritized essential services over the adoption of new technology, resulting in lower wearable technology adoption rates (Greenhalgh et al., 2004). This disparity in resource allocation highlighted a gap in the literature: while many studies emphasized the importance of organizational support, they often overlooked how resource limitations shaped adoption behaviors in diverse healthcare settings, such as rural versus urban facilities.

Organizational readiness also played a crucial role in the adoption of wearable devices. A study by Rahimi and Vimarlund (2020) emphasized that the level of preparedness, including having an adaptable infrastructure and staff trained in new technologies, determines the likelihood of successful adoption. In organizations lacking such readiness, the implementation of wearables was often delayed or fraught with technical and logistical issues. For example, without adequate training, healthcare professionals may lack the skills to effectively interpret data generated by wearables, ultimately reducing the clinical utility of these devices. This observation aligns with findings from Jovanov and Milenkovic (2011), which suggest that organizational readiness can either facilitate or impede wearable adoption, depending on the level of preparation and resource allocation.

Policy and Regulatory Frameworks

The influence of policy and regulatory frameworks on wearable adoption was another area that had garnered considerable attention in recent research. Policy initiatives at both institutional and governmental levels can significantly impact adoption rates by establishing standards, providing funding, and offering incentives for the adoption of new healthcare technologies. Studies by Acquisti et al. (2015) and Chau and Hu (2021) highlighted that healthcare facilities often followed governmental guidance regarding technology adoption, particularly in publicly funded institutions. Policies that supported telemedicine and remote monitoring technologies have indirectly bolstered the adoption of wearables by emphasizing the need for innovative tools that improve patient outcomes in diverse clinical environments. However, the literature revealed a divergence in views regarding the effectiveness of these policies. Some research, such as Alami et al. (2021), has argued that current policies lack the specificity needed to encourage widespread wearable adoption, especially in rural healthcare settings where policies may not adequately address unique local challenges. Policies designed for broader digital health initiatives often overlook specific needs related to wearables, including data privacy, integration standards, and reimbursement for wearable device usage. This divergence in perspectives highlighted a research gap, as few studies provided a thorough analysis of how policy effectiveness varied across different healthcare environments and how policies might be tailored to better support wearable adoption.

Regulatory requirements surrounding data security and patient privacy were crucial considerations in the adoption of wearable devices. Given that wearable devices frequently collect sensitive patient data, adherence to data protection policies, such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States, was vital (Kim & Park, 2012). Research by Martin et al. (2021) suggested that policies ensuring patient data security and privacy not only enhanced trust among healthcare professionals but also supported compliance with ethical and legal standards, which was crucial for adoption. However, as wearable technology continued to evolve, some studies suggested that existing data protection policies may have been insufficient, failing to fully account for new types of data generated by wearables (Greenhalgh et al., 2004). This indicated an evolving gap in policy that requires continual updates to address emerging privacy issues associated with wearable technology.

Organizational Culture and Leadership Influence

Organizational culture and leadership support were significant determinants of wearable adoption, as healthcare professionals often looked to institutional leaders to signal the importance of adopting new technologies. Research consistently shows that organizations with a culture of innovation and leadership that champion technology adoption tend to have higher rates of wearable technology adoption (Kang & Exworthy, 2022). For instance, in settings where department heads or senior administrators actively promoted the use of wearables, healthcare professionals felt encouraged to adopt and experiment with these tools. Studies by Chau and Hu (2021) and Karahanna et al. (1999) emphasized that organizational leaders who advocated for new technologies created a culture that normalizes their use, which, in turn, fostered adoption. Conversely, studies also suggested that in organizations with risk-averse cultures or where leadership is indifferent to technological advancements, wearable adoption rates were significantly lower (Jovanov & Milenkovic, 2011). In such environments, healthcare professionals may have perceived wearable technology as non-essential or even disruptive, particularly if they felt that leadership did not value innovation. This divergence highlighted the role of leadership in shaping organizational attitudes toward technology adoption and revealed a gap in research exploring how varying leadership styles influence wearable technology adoption across different healthcare institutions.

Incentives and Reimbursement Policies

Financial incentives and reimbursement policies were also crucial in promoting the adoption of wearable devices. Studies indicated that reimbursement for services involving wearable devices, such as remote patient monitoring, encouraged healthcare facilities to invest in these technologies (Lee et al., 2020). Kang and Exworthy (2022) argued that reimbursement policies could reduce the financial burden on healthcare providers, making wearable adoption a more viable option for institutions that might otherwise avoid it due to cost concerns. However, the effectiveness of these incentives appears to have varied widely across different healthcare settings. While some studies have highlighted the success of reimbursement models in promoting wearable device adoption, others have pointed out limitations, particularly in rural or under-resourced settings where reimbursement policies may not have fully offset the costs of technology adoption (Rahimi & Vimarlund, 2020). For instance, in regions where financial support was limited, smaller facilities may have struggled to adopt wearables despite the availability of reimbursement programs. This variance revealed a gap in understanding the nuanced role of reimbursement policies and highlighted the need for research that examines how financial incentives influence the adoption of wearable devices across different healthcare contexts and provider types.

Biases in Organizational and Policy-Related Research

The existing research on organizational and policy influences in wearable adoption has demonstrated some bias, particularly in studies funded by technology manufacturers or organizations with a vested interest in wearable adoption. Studies funded by the technology industry often emphasized organizational readiness and incentives as key drivers of adoption while underreporting challenges related to resource constraints or policy inadequacies (Aggelidis

& Chatzoglou, 2009). In contrast, independently funded studies, particularly those from academic institutions, were more likely to address practical barriers to adoption, such as insufficient training or lack of IT support, providing a more balanced perspective (Greenhalgh et al., 2004). This discrepancy suggested a need for more independent and unbiased research to better understand the organizational and policy dynamics that affect wearable adoption in healthcare settings.

The literature on organizational and policy influences revealed a complex interplay of factors that affected wearable adoption among healthcare professionals. While there was consensus that organizational support, resource allocation, and leadership played critical roles in fostering wearable adoption, divergences emerged regarding the effectiveness of existing policies, reimbursement models, and data security regulations. Studies varied in their assessment of how policies impact wearable adoption, with some emphasizing the need for more specific, localized policies and others advocating for broader digital health initiatives that incorporated wearable technology. This section underscores gaps in the literature, particularly in understanding how policy and organizational dynamics vary across different healthcare settings, such as rural versus urban institutions. By focusing on the unique healthcare landscape of Oregon, this study addressed these gaps, exploring how policy frameworks and organizational support can facilitate or hinder the adoption of wearable technology within the state.

Data Security, Privacy, and Ethical Considerations

Data security, privacy, and ethical considerations were pivotal issues in the adoption of wearable technology in healthcare. As wearables continuously collect sensitive patient data, often outside of clinical settings, their integration into healthcare introduces unique privacy risks and ethical dilemmas. This section critically examines the literature surrounding these concerns, highlighting areas of convergence and divergence in understanding data security, patient privacy, and ethical implications associated with wearable adoption. The review also addresses potential biases in existing studies and gaps in the current research on these critical factors.

Data security has been widely acknowledged as a core consideration in the adoption of wearable technology, as these devices often collect, store, and transmit sensitive health information (Martin et al., 2021). The constant flow of patient data through wearable devices to healthcare systems poses significant risks if not managed securely. Studies emphasized the need for robust encryption and secure data transfer protocols to protect patient information from unauthorized access and breaches (Alami et al., 2021). The literature agreed that data encryption and user authentication mechanisms were essential to ensure that wearable data remained protected throughout its transmission and storage.

Studies diverged on the effectiveness of existing security measures. While some research has reported high levels of data security in well-resourced healthcare facilities with advanced IT support, other studies have revealed that less-resourced healthcare environments face significant challenges in implementing sufficient data security protocols (Kang & Exworthy, 2022). In rural or smaller facilities, where resources for IT security infrastructure may be limited, the risk of data breaches is notably higher. This disparity suggested that data security in wearable technology adoption was context-dependent, influenced by the level of organizational resources and IT infrastructure available.

Patient privacy was another critical issue, with numerous studies highlighting that wearable devices often collected highly personal data, such as real-time physiological metrics, location, and even lifestyle behaviors (Greenhalgh et al., 2004). This constant data collection raised concerns about how patient privacy could be maintained while maximizing the clinical utility of wearable data. The literature consistently emphasized that patients should have control over their data and be informed about how it will be used, stored, and shared within the healthcare system (Rahimi & Vimarlund, 2020). Yet, a lack of consensus remained on how to effectively balance patient autonomy with the clinical value derived from wearables, resulting in a divergence in recommended privacy practices.

Ethical Implications of Continuous Monitoring

The ethical concerns surrounding wearable technology primarily revolved around issues of patient autonomy, informed consent, and the potential for increased surveillance (Lupton, 2016). Continuous monitoring, while beneficial for tracking chronic conditions and improving patient outcomes, can infringe on personal privacy, as it involves tracking health data outside of traditional clinical environments. Studies have shown that patients may experience a loss of autonomy when monitored consistently, raising ethical questions about consent and the ability to withdraw from monitoring when desired (Acquisti et al., 2015). The literature suggests that while wearables offer clinical advantages, they also blur the boundaries between patient care and surveillance, potentially leading to discomfort and resistance among patients.

There is general agreement in the literature that informed consent is essential for the ethical use of wearable devices. Patients must be fully aware of the extent of data collection and their rights regarding data access and control. However, research diverged on the implementation of informed consent protocols, particularly regarding the use of wearable data in longitudinal studies or its sharing across different healthcare providers (Lee et al., 2020). Some studies have advocated for a dynamic consent model, where patients can adjust their consent preferences as they become more familiar with how wearables impact their healthcare. Others proposed one-time consent processes that informed patients about data collection upfront. This divergence suggested a gap in standardized practices for obtaining and managing consent in the context of wearable technology.

Balancing Clinical Utility with Privacy Protections

Another area of contention in the literature is how to balance the clinical utility of wearables with rigorous privacy protections. Healthcare providers valued wearable technology for its ability to provide continuous, real-time health data that can inform treatment decisions and facilitate preventative care (Huhn et al., 2022). For example, wearable devices enable more effective monitoring of chronic conditions, such as diabetes and cardiovascular disease, allowing for timely interventions. However, the continuous collection of detailed health data can conflict with privacy regulations, such as the Health Insurance Portability and Accountability Act (HIPAA), which mandates strict data protection protocols for patient information.

Some researchers argued that the clinical benefits of wearable technology justified a certain degree of privacy risk, as long as organizations implemented robust data security measures (Jovanov & Milenkovic, 2011). This perspective was often seen in studies that prioritized clinical outcomes, suggesting that wearable adoption should proceed if it significantly improved patient care. Conversely, other researchers have emphasized the necessity of strict privacy standards, even if these standards limit the scope of wearable data collection or slow down technology adoption (Or & Tao, 2022). This divergence reveals an underlying tension in the literature between prioritizing patient outcomes and ensuring privacy rights, with each perspective grounded in differing assumptions about the primary responsibility of healthcare providers.

Organizational Bias and Regulatory Limitations

In evaluating the existing literature, it was essential to acknowledge potential biases stemming from the funding and objectives of various studies. Studies funded by wearable technology manufacturers often emphasized the clinical benefits of wearables, sometimes downplaying privacy concerns or the limitations of current data security protocols (Acquisti et al., 2015). These studies may have focused on immediate clinical gains without sufficiently addressing the long-term privacy implications for patients, suggesting a bias that could have influenced healthcare professionals' perceptions of wearable technology adoption. On the other hand, independent academic studies tended to highlight ethical considerations and data security issues more comprehensively, presenting a more balanced perspective but often focused on hypothetical risks without substantial evidence of actual data breaches or privacy violations.

Another gap in the literature was the limited exploration of regulatory frameworks that could have adequately addressed wearable-specific privacy concerns. Existing regulations, such as HIPAA in the U.S., provided general guidelines for health data protection but did not specifically account for the unique privacy challenges posed by wearable technology (Greenhalgh et al., 2004). As wearable devices become more sophisticated, collecting increasingly granular data on patients' physical and mental health, regulatory policies may need to be updated to ensure comprehensive protection. The lack of wearable-specific regulations presents a vulnerability in patient data protection, as standard health data policies may not fully cover the complex data flows involved in wearable technology.

Challenges in Standardizing Ethical Practices

The literature highlighted challenges in standardizing ethical practices for wearable technology adoption, especially in multi-provider healthcare systems where data-sharing practices varied. When multiple providers access and analyze wearable data, ensuring consistent ethical standards can be difficult. Research by Martin et al. (2021) revealed that ethical practices varied significantly among institutions, depending on the availability of resources, organizational policies, and individual provider discretion. This inconsistency could have led to ethical dilemmas, such as when a patient's wearable data was accessed by providers not directly involved in their care, raising questions about the boundaries of ethical data sharing. To address these challenges, some researchers advocated for the establishment of universal ethical guidelines that dictate how wearable data should be used and shared among healthcare providers (Lee et al., 2020). However, others argued that universal guidelines may be too rigid to accommodate the diverse ways in which wearable data can support patient care, particularly in specialized medical fields. This lack of consensus on standardized ethical practices highlighted a gap in the literature, as there was currently no clear framework for guiding the ethical use of wearables across different healthcare settings.

The literature on data security, privacy, and ethical considerations in the adoption of wearable technology reveals both consensus and significant areas of divergence. While there was widespread agreement on the need for robust data security measures and patient control over health data, studies varied in their emphasis on clinical utility versus privacy protection. Additionally, existing regulatory frameworks were often outdated or insufficient to address the specific challenges of wearable technology, underscoring the need for updated policies that can protect patient privacy without compromising the clinical benefits of wearable devices. Ethical considerations, such as continuous monitoring and informed consent, presented further challenges, as healthcare providers strived to balance patient autonomy with the clinical advantages of wearables. The literature highlighted a critical gap in understanding how privacy and ethical concerns impacted wearable adoption, particularly in diverse healthcare contexts. Many studies focused on general privacy issues but lack wearable-specific insights, leaving unanswered questions about how these concerns influenced healthcare professionals' adoption decisions. Addressing these gaps in future research is essential for developing privacy practices and ethical standards that align with the evolving capabilities of wearable technology, ensuring that these devices enhance patient care while safeguarding individual rights.

Summary

This chapter provided an in-depth critical analysis of the literature concerning the adoption of wearable technology in healthcare, focusing on its perceived benefits, factors influencing adoption, operational integration challenges, and broader organizational, policy, and ethical considerations. The discussion began by examining the perceived benefits and value of wearable technology, noting that wearables offer significant potential for enhancing patient monitoring, improving chronic disease management, and increasing patient engagement. However, the literature diverged on the degree to which these benefits translated into long-term clinical outcomes, particularly given the challenges of maintaining sustained usage among healthcare professionals.

The chapter continued with an exploration of the operational integration of wearable technology in clinical workflows, revealing both strengths and limitations. Although wearables can streamline certain tasks and enable more efficient data access, their integration remained inconsistent across different healthcare settings, with many studies identifying compatibility with existing systems and resource limitations as barriers. These operational challenges highlighted a gap in understanding how specific settings, such as rural versus urban areas, impacted the successful integration of wearables within healthcare.

Professional and patient perceptions emerged as another critical area, showing a divergence between patients' enthusiasm for wearables as self-management tools and healthcare professionals' concerns over device accuracy, usability, and clinical relevance. This divide underscored the need for further investigation into the specific factors that healthcare providers considered essential for adopting wearable technology in clinical settings, especially within the unique regional context of Oregon. The chapter's synthesis of this literature highlighted that existing studies often generalized adoption trends across different user groups without accounting for distinct perspectives in the healthcare profession. The chapter discussed key factors influencing healthcare professionals' adoption of wearables, including performance expectancy, effort expectancy, social influence, and facilitating conditions. While the Unified Theory of Acceptance and Use of Technology (UTAUT) effectively captured many of these elements, the literature revealed gaps in its application to the healthcare sector, where institutional norms, workflow compatibility, and specific professional expectations introduce unique complexities. Moreover, organizational and policy influences were under-explored, despite evidence that supportive policies, training, and financial incentives play critical roles in adoption decisions.

Data security, privacy, and ethical considerations were also analyzed, highlighting concerns around patient privacy, consent, and the ethical implications of continuous monitoring. While there is consensus on the importance of robust data protection measures, existing studies differ in their approaches to managing these issues, highlighting a need for wearable-specific guidelines and policies. Furthermore, regulatory frameworks for wearable technology remained insufficiently detailed, underscoring a gap in research on how updated privacy and ethical standards might impact the adoption of these devices in healthcare. This chapter synthesized the literature to identify areas of convergence, such as the acknowledged benefits of wearables and the importance of privacy protections, alongside areas of divergence, including perspectives on clinical versus patient utility and the variability in operational integration. The gaps in understanding healthcare professionals' adoption decisions, as well as the unique regional and professional factors influencing these decisions, supported the need for this study. These insights provided a foundation for Chapter 3, where the research methodology and design are discussed to address the complexities identified and investigate the specific factors affecting the adoption of wearable technology among healthcare professionals in Oregon.

Chapter 3: Research Methodology

The problem addressed in this study was the lack of understanding of the factors influencing healthcare professionals' decisions to adopt wearable smart devices in the state of Oregon. While wearable smart devices have gained popularity in consumer markets (Poongodi et al., 2019), their adoption in professional healthcare settings remains uneven and under-researched (Kang & Exworthy, 2022). This uneven adoption exists despite the potential benefits these technologies offer in enhancing health monitoring, improving patient care, and supporting personal well-being (Kumar, 2022; Robertson, 2020). This is particularly concerning given that healthcare professionals are not only potential users but also key advocates for these technologies within their patient populations (Taib, 2021). This has led to a lack of comprehensive understanding of the specific cultural, demographic, and regional factors that influence healthcare professionals' decisions to adopt these devices (Cannali et al., 2022).

Existing research has primarily focused on general consumer populations, often neglecting the unique context of healthcare professionals, who may have different motivations, concerns, and barriers to adoption (Skokin, 2022). For example, while factors such as perceived usefulness, ease of use, and social influence have been well-documented in broader studies, there is limited insight into how these factors interact with other adoption drivers, such as attitude toward using technology (ATUT), self-efficacy (SE), and anxiety (ANX), within the healthcare industry (Ryu, 2023). The lack of adoption among healthcare professionals can have significant negative consequences, including missed opportunities to improve patient outcomes, reduce healthcare costs, and advance the integration of technology in clinical practice. If these barriers are not addressed, the potential benefits of wearable devices in healthcare may remain unrealized, leading to slower innovation and lower overall healthcare quality. This study addresses this gap by examining how performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), attitude toward using technology (ATUT), self-efficacy (SE), and anxiety (ANX) influence the intention to use wearable smart devices among healthcare professionals in Oregon, and by identifying key factors driving adoption and potential areas for improvement.

The purpose of this quantitative survey study was to understand the factors that influenced the decision to adopt wearable smart devices among healthcare professionals in the state of Oregon. The goal of this study was to develop a unified model that predicts and explains adoption behaviors by examining how the specified independent variables (PE, EE, SI, FC, ATUT, SE, and ANX) influence the dependent variable, which is the decision to adopt wearable technologies. In this research, the independent variables were measured through validated survey items designed to assess their relationship to behavioral intention. Each independent variable was examined to determine the extent to which it influenced healthcare professionals' choices regarding wearable smart devices, providing a deeper understanding of the forces that shape adoption. Additionally, the study examined potential moderating factors, including cultural attitudes, perceived usefulness, and security concerns, that may influence the strength of the relationship between the independent variables and the decision to adopt wearable technologies. The conceptual relationships among these constructs are illustrated in Figure A1 (see Appendix A), which shows how the independent variables were theorized to influence behavioral intention to adopt wearable smart devices.

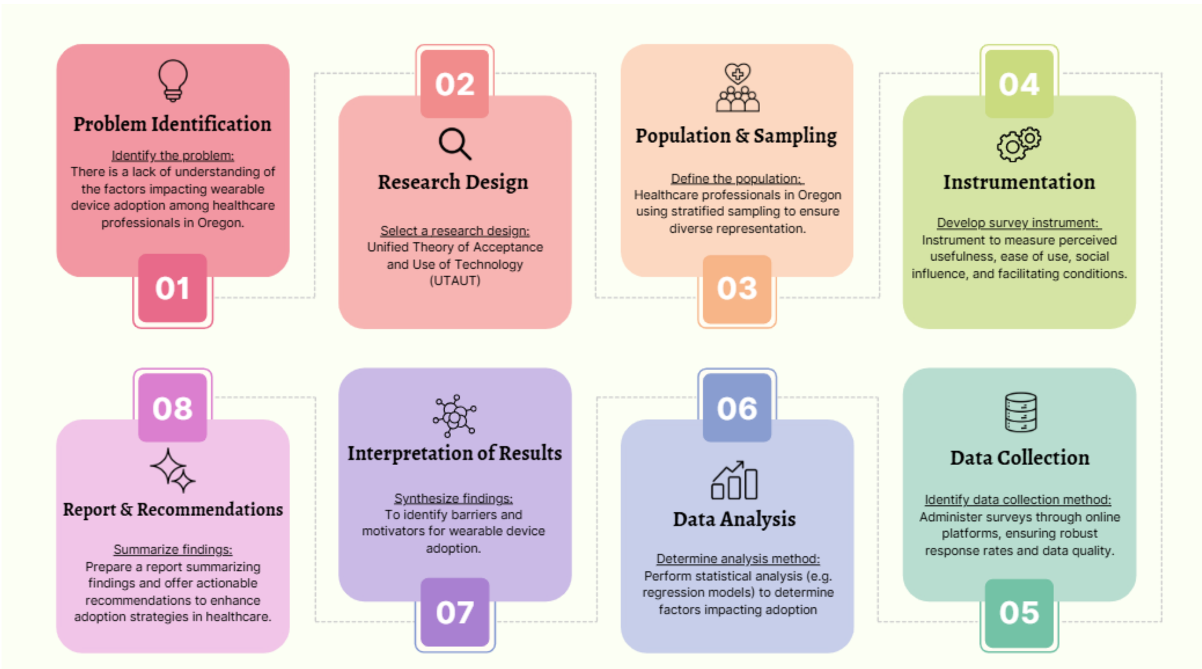
This chapter outlines the research method used to address the study's problem and achieve its purpose. It begins by describing the research methodology and design, which were justified as the most appropriate approach to explore the research questions and provide measurable data. The population and sample section details how the study's target population was defined, how participants were selected, and how the sample ensured representation of healthcare professionals in Oregon across diverse settings, roles, and levels of experience. The instrumentation section discusses the survey tools used to measure key variables, ensuring they are aligned with established theoretical frameworks and are both valid and reliable based on prior empirical studies. Operational definitions clarify how each variable was measured and analyzed, establishing a clear framework for data collection and interpretation while maintaining consistency with the constructs outlined in the conceptual model presented in Chapter 2. This structured approach ensures that the methodology directly supports the study's hypotheses and provides the rigor necessary for replicability in future research.

The chapter then describes the study procedures, including the step-by-step process used for collecting data, followed by the data analysis plan utilized, which specifies the statistical methods used to test the hypotheses and answer the research questions. Special attention is given to the choice of structural equation modeling (SEM) as the primary analytical technique, due to its ability to simultaneously assess direct and indirect effects among multiple variables while accounting for potential moderating influences. Assumptions, limitations, and delimitations are addressed to provide transparency and acknowledge the boundaries of the study, including the scope of generalization and potential sources of bias. Finally, the ethical considerations section outlines the measures taken to protect participants and ensure integrity throughout the research process, including informed consent procedures, data security protocols, and adherence to Institutional Review Board (IRB) guidelines. By systematically detailing each of these methodological elements, the chapter reinforces the connection between the research design, the theoretical framework, and the study's overarching goal of generating actionable insights into wearable smart device adoption among healthcare professionals.

Research Methodology and Design Process Diagram

Figure 1

Process Diagram for Research Methodology



Note. This figure is a diagram that describes the study process and depicts all stages of the research.

Research Methodology and Design

The choice of a quantitative survey study was well-aligned with the purpose of this research, which aimed to gather empirical evidence regarding the factors that influence technology adoption. This method is commonly used in technology adoption studies due to its ability to quantify behavioral intentions and perceptions using standardized instruments (Davis, 1989; Venkatesh et al., 2003). The survey instrument was designed to capture key constructs based on established theoretical frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), while also incorporating extended constructs relevant to healthcare contexts. These constructs included performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), attitude toward using technology (ATUT), self-efficacy (SE), anxiety (ANX), and behavioral intentions (BI). As depicted in Figure A1 (see Appendix A), these constructs were theorized to influence BI, with the model reflecting both core UTAUT variables and additional factors identified in prior research as relevant to healthcare technology adoption (Holden & Karsh, 2010; Maillet et al., 2015; Venkatesh et al., 2012).

By quantifying responses from a broad sample of healthcare professionals, the study assessed the significance and strength of these factors in relation to the adoption of wearable devices. Quantitative research has been demonstrated to facilitate pattern identification and generalization across populations in studies examining healthcare technology adoption (Chau & Hu, 2002; Morris & Venkatesh, 2000). The structured nature of a survey aligned directly with the research questions and hypotheses, as it allowed for the systematic measurement of predefined constructs using validated scales. These scales, derived from TAM, UTAUT, and extended UTAUT models, have been widely used to explore the psychological and contextual factors influencing technology adoption, particularly in clinical and healthcare settings (Chismar & Wiley-Patton, 2003; Wu et al., 2007). The quantitative approach facilitated the application of statistical methods, enabling the researcher to test hypotheses about relationships between variables, such as PE and adoption decisions, SI and FC, or the moderating effects of SE, ATUT, and ANX, within the healthcare professional population (Venkatesh & Bala, 2008).

TAM and UTAUT emphasize the importance of quantitatively assessing constructs like PE and EE to predict BI and use behavior. Both models have been validated in multiple studies involving healthcare professionals and technology adoption (Holden & Karsh, 2010; Maillet et al., 2015). UTAUT extends TAM by incorporating constructs such as SI and FC, whereas prior extensions have integrated ATUT, SE, and ANX to enhance the explanatory power of the model in specialized populations, including healthcare workers (Khechine et al., 2016; Rahimi et al., 2018). These frameworks support a survey-based methodology because they rely on standardized measurements that can be statistically analyzed to determine how well the theoretical constructs explain adoption behaviors. For example, the TAM model posits that perceived usefulness and perceived ease of use are central predictors of technology acceptance, both of which can be effectively measured through structured survey items (Davis, 1989). UTAUT and its extensions build on this by including constructs such as SI, FC, ATUT, SE, and ANX, which are particularly relevant for understanding technology adoption in high-responsibility professions like healthcare (Venkatesh et al., 2003).

By aligning the survey instrument with these theoretical frameworks, the study ensured a robust and theoretically grounded exploration of its research questions. While other research methodologies, such as qualitative approaches (e.g., interviews or focus groups) or mixed methods designs, were considered, they were deemed less suitable for this study for several reasons. Studies utilizing UTAUT and extended UTAUT in healthcare settings have consistently demonstrated their effectiveness in explaining adoption behaviors, making these frameworks highly relevant to the current research (Chau & Hu, 2002; Yi et al., 2006). Although qualitative research could have provided rich, in-depth insights into the perceptions and experiences of healthcare professionals regarding wearable technology, it would not have allowed for the generalization of findings across the broader population (Creswell & Poth, 2016). Given the study's focus on quantifying factors influencing adoption decisions, qualitative methods would not have adequately addressed the need for statistical validation of relationships among the variables. Moreover, qualitative approaches are less effective in providing the standardized, numerical data required to test hypotheses and draw generalizable conclusions, which were central to the study's objectives (Flick, 2018).

While a mixed-methods approach could have offered a comprehensive perspective by combining qualitative and quantitative data, it would also have introduced complexities related to data integration and interpretation (Creswell & Plano Clark, 2017), making a focused quantitative survey design more streamlined and efficient for this purpose. Additionally, mixed-methods research requires substantial time and resources, which could have detracted from the primary objective of understanding adoption factors through a quantitative lens (Tashakkori & Teddlie, 2010). The theoretical frameworks (TAM, UTAUT, and extended UTAUT) also emphasize quantifiable constructs, further supporting the appropriateness of a purely quantitative methodology for this study (Davis, 1989; Venkatesh et al., 2003). Experimental designs, which involve manipulating variables to observe effects, were not applicable to this research question as the study did not seek to establish causal relationships through intervention. Instead, it aimed to identify and measure existing factors influencing adoption decisions. A survey design was better suited to capturing healthcare professionals' self-reported perceptions and behaviors, which align with the constructs defined in TAM, UTAUT, and extended UTAUT models (Holden et al., 2012; Wu et al., 2007).

The selected quantitative survey methodology was the most appropriate approach for this study, given its capacity to systematically explore and analyze the relationships between various factors influencing the adoption of wearable smart devices among healthcare professionals. By leveraging validated theoretical frameworks, the study ensured that the constructs being measured were theoretically and empirically sound, allowing for meaningful interpretation of the data (Chau & Hu, 2002; Venkatesh et al., 2012). Furthermore, the ability to analyze responses statistically facilitated the identification of trends, correlations, and differences among subgroups (e.g., clinical vs. non-clinical healthcare professionals), providing actionable insights to inform strategies for promoting wearable technology adoption in healthcare contexts (Maillet et al., 2015; Yi et al., 2006). This methodological rigor also enabled the study to explore potential moderating effects, such as cultural attitudes or data security concerns, which could alter the strength or direction of adoption drivers. In doing so, the research design created a clear pathway from theoretical constructs to practical recommendations, strengthening the study's ability to contribute meaningfully to both scholarly literature and industry practice.

The quantitative survey method aligned closely with the theoretical underpinnings of TAM, UTAUT, and extended UTAUT, as well as with the study's research questions and hypotheses. This approach enabled the study to contribute robust, generalizable findings to the understanding of technology adoption among healthcare professionals in Oregon, effectively addressing the research problem and providing a foundation for future research and practical application (Holden & Karsh, 2010; Venkatesh & Bala, 2008). By systematically applying these frameworks to a targeted professional population, the study not only identified the factors that most significantly influenced adoption but also provided evidence-based guidance for developers, administrators, and policymakers seeking to increase the uptake of wearable technology. These findings have the potential to inform both organizational strategies within healthcare systems and broader public health initiatives, ensuring that the benefits of wearable smart devices can be realized more fully across clinical environments.

Population and Sample

The target population for this study consisted of healthcare professionals in the state of Oregon who are engaged in various roles within the healthcare system, including but not limited to clinical healthcare professionals (e.g., physicians), non-clinical healthcare professionals (e.g., caregivers), administrative healthcare professionals (e.g., support associates), and allied health professionals (e.g., registered dieticians). Based on data from the Oregon Health Authority (OHA) and the American Medical Association (AMA), the estimated population size of healthcare workers is approximately 100,000 (American Medical Association, 2021; Oregon Health Authority, 2021). This population is characterized by diverse specializations, varying levels of technological proficiency, and a range of attitudes toward adopting wearable smart devices. Prior research has demonstrated that healthcare professionals' roles and technological exposure are important factors influencing their attitudes toward adopting new healthcare technologies (Holden & Karsh, 2010; Venkatesh et al., 2012).

This population is directly aligned with the research questions, which aim to identify the factors that influence healthcare professionals' decisions to adopt wearable smart devices. Similar studies focusing on healthcare technology adoption emphasize the importance of targeting populations that directly engage with technology in professional practice to ensure relevance and practical insights (Chau & Hu, 2002; Maillet et al., 2015). By focusing on healthcare professionals, the study was able to examine their specific perceptions, attitudes, and experiences, which were critical for understanding the barriers and facilitators of wearable technology adoption in healthcare settings. Research on healthcare technology adoption emphasizes the importance of examining diverse roles, as job responsibilities and exposure to technology significantly influence adoption behaviors (Wu et al., 2007).

The sample for this study consisted of approximately 270 healthcare professionals from the target population. This sample size is determined through a power analysis to achieve sufficient statistical power for detecting meaningful relationships between variables (Cohen, 1988). A sample of this size is slightly higher, but still within the range of other studies on healthcare technology adoption, which have successfully used similar sample sizes to explore adoption factors (Chau & Hu, 2002; Venkatesh et al., 2003). The sample included participants from various healthcare roles and settings, such as hospitals, community health centers, and private practices, ensuring representation across different sectors of the healthcare system (Holden et al., 2012).

The selected sample was well-suited for addressing the research questions because it represents the breadth of healthcare professionals, who are potential users of wearable technology. Similar studies on technology adoption in healthcare have shown that capturing diverse perspectives across professional roles enhances the generalizability and depth of the findings (Venkatesh & Bala, 2008; Yi et al., 2006). This diversity is critical for understanding how factors such as perceived usefulness, ease of use, social influence, and facilitating conditions may differ across subgroups. A representative sample enabled the findings to be generalized to the broader population of healthcare professionals in Oregon, thereby enhancing the study's validity and relevance (Chismar & Wiley-Patton, 2003).

This study employed a stratified random sampling method, which is particularly advantageous for addressing the research questions. Stratified sampling ensures that specific subgroups within the population, such as clinical and non-clinical health professionals, are proportionately represented in the sample (Fowler, 2014). By dividing the population into strata based on professional roles, the study can systematically draw samples from each group, allowing for meaningful comparisons between subgroups (Creswell & Plano Clark, 2017).

Research on healthcare professionals' technology adoption has highlighted the importance of comparing subgroups, as job responsibilities and exposure to technology can significantly influence attitudes and adoption behaviors (Maillet et al., 2015; Wu et al., 2007). The rationale for stratified sampling is its ability to enhance the precision and generalizability of the findings. For example, healthcare professionals in different roles may perceive wearable technology differently due to variations in job responsibilities and technological exposure. Stratified sampling ensured that such variations were captured, minimizing selection bias and enhancing the study's validity and reliability (Tashakkori & Teddlie, 2010).

A power analysis was conducted to determine the required sample size for reaching a statistically significant conclusion. The software G-Power was used to make an analysis, with the following values, based on the established guidelines for medium effect sizes in behavioral research (Cohen, 1988):

- Effect size (f^2): 0.15 (medium effect size)
- Alpha level (α): 0.05 (5% significance level)
- Beta level (β): 0.20 (80% power)
- Number of predictors: 8

A Type I error (α), typically set at a significance level of .05, represents the probability of incorrectly concluding that an effect exists when it does not (De Winter, 2019). Conversely, a Type II error (β) reflects the likelihood that a statistical test fails to detect a true effect (De Winter, 2019). The statistical power of a test, expressed as $1 - \beta$ and commonly targeted at 0.8, indicates the test's capacity to correctly identify an existing effect (Meyvis & Van Osselaer, 2018). One of the most effective ways to enhance statistical power and reduce the risk of both false positives and false negatives is by increasing the sample size (Meyvis & Van Osselaer, 2018). Effect size quantifies the strength of the relationship between the independent and dependent variables, with values ranging from 0 to 1. A recommended benchmark for effect size is .15 (De Winter, 2019). In this study, the analysis includes eight predictors, meaning that eight independent variables are being examined. Appendix B provides the input parameters and output interface used during the power analysis. Based on these calculations, a minimum sample size of 109 participants is required to adequately power the analysis and ensure valid statistical results. Studies on technology adoption in healthcare settings have used similar parameters to establish adequate sample sizes (Holden & Karsh, 2010; Venkatesh et al., 2003).

Participants were recruited by a market research company, Centiment, through a combination of strategies to ensure a diverse and representative sample. Recruitment methods aligned with those used in prior healthcare technology adoption studies to maximize participation and diversity (Chau & Hu, 2002; Maillet et al., 2015). These strategies included:

1. Email Lists from Professional Organizations: Collaborations with professional healthcare associations in Oregon were sought to access their membership lists for email distribution. Organizations such as the Oregon Nurses Association and the Oregon Medical Association were approached for participation. Studies have demonstrated that professional organizations are effective channels for recruiting diverse participants (Wu et al., 2007).
2. Social Media and Online Platforms: Recruitment was also conducted through social media channels and online forums frequented by healthcare professionals, such as

LinkedIn and specialty-focused groups on Facebook. Online recruitment is increasingly common in survey-based research due to its broad reach (Fowler, 2014).

3. Incentives for Participation: To enhance response rates, small incentives such as gift cards were offered to participants who completed the survey. This has been shown to enhance response rates in survey research (Fowler, 2014).

These strategies were designed to minimize potential biases and achieve a robust dataset for analysis. By covering healthcare professionals from diverse roles, settings, and geographic areas within Oregon, the recruitment plan ensures the sample is representative and aligned with the study's objectives (Venkatesh et al., 2003).

The target population and sample were carefully selected to align with the research questions and objectives of this study. The stratified random sampling method ensured representation across key subgroups, enabling the study to examine variations in adoption factors comprehensively. The sample size, determined through a rigorous power analysis, provided sufficient statistical power to draw meaningful conclusions. These design choices enhanced the study's validity, reliability, and generalizability, contributing to a better understanding of the factors influencing the adoption of wearable smart devices among healthcare professionals in Oregon (Holden & Karsh, 2010; Maillet et al., 2015).

Instrumentation

This study employed a structured questionnaire designed to assess the factors influencing the adoption of wearable smart devices among healthcare professionals in the state of Oregon. The questionnaire was grounded in established theoretical frameworks, particularly the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh in 2003, and incorporated validated measures that captured essential constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions (see Appendix C). In addition, measures for attitude toward using technology, self-efficacy, and anxiety were included to provide a more comprehensive understanding of the drivers of adoption.

The questionnaire consisted of the following components:

1. Demographic Information: This section collected data on participants' professional roles, years of experience, and familiarity with wearable devices.
2. Performance Expectancy: Adapted from scales developed by Venkatesh et al. (2003), this construct evaluated participants' beliefs regarding the extent to which wearable devices will enhance their job performance.
3. Effort Expectancy: This component measured the perceived ease of use of wearable devices using items derived from Davis's (1989) Technology Acceptance Model (TAM).
4. Attitude Toward Using Technology: Based on validated scales from Venkatesh et al. (2003) and related extensions of UTAUT, this construct measured participants' overall positive or negative feelings about adopting and using wearable smart devices in their professional practice.
5. Social Influence: Drawing from scales created by Venkatesh et al. (2003), this section assessed how much participants felt that significant others believed they should adopt wearable devices.
6. Facilitating Conditions: Based on established scales from Venkatesh et al. (2003), this section assessed the availability of resources and organizational support for the use of wearable devices.

7. Self-Efficacy: Adapted from scales developed by Venkatesh et al. (2003), this section assessed participants' confidence in their ability to effectively use wearable smart devices without requiring extensive external assistance.
8. Anxiety: Drawing from scales created by Venkatesh et al. (2003), this component measured participants' apprehension or discomfort associated with using wearable technology in their professional roles.
9. Behavioral Intentions: Based on established scales from Venkatesh et al. (2003), this section evaluated participants' likelihood of adopting and regularly using wearable smart devices in their healthcare practice.

The selected instruments were based on well-established measures with strong evidence of reliability and validity:

- Reliability: The scales used in this questionnaire demonstrated high internal consistency in prior studies. For example:
    - Performance expectancy: Cronbach's alpha values typically range between 0.85 and 0.91.
    - Effort expectancy: Previous studies report Cronbach's alpha values between 0.80 and 0.88.
    - Attitude Toward Using Technology: Cronbach's alpha values for this construct have been reported between 0.84 and 0.90 in prior research, indicating strong reliability in capturing overall user attitudes.
    - Social influence: Cronbach's alpha values for this construct generally range from 0.82 to 0.87.

    - Facilitating conditions: Reliability for this scale has been reported with Cronbach's alpha values ranging from 0.84 to 0.89.
    - Self-Efficacy: Prior research has demonstrated reliability coefficients ranging from 0.70 to 0.86 for this construct (Compeau & Higgins, 1995).
    - Anxiety: Reported Cronbach's alpha values for this construct range from 0.80 to 0.85, indicating acceptable internal consistency (Venkatesh et al., 2003).
    - Behavioral Intentions: This scale has consistently shown high reliability, with alpha values typically reported between 0.87 and 0.94 (Venkatesh et al., 2003).
- Validity: Subject matter experts were consulted during the development phase of the instrument to ensure content validity. Their input confirmed that the survey items accurately reflected the theoretical constructs within the context of wearable technology adoption. Additionally, prior studies using these scales have provided evidence of construct validity, demonstrating that the measures effectively capture the intended theoretical constructs.

Before the main data collection, a pilot study was conducted with a sample of approximately 18 healthcare professionals. Pilot testing is a widely accepted practice in survey-based research, as it helps refine instruments, enhance clarity, and address methodological issues before full-scale implementation (Krosnick, 2018; Van Teijlingen & Hundley, 2001). The pilot test served several important purposes:

1. Clarity of Items: Participants provided feedback on the clarity and comprehensibility of the questionnaire items, allowing for necessary revisions to enhance understanding. Prior

studies have emphasized the importance of ensuring clarity in survey items to minimize response errors and improve data quality (Fowler, 2014).

2. Reliability Assessment: The pilot test facilitated an initial evaluation of the internal consistency of the scales using Cronbach's alpha, ensuring the reliability of the measurements. High Cronbach's alpha values (≥ 0.70) indicated good internal consistency, which is a standard threshold in psychometric evaluations (Nunnally & Bernstein, 1994).
3. Completion Time: The pilot study helped estimate the average time required for participants to complete the questionnaire, ensuring that it was manageable and feasible. Research has shown that shorter surveys with clear instructions enhance participant retention and response quality (Lavrakas, 2008).

Feedback from pilot testing was carefully reviewed, and necessary adjustments, such as rephrasing unclear questions, modifying response formats, and refining constructs, were incorporated into the final version of the questionnaire. These revisions ensured the instrument was both valid and user-friendly, as recommended in survey methodology literature (Dillman et al., 2014).

As the questionnaire included validated scales developed by other researchers, permission was sought for their use. Ethical and methodological guidelines in research emphasize the importance of obtaining explicit permission for using copyrighted or proprietary instruments to maintain transparency and integrity (Resnik, 2020). Documentation of these permissions can be found in Appendix E. The final instrument, including modifications made during pilot testing, is presented in Appendix C to facilitate replicability in future studies. This practice aligns with best practices in academic research, ensuring that future researchers can reproduce and build upon the study (Van Teijlingen & Hundley, 2001).

This structured questionnaire, based on validated and reliable scales, served as the primary data collection tool in this study. By leveraging well-established measures and incorporating feedback from pilot testing, the instrument was designed to accurately capture the factors influencing the adoption of wearable smart devices among healthcare professionals in Oregon. Evidence of the instrument's reliability and validity is presented in Chapter 4, ensuring that the findings are robust, replicable, and aligned with the research objectives.

Operational Definitions of Variables

In quantitative research, operational definitions are essential for clearly specifying how each variable is measured and interpreted within the context of a study. These definitions enhance both transparency and replicability by outlining exactly how theoretical constructs are translated into measurable indicators (Babbie, 2020). This study employed operational definitions grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), as well as extensions of the model used in healthcare research (Venkatesh et al., 2003; Maillet et al., 2015).

All variables in this study were measured using multi-item Likert-type scales, ranging from 1 (strongly disagree) to 5 (strongly agree). The survey instrument was developed using validated items from prior studies. Each construct was treated as a continuous interval-level variable, and final values for each participant were calculated as mean scores across the items for each scale. These operationalizations were selected to facilitate valid statistical analysis, including multiple linear regression, and to ensure alignment with the study's research questions.

Performance Expectancy

Performance expectancy refers to the degree to which healthcare professionals believe that using wearable smart devices will enhance their job performance, resulting in improved clinical outcomes and increased efficiency.

Operationalization. This variable was measured using a validated scale adapted from the UTAUT framework, which has been extensively applied in studies examining the technology adoption of healthcare professionals (Holden & Karsh, 2010; Venkatesh et al., 2003). The scale included four items that assess various aspects of performance expectancy, such as perceived improvements in patient monitoring, efficiency in data collection, and overall enhancement of care delivery. Each item was rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Level of Measurement. Interval

Potential Scores. The total score ranged from 4 to 20, where higher scores indicate a greater belief in the positive impact of wearable smart devices on performance. For analysis, a mean score was calculated, providing a clear indicator of the overall perception of performance expectancy among the samples.

Effort Expectancy

Effort expectancy refers to the perceived ease of use associated with wearable smart devices among healthcare professionals, influencing their willingness to adopt these technologies.

Operationalization. This variable was assessed using a validated scale derived from the Technology Acceptance Model (TAM), which emphasizes ease of use as a critical determinant of adoption (Davis, 1989; King & He, 2006). The scale consisted of four items that evaluated aspects such as the user-friendliness of the devices, ease of learning to operate them, and overall comfort in using the technology. Responses were collected on a 5-point Likert scale.

Level of Measurement. Interval

Potential Scores. The total score ranged from 4 to 20, where higher scores reflect a stronger belief in the ease of use of wearable smart devices. A mean score was calculated for analysis, enabling a nuanced understanding of how effort expectancy influences adoption decisions.

Social Influence

Social influence pertains to the extent to which healthcare professionals perceive that key stakeholders (such as peers, supervisors, and organizational culture) believe they should adopt wearable smart devices.

Operationalization. This variable was measured using a validated scale from the UTAUT framework, which captures perceptions of social pressure and encouragement from colleagues and supervisors (Venkatesh et al., 2003; Wu et al., 2007). It consists of four items designed to capture perceptions of social pressure and encouragement from others in the healthcare setting. Participants will respond to statements about their colleagues' and supervisors' attitudes toward the adoption of wearable technology using a 5-point Likert scale.

Level of Measurement. Interval

Potential Scores. The total score ranged from 4 to 20, with higher scores indicating a stronger perception of social influence. A mean score was derived for analysis, highlighting the role of social factors in the adoption process.

Facilitating Conditions

Facilitating conditions refer to the resources, support, and infrastructure that healthcare professionals believe are available to them for effectively utilizing wearable smart devices in their practice.

Operationalization. This variable will be assessed using a validated scale from the UTAUT framework, focusing on organizational support, access to technology, and training opportunities (Chismar & Wiley-Patton, 2003; Venkatesh et al., 2003). It will consist of five items that evaluate perceptions of organizational support, access to technology, training opportunities, and availability of technical assistance. Each item will be rated on a 5-point Likert scale.

Level of Measurement. Interval

Potential Scores. The total score ranged from 4 to 20, where higher scores indicate better perceived facilitating conditions. A mean score was computed for analysis, providing insights into how support and resources influence technology adoption.

Self-Efficacy (SE)

Self-efficacy refers to the individual's belief in their ability to independently use wearable smart devices in a professional healthcare setting.

Operationalization. Self-efficacy was operationalized using four items adapted from technology acceptance literature, particularly from Compeau and Higgins (1995) and Venkatesh et al. (2003), both of which have been widely used in studies involving technological competence in workplace contexts. The items were designed to measure respondents' perceived confidence in their own ability to learn, operate, and troubleshoot wearable devices without external assistance. Examples of items included statements such as "I feel confident in my ability to figure out how to use a wearable smart device on my own" and "Even if no one is available to help me, I believe I can learn to use a wearable device effectively." Responses were collected using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), allowing respondents to express varying levels of confidence.

Level of Measurement. Interval

Potential Scores. Each participant could receive a total score ranging from 4 to 20, with higher scores indicating a greater sense of self-efficacy. Mean scores were calculated across the four items to generate a single self-efficacy score per respondent. These averaged scores allowed for comparability across participants and were used in subsequent statistical analyses to assess the impact of self-efficacy on behavioral intention.

Anxiety (ANX)

Anxiety refers to the extent to which healthcare professionals experience fear, discomfort, or unease when considering or using wearable devices.

Operationalization. Anxiety was measured using four items adapted from the UTAUT framework and related technology stress literature, particularly from Venkatesh et al. (2003) and Ragu-Nathan et al. (2008). These items were designed to capture emotional discomfort, apprehension, and fear related to using wearable smart devices in professional practice. Sample items included "I feel anxious when I think about using a wearable smart device" and "I worry I might make mistakes when using wearable technology." The Likert-scale responses ranged from 1 (strongly disagree) to 5 (strongly agree), allowing participants to indicate their level of anxiety toward this specific type of health technology.

Level of Measurement. Interval

Potential Scores. Scores ranged from 4 to 20. Higher scores indicated higher levels of anxiety or unease toward wearable smart device usage. Mean scores were computed across the four items for each respondent and used in the regression analysis to determine whether anxiety served as a barrier to adoption.

Attitude Toward Using Technology (ATUT)

Attitude toward using technology refers to a healthcare professional's overall positive or negative affective evaluation of using wearable smart devices.

Operationalization. This construct was measured using four items adapted from TAM and UTAUT, as described by Venkatesh and Davis (2000), to capture general sentiment and emotional response toward wearable technology. Items assessed both affective and cognitive attitudes, such as "Using wearable smart devices would be a good idea for my work" and "I am enthusiastic about the idea of integrating wearable technology into my daily clinical activities." These items aimed to determine the respondent's favorable or unfavorable disposition toward adoption. A 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) was used to capture participant responses.

Level of Measurement. Interval

Potential Scores. Each participant's total raw score could range from 4 to 20. Higher scores indicated a more favorable attitude toward the use of wearable devices. For data analysis, mean scores were calculated to provide a standardized measurement of participants' attitudes, allowing the variable to be used in correlational and regression analysis alongside other predictors of adoption.

Behavioral Intentions (BI)

Behavioral intentions refer to the extent to which healthcare professionals intend to adopt or continue using wearable smart devices in their clinical workflows.

Operationalization. Behavioral intentions were assessed using four items based on the UTAUT model developed by Venkatesh et al. (2003). These items focused on the respondents' future plans, commitment, and readiness to adopt wearable technologies. Example statements included "I intend to use wearable smart devices in the near future" and "I plan to integrate wearable technology into my daily clinical practice." Responses were rated using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), providing a continuous measure of the strength of intention.

Level of Measurement. Interval

Potential Scores. Mean scores were calculated across the four items to generate a composite variable for statistical analysis. This construct served as the dependent variable in the multiple regression model, capturing the likelihood that participants would engage in future adoption behavior.

Operational Definitions

These operational definitions offer a comprehensive framework for measuring the critical variables in this study, ensuring that each construct is assessed using established, reliable, and valid instruments. The operationalization of each variable aligns directly with the research questions, allowing for an in-depth exploration of the factors influencing the adoption of wearable smart devices among healthcare professionals in Oregon. By employing well-defined metrics and scales, the study aimed to yield quantitative data that could provide valuable insights into the dynamics of technology adoption in healthcare settings. This approach contributed to a richer understanding of the interplay between performance expectancy, effort expectancy, social influence, facilitating conditions, attitude toward using technology, self-efficacy, anxiety, and the overall decision to adopt wearable technologies in clinical practice.

Study Procedures

To effectively collect data for this study, a systematic and structured approach was employed. The following steps outline the detailed procedures that were followed to ensure rigorous data collection and the replicability of the study. Before data collection began, all research instruments, including the survey questionnaire based on the UTAUT model, were finalized and reviewed for clarity through a pilot test. This is a well-established practice in survey research, aimed at improving reliability and validity (Dillman et al., 2014; Van Teijlingen & Hundley, 2001). Pilot testing ensures that a survey is comprehensible and aligned with the study's objectives, which is particularly important when adapting theoretical constructs to specific populations such as healthcare professionals (Holden & Karsh, 2010).

Participants will be recruited through multiple channels to ensure a diverse sample of healthcare professionals across the state of Oregon. Multi-channel recruitment strategies, including email campaigns, social media, and physical outreach, have been shown to increase response rates and sample diversity (Shaghaghi et al., 2011). These channels will include:

- Email Campaigns: Targeted email invitations will be sent to members of professional organizations, such as the Oregon Medical Association and the Oregon Nurses Association, which is a common strategy for accessing professional networks (Dillman et al., 2014).

- Social Media: Posts will be made on professional networking sites, such as LinkedIn, and community health forums. This will encourage participation by reaching professionals in a convenient manner (Whitaker et al., 2017).

Data collection took place over a four-week period. This timeline ensured sufficient time to achieve the desired response rate while allowing follow-ups to increase participation, a strategy supported by research on survey administration best practices (Dillman et al., 2014).

The survey was administered online using a secure survey platform, which allows for easy distribution and collection of responses. Online surveys are widely used in healthcare research due to their convenience and cost-effectiveness (Evans & Mathur, 2005). Participants received a unique link to the survey, ensuring anonymity and confidentiality. The survey included informed consent at the beginning, outlining the study's purpose, procedures, and the participant's rights, as outlined in Appendix F (Fowler, 2014).

Responses were securely stored in a password-protected database, with identifying information removed to maintain confidentiality. These procedures align with data protection standards and ethical research guidelines (Resnik, 2020). Regular monitoring of responses ensured completeness and allowed for immediate identification of any issues requiring follow-up, an approach endorsed for maintaining data integrity (Van den Broeck et al., 2005). A follow-up reminder was sent via email one week after the initial invitation, with an additional reminder at the midpoint of the data collection period. Research shows that reminders significantly improve response rates in survey studies (Dillman et al., 2014). At the end of the four-week period, data collection was officially closed. A final review of the dataset ensured all responses were recorded and that data quality standards were met (Fowler, 2014). By adhering to this structured approach, the study aimed to gather robust and reliable data that contribute to understanding the factors influencing the adoption of wearable smart devices among healthcare professionals in Oregon. This meticulous process also ensured that the research could be replicated in future studies, enhancing the overall contribution to the field.

Data Analysis

Data analysis was conducted using a systematic and rigorous approach to ensure that the findings accurately addressed the research questions and hypotheses of this study. The analysis involved several key steps and utilized statistical software to facilitate the coding, analysis, and interpretation of the data. Upon completion of data collection, the responses were imported into statistical analysis software, SPSS (Statistical Package for the Social Sciences), for further analysis. Coding variables numerically is standard practice in quantitative research to facilitate statistical analysis (Pallant, 2020). Each variable was then coded numerically to facilitate analysis. For instance, Likert scale responses were assigned numerical values (e.g., 1 for "Strongly Disagree" to 5 for "Strongly Agree"). Missing data were addressed by excluding incomplete responses, following best practices in quantitative analysis (Schafer & Graham, 2002).

Initial analyses included descriptive statistics to summarize the demographic characteristics of the sample (e.g., professional role, years in their field) and to provide a general overview of the survey responses. This involved calculating measures such as means, standard deviations, frequencies, and percentages. Descriptive statistics helped establish the context for the subsequent inferential analyses. These analyses provided context and ensured the sample reflected the target population, a key step in survey research (Field, 2017). To test the hypotheses outlined in this study, inferential statistical methods were employed. The specific analyses used were based on the nature of the research questions:

- Hypothesis Testing: The primary hypotheses were tested using multiple regression analysis, where the adoption of wearable smart devices served as the dependent variable, while the independent variables included performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intentions, as outlined in the UTAUT framework. Multiple regression analysis is suitable for determining the strength and direction of relationships between the predictors and the dependent variable, and it is widely used in technology adoption studies, aligning with the UTAUT framework (Holden & Karsh, 2010; Venkatesh et al., 2003).
- Assumptions Checking: to conducting regression analyses, assumptions of normality, linearity, homoscedasticity, and multicollinearity were assessed to ensure that the data met the requirements for regression analysis. These assumptions were evaluated through visual inspections of residual plots and statistical tests (e.g., the Shapiro-Wilk test for normality). Meeting these assumptions ensures the validity and reliability of the inferential results. These diagnostics are crucial for robust inferential statistics (Field, 2017).
- Additional Statistical Tests: Based on the research questions, additional statistical methods such as ANOVA (Analysis of Variance) were used to examine differences in wearable device adoption across demographic subgroups (e.g., healthcare roles). ANOVA is a standard technique for comparing means across multiple groups in behavioral research (Tabachnick & Fidell, 2013). These analyses provided insights into whether specific demographic factors influence adoption patterns.

Effect sizes (e.g., Cohen’s d for group comparisons, R^2 for regression) were calculated to provide insight into the practical significance of the findings. This complements the use of p-values and follows APA guidelines recommending the reporting of effect sizes (Wilkinson, 1999). Reporting effect sizes offers a clearer understanding of the magnitude of the observed effects, which is essential for evaluating the real-world implications of the results. An alpha level of 0.05 was set for determining statistical significance, balancing the need to detect meaningful effects with the risk of Type I error.

The data analysis in this study primarily utilized SPSS for statistical computations and visualizations, as this platform is widely used and trusted for its robust analytical capabilities in survey-based research (Pallant, 2020). It also provides a user-friendly interface for conducting various statistical tests and allows for efficient data handling. The results of the statistical analysis are interpreted in the context of the study's research questions and hypotheses. For instance:

- The significance and strength of the relationships identified in the regression analyses indicate which factors (e.g., performance expectancy, social influence) have the greatest impact on wearable device adoption among healthcare professionals, consistent with prior technology acceptance studies (Venkatesh et al., 2003).
- ANOVA findings reveal significant differences in adoption based on demographic factors, such as professional roles or years of experience, consistent with methods used in healthcare adoption studies (Chau & Hu, 2002).
- Descriptive statistics will contextualize the findings by providing an overview of the general attitudes and behaviors of the sample population.

These interpretations are directly aligned with the research questions, ensuring that the findings address the problem statement and provide actionable insights into the factors influencing wearable device adoption. The discussion of results integrates these interpretations with existing literature, highlighting how this study advances understanding of healthcare technology adoption. By employing these comprehensive data analysis strategies, the study derives meaningful insights into the factors influencing the adoption of wearable smart devices by healthcare professionals in Oregon. This approach ensures that the analyses are rigorous, transparent, and replicable, ultimately contributing to the advancement of knowledge in the field.

Assumptions

In conducting this quantitative survey study, several key assumptions underlie the research methodology and design. These assumptions are critical as they shape the interpretation of the findings and the conclusions drawn from the data. Understanding these assumptions ensured the study's validity and reliability and guided the structure of the data analysis plan. Additionally, strategies were outlined to address violations of these assumptions, ensuring robust and credible findings.

It was assumed that the data collected from participants would follow a normal distribution. This assumption was essential for applying parametric statistical tests, such as multiple regression analysis, which require normally distributed residuals for accurate results (Field, 2017). The Central Limit Theorem supports this assumption, suggesting that with a sufficiently large sample size (e.g., the planned 200+ participants), the distribution of sample means will approximate normality, even if the population distribution is not perfectly normal (Pallant, 2020). Normality was assessed using visual methods (e.g., Q-Q plots) and statistical tests (e.g., Shapiro-Wilk test), which are recommended practices for validating this assumption (Razali & Wah, 2011). If violations of normality were detected, transformations (e.g., log or square-root transformations) would have been applied to normalize the data, a strategy commonly employed in similar studies (Osborne, 2010), but no violations of normality were detected. Alternatively, non-parametric methods, such as the Kruskal-Wallis test, would have been considered if normality could not be achieved without compromising the integrity of the data (Conover & Iman, 1981).

The study assumed that responses from participants were independent of one another, meaning that one participant's responses did not influence those of another. This is a fundamental assumption for the validity of statistical analyses used in this study, such as regression and ANOVA (Tabachnick & Fidell, 2013). Independence is inherently supported by the study's survey design, where each participant completes the survey individually and anonymously (Fowler, 2014). Any violation of this assumption, such as participants discussing their responses with each other or patterns indicating non-independent data (e.g., cluster effects), was investigated by examining residual plots and inter-cluster correlations (Hox, 2010). If a lack of independence were detected, adjustments such as hierarchical linear modeling (HLM) would have been used to account for clustered data, as recommended in similar research contexts (Raudenbush & Bryk, 2002).

It was assumed that a linear relationship exists between the independent variables (performance expectancy, effort expectancy, social influence, facilitating conditions, attitude toward using technology, self-efficacy, and anxiety) and the dependent variable (adoption of wearable smart devices). This assumption aligns with the Unified Theory of Acceptance and Use of Technology (UTAUT), which posits direct, linear relationships between these factors and technology adoption (Venkatesh et al., 2003). Linearity will be assessed by plotting residuals against predicted values and examining scatterplots for each independent variable (Field, 2017). If deviations from linearity were observed, transformations or polynomial terms would have been introduced to better model the relationships, as outlined by Osborne and Waters (2002).

The study assumed that the variance of residuals was constant across all levels of the independent variables, a condition known as homoscedasticity. This assumption is critical for ensuring unbiased and efficient estimates in regression analysis (Pallant, 2020). Homoscedasticity was checked using residual plots, where residuals are plotted against predicted values, as recommended by Tabachnick and Fidell (2013). If heteroscedasticity (non-constant variance) was detected, robust standard errors or generalized least squares (GLS) methods would have been employed to account for unequal variances, as demonstrated in prior studies (Hayes & Cai, 2007).

It was assumed that the independent variables included in the regression model were not highly correlated with one another. Multicollinearity could have inflated standard errors and complicated the interpretation of regression coefficients, making it challenging to determine the individual contribution of each predictor (Hair et al., 2018). The rationale for this assumption was based on prior research indicating that the selected independent variables, derived from the UTAUT framework, had been shown to provide distinct constructs that influenced technology adoption (Venkatesh et al., 2003). By acknowledging these assumptions and their underlying rationales, the study aimed to maintain the integrity of its research design and analysis. The awareness of these assumptions enabled appropriate checks and balances throughout the research process, ensuring that the findings contributed valuable insights into the factors influencing the adoption of wearable smart devices by healthcare professionals in Oregon. If any assumption violations had occurred, the following steps would have been taken to address them:

- Diagnostics: Conduct thorough diagnostic analyses to identify the nature and extent of the violation (Field, 2017).

- Adjustments: Apply appropriate corrective measures, such as data transformations, robust statistical techniques, or alternative analytical methods (Osbourne, 2010).
- Transparency: Document all assumption checks, identified violations, and the corrective steps in the final reporting of results to maintain transparency and credibility (Wilkinson, 1999).
- Sensitivity Analysis: Conduct sensitivity analyses to determine whether the conclusions are robust to the adjustments made for assumption violations (Schafer & Graham, 2002).

By explicitly linking these assumptions to the data analysis plan and addressing potential violations, the study ensured a rigorous analytical process that yielded valid and reliable insights into the factors influencing the adoption of wearable smart devices among healthcare professionals in Oregon.

Limitations

While this study aimed to provide valuable insights into the factors influencing healthcare professionals' adoption of wearable smart devices in Oregon, several limitations must be acknowledged. Understanding these limitations was crucial for contextualizing the findings and recognizing areas for future research. One limitation of this study was the potential lack of representativeness of the sample. While efforts were made to recruit a diverse group of healthcare professionals across various disciplines and settings, there was a possibility that certain groups were underrepresented. For example, healthcare professionals from rural areas or smaller healthcare facilities might not have participated at the same rate as those from urban or larger institutions. This could have limited the generalizability of the findings. To mitigate this limitation, the study employed stratified sampling techniques to ensure representation from different healthcare settings and professional backgrounds, a method supported by the literature for enhancing generalizability (Morrow et al., 2021). Additionally, targeted recruitment efforts, such as outreach through professional organizations and associations, helped engage a broader range of participants (Venkatesh et al., 2003).

Another potential limitation was response bias, where participants might have provided socially desirable answers rather than their true feelings or experiences regarding wearable smart devices. Response bias had been identified as a common concern in survey-based research, particularly in studies involving technology adoption (Podsakoff et al., 2003). This bias could have skewed the results and misrepresented the actual factors influencing adoption. To minimize this risk, the survey emphasized anonymity and confidentiality, measures that had been shown to reduce response bias in prior research (Tourangeau & Yan, 2007). Clear instructions were also provided to encourage honest and thoughtful responses, consistent with recommendations from Fowler (2014).

The cross-sectional nature of this study limited the ability to establish causal relationships between the identified factors and the adoption of wearable smart devices. While cross-sectional designs were valuable for exploring associations and testing theoretical models, they could not confirm causality, as noted in the methodological guidelines of Tabachnick and Fidell (2013). To address this limitation, the study discussed the findings within the context of existing literature and theoretical frameworks, providing a nuanced interpretation of the relationships rather than asserting causality (Hair et al., 2018). Future longitudinal studies could have built on this research to explore causal mechanisms over time, as recommended by Venkatesh et al. (2003).

The reliance on self-reported survey data introduced potential measurement errors, such as participants misinterpreting questions or providing incomplete responses. Additionally, self-reported measures might not have fully captured the complexity of factors influencing wearable adoption, particularly those that were context-dependent or influenced by subtle organizational dynamics (Podsakoff et al., 2003). Future studies could incorporate mixed-methods approaches, combining quantitative surveys with qualitative interviews or focus groups, to provide a richer understanding of the factors driving adoption. This recommendation aligns with research suggesting that mixed methods can capture nuanced perspectives that are not easily measured in surveys alone (Creswell & Plano Clark, 2017).

This study's focus on healthcare professionals in Oregon may have limited the applicability of its findings to other regions or contexts. Factors influencing adoption, such as regulatory environments, funding structures, and patient demographics, could have varied significantly across different states and countries (Adapa et al., 2018). Consequently, the findings may not be generalized to healthcare systems with differing technological, cultural, or organizational characteristics. Future research should have expanded the geographic scope to include national or international samples, enabling comparisons across different healthcare settings and identifying universal versus context-specific drivers of wearable device adoption (Taherdoost, 2018). Despite these limitations, the study laid an important foundation for understanding the adoption of wearable devices among healthcare professionals. To enhance the broader applicability of its findings, future research could:

- Expand Sample Diversity: Include healthcare professionals from diverse backgrounds, including various states, rural settings, and resource-limited environments, to identify regional or demographic differences in adoption factors (Morrow et al., 2021).
- Incorporate Longitudinal Designs: Track healthcare professionals over time to capture evolving attitudes, organizational influences, and the long-term impacts of wearable device adoption (Venkatesh et al., 2003).

- Integrate Behavioral Data: Use real-world usage data from wearable devices to validate self-reported adoption patterns and uncover discrepancies between stated intentions and actual behavior (Adapa et al., 2018).
- Examine Organizational Contexts: Investigate how factors such as leadership support, technological infrastructure, and institutional culture mediate the adoption process (Hair et al., 2018).
- Explore Patient Influences: Analyze how patient demand for wearable devices influences healthcare professionals' attitudes and decisions regarding their adoption (Taherdoost, 2018).

By addressing these limitations and pursuing these research directions, future studies could build on the insights from this research to create a more comprehensive understanding of wearable technology adoption in diverse healthcare contexts. These efforts would ultimately support the effective integration of wearable devices into clinical practice, improving healthcare outcomes and professional workflows.

Delimitations

Delimitations defined the boundaries of this study and established the specific parameters the researcher intentionally set to focus the investigation. Understanding these delimitations is crucial for interpreting the findings within the intended scope. In this study, delimitations included a focus on healthcare professionals in Oregon, the exclusion of non-healthcare populations, and a specific emphasis on wearable smart devices used for health monitoring. These parameters were selected to ensure alignment with the research problem, purpose, and questions and to provide a manageable and relevant scope for analysis.

This study specifically focused on healthcare professionals in the state of Oregon. By narrowing the target population, the research aimed to explore the unique contextual factors influencing the adoption of wearable smart devices within this geographic and professional setting. Regional studies have been shown to provide valuable insights into localized factors affecting technology adoption, such as healthcare policies and professional culture (Adapa et al., 2018). Similar studies had successfully utilized state-specific populations to analyze technology adoption in healthcare (Taherdoost, 2018). This choice aligned with the problem statement, which identified a lack of understanding among healthcare professionals in Oregon regarding adoption factors.

Within the target population, this study included healthcare professionals from various disciplines, including nurses, physicians, allied health professionals, and administrators. However, the focus did not extend to non-healthcare professionals or patients. This delimitation ensured that the findings were relevant to those who directly influenced or were involved in the adoption of wearable technologies in clinical practice, a focus consistent with prior research on technology adoption in healthcare settings (Venkatesh et al., 2003). This decision was rooted in the research questions, which specifically sought to uncover the factors affecting healthcare professionals' decision-making processes regarding technology adoption.

The research exclusively investigated wearable smart devices intended for health monitoring and management, including fitness trackers, smartwatches, and health monitoring devices. Prior studies had emphasized the importance of focusing on specific technology types to conduct a detailed analysis of adoption factors (Davis, 1989; Venkatesh et al., 2003). Other forms of technology, such as mobile applications or non-wearable devices, were not included. This focus facilitated a deeper understanding of the unique contextual challenges and benefits of wearable devices, aligning with the purpose statement to address the adoption of wearable technology in healthcare.

The study employed a quantitative survey methodology to collect data. Qualitative approaches, such as interviews or focus groups, were not utilized in this research. This delimitation was intentional, as the researcher aimed to gather quantifiable data that could be statistically analyzed to identify patterns and correlations among the variables of interest. Quantitative methods were well-suited for identifying patterns and testing hypotheses about technology adoption, as demonstrated in previous research using TAM and UTAUT frameworks (Taherdoost, 2018; Venkatesh et al., 2003). Excluding qualitative methods ensured a streamlined approach to analyzing predefined constructs and variables relevant to wearable technology adoption (Hair et al., 2018).

The data collection was conducted within a defined time frame, specifically during the academic year 2024–2025. This delimitation helped to establish a clear timeline for the research, enabling the study to capture the current state of technology adoption among healthcare professionals at a specific point in time, as highlighted in longitudinal and cross-sectional adoption research (Creswell & Plano Clark, 2017). By concentrating on this time frame, the research provided insights relevant to current trends and challenges in the adoption of wearable technologies. By clearly defining these delimitations, this study aimed to maintain a focused approach that aligned with the existing literature and theoretical frameworks. These choices were designed to address the identified problem statement, achieve the study's purpose, and effectively answer the research questions. Future research may build upon these findings by exploring broader populations, different types of technologies, or alternative methodologies, thereby contributing to a more comprehensive understanding of technology adoption in healthcare settings.

Ethical Assurances

This study adhered to rigorous ethical standards to protect the rights and well-being of all participants. The following ethical assurances and procedures were implemented throughout the research process to maintain integrity, transparency, and respect for participants. The study received approval from the University's Institutional Review Board (IRB) prior to data collection. The IRB review ensured that the study adhered to ethical principles, particularly regarding the treatment of human subjects, informed consent, and data protection, as outlined in the Belmont Report (National Commission for the Protection of Human Subjects, 1979). The IRB assessed potential risks to participants, the adequacy of safeguards, and the appropriateness of the proposed procedures, consistent with guidelines established by Creswell and Plano Clark (2017). The IRB approval letter is included in Appendix G, providing documentation of ethical compliance.

While this study involved minimal risk to participants, ethical considerations remained paramount. Participants may have experienced minor discomfort while reflecting on their experiences and perceptions regarding the adoption of wearable technology in healthcare. To mitigate this, participants were informed of their right to withdraw at any point without consequence, a standard practice supported by Fowler (2014) and Hair et al. (2018). This ensured participants felt empowered to make decisions about their participation freely. A robust informed consent process was implemented to ensure that participants were fully aware of the study's purpose, procedures, potential risks, and benefits. The informed consent form included the following elements, consistent with ethical research guidelines (Creswell & Plano Clark, 2017; Fowler, 2014):

- Study Purpose and Objectives: A concise explanation of the study's aims to examine factors influencing the adoption of wearable smart devices among healthcare professionals in Oregon.
- Voluntary Participation: Participants were explicitly informed that their participation was entirely voluntary, with no obligation to complete the survey and no negative consequences for withdrawal at any time.
- Procedures and Duration: Detailed descriptions of the procedures, including survey completion and estimated time commitment (approximately 15–20 minutes), were provided.
- Risks and Benefits: Any potential risks (e.g., discomfort in answering specific questions) and benefits (e.g., contributing to knowledge that may improve healthcare practices) were clearly outlined.
- Confidentiality Assurance: A detailed explanation of how data was de-identified and stored securely, ensuring participants' privacy.
- Contact Information: The researcher's and IRB's contact details were provided so that participants could seek further clarification or report concerns.

The consent form was presented digitally through the survey platform, requiring participants to indicate their agreement (e.g., by selecting a checkbox) before proceeding to the survey. This ensured clarity and documentation of consent, aligning with online survey best practices (Tourangeau & Yan, 2007).

To protect participant privacy, all responses were de-identified during the data processing stage. Names or other personally identifiable information were not collected. Instead, each participant was assigned a unique identifier to facilitate secure data management and tracking. Results were reported in aggregate form, ensuring that individual responses could not be traced back to specific participants. The informed consent document explicitly highlighted these confidentiality measures to reassure participants about the security of their data. This approach aligned with confidentiality practices in healthcare research (Hair et al., 2018; Taherdoost, 2018). Data were securely stored in accordance with IRB requirements to prevent unauthorized access. Digital data were saved on password-protected devices and backed up on encrypted servers, consistent with secure data management practices in research (Creswell & Plano Clark, 2017). Any physical documentation (e.g., printed materials for pilot testing) was stored in a locked cabinet accessible only to the researcher. Data were retained for three years following the study, after which they were permanently destroyed (e.g., shredding hard copies, securely deleting digital files).

The researcher maintained a neutral and professional role throughout the study. To address potential biases, the researcher adopted reflexive practices, such as journaling personal reflections and assumptions, to ensure they did not influence data interpretation. Regular feedback from academic advisors and peer reviewers further safeguarded against biases (Podsakoff et al., 2003). By focusing on data-driven analyses and adhering to established statistical methods, the study aimed for objectivity and accuracy in its findings. To maintain participant trust and comply with ethical standards, the study aligned with the principles outlined in the Belmont Report, emphasizing respect for persons, beneficence, and justice (National Commission for the Protection of Human Subjects, 1979). By fostering transparency, upholding confidentiality, and ensuring voluntary participation, this study has contributed to the field of healthcare technology adoption with ethically sound research. By implementing these comprehensive ethical measures, this study aimed to prioritize participant welfare, maintain data integrity, and contribute to a deeper understanding of wearable smart device adoption among healthcare professionals.

Summary

In this chapter, the research methodology for investigating the factors influencing the adoption of wearable smart devices among healthcare professionals in Oregon was outlined comprehensively. This chapter directly addressed the study's problem statement of the lack of understanding of why healthcare professionals in Oregon were hesitant to adopt wearable technologies despite their potential benefits (Taherdoost, 2018; Venkatesh et al., 2003). It also aligned with the purpose statement, which aimed to explore and quantify the factors influencing these adoption decisions through a quantitative survey approach. By detailing the methodology, this chapter established a clear framework for how the research systematically addressed the study's objectives.

The chapter began by restating the problem and purpose statements, emphasizing the need to understand the barriers and motivators affecting wearable smart device adoption in clinical settings. The chosen quantitative survey methodology was described in detail, demonstrating its suitability for capturing empirical data and testing hypotheses related to key constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions. This approach ensured that the research questions were addressed through statistical analysis, yielding findings that are generalizable and applicable to healthcare professionals in Oregon.

The population and sample were defined to ensure relevance to the study's objectives, with healthcare professionals in Oregon identified as the target population. The decision to focus on this group reflected findings from previous studies that emphasized the critical role of healthcare professionals in influencing technology adoption in clinical settings (Rogers, 2003; Skokin, 2022). A stratified random sampling method was chosen to ensure representation across various subgroups, enhancing the reliability and applicability of the findings (Fowler, 2014). The rationale behind this sampling strategy was to understand diverse perspectives within the healthcare field. A power analysis confirmed that the sample size was sufficient to achieve statistically significant results (Hair et al., 2018). Instrumentation was described in detail, with a focus on the use of validated scales grounded in theoretical frameworks, such as the Unified Theory of Acceptance and Use of Technology (UTAUT). These instruments were selected for their demonstrated reliability and validity in prior research, ensuring that the constructs being measured accurately reflected the factors influencing the adoption of wearable technology (Venkatesh et al., 2003). Pilot testing procedures were outlined to refine the survey and address potential issues, further strengthening the study's methodological rigor (Creswell & Plano Clark, 2017; Fowler, 2014).

Operational definitions of variables were provided to clarify how key constructs were measured, ensuring consistency and alignment with the statistical analyses planned for the study. These definitions aligned with best practices for operationalizing variables in adoption studies (Hair et al., 2018; Taherdoost, 2018). Detailed study procedures were outlined, including participant recruitment methods, data collection steps, and strategies for maintaining confidentiality and ensuring data security. These procedures were designed to ensure transparency and replicability while adhering to ethical standards, as highlighted in similar studies (Creswell & Plano Clark, 2017; Tourangeau & Yan, 2007). The data analysis section outlined the statistical techniques that were employed to examine the research questions and hypotheses. These included descriptive statistics, multiple regression analysis, and assumption testing, all of which were standard in studies employing UTAUT and TAM frameworks (Hair et al., 2018; Venkatesh et al., 2003). By addressing the assumptions of statistical tests and describing the handling of potential violations, this section demonstrated a thoughtful and systematic approach to analyzing the data and interpreting the results (Podsakoff et al., 2003).

Ethical assurances were also addressed, detailing how participant rights were protected through informed consent, anonymity, and secure data storage. These ethical considerations aligned with the principles of respect, beneficence, and justice outlined in the Belmont Report (National Commission for the Protection of Human Subjects, 1979). Similar research highlighted the importance of upholding these principles to maintain participant trust and research integrity (Fowler, 2014; Taherdoost, 2018). The limitations and delimitations of the study were acknowledged, providing transparency about the constraints of the research and how they might have impacted the broader applicability of the findings. Limitations such as the cross-sectional design and the focus on a single geographic region were consistent with those noted in related adoption studies (Adapa et al., 2018; Davis, 1989). Directions for future research were proposed, emphasizing the potential for further exploration of wearable technology adoption in other regions or healthcare contexts (Rogers, 2003; Venkatesh et al., 2003).

By outlining the research methodology in this structured and detailed manner, this chapter establishes a robust foundation for addressing the problem and purpose statements. It ensured that the study was methodologically sound, ethically responsible, and capable of generating meaningful insights. As the study transitioned to the next chapter, the findings derived from the data analysis were presented, shedding light on the key factors influencing healthcare professionals' decisions to adopt wearable smart devices. These findings contributed to the growing body of knowledge on technology adoption in healthcare, offering actionable recommendations for enhancing the integration of wearable technologies in clinical practice.

Chapter 4: Findings

The problem addressed in this study was the lack of understanding of the factors influencing healthcare professionals' decisions to adopt wearable smart devices in the state of Oregon. The purpose of this quantitative study was to explore the extent to which performance expectancy, effort expectancy, social influence, facilitating conditions, attitude toward using technology, self-efficacy, and anxiety influence the adoption of wearable smart devices among healthcare professionals in Oregon. By systematically analyzing the relationships between key UTAUT variables, such as performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), and behavioral intention (BI), a clearer picture of the underlying factors influencing healthcare professionals' adoption of wearable smart devices in Oregon was achieved. A variable-driven approach was used to understand the factors influencing the adoption of wearable smart devices among healthcare professionals in Oregon. The findings provided valuable evidence to address barriers and inform strategies for supporting the effective integration of wearable technology in clinical practice.

The results of the data analysis conducted on survey responses collected from 270 healthcare professionals using a structured instrument aligned with the Unified Theory of Acceptance and Use of Technology (UTAUT) are presented in this chapter. The extent to which independent variables predicted behavioral intention to adopt wearable technologies was evaluated, along with whether the necessary statistical assumptions for valid regression analysis were met, such as normality, linearity, multicollinearity, and homoscedasticity. The analysis began with an assessment of the instrument's validity and internal consistency, including Cronbach's alpha reliability testing. A detailed overview of descriptive statistics, visual data displays, and demographic characteristics is then provided. A multiple regression model was then constructed, and inferential statistics, including t-tests and ANOVA, were used to test each hypothesis. The model also generated a regression equation that quantified the relationship between the independent variables and behavioral intention, allowing for the prediction of adoption likelihood based on construct scores. Results are presented in tables and figures, aligned with the research questions, which form the basis for interpretation. The chapter is structured into four main sections: Validity and Reliability of the Data, Results, Evaluation of the Findings, and Summary, concluding with key findings that inform the implications and recommendations discussed in Chapter 5.

Validity and Reliability of the Data

To ensure the statistical rigor of this quantitative correlational study, a priori power analysis was conducted using G*Power software to determine the minimum required sample size for detecting significant relationships among the study variables. The analysis was based on a conventional alpha level (α) of .05; a statistical power ($1 - \beta$) of .80; an effect size (f^2) of 0.15, representing a medium effect; and a model including eight predictor variables. These parameters reflect established conventions for avoiding both Type I errors (false positives) and Type II errors (false negatives), while ensuring the study maintains a reasonable likelihood of identifying actual effects when they exist (Cohen, 1988).

The results of this analysis revealed that a minimum of 109 complete responses was necessary to achieve adequate statistical power (see Appendix B for full power analysis test and results). This threshold ensures that the regression analysis can detect medium-sized effects in the relationships between independent variables, such as performance expectancy and effort expectancy, and the dependent variable of behavioral intention to adopt wearable smart devices. Ultimately, 270 complete and valid survey responses were collected for this study, significantly exceeding the minimum requirement. This robust sample size not only enhances the generalizability of the findings but also strengthens the credibility and stability of the inferential statistical analyses performed in subsequent sections. The sample was representative of the target population of healthcare professionals in Oregon, as it included a diverse range of roles, clinical settings, and demographic characteristics aligned with state-level workforce distributions.

In quantitative research, reliability refers to the consistency and stability of an instrument in measuring a concept across different observations or over time (Sürücü & Maslakci, 2020). In this study, internal consistency reliability was evaluated using Cronbach's alpha for each construct measured by the survey instrument. Cronbach's alpha values range from 0 to 1, with values between 0.70 and 0.95 generally considered acceptable (Tavakol & Dennick, 2011). Values below 0.70 may suggest low internal consistency, whereas values above 0.95 may indicate redundancy among items.

Table 1 presents the Cronbach's alpha values calculated for each construct in the study. Performance Expectancy (PE), Effort Expectancy (EE), Attitude Toward Using Technology (ATUT), Social Influence (SI), Self-Efficacy (SE), Anxiety (ANX), and Behavioral Intention (BI) all demonstrated acceptable to excellent internal consistency, with values ranging from 0.70 to 0.97. Self-Efficacy (SE) showed marginal reliability ($\alpha = 0.65$). Facilitating Conditions (FC), which originally exhibited poor internal consistency (Cronbach's $\alpha = 0.30$), was reanalyzed after identifying and addressing a negatively worded item that undermined the scale's reliability. Specifically, Item Q28, "A specific person (or group) is available for assistance with wearable smart device difficulties," was reverse-scored and ultimately removed from the construct due to its weak corrected item-total correlation and low contribution to the overall scale coherence. Once this item was excluded, the revised FC construct, now comprised of three positively framed items (Q26, Q27, and Q29), yielded a Cronbach's alpha of 0.52. Although this value remains below the generally accepted threshold of 0.70, it indicates moderate reliability and a meaningful improvement in internal consistency. Within social science research, especially in exploratory studies or those involving newly adapted instruments, alpha values in the 0.50–0.60 range may be considered adequate for preliminary analysis when supported by theoretical justification (Nunnally, 1978; Gliem & Gliem, 2003). Given the construct's relevance within the UTAUT framework and its improved psychometric performance, FC was retained for further analysis, with interpretations made cautiously. Detailed item-total reliability statistics are provided in Appendix H.

Table 1

Cronbach's Alpha Reliability Results by Construct

	Cronbach's Alpha
Performance Expectancy (PE)	0.85
Effort Expectancy (EE)	0.86
Attitude Toward Using Technology (ATUT)	0.84
Social Influence (SI)	0.70
Facilitating Conditions (FC)	0.52
Self-Efficacy (SE)	0.65
Anxiety (ANX)	0.86
Behavioral Intentions (BI)	0.97

Note. This table displays the Cronbach's Alpha value for each variable examined in the study.

To assess construct validity, Principal Component Analysis (PCA) was conducted to determine whether survey items clustered in a manner consistent with the theoretical structure of the Unified Theory of Acceptance and Use of Technology (UTAUT). The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy was .852, exceeding the recommended threshold of .60, and Bartlett's Test of Sphericity was statistically significant ($\chi^2 = 850.757$, df = 28, $p < .001$). These results indicated that the dataset was suitable for factor analysis, confirming that the correlations among variables were sufficiently strong to extract meaningful components. Additionally, the strength of the KMO value further suggests that the patterns of correlations are compact, which allows for reliable factor solutions (see Appendix I).

Table 2

Component Matrix (Principal Component Analysis)

Variable	**Component 1**	**Component 2**
Performance Expectancy (PE)	0.734	0.417
Effort Expectancy (EE)	0.769	-0.207
Attitude Toward Using Technology (ATUT)	0.837	0.191
Social Influence (SI)	0.740	0.247
Facilitating Conditions (FC)	0.729	-0.151
Self-Efficacy (SE)	0.560	0.214
Anxiety (ANX)	-0.420	0.820
Behavioral Intentions (BI)	0.748	-0.206

Note. This table shows the two components extracted as part of the principal component analysis.

The PCA yielded two components with eigenvalues greater than 1.0, indicating that these components accounted for a significant proportion of the total variance in the dataset. Component 1 explained 47.98% of the variance, and Component 2 contributed an additional 13.69%, resulting in a cumulative total of 61.67%, which exceeds the 50% threshold commonly used to support convergent validity (Hair et al., 2010). The Component Matrix showed that Performance Expectancy (PE), Effort Expectancy (EE), Attitude Toward Using Technology (ATUT), Social Influence (SI), Facilitating Conditions (FC), Self-Efficacy (SE), and Behavioral Intentions (BI) all loaded strongly on Component 1, with loadings ranging from .560 to .837. These findings suggest that these constructs share a common latent structure related to technology acceptance. The strong and distinct loading of Anxiety (ANX) on Component 2 highlights its unique contribution to the measurement model. The clear differentiation between the two components further reinforces the robustness of the factor solution and its alignment with the underlying theoretical framework.

In contrast, Anxiety (ANX) showed a high positive loading on Component 2 (.820) and a negative loading on Component 1 (-.420), confirming its conceptual role as a distinct psychological construct that may hinder rather than support behavioral intention to adopt wearable smart devices. This finding aligns with prior research suggesting that anxiety functions as a barrier within technology adoption frameworks (Ragu-Nathan et al., 2008). The distinct loading pattern of ANX enhances discriminant validity by confirming its uniqueness from the other predictors. Together, the PCA results reinforce the validity of the measurement instrument. The clustering of adoption-promoting variables on a single component and the distinct loading of ANX onto a separate component support both convergent and discriminant validity. These findings validate the theoretical framework and justify proceeding with inferential statistical analyses.

Communalities derived from the PCA, shown in Table 3, further support the instrument's construct validity. Most variables demonstrated moderate to strong extraction values, indicating that the two extracted components accounted for a meaningful proportion of variance across the constructs. Specifically, Performance Expectancy (PE = 0.71), Effort Expectancy (EE = 0.63), Attitude Toward Using Technology (ATUT = 0.74), Social Influence (SI = 0.61), and Behavioral Intentions (BI = 0.60) all exceeded the 0.60 threshold, suggesting strong representation within the extracted factor structure. However, Facilitating Conditions (FC = 0.55) and Self-Efficacy (SE = 0.36) exhibited relatively lower communalities, which may reflect measurement issues or conceptual distance from the central factor of technology acceptance. Despite these slightly weaker values, both constructs were retained due to their theoretical significance in the UTAUT framework. Anxiety (ANX), with a high communality of 0.85, was well captured by the second component and further reinforced its conceptual uniqueness as a psychological barrier to adoption.

Table 3

Communalities (Principal Component Analysis)

Variable	**Extraction**
Performance Expectancy (PE)	0.71
Effort Expectancy (EE)	0.63
Attitude Toward Using Technology (ATUT)	0.74
Social Influence (SI)	0.61
Facilitating Conditions (FC)	0.55
Self-Efficacy (SE)	0.36
Anxiety (ANX)	0.85
Behavioral Intentions (BI)	0.60

Note. This table shows the extraction value for each variable examined in this study.

Results

A total of 291 survey responses were collected from healthcare professionals representing a wide range of roles, specialties, and practice settings across the state of Oregon. These participants were recruited to provide insights into the factors influencing the adoption of wearable smart devices in healthcare. Prior to conducting statistical analyses, the dataset underwent a series of data cleaning and validation procedures to ensure accuracy and reliability. This process included screening for missing responses, identifying inconsistent or illogical answer patterns, and applying eligibility filters to confirm that respondents met the inclusion criteria. As a result, 21 incomplete or invalid cases were removed from the dataset. The final analytic sample consisted of 270 valid responses, which exceeded the minimum sample size of 109 determined by a priori power analysis. Surpassing this threshold increased the statistical power of the study, thereby enhancing the reliability and generalizability of the findings.

Participants provided demographic and professional background information, including their current professional role, total years of experience in the healthcare field, and primary work setting. These data allowed for a comprehensive understanding of the sample's composition and ensured that the perspectives reflected a broad cross-section of healthcare professionals in Oregon. Table 4 presents the frequency and percentage distribution of participants across professional roles, years in the field, and professional work environments. The sample included clinical and non-clinical healthcare providers, allied health professionals, and administrative personnel, with experience levels ranging from less than one year to over a decade of experience. Work settings were similarly diverse, spanning hospitals, private clinics, community health centers, home healthcare, specialty centers, administrative offices, and remote positions. All participants were at least 18 years of age. The study's independent and dependent variables were computed as continuous measures by averaging responses to multi-item Likert-type scales, producing values ranging from approximately 1 to 5. This approach ensured the data were appropriate for parametric statistical testing, including the multiple linear regression analyses used to evaluate the study's research questions.

Table 4

Demographic Characteristics of Participants

	Variable	Participants (n)	Participants (%)
Professional Role	Non-Clinical Healthcare Professional	124	45.9%
	Clinical Healthcare Professional	98	36.3%
	Allied Healthcare Professional	39	14.4%
	Administrative Healthcare Professional	9	3.3%
Years in Field	Less than 1 year	11	4.1%
	1-5 years	95	35.2%
	6-10 years	48	17.8%
	More than 10 years	116	43%
Professional Work Setting	Administrative Office or Facility	6	2.2%
	Community Health Center	25	9.3%
	Home Healthcare	54	20%
	Hospital	77	28.5%
	Private Clinic or Facility	90	33.3%
	Remote	7	2.6%
	Specialty Center	11	4.1%

Note. This table summarizes the professional roles, years of experience, and work settings of the 270 participants.

Performance Expectancy: Research Question 1

The first research question examined whether Performance Expectancy (PE) significantly predicted healthcare professionals' behavioral intention (BI) to adopt wearable smart devices. PE reflects the degree to which an individual believes that using the technology will enhance their job performance, making it a central construct in the Unified Theory of Acceptance and Use of Technology (UTAUT). The null hypothesis (H_{1o}) stated that PE would not significantly influence BI, while the alternative hypothesis (H_{1a}) stated that PE would significantly influence BI. Given its prominence in the UTAUT framework, PE is often considered a primary driver of technology adoption decisions, particularly in professional contexts where measurable performance gains are highly valued.

Descriptive statistics indicated that PE scores ranged from 1 to 5, with a mean of 3.51 (SD = 0.96) and skewness of −0.52 (Table 5), suggesting a slight tendency toward agreement but a relatively balanced distribution of responses. BI, the dependent variable, had a mean score of 3.82 (SD = 1.30) and skewness of −0.82 (Table 5), indicating moderately high intentions to adopt these devices. These values suggest that while respondents were moderately positive about the performance benefits of wearable devices, they expressed even stronger intentions to adopt them overall, implying that other factors may be driving their intentions more strongly than PE. This gap between perceived performance benefits and adoption intention may indicate that motivational drivers beyond functional utility, such as workplace norms, personal attitudes, or organizational support, play a more critical role in shaping healthcare professionals' willingness to adopt new technologies.

Table 5

Descriptive Statistics of Independent and Dependent Variables

										Skewness	
	N	Range	Min	Max	Mean	Med	Mode	Std. Dev	Var	Stat	Std. Err
PE	270	4	1	5	3.51	3.50	3	0.96	0.91	-0.52	0.148
EE	270	4	1	5	4.16	4.25	5	0.81	0.65	-1.17	0.148
ATUT	270	4	1	5	3.80	3.88	5	0.86	0.75	-0.67	0.148
SI	270	4	1	5	3.19	3.13	3	0.82	0.67	-0.24	0.148
FC	270	4	1	5	3.72	3.67	4	0.75	0.57	-0.91	0.148
SE	270	4	1	5	3.79	3.75	4	0.75	0.56	-0.61	0.148
ANX	270	4	1	5	2.15	2.00	1	1.07	1.15	0.67	0.148
BI	270	4	1	5	3.82	4.00	5	1.30	1.70	-0.82	0.148

Note. This table includes the number of samples (N), range, minimum (Min), maximum (Max), mean, median (Med), mode, standard deviation (Std. Dev), variance (Var), skewness value (Skewness Stat), and skewness standard error (Skewness Std. Err) for each variable.

Prior to hypothesis testing, regression assumptions were examined in order to ensure the reliability of the statistical inferences drawn from the analysis. Multicollinearity diagnostics revealed a variance inflation factor (VIF) of 2.058 and a tolerance value of 0.486 for PE (Table 6). Both values fall well below the most conservative recommended thresholds, indicating that PE was sufficiently independent from other predictors in the model and that its relationship with BI could be assessed without distortion from excessive shared variance. This finding is important because high multicollinearity can mask the true effect of a variable or inflate standard errors, but in this case, the independence of PE supports the stability of the regression coefficients.

Table 6

Summary of Multicollinearity Statistic

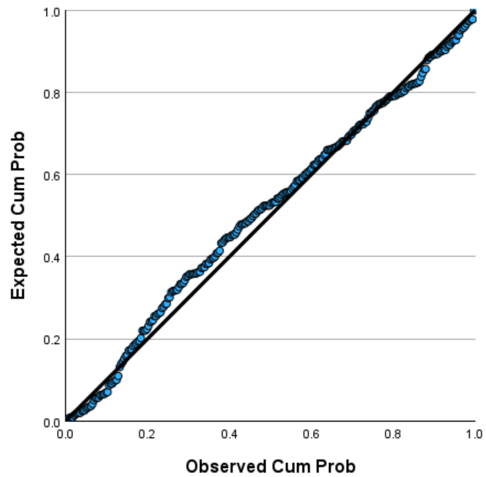
		Collinearity	
		Tolerance	**VIF**
1	Performance Expectancy (PE)	0.486	2.058
	Effort Expectancy (EE)	0.483	2.071
	Attitude Towards Using Technology (ATUT)	0.391	2.559
	Social Influence (SI)	0.563	1.775
	Facilitating Conditions (FC)	0.588	1.700
	Self-Efficacy (SE)	0.754	1.327
	Anxiety (ANX)	0.799	1.251

Note. This table includes the tolerance and VIF for each independent variable, with the dependent variable being Behavior Intention (BI).

The residuals also met the assumption of multivariate normality, which is a critical prerequisite for valid parametric testing. Evidence of normality was obtained from multiple sources: a bell-shaped histogram of standardized residuals, close alignment of observed values with the diagonal line in the P–P plot (Figure 2), and a non-significant Shapiro–Wilk test result. Taken together, these indicators suggest that deviations from the expected normal distribution were minimal, thereby allowing the use of inferential statistical tests without concern for biased parameter estimates.

Figure 2

P-P Plot Regression Standardized Residuals

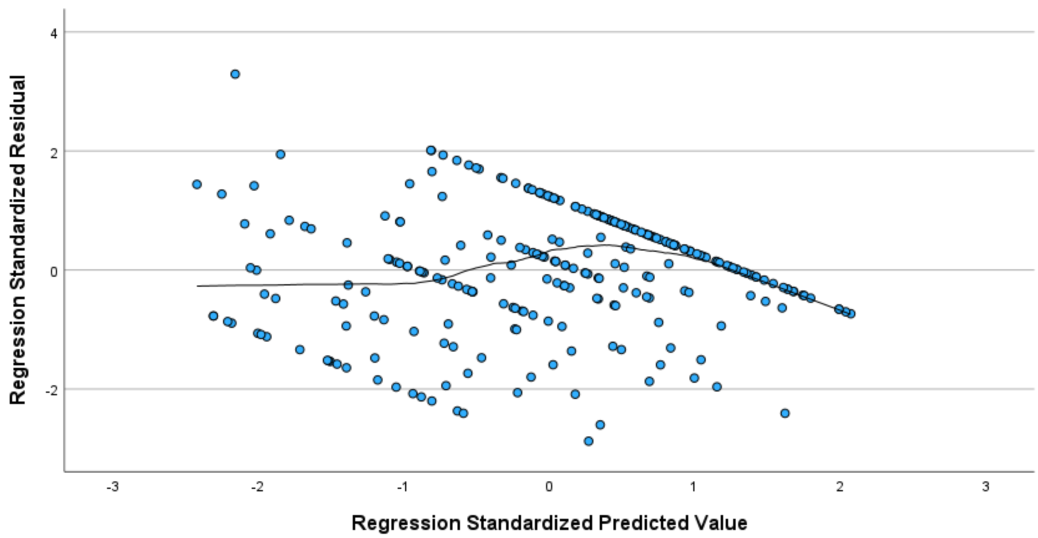


Note. This plot shows the expected versus observed cumulative probability for regression-standardized residuals.

Finally, the assumption of homoscedasticity was confirmed, meaning that the variance of the residuals was consistent across all levels of predicted BI. This was visually supported by a scatterplot of standardized residuals, which showed no discernible pattern, along with a LOESS curve that remained flat and did not indicate any systematic curvature or variance funneling (Figure 3). The presence of homoscedasticity strengthens confidence that the standard errors of the coefficients are unbiased, ensuring that significance tests for PE and the other predictors remain valid and interpretable. This stability across the range of predicted values suggests that the model's predictive accuracy is equally reliable for respondents with both lower and higher anticipated adoption intentions.

Figure 3

Regression Standardized Predicted Value with LOESS curve



Note. This scatter plot shows regression standard residual actual versus predicted values with a LOESS fit curve.

The multiple regression model including all seven predictors was statistically significant, $F(7, 262) = 34.73$, $p < .001$, explaining 48.1% of the variance in BI. However, PE itself was not a significant predictor ($B = 0.088$, $\beta = 0.065$, $p = .312$; Table 7). This result supports H_{1o} and rejects H_{1a}, indicating that, after controlling for other variables, the extent to which respondents believed wearable devices would enhance their job performance did not meaningfully influence their intention to adopt them. In the full regression equation below, the PE coefficient reflects a small, non-significant positive relationship.

$$BI = 0.709 + 0.088(PE) + 0.090(EE) + 0.485(ATUT) + 0.322(SI) + 0.197(FC) - 0.139(SE) - 0.299(ANX) \quad (1)$$

While the overall model fit demonstrates that the predictors collectively explain a substantial portion of BI variance, the lack of significance for PE suggests that perceived performance benefits alone may not be a primary driver of adoption among Oregon healthcare professionals.

Table 7

Multiple Linear Regression Output Summary

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	0.709	0.461		1.538	0.125
Performance Expectancy (PE)	0.088	0.087	0.065	1.013	0.312
Effort Expectancy (EE)	0.090	0.103	0.056	0.870	0.385
Attitude Towards Using Technology (ATUT)	0.485	0.107	0.322	4.520	<0.001
Social Influence (SI)	0.322	0.094	0.202	3.414	<0.001
Facilitating Conditions (FC)	0.197	0.100	0.114	1.960	0.051
Self-Efficacy (SE)	-0.139	0.090	-0.079	-1.551	0.122
Anxiety (ANX)	-0.299	0.061	-0.246	-4.936	<0.001

Note. This table displays the regression output for each independent variable as compared to the dependent variable of Behavioral Intentions (BI).

Effort Expectancy: Research Question 2

The second research question investigated whether Effort Expectancy (EE) significantly predicted BI. EE represents the perceived ease of using the technology, a factor often critical in fast-paced healthcare environments where usability and efficiency are paramount. The null hypothesis (H_{2o}) proposed that EE would not significantly influence BI, while the alternative hypothesis (H_{2a}) suggested that EE would significantly influence BI.

Descriptive statistics showed EE scores ranged from 1 to 5, with a mean of 4.16 (SD = 0.81) and skewness of −1.17 (Table 5), indicating that most respondents perceived wearable devices as relatively easy to use. This stronger skew toward agreement, compared with PE's distribution, suggests that ease-of-use perceptions are more consistently positive across the sample. BI descriptive statistics were consistent with those reported in RQ1, maintaining a mean of 3.82 and a skewness of −0.82, indicating consistently high adoption intentions across all specific predictors considered.

Prior to hypothesis testing, regression assumptions were reviewed to ensure that EE's coefficient could be interpreted with confidence. Multicollinearity diagnostics indicated that EE was sufficiently independent from other predictors, with a VIF of 2.071 and a tolerance of 0.483 (Table 6). These values fall comfortably within recommended limits, which is important because high intercorrelation between predictors can distort the apparent influence of each variable, making effects appear weaker or stronger than they truly are. The independence of EE here suggests that its relationship with BI is not confounded by excessive overlap with other UTAUT constructs.

The residuals associated with the model met the assumption of multivariate normality. A visual inspection of the P–P plot (Figure 2) revealed that observed residuals closely followed the diagonal reference line, while the histogram of residuals demonstrated the expected bell-shaped distribution. This pattern was further reinforced by a non-significant Shapiro–Wilk test, confirming that deviations from normality were minimal. Meeting this assumption is essential because it ensures that the inferential tests applied to EE's coefficient yield accurate p-values and confidence intervals, without bias caused by skewed error terms.

Finally, the assumption of homoscedasticity was evaluated and confirmed. The scatterplot of standardized residuals against predicted BI values, supplemented by the LOESS curve (Figure 3), revealed no funnel shapes or curvature, suggesting that variance in residuals remained constant across all levels of predicted BI. This uniform variance increases the reliability of significance testing for EE, ensuring that any conclusions drawn about its role in adoption are not undermined by heteroscedasticity.

The overall regression model remained statistically significant, $F(7, 262) = 34.73$, $p < .001$, explaining 48.1% of the variance in BI. However, EE's coefficient was small and non-significant ($B = 0.090$, $\beta = 0.056$, $p = .385$; Table 7). This finding supports H20 and rejects H2a, indicating that while respondents generally viewed wearable devices as easy to use, this perception alone did not significantly influence their adoption intentions when other factors were taken into account. The positive but non-significant coefficient suggests that ease of use may function as a baseline expectation in this context, meaning it is important but not decisive in driving adoption decisions.

Social Influence: Research Question 3

The third research question explored whether Social Influence (SI) predicted BI. SI refers to the degree to which individuals perceive that important others, such as colleagues, supervisors, or the broader workplace culture, believe they should use the technology. The null hypothesis ($H3_0$) stated that SI would not significantly influence BI, whereas the alternative hypothesis ($H3_a$) stated that SI would significantly influence BI. In technology adoption theory, SI is often conceptualized as a key driver in contexts where organizational norms and peer endorsement play a central role, making it a particularly relevant factor to examine in healthcare settings where team-based decision-making is common.

SI scores in this study ranged from 1 to 5, with a mean of 3.19 (SD = 0.82) and a skewness of −0.24 (Table 5). This distribution indicates a relatively balanced spread of responses, with only a slight lean toward agreement, suggesting that while some healthcare professionals felt notable encouragement from peers or superiors to adopt wearable devices, others perceived minimal or no such influence. The moderate variability also suggests that social and cultural dynamics vary across work settings, potentially influencing adoption behaviors in non-uniform ways.

Before hypothesis testing, a thorough set of assumption checks was conducted to ensure the validity of regression estimates for SI. Multicollinearity diagnostics revealed a VIF of 1.775 and a tolerance value of 0.563 (Table 6), which fall comfortably within recommended thresholds. These results confirm that SI maintained statistical independence from other predictors, reducing the risk of inflated standard errors or confounded effects due to overlap with related constructs such as ATUT or FC. The independence of SI strengthens the interpretability of its coefficient, ensuring that any observed relationship with BI can be more confidently attributed to the unique influence of social norms.

Residual normality was supported by multiple converging pieces of evidence. The P–P plot of standardized residuals (Figure 2) displayed a close alignment between observed values and the diagonal reference line, suggesting that residuals approximated a normal distribution. This visual evidence was reinforced by a histogram of residuals, which exhibited a symmetrical, bell-shaped curve consistent with the expected pattern for normally distributed errors. Furthermore, the Shapiro–Wilk test was non-significant, which statistically confirmed the absence of major deviations from normality. Together, these results provide a solid basis for interpreting statistical significance without concerns about bias from non-normal residuals.

The assumption of homoscedasticity was also satisfied. The scatterplot of standardized residuals against predicted BI values showed no visual pattern that would indicate changing variance across the prediction range. In addition, the LOESS curve (Figure 3) remained essentially flat, further supporting the conclusion that residual variance was stable. This finding enhances confidence in the reliability of standard errors and p-values for SI, as violations of this assumption can lead to misleading inferential results.

The full regression model was statistically significant, $F(7, 262) = 34.73$, $p < .001$, accounting for 48.1% of the variance in BI. Within this model, SI emerged as a statistically significant positive predictor, with a beta coefficient of 0.322 ($\beta = 0.202$, $p < .001$; Table 7). This leads to the rejection of $H3_0$ and acceptance of H3a, indicating that higher levels of perceived encouragement or expectations from influential others were associated with a greater likelihood of adopting wearable devices. The magnitude of SI's effect suggests that social norms and peer expectations are not only relevant but may exert a stronger motivational force than perceived functional advantages or ease of use in this professional context.

Facilitating Conditions: Research Question 4

The fourth research question assessed whether Facilitating Conditions (FC) predicted BI. FC represents the degree to which individuals believe that organizational and technical infrastructure exists to support technology use. The null hypothesis ($H4_0$) proposed that FC would not significantly influence BI, while the alternative hypothesis (H4a) suggested that FC would significantly influence BI. In many organizational technology adoption studies, FC is viewed as a critical enabler of sustained use, particularly when technologies necessitate integration into existing workflows.

Descriptive analysis revealed that FC scores ranged from 1 to 5, with a mean of 3.72 (SD = 0.75) and a skewness of −0.91 (Table 5). This negatively skewed distribution indicates that a majority of respondents agreed that facilitating conditions were present in their workplace, though there remained meaningful variation in perceptions of organizational readiness and available resources. Such variation may reflect differences between large, resource-rich institutions and smaller or under-resourced healthcare settings, where the availability of technical support or infrastructure may be less consistent.

Regression diagnostics confirmed that FC maintained independence from the other predictors, as indicated by a VIF of 1.700 and a tolerance value of 0.588 (Table 6). These results suggest that multicollinearity was not an issue, allowing for the unique contribution of FC to BI to be interpreted without distortion from overlapping variance with related constructs such as PE or SI. This independence is essential for understanding whether organizational infrastructure itself, rather than related attitudes or social factors, has a direct link to adoption intentions.

The normality of residuals was supported by the P–P plot (Figure 2), which showed that the residuals closely followed the diagonal reference line, indicating minimal departure from normality. The histogram of residuals further confirmed this, displaying a symmetric bell-shaped curve. A non-significant Shapiro–Wilk test provided additional statistical confirmation that residuals were normally distributed, reinforcing the appropriateness of parametric tests for FC. The homoscedasticity assumption was also satisfied, as evidenced by the scatterplot of residuals and the corresponding LOESS curve (Figure 3), which both show consistent variance across predicted BI values. This finding is critical because it confirms that the standard errors for FC's coefficient are unbiased, enabling valid hypothesis testing. Without homoscedasticity, p-values could be either inflated or deflated, leading to incorrect conclusions.

The regression model, including FC alongside the other six predictors, remained statistically significant, $F(7, 262) = 34.73$, $p < .001$, explaining 48.1% of the variance in BI. FC's coefficient was positive ($B = 0.197$, $\beta = 0.114$) but narrowly missed the conventional $p < .05$ significance threshold ($p = .051$; Table 7). While this supports $H4_0$ and rejects $H4_a$ in strict statistical terms, the proximity to significance suggests a potentially meaningful trend that may have practical implications. This finding indicates that while organizational support and infrastructure are valued, their influence on behavioral intention may operate indirectly, perhaps by shaping attitudes or reinforcing social norms rather than directly driving adoption decisions.

Additional Predictors: ATUT, SE, and ANX

Beyond the four primary UTAUT constructs, the regression model incorporated three additional predictors of Attitude Toward Using Technology (ATUT), Self-Efficacy (SE), and Anxiety (ANX) to capture broader psychological and affective influences on adoption. While these variables were not tied to specific research questions, their inclusion enriches the understanding of adoption drivers by examining motivational and emotional factors alongside functional and organizational considerations.

Descriptive statistics revealed generally favorable perceptions for ATUT ($M = 3.80$, $SD = 0.86$, skewness $= -0.67$) and SE ($M = 3.79$, $SD = 0.75$, skewness $= -0.61$), paired with relatively low levels of ANX ($M = 2.15$, $SD = 1.07$, skewness $= 0.67$) (Table 5). These findings suggest that, overall, respondents approached wearable devices with positive attitudes, felt capable of using them, and experienced comparatively little apprehension toward their adoption.

However, the variation within these distributions indicates that subgroups with less favorable attitudes or higher anxiety exist and may require targeted interventions.

Multicollinearity diagnostics confirmed that all three predictors were independent of the other variables in the model, with VIF values of 2.559 for ATUT, 1.327 for SE, and 1.251 for ANX (Table 6). These values fall well below conservative cutoffs, ensuring that their coefficients can be interpreted without concern for inflated standard errors or suppression effects. This independence is particularly important for ATUT and SE, which could theoretically overlap with PE or EE, but in this dataset did not exhibit problematic correlation levels.

The assumption of residual normality was met for all three variables. P–P plots (Figure 2) displayed close alignment of residuals to the diagonal reference line, and histograms demonstrated symmetrical, bell-shaped curves. Shapiro–Wilk tests for each variable were non-significant, providing statistical confirmation of normality and supporting the validity of the inferential results. The homoscedasticity assumption was likewise upheld, as residual scatterplots and LOESS curves (Figure 3) indicated stable variance across predicted BI values. This uniformity ensures that the significance levels for ATUT, SE, and ANX can be trusted as unbiased indicators of their relationships with BI.

The full regression model remained highly significant, $F(7, 262) = 34.73$, $p < .001$, explaining 48.1% of the variance in BI. Among these additional predictors, ATUT emerged as the strongest positive predictor in the entire model ($B = 0.485$, $\beta = 0.322$, $p < .001$; Table 7), underscoring the central role of favorable attitudes toward technology in driving adoption. ANX also reached statistical significance but with a negative relationship ($B = -0.299$, $\beta = -0.246$, $p < .001$), indicating that higher levels of technology-related anxiety substantially reduced adoption intentions. SE, while conceptually relevant, did not achieve statistical significance ($B = -0.139$,

$\beta = -0.079$, $p = .122$), suggesting that confidence in one's technical abilities alone may not be sufficient to motivate adoption in this context.

Together, these results highlight the importance of considering psychological and emotional factors in addition to the traditional UTAUT constructs when seeking to understand technology adoption in healthcare. Favorable attitudes appear to actively encourage adoption, whereas anxiety functions as a barrier even when other facilitating conditions are present. By contrast, technical self-confidence, while beneficial for user competence, does not necessarily translate into a greater intention to adopt without positive perceptions and reduced apprehension.

Evaluation of the Findings

The purpose of this section is to interpret the results presented in the previous section within the context of the research questions, hypotheses, theoretical framework, and relevant literature. The Unified Theory of Acceptance and Use of Technology (UTAUT) and related constructs provided the primary lens for analysis. Each construct's role in predicting behavioral intention (BI) is evaluated to determine whether the findings align with, extend, or diverge from prior scholarship. This process not only highlights the statistical outcomes but also situates them within the broader discourse on technology adoption in healthcare. Doing so enables a more nuanced understanding of both the theoretical and practical significance of the results, while also identifying areas where the data challenge prevailing assumptions.

Performance Expectancy: Research Question 1

Research question one asked, "To what extent does performance expectancy influence the decision of healthcare professionals to adopt wearable smart devices in Oregon?" Performance Expectancy (PE) reflects the degree to which an individual believes that using a technology will enhance their job performance. The null hypothesis ($H1_0$) proposed no significant influence on BI, while the alternative hypothesis ($H1_a$) predicted a significant positive effect. The regression analysis yielded a p-value of .280, indicating that PE was not a statistically significant predictor of BI in this sample. This outcome contrasts with much of the UTAUT literature, where PE is often one of the most robust predictors of technology adoption (Venkatesh et al., 2003).

The lack of statistical significance in this context suggests that healthcare professionals in Oregon may not strongly associate wearable device use with direct improvements in their clinical effectiveness or efficiency. Another plausible explanation is that wearable devices may still be perceived as supplementary rather than essential tools in healthcare delivery. Furthermore, it is possible that the benefits of wearable devices are seen as more relevant to patient self-monitoring than to the professionals' own performance metrics, thereby diminishing the influence of PE on BI. This divergence from established findings highlights the need for further investigation into how performance-related benefits are communicated, demonstrated, and evaluated in healthcare settings.

Effort Expectancy: Research Question 2

Research question two asked, "To what extent does effort expectancy influence the decision of healthcare professionals to adopt wearable smart devices in Oregon?" Effort Expectancy (EE) measures the perceived ease of learning and using a technology. The null hypothesis ($H2_0$) stated that EE would not significantly influence BI, while the alternative hypothesis ($H2_a$) predicted a positive effect. The regression results showed a p-value of .280, indicating that EE was not a statistically significant predictor in this model. This is somewhat surprising given EE's established role as a key determinant of technology acceptance in prior UTAUT-based research.

Several factors may explain this finding. The sample's relatively high mean EE score suggests that most participants already viewed wearable devices as easy to use, which could have reduced variability and limited the ability of EE to predict BI. Additionally, healthcare professionals are accustomed to integrating various forms of technology into their workflows, which may reduce the influence of perceived ease of use on adoption decisions. If ease of use is uniformly high across respondents, it may function more as a baseline expectation than a differentiating factor in adoption intention. This ceiling effect highlights the importance of understanding context-specific user experiences when evaluating the predictive power of EE.

Social Influence: Research Question 3

Research question three asked, "To what extent does social influence impact the decision of healthcare professionals to adopt wearable smart devices in Oregon?" Social Influence (SI) refers to the degree to which individuals perceive that important others (such as colleagues, supervisors, or workplace culture) believe they should use the technology. The null hypothesis ($H3_0$) proposed no significant influence on BI, while the alternative hypothesis ($H3_a$) predicted a significant positive effect. The analysis revealed that SI was a statistically significant predictor, with a p-value of $< .001$.

This result confirms the impact of organizational norms, peer expectations, and leadership endorsement on driving adoption. The finding is consistent with the UTAUT framework, which emphasizes that SI tends to be especially important in environments where usage is either mandated or culturally reinforced. In healthcare, where professional reputation, standard of care alignment, and team cohesion are critical, social and organizational pressures can significantly influence individual adoption decisions. Practically, this suggests that initiatives to promote wearable device adoption could benefit from leveraging respected opinion leaders, peer champions, and visible managerial support. By embedding the use of wearable devices into the organizational culture, adoption may be enhanced, even in the absence of strong perceptions of performance benefits or ease of use.

Facilitating Conditions: Research Question 4

Research question four asked, "To what extent do facilitating conditions influence the decision of healthcare professionals to adopt wearable smart devices in Oregon?" Facilitating Conditions (FC) reflect the extent to which individuals believe the technical and organizational infrastructure exists to support the use of a given technology. The null hypothesis ($H4_0$) proposed no significant influence on BI, while the alternative hypothesis ($H4_a$) predicted a significant positive effect. FC approached statistical significance, with a p-value of .051, falling just short of the conventional $\alpha = .05$ threshold.

Although this result does not meet the formal criterion for significance, it suggests a potential practical influence that warrants further investigation. Organizational and technical readiness, such as the availability of technical support, integration with existing systems, and adequate training, may not have been the most immediate driver of adoption intention; however, these factors could still play a critical role in sustaining long-term usage. The improved Cronbach's alpha for FC (.52, up from .30 in earlier analyses) also strengthens confidence in the construct's measurement reliability. These findings align with prior research that emphasizes the foundational importance of infrastructure in enabling technology adoption, particularly in complex and resource-dependent environments such as healthcare.

Other Predictors: Attitude Toward Using Technology, Self-Efficacy, and Anxiety

Beyond the four core UTAUT constructs, three additional predictors were examined to capture attitudinal and affective dimensions of technology adoption: Attitude Toward Using

Technology (ATUT), Self-Efficacy (SE), and Anxiety (ANX). ATUT emerged as the strongest positive predictor in the model ($\beta = 0.318$, $p < 0.001$), underscoring the central role of a user's general disposition toward technology in shaping their adoption intentions. This finding aligns with the extended UTAUT2 framework and with research in technology readiness, which emphasizes optimism and innovativeness as key drivers of adoption. In practical terms, interventions aimed at cultivating positive technology attitudes, such as early exposure to success stories, peer modeling, and low-stakes trial opportunities, may yield greater adoption gains than focusing solely on functional performance or ease of use.

Self-Efficacy (SE), defined as a user's confidence in their ability to operate wearable devices effectively, did not reach statistical significance ($\beta = -0.079$, $p = .122$). While prior studies have often linked high SE to a greater likelihood of adoption, the null result here may be explained by the uniformly high confidence levels reported by participants, resulting in a restricted range and reduced predictive variance. In such contexts, SE may function as a threshold condition, necessary for adoption but insufficient to explain variation among already capable users. This finding suggests that resources devoted solely to boosting confidence may have a limited incremental impact in similar professional populations unless aimed at specialized subgroups with lower baseline technological competence.

Anxiety (ANX) exhibited a strong negative relationship with BI ($\beta = -0.250$, $p < .001$), indicating that apprehension, discomfort, or fear of failure can meaningfully deter adoption, even among trained professionals. This aligns with affective computing research and technology acceptance studies, which highlight emotional barriers as significant obstacles to technology adoption. In healthcare environments, anxiety may be compounded by concerns about device reliability, patient data privacy, or the potential for reputational harm if technology use leads to errors. Notably, the influence of ATUT and ANX may be interdependent. Users with high ATUT may be less susceptible to the deterrent effects of ANX, while those with lower ATUT may find their hesitations amplified by anxiety. This interplay suggests that strategies to promote adoption should aim to both cultivate positive attitudes and proactively address sources of apprehension, such as through reassurance, transparent privacy safeguards, and gradual onboarding.

From a longitudinal perspective, ATUT and ANX are likely to evolve with real-world exposure to wearable devices. Positive early experiences can reinforce favorable attitudes and diminish anxiety, while negative or stressful experiences can have the opposite effect. This dynamic underscores the importance of sustained support mechanisms, continuous feedback loops, and opportunities for professional users to share both challenges and successes over time. Collectively, these results suggest that attitudinal and emotional factors, particularly ATUT and ANX, may have a more consistent and enduring influence on adoption than traditional UTAUT constructs, such as PE and EE, in this healthcare-specific context.

Summary

This chapter presents a comprehensive analysis of data from 270 valid survey responses from healthcare professionals in Oregon, examining the factors that influence the adoption of wearable smart devices. Guided by the Unified Theory of Acceptance and Use of Technology (UTAUT), the analysis evaluated the assumptions of multiple linear regression, including reliability, validity, normality, multicollinearity, and homoscedasticity. All assumptions were adequately met, and the instrument demonstrated strong psychometric properties, with acceptable reliability and validity. Descriptive statistics provided insight into the overall patterns in the dataset, including means, ranges, variances, and symmetry of distribution for key variables. Multiple data visualizations confirmed near-normal distribution of the variables and residuals, supporting the appropriateness of linear regression analysis.

The regression model was statistically significant, explaining 48.1% of the variance in behavioral intention to adopt wearable smart devices. While performance expectancy (PE), effort expectancy (EE), and self-efficacy (SE) were not statistically significant predictors in this study, attitude toward using technology (ATUT), social influence (SI), and anxiety (ANX) were found to be significant. ATUT and SI demonstrated a positive relationship with behavioral intention, whereas ANX showed a significant negative association. Facilitating conditions (FC) approached significance with a p-value of .051 and demonstrated improved internal reliability ($\alpha = .52$), suggesting it may exert a meaningful, though not conclusive, influence on adoption behaviors.

The strong performance of attitudinal and emotional variables within this framework both supports and challenges aspects of the original UTAUT model, suggesting that in this healthcare context, personal attitudes and emotional responses to technology may outweigh perceived ease of use, expected performance benefits, or self-efficacy. Altogether, these findings provide a robust model that accounts for nearly half (48.1%) of the variance in behavioral intention to adopt wearable devices, underscoring the combined importance of cognitive, social, and affective influences in shaping technology acceptance among healthcare professionals.

Chapter 5: Implications, Recommendations, and Conclusions

The purpose of this quantitative study was to gain a deeper understanding of the factors that drive or hinder healthcare professionals in Oregon from adopting wearable smart devices. While these tools hold considerable promise for improving patient outcomes, enabling remote monitoring, and supporting proactive care (Kang & Exworthy, 2022; Piwek et al., 2016), their use in clinical practice has remained inconsistent. Grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), the influence of seven key factors on behavioral intention was explored: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Self-Efficacy (SE), Anxiety (ANX), and Attitude Toward Using Technology (ATUT) (Venkatesh et al., 2003).

Findings from 270 healthcare professionals revealed that ATUT and SI were significant positive predictors of adoption, while ANX was a significant negative predictor. SE, PE, and EE were not statistically significant, and FC approached but did not reach significance. These results indicate that attitudinal and emotional variables, such as openness to technology, social endorsement, and anxiety, played a stronger role in predicting adoption than traditional usability-related factors. This divergence is important. Much of the existing research has focused on general consumer populations or broad healthcare settings, often emphasizing perceived usefulness and ease of use as central drivers of technology adoption (Aggelidis & Chatzoglou, 2009; Davis, 1989). However, among healthcare professionals, particularly in a region like Oregon, the emotional and social dimensions of technology use may be more influential than usability concerns alone. These findings are supported by the literature, which emphasizes the role of professional culture, peer influence, and individual psychological readiness in healthcare technology decisions (Acquisti et al., 2015; Legris et al., 2003).

This research matters not only for challenging assumptions in the literature but also for offering practical and timely insights into how to support the integration of wearable technology in real clinical environments. For healthcare leaders, the findings highlight the need to go beyond training and system design (Greenhalgh et al., 2004). Building trust in technology, addressing anxiety, and cultivating a socially supportive workplace culture may be just as crucial, if not more so, for encouraging adoption (Wu et al., 2007; Yusif et al., 2016). For developers and policymakers, the results underscore the importance of human-centered design and implementation strategies that account for emotion, perception, and peer influence, not just functionality (Or & Tao, 2012; Rahimi & Vimarlund, 2007).

What makes this study especially compelling is that researchers and practitioners are prompted to consider the overlooked dimensions of adoption and to ask new questions. Even the most advanced devices can be ignored if people feel uncertain or unsupported (Kim & Park, 2012). The findings reinforce that peer endorsement and workplace culture are important (Karahanna et al., 1999) and challenge the notion that better features automatically lead to higher adoption rates (Pai & Huang, 2011). Fresh data from an understudied region offers insights that may apply to similar communities across the country (Cresswell & Sheikh, 2013). Attitudes shaped by experience, fear, and hope can powerfully influence behavior in ways that traditional models may not fully capture (Chau & Hu, 2002; Kang & Exworthy, 2022).

Ultimately, both researchers and practitioners can draw theoretical and practical value from this study. Understanding what drives wearable tech adoption can be expanded by revisiting and reordering familiar constructs, providing concrete direction for those seeking to bring meaningful innovation into the hands of healthcare professionals. As the industry continues to adopt digital tools, these insights will be crucial for designing interventions that effectively meet the needs of those delivering care (Canali et al., 2022; Lu et al., 2020). In doing so, future adoption strategies can be tailored not only to address functional requirements but also to proactively foster the social support and emotional confidence needed for long-term, sustained use.

Implications

Empirical evidence is presented that refines the application of the Unified Theory of Acceptance and Use of Technology (UTAUT) in professional healthcare settings, contributing to a broader understanding of technology adoption in clinical contexts. The prominence of social influence, anxiety, and attitude toward using technology, rather than the traditionally dominant constructs of performance expectancy and effort expectancy, suggests that existing models for implementation, training, and policy development should be re-evaluated to account for the social and emotional dimensions of adoption. Implications for technology developers, healthcare administrators, and policymakers are indicated, particularly with respect to fostering more human-centered strategies for integrating wearable smart devices in healthcare settings.

From a policy perspective, the findings point to the need for institutional and regional frameworks that support culture-building and peer-led advocacy, rather than relying solely on mandates or incentives for technology adoption (Chau & Hu, 2002; Greenhalgh et al., 2004). Emphasis should be placed on policies that actively address digital confidence and emotional readiness among clinical staff, given the role of anxiety as a significant barrier to behavioral intention (Yusif et al., 2016). Regulatory clarity around data security, interoperability, and the use of patient-generated health data can also contribute to reducing skepticism and promoting more consistent adoption (Acquisti et al., 2015).

For healthcare administrators, a reorientation toward socially reinforced, emotionally supportive implementation strategies is warranted. The development of "digital champion" programs, wherein respected peers model, reinforce, and normalize the use of wearable devices, may be particularly effective in mitigating anxiety and improving overall attitudes toward adoption (Legris et al., 2003; Venkatesh et al., 2003). Training efforts should move beyond simple functionality demonstrations to include narrative examples of clinical success, opportunities for hands-on experimentation, and structured support that prioritizes psychological comfort and gradual exposure (Or & Tao, 2012; Wu et al., 2007).

For developers, the importance of designing for clinical applicability rather than consumer aesthetics alone is emphasized in the results. Greater attention must be given to interface simplicity, workflow compatibility, and emotional usability, as these factors can reduce anxiety and strengthen adoption among time-constrained and risk-averse healthcare professionals (Jovanov & Milenkovic, 2011; Patel et al., 2015). Design processes that include clinician input during early development stages can enhance the relevance, trustworthiness, and usability of wearable smart devices in clinical settings (Cresswell & Sheikh, 2013).

Overall, traditional implementation models, those focused primarily on improving usability, appear insufficient. A more holistic approach is needed, one that considers psychological readiness, peer influence, and institutional context. As digital transformation accelerates across healthcare systems, these insights can support more effective strategies for integrating wearable technology into routine clinical care (Canali et al., 2022; Kang & Exworthy, 2022).

Research Question 1/Hypothesis: Performance Expectancy

The first research question asked: To what extent does performance expectancy influence the decision of healthcare professionals to adopt wearable smart devices in Oregon? The corresponding hypothesis tested whether performance expectancy (PE), defined as the degree to which a user believes that using a specific technology will help attain gains in job performance, significantly predicts behavioral intention to adopt such devices (Venkatesh et al., 2003). Contrary to the expectations set by the original UTAUT framework, the results of this study revealed that PE did not significantly influence behavioral intention in this context, with a p-value of .280. This finding stands in marked contrast to the body of antecedent literature in which PE consistently emerged as one of the strongest predictors of adoption across various healthcare technologies (Aggelidis & Chatzoglou, 2009; Holden & Karsh, 2010; Maillet et al., 2015;). In many of those studies, professionals who believed technology would enhance outcomes or efficiency were significantly more likely to adopt said technology. The divergence observed in this study, therefore, signals an important shift, or at least a contextual deviation, from previous assumptions about what drives adoption behavior in clinical environments.

Several possible explanations for this inconsistency can be considered. First, it is possible that wearable smart devices have not yet demonstrated strong or consistent clinical value in the everyday workflows of healthcare professionals in Oregon. Unlike electronic health records (EHRs) or clinical decision support tools, which have direct and well-documented impacts on task performance, wearable technologies may be perceived more as adjunct wellness tools than as clinical necessities (Kang & Exworthy, 2022). If professionals do not view wearables as devices that materially improve patient care or streamline their clinical responsibilities, the perceived performance benefit may be low or ambiguous, thus diminishing PE's influence on adoption.

Integration challenges may also contribute to this perception. Wearable device data may not yet be effectively incorporated into the platforms clinicians rely on, such as Electronic Health Records systems (EHRs), or may be seen as redundant to information gathered through traditional diagnostic methods. Prior studies have emphasized the importance of interoperability and seamless data integration for the adoption of healthcare technology (Jovanov & Milenkovic, 2011; Rahimi & Vimarlund, 2007). Without a clear pathway from data collection to clinical action, the utility of wearable technology may be perceived as limited, regardless of its technical capabilities

This outcome also aligns with recent findings that call into question the universal relevance of performance expectancy (PE) across all technology types and user groups. For instance, Cresswell and Sheikh (2013) found that performance-based motivations were weaker among clinicians evaluating newer or less institutionalized technologies, where risk aversion and uncertainty were more prominent than anticipated gains. This suggests that PE may be highly sensitive to both the maturity of the technology and the specificity of its use case.

The implications of these findings are significant for both policy and practice. For technology developers and implementation teams, these results indicate that simply promoting the functional or performance-based benefits of wearable devices may not be sufficient to drive clinician adoption. Instead, emphasis should be placed on demonstrating clinical relevance through pilot programs, research validation, and integration with core healthcare systems. Clear case studies showing how wearable data translates into better care decisions or more efficient workflows could help shift perceptions and re-establish PE as a motivator.

For administrators and policymakers, efforts to promote wearable adoption must go beyond marketing their technical potential, according to the study's findings. Adoption strategies should be embedded within broader digital health transformation initiatives that prioritize interoperability, cross-platform utility, and clinician education. Policies that support system-level integration of wearable data and encourage research into clinical applications could help build the foundation necessary for PE to become more salient.

The lack of significance for performance expectancy in this study both contrasts with and complicates the prevailing literature. Rather than indicating that PE is irrelevant, this finding points to the importance of context, particularly the maturity of the technology, its visibility in day-to-day practice, and the clarity of its clinical utility. Future research and policy initiatives should account for these contextual factors to better align implementation strategies with the realities of healthcare professionals' experience.

Research Question 2/Hypothesis: Effort Expectancy

The second research question asked: To what extent does effort expectancy influence the decision of healthcare professionals to adopt wearable smart devices in Oregon? In the UTAUT model, effort expectancy (EE) refers to the degree of ease associated with using a given system (Venkatesh et al., 2003). Based on the regression analysis in this study, EE was not a statistically significant predictor of behavioral intention to adopt wearable smart devices ($p = .280$), indicating that perceived ease of use did not significantly impact adoption decisions among participants.

This result diverges from foundational findings in both the Technology Acceptance Model (TAM) and UTAUT, where perceived ease of use is traditionally identified as a key factor influencing adoption, particularly for new or unfamiliar technologies (Davis, 1989; Venkatesh et al., 2003). In numerous studies focused on clinical technology, EE has been shown to play a crucial role in determining whether healthcare professionals accept or resist digital tools, particularly those that add complexity to existing workflows (Aggelidis & Chatzoglou, 2009; Maillet et al., 2015). However, the results of the present study align with a growing body of more recent literature suggesting that effort expectancy may be declining in influence, particularly in environments where digital literacy is already well-developed and users have extensive exposure to similar technologies. Kim & Park (2012) and Taherdoost (2018), for instance, argue that as general familiarity with digital tools increases among professionals, ease of use becomes less of a distinguishing factor in adoption decisions. This is especially true in populations where baseline comfort with mobile technology and consumer-grade devices, such as fitness trackers and smartwatches, is already high.

Several contextual factors may help explain this diminished role of EE in the present study. First, the sample consisted of healthcare professionals in Oregon, a region where technology use is relatively high in both professional and personal settings, particularly in urban healthcare environments. It is plausible that respondents, already familiar with consumer-facing wearables, did not view these tools as complex or intimidating. If the technology is already perceived as accessible, ease of use becomes a non-issue and, consequently, a non-factor in driving behavior.

The nonsignificant influence of EE may reflect a more emotionally or socially driven adoption context. As demonstrated in this study, constructs such as anxiety and attitude toward technology were statistically significant predictors, suggesting that how people feel about wearable technology and how they perceive it may outweigh practical considerations like simplicity or effort. This aligns with research by Or & Tao (2012) and Wu et al. (2007), who noted that once baseline usability is met, psychological and social factors take precedence in shaping behavior.

The implications of these findings are significant for developers, administrators, and implementation teams. For developers, the focus may need to shift away from minimizing friction in basic interaction design (which may already be sufficiently intuitive) toward addressing emotional usability, aesthetic comfort, and context-specific functionality. For example, wearables designed for clinicians should consider how the device is worn during long shifts, how unobtrusively it integrates with routines, and how it communicates clinically relevant and timely data, rather than just being "easy to use."

From an administrative perspective, resources traditionally devoted to basic user training on device operation may be more effectively reallocated toward building confidence, creating opportunities for peer-led demonstrations, and addressing latent anxieties or misconceptions about wearables. These findings support a transition from traditional "how-to" implementation strategies to more experience-based onboarding models that emphasize relevance, trust, and peer modeling. At the policy level, the findings suggest that general usability benchmarks are no longer sufficient as criteria for evaluating the readiness of new healthcare technologies for clinical deployment. Instead, adoption frameworks should account for broader environmental and workforce characteristics, including existing technology saturation, digital fluency, and emotional or cultural attitudes toward new tools. Funding and adoption initiatives may be more successful if they promote local pilot studies, user co-design, and feedback loops that assess both psychological readiness and technical feasibility.

While effort expectancy has historically been regarded as a core predictor of technology adoption, this study suggests its influence may be declining in highly digital-literate healthcare environments. Ease of use is no longer a sufficient condition for adoption, nor necessarily a compelling one. This shift underscores the increasing significance of the social and emotional aspects of technology acceptance, prompting a reassessment of what constitutes "barriers" in the contemporary clinical setting.

Research Question 3/Hypothesis: Social Influence

The third research question asked: To what extent does social influence impact the decision of healthcare professionals to adopt wearable smart devices in Oregon? The results showed that social influence (SI) was a statistically significant predictor of behavioral intention ($p < .001$), indicating a strong relationship between perceived peer expectations and an individual's likelihood of adopting wearable technology. This finding is highly consistent with the UTAUT model, which positions social influence as a key construct shaping behavioral intention, especially in environments where collective norms and hierarchical structures are prominent (Venkatesh et al., 2003). The significance of SI in this study also aligns with prior research in healthcare contexts, where clinical adoption patterns have repeatedly been shown to reflect broader professional culture, peer endorsement, and supervisor expectations (Legris et al., 2003; Wu et al., 2007). In team-based and collaborative care environments, such as hospitals and clinics, decisions about whether and how to use new technology are rarely made in isolation. Instead, they are shaped by informal feedback, observation, and modeling within a shared professional community.

The strength of this outcome can be partly attributed to the nature of clinical work, which depends heavily on trust, conformity to protocols, and mutual visibility of behaviors. In such settings, perceived approval or disapproval from respected peers and supervisors can validate or dissuade new behaviors. Research by Chau and Hu (2002) and Karahanna et al. (1999) supported this idea, showing that professionals often adopt technologies not solely because of their perceived usefulness, but because of social signals indicating that adoption is expected, appropriate, or beneficial for group cohesion. This dynamic is particularly pronounced in healthcare, where the consequences of technology use or non-use are closely tied to patient safety and team performance.

The results also align with more recent studies that emphasize the role of clinical champions, opinion leaders, and informal peer influencers in shaping technology adoption (Cresswell & Sheikh, 2013; Greenhalgh et al., 2004). These individuals often serve as both early adopters and trusted guides, helping colleagues navigate uncertainty and build confidence. The finding that social influence significantly predicts adoption behavior reinforces the critical importance of strategically engaging these individuals during implementation efforts. The implications of this outcome are clear for policy and practice. From an organizational perspective, implementation strategies should explicitly integrate peer influence mechanisms, including the identification and support of clinical “technology champions” who can model appropriate use, offer real-time support, and normalize wearable device adoption through daily interactions. Such individuals can bridge the gap between leadership directives and frontline engagement, helping to build a culture of acceptance around wearable technology.

For healthcare administrators, this means prioritizing peer-led training models, shared success stories, and formal recognition of teams that effectively integrate wearable tech into practice. Rather than relying solely on top-down mandates or training sessions focused on technical skills, initiatives should include social proof strategies, such as showcasing early adopters, highlighting department-wide milestones, and creating opportunities for peer discussion and Q&A. At the policy level, regional and institutional guidelines that encourage cross-functional collaboration and shared learning may help amplify the effects of social influence. For example, integrating wearable adoption metrics into team-based quality improvement goals or incentivizing interdepartmental mentoring around digital tools may foster the kind of collaborative engagement necessary for sustained use. Furthermore, social influence dynamics may be especially important in under-resourced or change-resistant settings, where hesitancy can be mitigated more effectively through peer reassurance than through external pressure.

The significance of social influence in this study aligns with a well-established theme in the literature, while also underscoring the importance of socially intelligent implementation practices. The adoption of wearable smart devices is not merely a matter of individual judgment; it is a socially embedded process shaped by interpersonal dynamics, professional trust, and perceived cultural norms. Future initiatives should be designed with this reality in mind to maximize adoption and meaningful use within healthcare environments.

Research Question 4/Hypothesis: Facilitating Conditions

The fourth research question asked: To what extent do facilitating conditions influence the decision of healthcare professionals to adopt wearable smart devices in Oregon? Facilitating conditions (FC), defined within the UTAUT framework as the degree to which an individual believes that organizational and technical infrastructure exists to support technology use, approached statistical significance in this study, with a p-value of .051 (Venkatesh et al., 2003). Although this falls just above the conventional alpha threshold of .05, the proximity suggests a noteworthy trend that may hold practical relevance, particularly when contextualized alongside improved construct reliability.

In earlier stages of analysis, the FC construct exhibited low internal consistency (Cronbach's alpha = 0.30), which limited its interpretability. However, following the removal of a poorly performing item and recalibration of scoring, the revised alpha rose to .52. While still below the ideal reliability threshold, this improvement enhances the credibility of the results and points to a more meaningful, if not yet fully confirmed, relationship between facilitating conditions and behavioral intention to adopt wearable smart devices.

These findings align closely with a substantial body of research indicating that adoption of health information technology is influenced by the availability of technical support, device compatibility, training resources, and leadership commitment (Jovanov & Milenkovic, 2011; Rahimi & Vimarlund, 2007; Venkatesh et al., 2012). Prior studies have shown that in clinical environments, especially those under strain from staffing shortages or infrastructure limitations, access to well-supported digital systems is a critical enabler of technology acceptance (Yusif et al., 2016). As such, the near-significance of FC in this study supports existing literature and suggests that healthcare professionals are aware of the availability (or lack thereof) of support structures when forming their intentions regarding the adoption of wearable technologies.

The marginal nature of the statistical result may reflect contextual factors specific to the healthcare landscape in Oregon. It is possible that respondents acknowledged the relevance of the facilitating conditions conceptually but did not consistently experience strong institutional or technical support in practice. For instance, differences between urban and rural healthcare settings may have introduced variance in perceived infrastructure readiness. Facilities with dedicated IT teams and access to pilot programs may have fostered stronger perceptions of support than those operating with limited resources. These contextual inconsistencies could have diluted the overall predictive strength of FC, even if it remains influential at the local or departmental level. Another consideration is that the construct items may not have fully captured the nuances of what facilitating conditions mean for wearable technology specifically, as opposed to general digital health systems. While much of the literature on FC focuses on traditional IT systems, such as EHRs, telehealth platforms, or hospital networks, wearable devices present unique challenges in terms of device integration, data interoperability, and frontline user support. Respondents may have perceived general IT support as present but inadequate for supporting wearable tech adoption, thus muting the construct's overall effect size.

The implications of these findings are especially important for healthcare administrators and policy leaders. Even in the absence of strict statistical significance, the demonstrated trend suggests that facilitating conditions should not be overlooked when designing implementation strategies for wearable technologies. Investments in technical infrastructure, such as Wi-Fi stability, device interoperability, and secure data management systems, will be essential to ensure wearables can function reliably in clinical settings. Likewise, institutions should consider formalizing training opportunities, IT helpdesk protocols, and ongoing user support specifically for the deployment of wearable devices.

At the policy level, regulatory and funding bodies may need to create incentives and guidelines that encourage organizations to develop dedicated support structures for wearable integration. These could include grants for infrastructure upgrades, cross-system interoperability standards, and workforce development programs tailored to the use of digital health tools. Inconsistent support across institutions may be a barrier not only to adoption but also to equitable access to the benefits that wearable technologies can provide to both providers and patients.

Although facilitating conditions were not statistically significant in this study, the results indicate a strong directional trend that aligns with prior research and holds important implications for practice. While healthcare professionals recognize the value of organizational and technical support, variability in access to such resources may suppress the overall influence of FC at a population level. Future researchers should continue to refine the measurement of this construct, particularly in the context of emerging technologies, such as wearable devices. Implementation efforts should prioritize robust and consistent support environments to ensure sustainable adoption and long-term success.

Additional Findings: Attitude Toward Using Technology (ATUT), Self-Efficacy (SE), and Anxiety (ANX)

Attitude toward using technology (ATUT) emerged as the strongest positive predictor of behavioral intention to adopt wearable smart devices ($\beta = .322$, $p < .001$), while self-efficacy (SE) and anxiety (ANX) also played notable roles in shaping adoption decisions. Although SE was not statistically significant in this study ($\beta = -0.079$, $p = .122$), its inclusion highlights an important psychological dimension in technology adoption literature, confidence in one's ability to effectively use a device. Prior research has shown that higher self-efficacy is generally associated with greater willingness to experiment with and adopt new technologies (Bandura, 1997; Compeau & Higgins, 1995). In this case, the lack of significance may reflect a relatively uniform level of technological confidence among participants, reducing variance and limiting predictive power. Nonetheless, SE remains a theoretically relevant construct that warrants continued attention in both research and implementation planning.

The positive influence of ATUT in this study aligns well with extended models of technology acceptance, such as UTAUT2, which incorporate personal attitudes, hedonic motivation, and emotional drivers as direct predictors of behavioral intention (Venkatesh et al., 2012). This finding supports a growing body of literature suggesting that a positive emotional orientation toward technology can facilitate openness, experimentation, and eventual adoption, particularly in environments where the perceived value of the technology is still evolving or unclear (Or & Tao, 2012; Taherdoost, 2018). Healthcare professionals who possess a general sense of curiosity or enthusiasm toward digital tools are more likely to adopt them, even when traditional performance-based drivers are weak.

Conversely, anxiety (ANX) demonstrated a strong negative influence on behavioral intention ($\beta = -0.246$, $p < .001$), consistent with prior research showing that fear, discomfort, or uncertainty regarding technology can significantly inhibit adoption (Chau & Hu, 2002; Kim & Park, 2012). In high-stakes clinical environments, where errors may have serious consequences, anxiety surrounding unfamiliar devices, particularly those not yet integrated into standard care pathways, can lead to avoidance behaviors. This finding echoes the work of Wu et al. (2007), who emphasized that emotional readiness and psychological safety are often prerequisites for successful technology use in healthcare. The prominence of these attitudinal and psychological constructs suggests a need to shift implementation strategies beyond usability and utility alone. Emotional and psychological comfort may be equally, if not more, important in determining whether healthcare professionals adopt wearable technologies. This is particularly relevant when devices are not mandated by institutional policy or embedded into core workflows but remain optional or supplementary.

From an organizational perspective, implementation plans should explicitly address emotional readiness, self-efficacy, and anxiety. Strategies may include peer modeling, early exposure through pilot programs, low-stakes experimentation, and consistent leadership messaging that frames wearable technology as a supportive tool rather than a monitoring mechanism. Creating psychologically safe spaces for asking questions, expressing concerns, and experimenting without fear of penalty can build both confidence and trust. In terms of training, programs should go beyond procedural instruction to include elements from change management and behavioral psychology. Storytelling, role modeling, and normalization of failure can help shift attitudes, reduce anxiety, and strengthen self-efficacy. Opportunities for clinicians to share positive experiences, co-design features, and witness benefits through peer use can further reinforce confidence.

At the policy level, healthcare institutions and governing bodies may want to consider incorporating psychological and emotional readiness assessments into their digital transformation planning. While infrastructure, security, and compliance remain essential, these findings suggest that affective responses, particularly attitudes, self-efficacy, and anxiety, can determine the ultimate success or failure of wearable technology integration. Policies that fund emotional readiness training, incorporate clinician feedback loops, and ensure supportive rollout environments can help bridge the gap between technical capability and sustained adoption. In this context, ATUT, SE, and ANX should not be treated as peripheral considerations but as central factors in determining whether wearable devices gain meaningful traction in clinical practice.

Significance to Society

The findings of this study hold broad and meaningful implications for society, particularly as healthcare systems continue to evolve through digital transformation. As wearable smart devices transition from consumer wellness tools to clinically relevant technologies, understanding the factors that influence adoption among healthcare professionals becomes crucial for realizing their full potential to enhance care delivery, promote health equity, and support the well-being of both patients and healthcare providers. Wearable technologies have been widely recognized for their ability to enhance clinical outcomes by enabling continuous monitoring, supporting early detection of disease, and personalizing care plans through real-time data collection. Devices such as continuous glucose monitors, cardiac event recorders, and pulse oximeters have demonstrated significant utility in managing chronic conditions and reducing hospitalizations (Lee & Lee, 2020; Patel et al., 2015; Piwek et al., 2016). However, these benefits can only be realized if healthcare professionals are willing and able to integrate such tools into their practice. Understanding what drives or impedes integration deepens when key predictors, such as attitude toward technology, self-efficacy, social influence, and anxiety, are considered alongside traditional performance or usability measures.

These findings underscore a significant shift in the literature from purely functional models of technology adoption toward more comprehensive frameworks that encompass emotional, psychological, and social dimensions. The strong predictive power of attitude and anxiety, coupled with the theoretical relevance of self-efficacy, echoes previous research that emphasizes the importance of considering users' feelings about technology, not just its functionality (Or & Tao, 2012; Venkatesh et al., 2012). This perspective is especially critical in healthcare, where decision-making is shaped not only by logic and workflow but also by trust, professional culture, and risk perception. A device perceived as stressful, intrusive, or unnecessary may be rejected even if it offers demonstrable clinical benefits. Therefore, addressing psychological barriers, reinforcing confidence in technology use, and shaping positive attitudes are essential to ensuring meaningful adoption.

The results of this study also have implications for clinician well-being and workforce sustainability. Burnout is a growing societal concern with consequences for provider retention, care quality, and patient safety (Dyrbye et al., 2017; Shanafelt et al., 2015). Wearable technologies, when thoughtfully implemented, can ease workloads, automate routine monitoring tasks, and provide biofeedback to support provider wellness (Bowman et al., 2021). However, poorly designed or insufficiently supported technologies can have the opposite effect, compounding stress and contributing to emotional fatigue. This study's emphasis on anxiety and emotional readiness, along with the potential role of self-efficacy, underscores the need for organizations to consider not only whether a tool works, but how it is experienced by those expected to use it.

Beyond individual clinics or institutions, the adoption of wearable technology among healthcare professionals is also a matter of public health and health equity. If adoption occurs primarily in well-funded urban centers, patients in rural or under-resourced regions may be excluded from the benefits of continuous, tech-enabled care. In Oregon and similar contexts, geographic disparities in infrastructure and support could widen existing health inequalities. Ensuring that wearable technology is supported by accessible training, consistent policies, and infrastructure investment is essential for equitable implementation. Prior studies have found that disparities in digital health adoption often reflect gaps in support and confidence, not just access to devices (Lu et al., 2020; Yusif et al., 2016). Expanding emotional and institutional support for healthcare workers may therefore have downstream effects on patient equity.

The significance of social influence as a predictor of adoption also underscores the importance of community and culture in the integration of technology. This aligns with prior research demonstrating that adoption is often driven by collective behavior, trust in leadership, and peer modeling (Chau & Hu, 2002; Greenhalgh et al., 2004). Strategies that engage clinical champions, encourage peer-to-peer demonstrations, and foster a visible culture of acceptance are likely to be more effective than isolated training sessions or top-down mandates. Societal benefit can be amplified when adoption is understood not as an individual decision but as a collective, relational process embedded in team dynamics and professional norms.

Furthermore, this study contributes to ongoing conversations about the evolution of digital health policy. Many policy frameworks focus primarily on access to devices and broadband infrastructure, with less emphasis on human-centered implementation practices. However, the findings here suggest that emotional readiness, confidence in use, workplace support, and positive attitudes are just as critical to successful adoption. Policymakers and institutional leaders should consider investing in implementation programs that integrate technical onboarding with confidence-building, emotional support, and peer-based learning. Initiatives that promote collaborative decision-making, offer pilot programs for early exposure, and integrate user feedback into design processes are more likely to foster sustained engagement and reduce technology abandonment.

This study underscores the need for a more comprehensive understanding of technology adoption, acknowledging the intricate interplay between individual emotions, self-efficacy, organizational culture, and systemic support. The societal relevance of these findings extends beyond wearable devices. As healthcare becomes increasingly digital, lessons from this research can inform the implementation of emerging technologies, from artificial intelligence to virtual care platforms. Successful digital transformation requires not only infrastructure and innovation, but also empathy, trust, and a human-centered approach. By identifying both the enablers and barriers to adoption, this research offers a foundation for more inclusive, sustainable, and emotionally intelligent healthcare innovation.

Recommendations for Practice

Several practical strategies can be implemented by healthcare organizations, technology developers, and clinical leaders to support the adoption of wearable smart devices in clinical settings. These recommendations are grounded in the study's statistically significant outcomes and contextualized within the broader research literature on technology adoption in healthcare environments. By applying these findings, stakeholders can better anticipate barriers, leverage key motivators, and design adoption strategies that maximize both individual and organizational readiness for change. Ultimately, these practices can help ensure that wearable technology integration is not only successful in the short term but also sustainable in the long term.

First, social influence was identified as a statistically significant predictor of behavioral intention ($p < .001$), reinforcing the importance of interpersonal dynamics in shaping adoption decisions. This supports the assertion by Venkatesh et al. (2003) that individuals are more likely to adopt a technology if they believe important others, such as colleagues, supervisors, or professional peers, expect or support its use. Similarly, Wu et al. (2007) found that in clinical contexts, physicians and nurses often defer to perceived social norms when deciding whether to engage with health information technologies. The present study confirms and extends these findings by illustrating that, even for emerging tools like wearable smart devices, social influence remains a dominant factor. Healthcare organizations should therefore invest in cultivating clinical champions, such as respected peers who can model the use of technology, offer real-time feedback, and normalize adoption behaviors. Such strategies leverage peer modeling and foster a culture of acceptance, consistent with the literature that emphasizes the value of professional identity and peer approval in medical decision-making (Greenhalgh et al., 2004; Karahanna et al., 1999).

Second, anxiety emerged as a strong negative predictor of adoption behavior ($\beta = -0.246$, $p < .001$), indicating that emotional discomfort with technology poses a significant barrier to uptake. Ragu-Nathan et al. (2008) conceptualized this phenomenon as “technostress” and argued that uncertainty, fear of failure, and cognitive overload can deter individuals from engaging with new digital tools. The present study reaffirms the critical role of emotional readiness in adoption decisions, particularly in high-stakes clinical environments where errors may have serious consequences. To mitigate this, healthcare organizations should design low-stakes, psychologically safe learning environments that prioritize exploration, trial and error, and ongoing support. Mentorship programs, tailored onboarding, and responsive IT support can alleviate anxiety and build user confidence. These interventions align with research advocating for affective support and stress-reduction mechanisms as essential elements of digital implementation strategies (Kim & Park, 2012; Tarafdar et al., 2015).

Third, attitude toward using technology was the strongest positive predictor of adoption behavior ($\beta = .322$, $p < .001$). This outcome is consistent with the UTAUT2 model, which expanded upon the original UTAUT by including personal attitudes and hedonic motivation as key predictors of behavioral intention (Venkatesh et al., 2012). Compared with earlier UTAUT-based studies that emphasized performance or effort expectancy, the current results affirm a growing recognition that emotional and evaluative perceptions of technology often drive real-world adoption, especially in non-mandated environments. Organizational leaders should proactively shape positive attitudes by showcasing success stories, rewarding early adopters, and highlighting the clinical value of wearable technologies. Offering continuing education credits, peer-led demonstrations, or storytelling about patient impact can reinforce favorable attitudes, a strategy supported by studies linking organizational culture and perceived usefulness to sustained technology engagement (Holden & Karsh, 2010; Klecun, 2016).

Fourth, while self-efficacy (SE) was not statistically significant in this study ($p = .122$), its negative coefficient suggests that confidence in one's own ability to use wearable devices may not always translate into intention to adopt, at least in this specific context. This contrasts with earlier research, where self-efficacy consistently served as a positive driver of technology acceptance (Agarwal et al., 2000; Compeau & Higgins, 1995). In practice, this finding suggests that high technical confidence alone may be insufficient if emotional or cultural barriers remain unaddressed. Healthcare organizations should consider pairing skill-building opportunities with initiatives that foster positive attitudes and reduce anxiety, ensuring that confidence is accompanied by motivation and support to use the technology in daily clinical work.

Fifth, although performance expectancy and effort expectancy were not statistically significant in this study, these constructs remain central to the broader technology acceptance literature. Davis (1989) originally proposed perceived usefulness and ease of use as the primary drivers of adoption in the Technology Acceptance Model (TAM), and Venkatesh et al. (2003) further incorporated these ideas into UTAUT. Many researchers have since corroborated their influence, particularly in contexts involving traditional clinical IT systems, such as EHRs or decision support tools (Holden & Karsh, 2010; Rahimi & Vimarlund, 2007). The absence of significance here may reflect a unique context where perceived emotional and social factors outweighed technical evaluations or may suggest that these variables no longer carry as much influence in tech-savvy healthcare environments. As noted by Jacob et al. (2019), null findings can be theoretically and practically meaningful, revealing shifts in adoption drivers or highlighting where assumptions need to be revisited. Therefore, this outcome suggests a need for clearer, more tailored communication about the clinical utility and operational advantages of wearable technologies. Developers and administrators should collaborate to produce context-specific examples, such as improved workflow, patient engagement, or early symptom detection, that clarify how wearables can deliver measurable value.

Sixth, while facilitating conditions did not reach conventional significance ($p = .051$), the near-threshold result, combined with improved reliability ($\alpha = .52$), suggests potential practical importance worth exploring. Venkatesh et al. (2003) defined facilitating conditions as the degree to which individuals perceive that an organizational and technical environment exists to support the use of a system. Numerous studies have found that perceived support, training, and infrastructure are critical for technology acceptance (Cresswell & Sheikh, 2013; Yusif et al., 2016). Although the internal consistency of the construct was modest in this study, the directional trend aligns with the existing literature, which highlights the importance of resource availability. Ensuring that wearable technologies are supported by strong infrastructure, including EHR integration, user-friendly interfaces, device interoperability, and accessible help desks, remains a key implementation priority. Literature on implementation science also emphasizes the importance of “readiness for change,” a concept that overlaps with facilitating conditions and has been found to predict successful health IT deployment (Weiner, 2009).

Lastly, there is a strong need for alignment between technology initiatives and organizational culture. When new technologies are introduced without considering existing values, workflows, or power dynamics, adoption often falters (Cresswell et al., 2013; Greenhalgh et al., 2004). Stakeholders must adopt a cross-functional approach that integrates input from IT professionals, clinical operations, end-users, and leadership throughout the planning and rollout phases. Literature in organizational change emphasizes the importance of co-creation and inclusive implementation planning as a means of fostering ownership, reducing resistance, and improving system fit (Waring & Bishop, 2010). Embedding wearable technology into existing practices, rather than imposing it externally, can help ensure it is perceived as supportive rather than disruptive. Policies that reflect user priorities, recognize departmental differences, and promote communication across silos are more likely to result in sustainable adoption. The findings of this study yield a set of actionable recommendations for practice that are firmly grounded in both empirical data and existing literature. To facilitate meaningful and widespread adoption of wearable smart devices in healthcare, implementation strategies must address not only technical performance and usability but also emotional readiness, peer influence, self-efficacy, organizational alignment, and system-level support.

Recommendations for Future Research

Several important directions for future research are identified based on the findings of this investigation. One priority is the exploration of demographic moderators, particularly age. Previous studies grounded in the UTAUT framework have established that age significantly moderates the effects of constructs such as performance expectancy and effort expectancy on behavioral intention (Morris & Venkatesh, 2000; Venkatesh et al., 2003). Older healthcare professionals may exhibit lower adoption rates due to decreased digital literacy, increased anxiety related to technology, or less frequent engagement with emerging tools (Czaja et al., 2006). Including age and generational cohorts in future models may yield valuable insights into how experience and comfort with technology shape intentions. Understanding these demographic differences can also guide the development of age-sensitive training programs and support structures, ensuring that adoption strategies are equitable and effective across the workforce. Research by Gagnon et al. (2016) demonstrated that younger clinicians exhibited greater openness to adopting new technologies, indicating that age-specific motivators and barriers may exist and should be addressed through differentiated engagement strategies.

Another area requiring further examination is the relationship between behavioral intention and actual usage behavior. While behavioral intention has been widely used as a proxy for adoption, prior literature has emphasized the need to study post-adoption behaviors to understand sustained technology use (Ajzen, 1991; Venkatesh et al., 2003). Gaps between intention and behavior may arise due to changes in environmental conditions, shifts in organizational priorities, or evolving user perceptions. Longitudinal studies are well-positioned to capture the trajectory from initial intention to actual and sustained use, offering insight into which variables influence ongoing engagement and what barriers emerge over time (Holden & Karsh, 2010; Lee & Lee, 2020). Tracking these patterns would help illuminate not only adoption but also integration into clinical workflow and sustained impact on practice.

The reliability of certain constructs, such as facilitating conditions and self-efficacy, also warrants additional scrutiny. In this study, internal consistency values for these constructs fell below commonly accepted thresholds, suggesting the need for refinement in measurement. Mixed-methods approaches, including cognitive testing of survey items, focus groups, and semi-structured interviews, are recommended to clarify the meaning of the construct and ensure the relevance of items to healthcare professionals (Creswell & Plano Clark, 2017). In related work by Or and Karsh (2009), such qualitative methods revealed critical insights into how clinicians interpret and respond to health IT interventions, ultimately improving instrument validity. Strengthening the measurement of these constructs could also enhance the explanatory power of future models and provide more actionable insights for implementers.

A broader geographic sampling is recommended to evaluate the generalizability of the observed patterns. The current study was limited to healthcare professionals in Oregon, which may not reflect broader national or international trends. Studies that include participants from other U.S. states or from healthcare systems abroad could uncover regional and cultural variations in adoption behavior. Prior work has shown that differences in policy frameworks, funding structures, and technological infrastructure significantly shape digital health uptake (Lu et al., 2020; Yusif et al., 2016). For example, research by Greenhalgh et al. (2017) identified how centralized health IT policy in countries such as the U.K. contributed to greater consistency in technology deployment and use compared to more fragmented systems. Cross-regional comparisons can identify enablers and constraints specific to local contexts, informing strategies for the scalable implementation of these initiatives.

The inclusion of alternative or complementary theoretical frameworks is another opportunity for advancement. While UTAUT provides a robust structure for understanding technology acceptance, additional constructs related to emotional, cultural, or ethical considerations may also play a significant role, particularly as wearable technologies become more personal and data-intensive. Frameworks such as the Health Belief Model (Rosenstock, 1974), the Technology Readiness Index (Parasuraman, 2000), and the Privacy Calculus Model (Dinev & Hart, 2006) offer pathways for exploring variables like trust, perceived risk, and data security concerns. For instance, Angst and Agarwal (2009) demonstrated that concerns over privacy significantly reduce willingness to adopt electronic health records, while Bélanger and Crossler (2011) found that trust is a major determinant of engagement in technology-mediated environments. As wearable technologies increasingly intersect with privacy, surveillance, and personal health autonomy, these frameworks may be necessary to fully capture the emerging dynamics of adoption. Taken together, these recommendations underscore the importance of demographic sensitivity, longitudinal behavioral measurement, enhanced construct validity, geographic diversity, and theoretical expansion. Addressing these areas will support the continued development of an inclusive, empirically grounded understanding of wearable technology adoption in healthcare, contributing to more effective and equitable digital health innovation. In doing so, future studies can not only advance academic knowledge but also directly inform implementation strategies, policy development, and technology design that better serve healthcare professionals and patients alike.

Conclusions

This research addresses the adoption of wearable smart devices in healthcare through the application of the Unified Theory of Acceptance and Use of Technology (UTAUT), with a focus on behavioral intention among healthcare professionals in Oregon. Analysis of the survey data from 270 participants revealed that social influence, attitude toward using technology, and anxiety were statistically significant predictors of behavioral intention. These findings contribute to a deeper understanding of the psychological and social dimensions of technology adoption in clinical contexts, highlighting the limitations of traditional models that center primarily on functional performance or ease of use.

Social influence is confirmed as a major factor shaping behavioral intention, reflecting the importance of professional norms, peer endorsement, and leadership modeling in environments where collaboration and trust are central to practice (Venkatesh et al., 2003; Wu et al., 2007). Similarly, the significance of attitude toward using technology aligns with UTAUT2 and other contemporary models that recognize the role of personal beliefs, value judgments, and emotional orientation in driving adoption behavior (Venkatesh et al., 2012). The inverse relationship observed between anxiety and behavioral intention also reinforces findings in technostress literature, where elevated stress and uncertainty have been shown to deter engagement with new technologies (Ragu-Nathan et al., 2008).

In contrast, performance expectancy and effort expectancy did not demonstrate statistically significant relationships with behavioral intention in this context. This divergence from earlier foundational studies suggests a shift in the relevance of these variables in increasingly digitally fluent healthcare environments. While these constructs remain central to models like TAM and UTAUT (Davis, 1989; Venkatesh et al., 2003), the lack of predictive value in this study underscores the need to more deeply consider contextual and affective influences, especially in domains where emotional readiness and peer validation may outweigh rational cost-benefit assessments (Holden & Karsh, 2010; Taherdoost, 2018).

The results also carry direct practical implications for clinical operations, leadership, and policy development. The successful implementation of wearable technologies requires more than just technical functionality; it also depends on cultivating a supportive culture, reducing anxiety through training and mentorship, and leveraging social networks to model and normalize their use. Although facilitating conditions did not reach statistical significance ($p = .051$), the near-threshold result, combined with improved construct reliability, indicates potential practical importance. As supported in prior literature, visible support systems, robust infrastructure, and integration with existing workflows are critical to fostering trust and reducing friction in adoption processes (Cresswell & Sheikh, 2013; Weiner, 2009).

This study contributes to the evolving discourse on digital health integration by demonstrating that adoption outcomes are shaped by a constellation of interrelated factors, including technical, emotional, and social aspects. Future research is needed to expand the theoretical scope, examine longitudinal behavior, improve construct validity, and investigate generational and geographic variability. Studies incorporating complementary models such as the Health Belief Model, Technology Readiness Index, or Privacy Calculus Model can help address constructs like trust, perceived risk, and ethical concern, which are particularly relevant as wearable technologies collect increasingly sensitive biometric data (Bélanger & Crossler, 2011; Dinev & Hart, 2006; Parasuraman, 2000; Rosenstock, 1974).

The findings presented here reaffirm that technology adoption in healthcare cannot be understood or influenced solely through technical optimization. Instead, it is a dynamic process shaped by cultural alignment, institutional readiness, emotional comfort, and interpersonal influence. Human-centered implementation strategies, those that recognize the cognitive and affective needs of users, will be essential to bridging the gap between technological innovation and clinical practice. By addressing these factors, this research lays the groundwork for developing more effective, equitable, and enduring approaches to digital health integration. The implications are clear: to achieve meaningful and sustained adoption of wearable technologies, strategies must account for the full spectrum of human experience and design environments that reinforce confidence, connection, and purpose. Ultimately, it is this integration of technology with human-centered care that will determine whether digital health innovations deliver their promised benefits.

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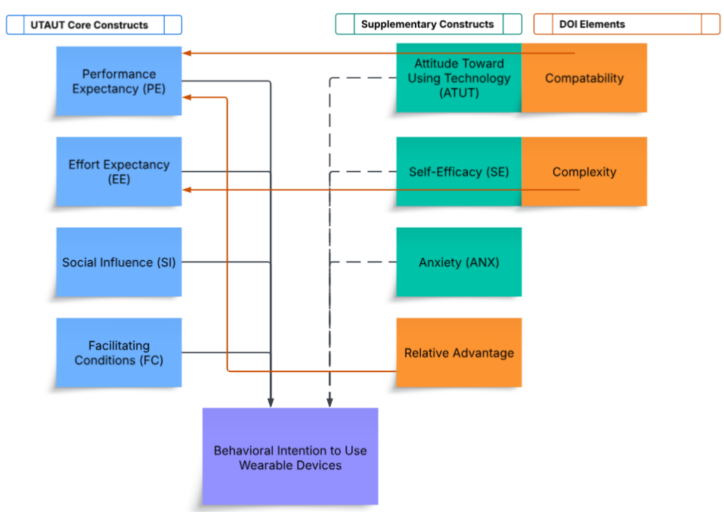
Appendix A: Integrated Theoretical Framework

The framework displayed in Figure A1 integrates the four core UTAUT constructs of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) as primary predictors of Behavioral Intention (BI). Supplementary constructs of Attitude Toward Using Technology, Self-Efficacy, and Anxiety are included to capture attitudinal and affective influences. Selected elements of Diffusion of Innovations (DOI), specifically Relative Advantage, Compatibility, and Complexity are mapped onto corresponding UTAUT constructs to situate the adoption process within the broader innovation diffusion context. Solid arrows indicate hypothesized relationships aligned with the research questions; dashed arrows represent exploratory pathways.

Figure 1

Integrated Theoretical Framework for Wearable Adoption Among Healthcare Professionals



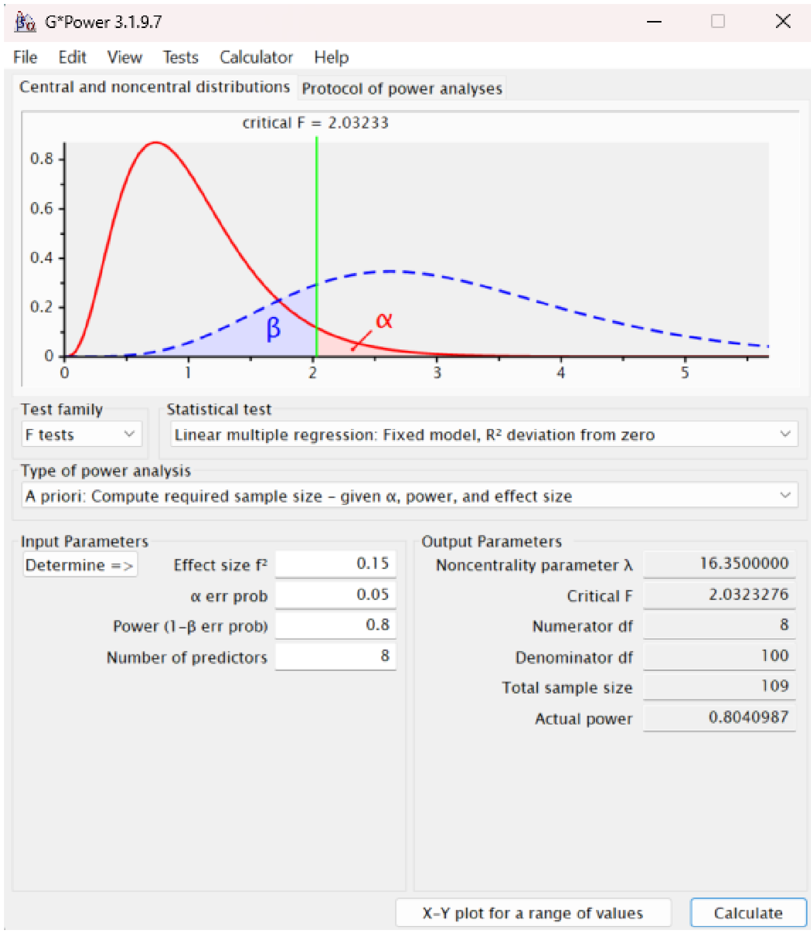
Note. The framework integrates the four core UTAUT constructs, supplementary constructs, and elements of Diffusion of Innovations (DOI) as predictors of Behavioral Intention (BI). Solid arrows indicate hypothesized relationships aligned with the research questions; dashed arrows represent exploratory pathways.

Appendix B: Parameter Values and Interface in Power Analysis

Expressed in Figure B1 is the output of the G-Power software interface used to conduct a priori power analysis for this study's multiple linear regression model illustrating the input parameters and resulting output values. The power analysis was conducted to determine the minimum sample size required to detect a medium effect size ($f^2 = 0.15$) with a significance level (α) of .05, statistical power of .80, and eight predictors. The output in the lower right section confirms the computed values based on the input: Numerator degrees of freedom: 8, Denominator degrees of freedom: 100, Noncentrality parameter (λ): 16.35, and Actual power achieved: 0.8049. These results indicated that a minimum of 109 valid survey responses were required for the regression model to have adequate power to detect statistically significant relationships. This criterion was surpassed in this study from the analysis of 270 valid responses.

Figure B1

G-Power Interface and Output



Note. The interface and output from the G-Power software used conduct a priori power analysis.

Appendix C: Research Study Survey Questions

Section 1: Demographic Information

1. What is your primary professional role?
    a. Physician
    b. Nurse
    c. Physician Assistant
    d. Allied Health Professional
    e. Other (please specify): ________
2. How many years have you been working in the healthcare field?
    a. Less than 1 year
    b. 1–5 years
    c. 6–10 years
    d. More than 10 years
3. What is the primary setting of your practice?
    a. Hospital
    b. Private Clinic
    c. Community Health Center
    d. Other (please specify): ________
4. How familiar are you with wearable smart devices (e.g., smartwatches, fitness trackers)?
    a. Not familiar at all
    b. Somewhat familiar
    c. Familiar
    d. Very familiar

5. Do you personally use wearable smart devices for personal health monitoring (e.g., fitness tracking, heart rate monitoring)?
    a. Yes
    b. No
6. If yes, which wearable device(s) do you currently use? (Select all that apply)
    a. Smartwatch (e.g., Apple Watch, Samsung Galaxy Watch)
    b. Fitness tracker (e.g., Fitbit, Garmin)
    c. Other (please specify): _________
7. If no, what are the main reasons for not using wearable devices? (Select all that apply)
    a. Lack of interest
    b. Cost
    c. Privacy/security concerns
    d. Not useful for my needs
    e. Other (please specify): _________

Section 2: Performance Expectancy

(1 = Strongly Disagree, 7 = Strongly Agree)

1. I would find wearable smart devices useful in my job.
2. Using wearable smart devices would enable me to accomplish tasks more quickly.
3. Using wearable smart devices would increase my productivity
4. If I use wearable smart devices, I will increase my chances of better achieving clinical outcomes.

Section 3: Effort Expectancy:

(1 = Strongly Disagree, 7 = Strongly Agree)

1. My interaction with wearable smart devices would be clear and understandable
2. It would be easy for me to become skillful at using wearable smart devices
3. I would find wearable smart devices easy to use
4. Learning to operate wearable smart devices is easy for me.

Section 4: Attitude Toward Using Technology

(1 = Strongly Disagree, 7 = Strongly Agree)

1. Using wearable smart devices is a good idea
2. Wearable smart devices would make work more interesting
3. Working with wearable smart devices is fun
4. I like working with wearable smart devices

Section 5: Social Influence:

(1 = Strongly Disagree, 7 = Strongly Agree)

1. People who influence my behavior think that I should use wearable smart devices
2. People who are important to me think that I should use wearable smart devices
3. The senior leadership in the healthcare facility I work are supportive in the use of wearable smart devices.
4. In general, the healthcare facility in which I work has supported the use of wearable smart devices

Section 6: Facilitating Conditions:

(1 = Strongly Disagree, 7 = Strongly Agree)

1. I have the resources necessary to use wearable smart devices
2. I have the knowledge necessary to use wearable smart devices
3. Wearable smart devices are not compatible with other applications I use at my job

4. A specific person (or group) is available for assistance with wearable smart device difficulties

Section 7: Self-Efficacy:

(1 = Strongly Disagree, 7 = Strongly Agree)

I could complete a job or task using the system…

1. If there was no one around to tell me what to do as I go
2. If I could call someone for help if I got stuck
3. If I had a lot of time to complete the job for which the device was provided
4. If I had just the built-in help facility for assistance

Section 8: Anxiety:

(1 = Strongly Disagree, 7 = Strongly Agree)

1. I feel apprehensive about using wearable smart devices
2. It scare me to think that I could use lose a lot of information using wearable smart devices by hitting the wrong key
3. I hesitate to use wearable smart devices for fer of making mistakes I cannot correct
4. Wearable smart devices are somewhat intimidating to me.

Section 9: Behavioral Intention to Use the System

(1 = Strongly Disagree, 7 = Strongly Agree)

1. I intent to use wearable smart devices in the next <n> months
2. I predict I would use wearable smart devices in the next <n> months
3. I plan to use wearable smart devices in the next <n> months

Appendix D: ANOVA Summary Table for Regression Model

Expressed in Table D1 are the ANOVA results conducted as part of the multiple linear regression analysis to test whether the seven independent variables significantly explained the variance in the dependent variable, behavioral intention (BI). The F-test yielded a significant result, $F(7, 262) = 34.73$, $p < .001$, indicating that the model provided a significantly better fit to the data than a model with no predictors.

Table D1

ANOVA Results from Regression Analysis

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	220.07	7	31.44	34.73	<.001[b]
	Residual	237.19	262	0.91		
	Total	457.26	269			

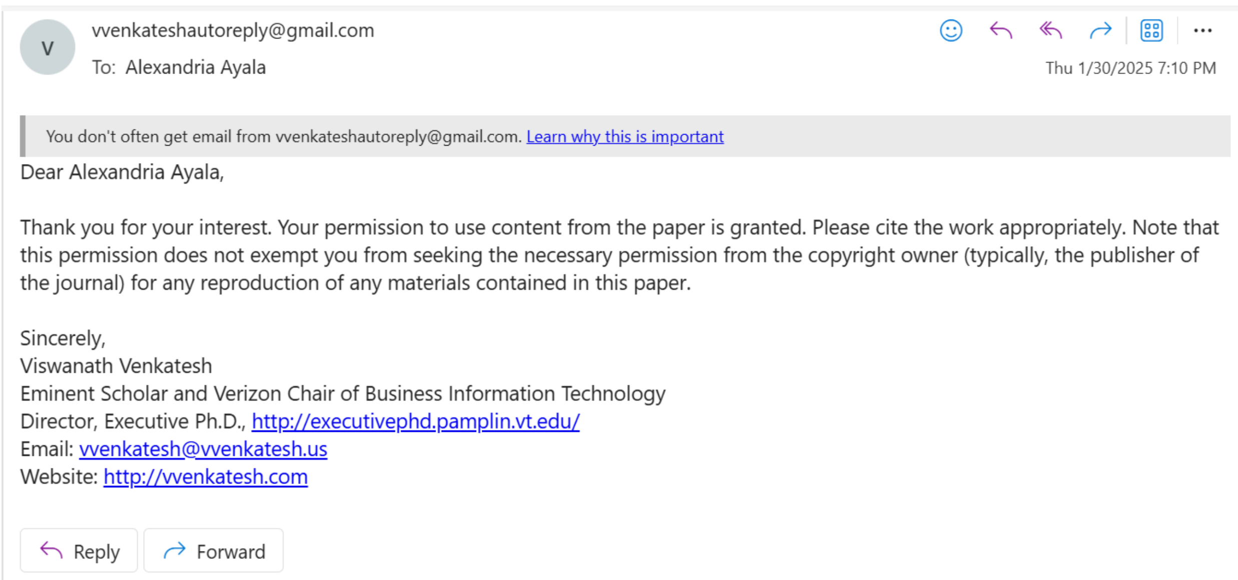
Note. Dependent Variable: Behavioral Intentions. Predictors: Performance Expectancy (PE), Effort Expectancy (EE), Attitude Toward Using Technology (ATUT), Social Influence (SI), Facilitating Conditions (FC), Self-Efficacy (SE), and Anxiety (ANX).

Appendix E: Survey Instrument Permission from Vanketesh

Displayed in Figure E1 is a copy of written approval from Dr. Viswanath Venkatesh to utilize content from his paper published in 2003 titled “User Acceptance of Information Technology: Toward a Unified View” where he formulated the UTAUT theory along with Dr. Morris, Dr., Gordon Davis, and Dr. Fred Davis.

Figure E1

Survey Instrument Permission



V

vvenkateshautoreply@gmail.com

To: Alexandria Ayala

Thu 1/30/2025 7:10 PM

You don't often get email from vvenkateshautoreply@gmail.com. Learn why this is important

Dear Alexandria Ayala,

Thank you for your interest. Your permission to use content from the paper is granted. Please cite the work appropriately. Note that this permission does not exempt you from seeking the necessary permission from the copyright owner (typically, the publisher of the journal) for any reproduction of any materials contained in this paper.

Sincerely,
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Eminent Scholar and Verizon Chair of Business Information Technology
Director, Executive Ph.D., http://executivephd.pamplin.vt.edu/
Email: vvenkatesh@vvenkatesh.us
Website: http://vvenkatesh.com

Reply Forward

Note. Email confirmation from Dr. Venkatesh to utilize his survey instrument.

Appendix F: Survey Consent Form

Expressed in Figure F1 is the consent form that was included on the first page of the survey that was shared with participants. The purpose of this consent form is to ensure participants understand what the study is for, how it will be used, and what qualifications they must have to participate in the study.

Figure F1

Survey Consent Form for Signature

Hello,

My name is Alexandria Ayala, and I am a doctoral student at National University. I am conducting an online survey to understand the factors that influence the decision to adopt wearable smart devices among healthcare professionals in Oregon.

In order to participate in this survey, you are required to have the following qualifications:

- You are age 18 or older.
- You are living in Oregon in the United States.
- You work as a healthcare professional for at least one year.

The following surveys includes questions about the Unified Theory of Acceptance and Use of Technology (UTAUT) model, Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). It will take approximately ten minutes of your time to complete the survey.

Your participation in this study is voluntary. If you decide to participate, your responses will be anonymous – that is, recorded without any identifying information that is linked to you. If you have any questions regarding this survey, please contact me at aayala4172@o365.ncu.edu.

If you have any questions regarding your rights as a human subject and participant in this study, or to report research-related problems, you may email the National University IRB at irb@nu.edu.

By clicking the next button and completing the survey you indicate that you have consented to participate in this research. If you do not want to participate, please close the browser.

- o Yes, I agree
- o No, I disagree

Note. Consent form included on introductory page of the survey provided to survey participants.

Appendix G: IRB Approval Letter

Displayed in Figure G1 is a copy of the approval letter received from the Institutional Review Board (IRB) to move forward with surveying individuals for the purpose of the submitted research study.

Figure G1

IRB Approval Letter

National
UNIVERSITY

9388 Lightwave Ave.
San Diego, CA 92123
irb@nu.edu

Notice of Exemption

February 13, 2025

To: Alexandria Ayala

Project Title: Understanding the Determinants of Wearable Smart Device Adoption: A Quantitative Analysis
NU IRB Number: IRB-FY24-25-654
Determination: Exempt from further review 45 CFR 46.101 Category 2.(i). Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording) if at least one of the following criteria is met: The information obtained is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained, directly or through identifiers linked to the subjects;

Status: Active - Research activities may begin as of February 13, 2025

Dear Alexandria Ayala:

The study referenced above has been reviewed by the National University IRB. The IRB has determined your research is exempt from further review under 45 CFR 46.104, which means you will not need to renew your study and may begin your study effective immediately. However, if you find the need to change your study in any way, you will need to submit a modification to the IRB prior to implementing the changes. This will allow the IRB to determine whether or not the study still meets exemption criteria.

Please review your Post Approval Responsibilities here: Approved Documents Guidelines

For any questions regarding your protocol, please reach out to the IRB at irb@nu.edu.

Note. Copy of approval letter from Institutional Review Board (IRB) to begin research activities.

Appendix H: Item-Total Reliability Statistics

Expressed in Table H1 are the item-total reliability statistics for the key constructs used in this study: Performance Expectancy (PE), Effort Expectancy (EE), Attitude Toward Using Technology (ATUT), Social Influence (SI), Facilitating Conditions (FC), Self-Efficacy (SE), Anxiety (ANX), and Behavioral Intentions (BI). The statistics included in table H1 includes:

- Scale Mean and Variance if Item Deleted: The scale's average and variability when the item is removed.
- Corrected Item-Total Correlation: The degree to which each item correlates with the overall scale.
- Cronbach's Alpha if Item Deleted: An estimate of internal consistency if the item is excluded.

The results show acceptable internal consistency for PE ($\alpha = .85$), EE ($\alpha = .86$), ATUT ($\alpha = .84$), SI ($\alpha = .70$), ANX ($\alpha = .86$), and BI ($\alpha = .97$), consistent with recommended thresholds above .70 (Sürücü & Maslakci, 2020). These findings suggest that items within these constructs were cohesive and reliably measured their intended theoretical dimensions. Facilitating Conditions (FC), after correction and removal of a reverse-coded item that suppressed the scale's consistency, yielded an improved Cronbach's alpha of .52. While this remains below the ideal .70 threshold, it represents a notable improvement over the prior value of .30. The revised FC construct included three items that measured perceived resource availability, knowledge, and support related to wearable smart device use. The relatively low alpha may still reflect heterogeneity in respondents' perceptions of available support or infrastructure across roles or organizations. Despite this limitation, FC was retained due to its central role in the UTAUT framework, and findings were interpreted with appropriate caution in the analysis.

Table H1

Item-Total Reliability Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Performance Expectancy (PE)	10.54	8.53	0.75	0.85
Effort Expectancy (EE)	12.48	6.08	0.76	0.86
Attitude Toward Using Technology (ATUT)	11.39	6.99	0.73	0.84
Social Influence (SI)	9.56	6.54	0.55	0.70
Facilitating Conditions (FC)	7.44	2.81	0.35	0.40
Self-Efficacy (SE)	11.38	5.49	0.50	0.65
Anxiety (ANX)	6.44	10.68	0.77	0.86
Behavioral Intentions (BI)	7.65	6.86	0.96	0.97

Note. Item-total reliability statistics for the key constructs used in this study.

Appendix I: KMO and Bartlett's Test

Expressed in Table I1 are the results of the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity, both of which assess the suitability of data for factor analysis. The KMO value was 0.852, which exceeds the commonly accepted threshold of 0.50, indicating a high degree of shared variance among variables and sampling adequacy for factor analysis (Erpurini et al., 2023). Bartlett's Test of Sphericity yielded a statistically significant result ($\chi^2(28) = 850.757$, $p < .001$), confirming the presence of correlations among variables sufficient for structure detection. Together, these results justify the application of exploratory factor analysis in this study's validation process.

Table I1

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.852
Bartlett's Test of Sphericity	**Approx. Chi-Square**	850.757
	df	28
	Sig.	<.001

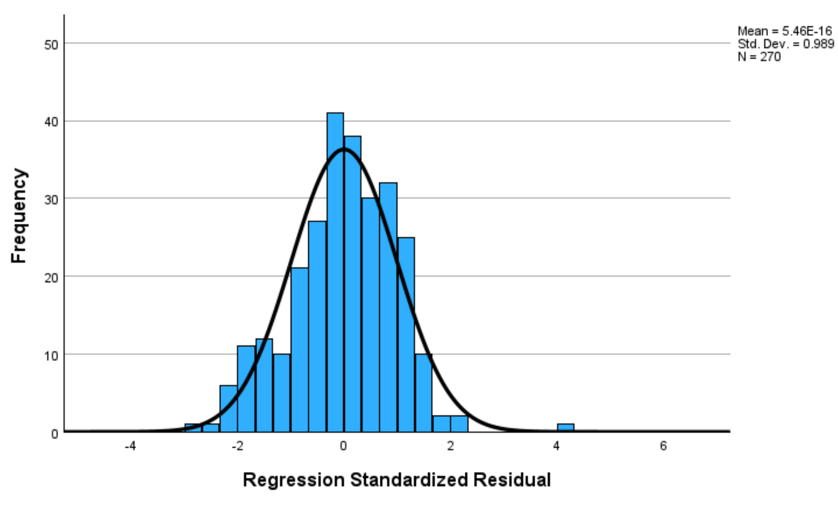
Note. Results of the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of Sphericity.

Appendix J: Histogram and Distribution of Regression Standardized Residual

Displayed in Figure J1 is a frequency distribution figure illustrating the frequency distribution and fitted normal curve of the standardized residuals derived from the multiple linear regression model. The histogram in Figure J1 displays a symmetric, bell-shaped curve centered around zero, indicating that the residuals are approximately normally distributed. The superimposed black curve represents the expected normal distribution, closely matching the pattern of the observed residuals. This visual evidence supports the assumption of multivariate normality, a key requirement for valid multiple regression analysis (Mishra et al., 2019). The mean of the standardized residuals was approximately 0 (5.46E–16), and the standard deviation was 0.989, both aligning closely with the expected values for a standard normal distribution. These findings confirm that the residuals did not deviate significantly from normality, reinforcing the credibility of the regression results presented in this study.

Figure J1

Frequency Distribution and Curve of Standardized Residuals



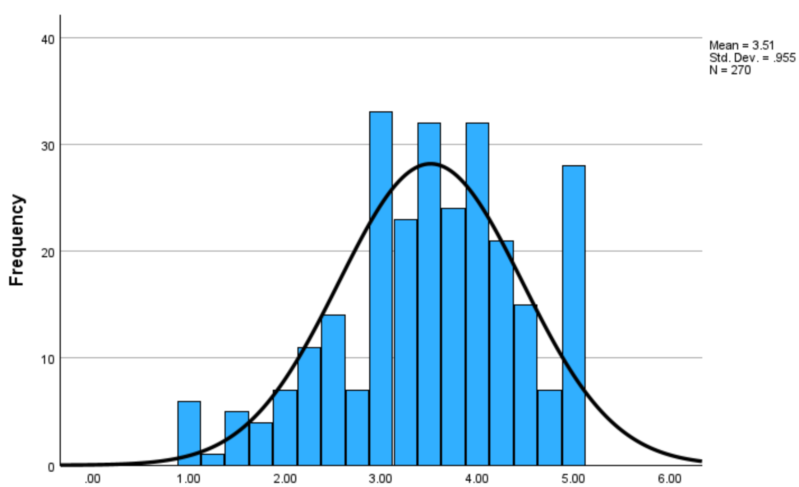
Note. The frequency distribution and fitted normal curve of the standardized residuals derived from the multiple linear regression model.

Appendix K: Histogram and Distribution Curve for Performance Expectancy (PE)

Displayed in Figure K1 is the performance expectancy (PE) histogram presenting a fitted normal distribution curve representing the PE variable, based on data collected from 270 participants. The blue bars depicted in the histogram of Figure K1 illustrate the frequency of participant responses across the PE scale. The black line overlaid on the histogram represents the normal distribution curve, allowing for visual comparison of the actual data distribution against the expected normal distribution. The data exhibit a relatively symmetrical pattern with a slight left skew, which remains within acceptable limits for parametric analysis. The mean of the PE scores was 3.51 with a standard deviation of 0.955, as shown in the figure's legend. The distribution suggests that most participants moderately agreed with the idea that wearable devices could enhance their job performance, contributing useful context for interpreting regression results in this study.

Figure K1

Histogram for Performance Expectancy (PE)



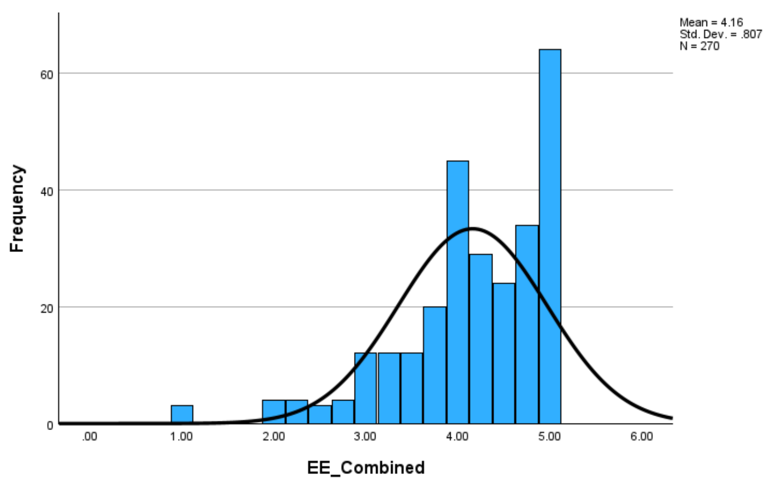
Note. Histogram and fitted normal distribution curve representing the variable Performance Expectancy (PE), based on data collected from 270 participants.

Appendix L: Histogram and Distribution Curve for Effort Expectancy (EE)

Displayed in Figure L1 is the effort expectancy (EE) histogram with an overlaid normal distribution curve for the EE variable, based on 270 survey responses. Within Figure L1, the blue bars illustrate the frequency distribution of responses to EE items, while the black curve shows the theoretical normal distribution. The shape of the histogram demonstrates a left-skewed distribution, with a concentration of responses between 4.0 and 5.0, indicating that most participants perceived wearable devices as relatively easy to use. The mean score for EE was 4.16, and the standard deviation was 0.807. These statistics suggest moderate agreement among participants regarding the ease of using wearable smart devices. Although the distribution curve generally aligns with the histogram, the slight skewness suggests a modest deviation from normality. However, this deviation is not severe enough to violate assumptions of normality, as confirmed in the main analysis using additional diagnostic tests such as the Shapiro-Wilk test.

Figure L1

Histogram for Effort Expectancy (EE)



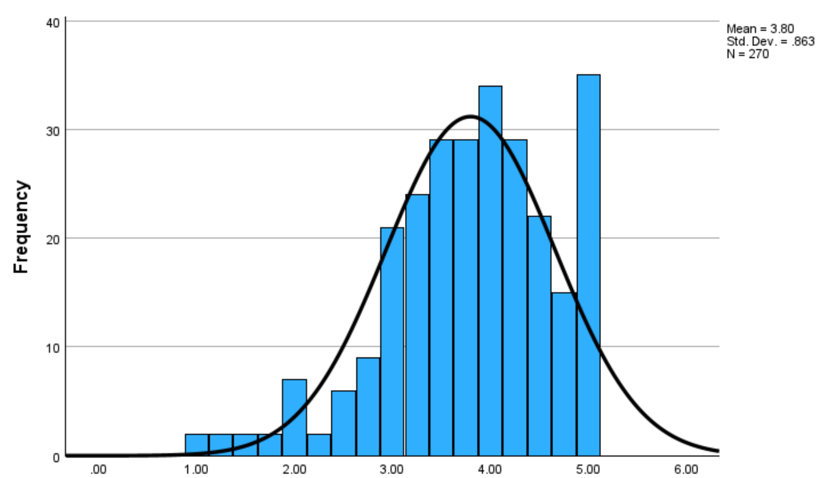
Note. Histogram with an overlaid normal distribution curve for the Effort Expectancy (EE) variable, based on 270 survey responses.

Appendix M: Histogram and Distribution Curve for Attitude Toward Using Technology (ATUT)

Displayed in Figure M1 is the attitude toward using technology (ATUT) histogram showing the distribution of responses for this construct overlaid with a normal distribution curve, based on data from 270 participants. The blue bars within Figure M1 represent the frequency of participant responses regarding their attitudes toward adopting wearable smart devices, while the black curve indicates a fitted normal distribution. The overall histogram of Figure M1 displays a moderately symmetrical distribution, centered around a mean of 3.80 with a standard deviation of 0.863. The concentration of values around the center suggests that many respondents had a neutral to positive attitude toward using technology. The shape of the histogram closely follows the normal distribution curve, which supports the assumption of approximate normality. This visual evidence aligns with findings from statistical tests reported in Chapter 4, which confirmed that the data for this construct met regression assumptions.

Figure M1

Histogram for Attitude Toward Using Technology (ATUT)



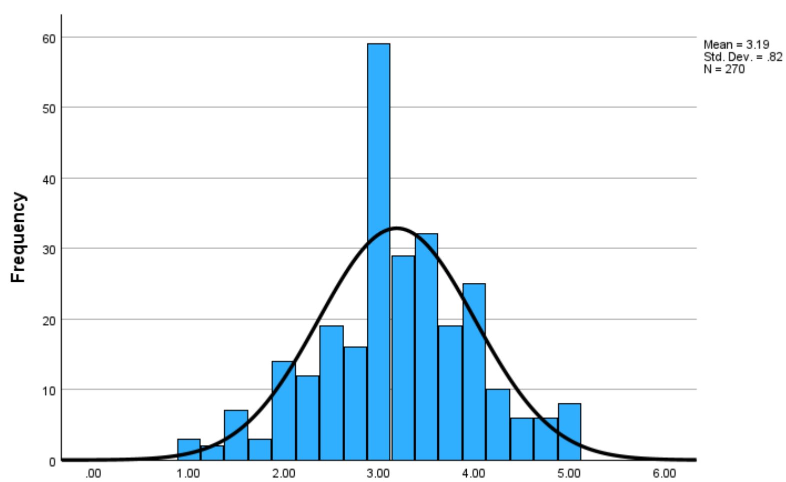
Note. Distribution of responses for the Attitude Toward Using Technology (ATUT) construct using a histogram overlaid with a normal distribution curve, based on data from 270 participants.

Appendix N: Histogram and Distribution Curve for Social Influence (SI)

Displayed in Figure N1 is the social influence (SI) histogram illustrating the distribution of responses for the SI variable and a fitted normal distribution curve, based on a sample of 270 healthcare professionals. Within Figure N1, the blue bars represent the frequency of survey responses to items measuring the extent to which social norms and peer influence affect wearable device adoption. The black curve represents a fitted normal distribution for visual comparison. The distribution has a mean of 3.19 and a standard deviation of 0.82, with a sharp peak at the center, indicating that a large portion of respondents rated social influence near the scale midpoint. Although the histogram approximates a bell-shaped curve, the prominent central spike suggests a possible clustering of responses at a neutral value. This may indicate hesitation or mixed attitudes regarding peer and organizational influence on technology adoption decisions. Despite this feature, the distribution does not display severe skewness or kurtosis, supporting the assumption of approximate normality as required for regression analysis.

Figure N1

Histogram for Social Influence (SI)



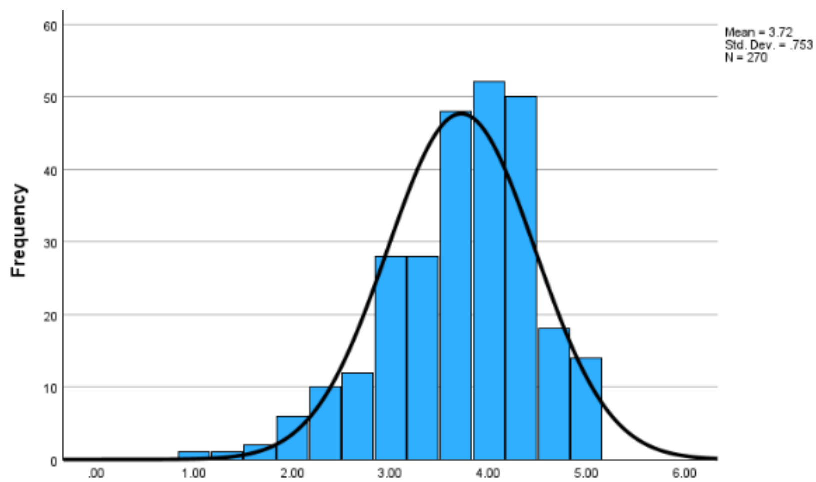
Note. Distribution of responses for the Social Influence (SI) construct using a histogram and a fitted normal distribution curve, based on a sample of 270 healthcare professionals.

Appendix O: Histogram and Distribution Curve for Facilitating Conditions (FC)

Displayed in Figure O1 is the facilitating conditions (FC) histogram presenting the distribution of responses for the FC variable with the blue bars representing the frequency of responses to items that measured perceptions about the availability of organizational and technical resources needed to adopt wearable technology. The black curve displays the theoretical normal distribution fitted to the data. The distribution has a mean of 3.72 and a standard deviation of 0.753, based on a total sample of 270 participants. The overall histogram of Figure O1 closely follows a bell-shaped pattern, indicating a reasonably normal distribution. The bulk of responses fall between the scores of 3.0 and 4.5, suggesting a generally moderate to high agreement that adequate support conditions are in place for wearable device adoption. This alignment with normality assumptions reinforces the suitability of this variable for inclusion in parametric statistical tests such as multiple regression. Despite the relatively low internal consistency reported for FC in reliability testing, the shape of this distribution supports its continued analytical use in this study.

Figure O1

Histogram for Facilitating Conditions (FC)



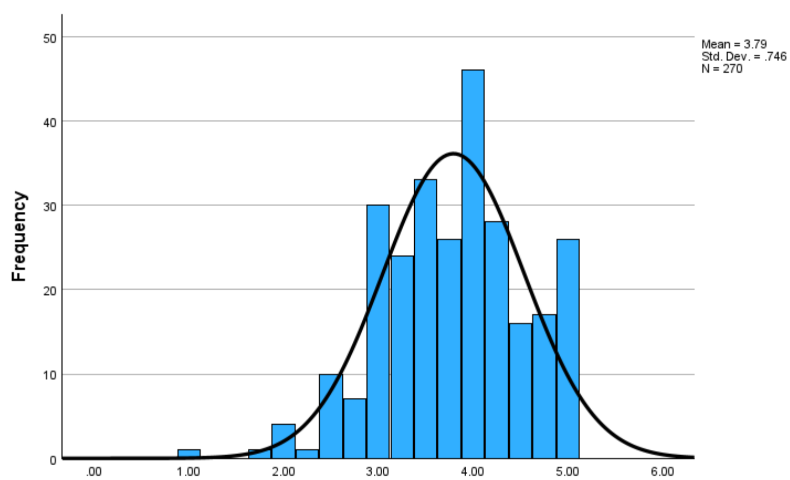
Note. Distribution of responses for the Facilitating Conditions (FC) variable using a histogram and a superimposed normal distribution curve.

Appendix P: Histogram and Distribution Curve for Self-Efficacy (SE)

Figure P1 presents the histogram for the Self-Efficacy (SE) construct. Responses were approximately normally distributed, with a mean of 3.79 and a standard deviation of 0.746 (N = 270). The distribution shows a central peak around scores of 3.5 to 4.0, indicating that most healthcare professionals in the sample reported moderate to high confidence in their ability to effectively use wearable smart devices without extensive external assistance. The relatively narrow spread suggests that perceptions of self-efficacy were fairly consistent across participants. These results support the construct's reliability and suitability for inclusion in the multiple regression analysis.

Figure P1

Histogram for Self-Efficacy (SE)



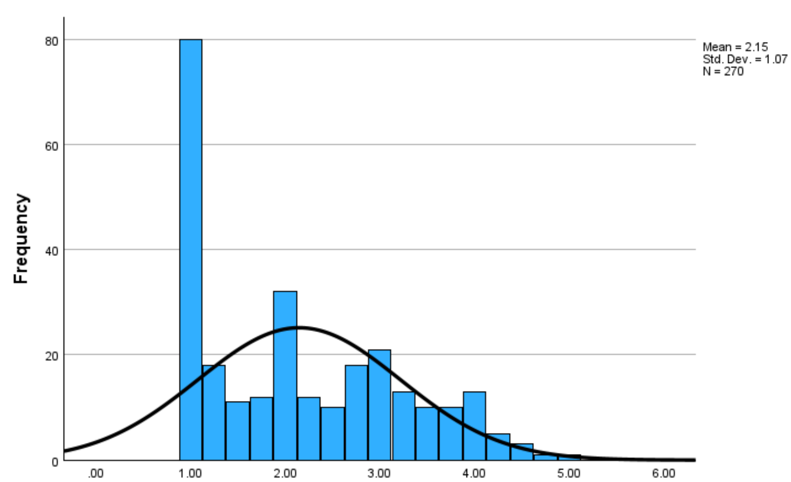
Note. Distribution of responses for the Self-Efficacy (SE)) variable using a histogram and a superimposed normal distribution curve.

Appendix Q: Histogram and Distribution Curve for Anxiety (ANX)

Displayed in Figure Q1 is the anxiety (ANX) histogram illustrating the frequency distribution and normal curve of the ANX variable based on survey responses from 270 healthcare professionals. The blue bars within Figure Q1 represents the distribution of participants' scores on the anxiety construct, which reflects the extent to which individuals feel uneasy or apprehensive about using wearable smart devices. The black line represents the theoretical normal distribution fitted to these responses. The data exhibit a pronounced right skew, with a notable spike at the lowest end of the scale (score = 1), indicating that a large proportion of participants reported very low levels of anxiety. The mean score for anxiety was 2.15, with a standard deviation of 1.07, suggesting that responses varied but were generally skewed toward low anxiety. This deviation from a perfectly normal distribution is expected in cases where participants overwhelmingly reject anxiety-related statements. Although this non-normality did not violate assumptions for multivariate analysis in this study, it provides useful insight into participant comfort levels with wearable technology.

Figure Q1

Histogram for Anxiety (ANX)



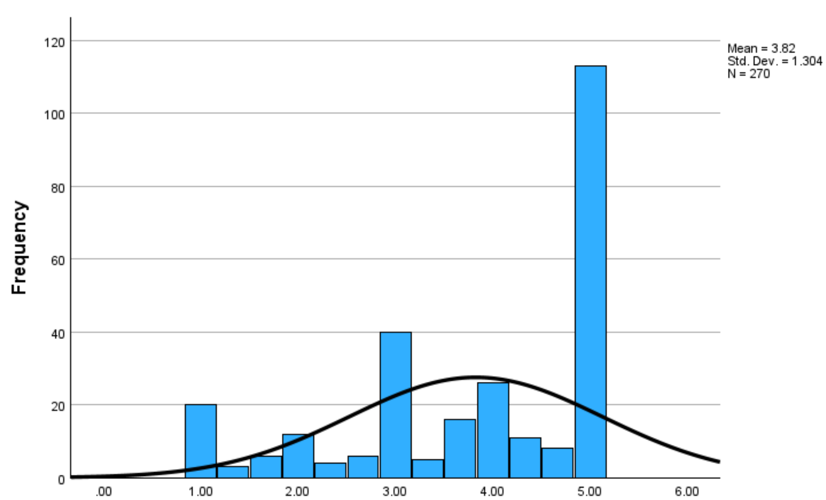
Note. Distribution and normal curve of the Anxiety (ANX) variable based on survey responses from 270 healthcare professionals.

Appendix R: Histogram and Distribution Curve for Behavioral Intentions (BI)

Displayed in Figure R1 is the behavioral intentions (BI) histogram displaying a fitted normal distribution curve for the BI variable, based on data from 270 healthcare professionals. Within Figure R1, the blue bars represent the observed frequency of participant responses related to their intention to adopt wearable smart devices, while the black curve represents the expected normal distribution. The BI construct within Figure R1 was measured using multiple Likert-scale items and reflects a respondent's overall willingness or plan to use wearable technology in a healthcare context. The distribution exhibits positive skewness, with a strong clustering of responses at the high end of the scale. This concentration suggests that many healthcare professionals expressed a strong behavioral intention to adopt wearable technology. The mean score was 3.82, with a relatively large standard deviation of 1.304, reflecting both a high central tendency and considerable variability. Although the distribution does not conform perfectly to the shape of a normal curve, it confirms an overall trend of high adoption among participants.

Figure R1

Histogram for Behavioral Intentions (B1)



Note. Histogram and fitted normal distribution curve for Behavioral Intentions (BI), based on data from 270 healthcare professionals.