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Factors Affecting the Adoption of Artificial Intelligence-Driven Wearable Technology in the Malaysian Healthcare Sector: A Conceptual Framework

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Abstract

This conceptual paper examines the adoption of Artificial Intelligence (AI) driven wearable technology, including smartwatches, fitness trackers, wearable ECGs, glucose monitors, and pain management devices, in transforming healthcare in Malaysia. Despite the extreme potential to enhance patient care and healthcare monitoring, the adoption of AI-driven wearable technology remains limited due to several persistent barriers. The purpose of this study is to examine these challenges and propose a framework to improve the integration of AI-driven wearable technology in Malaysia's healthcare system. Grounded in the Diffusion of Innovation (DOI) theory, this study examines how five key innovation attributes —relative advantage, compatibility, complexity, trialability, and observability—impact patient trust and the adoption of wearable technologies. A quantitative research design will be employed, utilizing structured surveys to collect data and analyze the relationships among the DOI factors, patient trust, and technology adoption. The expected outcome is a validated conceptual framework that identifies the barriers to adoption and provides empirical insights for strengthening digital healthcare initiatives. This research aligns with Malaysia's Shared Prosperity Vision 2030 and contributes to both academic literature and policy, ultimately offering actionable recommendations to enhance trust, accessibility, and the successful implementation of digital health technologies across Malaysia.

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1.0 Introduction

Artificial intelligence-driven wearable technologies are emerging as transformative tools in global healthcare by offering real-time health monitoring, early disease detection, and continuous patient engagement. These devices, such as smartwatches, biosensor patches, and fitness trackers, play a crucial role in enabling proactive health management and improving clinical outcomes, as highlighted by Alzghaibi (2025), Subhan et al. (2023), and Zaidan et al. (2022). Globally, these innovations have demonstrated the potential to alleviate healthcare burdens by supporting chronic disease management and reducing unnecessary hospital visits through early intervention (Kostkova et al., 2021). In Malaysia, the promise of wearable health technologies remains underutilized despite the rising interest in digital health solutions. Key adoption challenges include limited public awareness, high device costs, and inconsistent digital literacy across populations (Jembai et al., 2022; Hii et al., 2024; Subramaniam & Kanapathy, 2023). Furthermore, Malaysia's digital divide, particularly between urban and rural areas, exacerbates unequal access to these technologies (Hii et al., 2024). Trust concerns regarding data privacy, the ethical use of health data, and the lack of clear governance mechanisms also deter public engagement (Alzghaibi, 2025; Zaidan et al., 2022; Johnson & Saikia, 2024).

The adoption of these technologies can be better understood through the Diffusion of Innovation (DOI) theory by Rogers (2003). This framework identifies five core factors that influence and create barriers to technology adoption: relative advantage, compatibility, complexity, trialability, and observability. These attributes influence how users perceive the usefulness and trustworthiness of wearable health devices, particularly in culturally and economically diverse societies such as Malaysia (Subhan et al., 2023; Bouderhem, 2024). Using a quantitative research approach, this study aims to propose a research framework for enhancing the adoption of wearable technology in the Malaysian healthcare sector, with a focus on the five core elements mentioned above. The insights aim to support policymakers and stakeholders in developing trust-building strategies and inclusive digital health policies aligned with Malaysia's Shared Prosperity Vision (SPV) 2030.

2.0 Literature Review and Hypothesis Development

2.1 Adoption of AI-Driven Wearable Technology in Healthcare

The integration of artificial intelligence (AI) with wearable health technologies has marked a paradigm shift in healthcare delivery. These technologies, ranging from smartwatches to biosensors and wearable ECG monitors, support proactive and personalized patient care by continuously capturing physiological data in real-time (Yin et al., 2023; Al-Naji et al., 2022; Shajari et al., 2023). Artificial Intelligence (AI) algorithms process this data to identify anomalies, generate health insights, and predict potential health risks, enabling timely interventions and informed clinical decisions. In the global context, research has shown a substantial increase in the adoption of AI-enabled wearable devices for managing chronic diseases and remote monitoring, particularly in developed healthcare systems. For instance, findings by Yin et al. (2023) underscore the effectiveness of AI-integrated wearable ECG devices in predicting cardiac anomalies before clinical symptoms appear. However, in emerging economies like Malaysia, the adoption of such technologies is still in its infancy. Similarly, Canali et al. (2022) identify that contextual factors, such as limited healthcare infrastructure, digital literacy, and concerns over data privacy, pose significant barriers to widespread implementation.

It is significant to gain a deeper understanding of public perceptions and key factors that can influence them before promoting the adoption of AI-driven wearable health technologies within Malaysia's healthcare system. To understand this, the Diffusion of Innovations Theory, as proposed by Rogers (1962), is known to be helpful. This theory suggests that the adoption of new technologies is largely shaped by how people perceive their attributes, such as relative advantage, compatibility with existing practices, complexity, ease of use, and the visibility of the results to others (Rogers, 1995). By focusing on these elements, it becomes possible to identify strategies that could make wearable technology more appealing and accessible to its users. Therefore, this study proposes a conceptual framework to examine the effects of various antecedents on the adoption of AI-driven wearable technologies in the Malaysian healthcare context. While global research supports the efficacy of these devices, context-specific studies are needed to understand how Malaysian users perceive and adopt such technologies, as well as to identify barriers to their effective implementation.

2.2 Impact of Wearable Technology on Healthcare in Malaysia

Empirical studies have demonstrated that wearable technologies, powered by artificial intelligence, have a positive impact on disease prevention and health promotion in Malaysia. For instance, Ali et al. (2023) report that smartwatches and fitness trackers have improved users' engagement in physical activities and helped monitor conditions like diabetes, hypertension, and cardiovascular diseases. These devices enable continuous health tracking, allowing physicians to provide timely advice or adjust treatment plans, thereby enhancing clinical outcomes. AI-powered wearables also facilitate remote diagnostics and enhance the capacity for predictive healthcare. Stoumpos et al. (2023) demonstrated that artificial intelligence models trained on wearable sensor data can accurately predict acute health events, such as cardiac arrests or hypoglycemic episodes. This efficient capability significantly enhances Malaysia's ongoing efforts to decentralize healthcare services through digital transformation (Zainuddin et al., 2024). Despite their promise, wearable technologies face contextual constraints in Malaysia. The affordability of devices, lack of widespread digital infrastructure, and gaps in health literacy influence adoption rates (Canali et al., 2022). These challenges underscore the importance of tailored public health interventions and regulatory frameworks to make AI-driven wearables more accessible and culturally relevant within local healthcare dynamics.

2.3 Perception Related to Security and Privacy Concerns

The AI-driven wearable technology offers numerous benefits; however, research has shown significant concerns regarding security and privacy, which continue to be major obstacles to widespread adoption (Phang et al., 2024). The collection of sensitive health information by these devices naturally raises questions about how that information is protected and kept confidential. Research has pointed out that the rapid advancement of wearable technology often outpaces regulatory efforts, leaving gaps that could potentially expose personal health information (PHI) to breaches and misuse (Bouderhem, 2024). This study will emphasize the need for stronger regulatory frameworks to address these vulnerabilities. The above-stated constraint is further supported by a past study by Phang et al. (2024), who conducted a thorough review of privacy challenges related to wearable devices, highlighting critical issues such as unauthorized access and data leakage. Key findings suggest that leveraging advanced techniques, such as differential privacy and federated learning, can significantly enhance data security. These methods enable the analysis of health data without compromising individual privacy, thereby enhancing user trust and promoting the safer adoption of wearable health technologies.

2.4 Advancements in Health Technologies

The constant development of AI-driven wearable technology is closely linked to innovations in the field of science. The advancements in AI methodologies within the healthcare sector have led to a breakthrough in achieving highly accurate and efficient wearable sensors that can monitor a diverse range of physiological parameters, helping to identify underlying health conditions more reliably. This notion has led to availing the real time tracking information of patient's health via collecting data of vital indicators such as heart rate and glucose levels, the key findings from the research suggest that these improvements not only make health monitoring more precise but also enhance the overall user experience, encouraging better engagement (Tung & Dong, 2023). Moving further, digital twins are a new emerging concept in healthcare, where data from wearable devices are employed to create virtual models that represent individual or population health profiles. The given approach has helped in creating tailored treatment plans and simulating clinical scenarios (Johnson & Saikia, 2024). Furthermore, the potential of digital twins to transform patient care is immense, offering innovative opportunities for research and personalized medicine. Further research has emphasized the application of AI-integrated wearable devices for monitoring students' mental health, showcasing the versatility of these technologies beyond traditional healthcare settings (Upadhyay, 2023).

2.5 Challenges and Limitations

Despite the rapid evolution and potential of AI-driven wearable technology in healthcare, numerous challenges impede its widespread adoption in Malaysia. A core concern centres around the accuracy and reliability of data collected through these devices. Discrepancies in sensor technologies, variations in calibration, and environmental factors can significantly compromise data integrity. As noted by Wadden (2022), inconsistencies in wearable sensor outputs may lead to erroneous interpretations, which, in critical care scenarios, could result in misdiagnoses or inappropriate interventions. This raises legitimate concerns about the clinical applicability and trustworthiness of such technologies in real-world medical settings. Moreover, trust and acceptance among healthcare providers and the general public remain significant barriers to effective communication. The successful implementation of wearable technology is influenced not only by its technical capabilities but also by user confidence and digital literacy. Shajari et al. (2023) further emphasize the necessity for targeted educational interventions to address technological apprehensions and increase awareness of both the benefits and limitations of wearable devices. Without such educational initiatives, misconceptions and resistance may persist, hindering broader integration into health systems.

Infrastructure limitations and data security concerns further compound the problem. In Malaysia, disparities in digital infrastructure, particularly between urban and rural regions, can restrict access to real-time health monitoring platforms. Additionally, concerns over data privacy and the ethical use of personal health information are critical. As highlighted by Gerke et al. (2020), a lack of robust legal frameworks governing data ownership and AI ethics could undermine public trust and institutional commitment. Finally, economic factors, including device affordability and lack of insurance reimbursement models for wearable technology, can deter adoption. Research by Al Mahmud et al. (2023) found that high initial costs and limited funding for digital innovations pose practical challenges, especially in developing country contexts such as Malaysia. In summary, while the transformative potential of AI-driven wearables is evident, overcoming technical, social, infrastructural, and policy-related barriers is equally essential for fostering long-term integration and acceptance within the Malaysian healthcare scene.

2.6 Diffusion of Innovation Theory (DOI)

To contextualize the adoption of AI-driven wearable technologies in Malaysian healthcare, this study employs the Diffusion of Innovation (DOI) Theory, proposed by Everett Rogers (1995). This theory offers a comprehensive framework for examining how innovations disseminate within social systems and the factors that influence individual adoption decisions. The theory posits that five primary attributes —relative advantage, compatibility, complexity, trialability, and observability —play crucial roles in shaping users' willingness to adopt new technologies (Rogers, 1995). According to Rogers (1995), the innovation itself must present a distinct benefit over existing practices (relative advantage), align with users' existing values and needs (compatibility), and be simple to understand (low complexity) coupled with innovations that can be experimented with (trialability) and whose outcomes are visible to others (observability) are more likely to be accepted. These attributes offer a foundational structure for evaluating AI-driven wearables in the Malaysian healthcare context. Additionally, adoption is influenced by communication channels (including mass media, social media, and interpersonal dialogue), time (the rate of adoption), and the social system (the norms and dynamics of a community or organization) (Greenhalgh et al., 2004). These elements are critical in healthcare systems, where peer influence, professional hierarchy, and policy incentives can accelerate or hinder the diffusion.

2.6.1 Compatibility

Compatibility, as defined within the Diffusion of Innovations (DOI) theory by Rogers (1995), refers to the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters. It is a critical factor influencing the adoption of new technologies, including wearable health devices, because users are more likely to accept innovations that fit well with their lifestyle and habits (Rogers 2003; Choe & Noh, 2018). In the context of wearable technology, compatibility encompasses how well the device integrates with users' daily routines, aligns with their health goals, and matches their technological proficiency and aesthetic preferences.

Empirical studies have consistently shown that compatibility has a positive effect on users' intention to adopt wearable devices.

For example, Choe and Noh (2018) found that compatibility has a significant influence on perceived usefulness, which in turn affects the behavioral intention to use smartwatches. This suggests that when users perceive wearable devices as fitting naturally into their lifestyle and offering functionalities similar to familiar technologies (e.g., smartphones or traditional watches), they are more likely to recognize the device's usefulness and adopt it. Similarly, a study examining consumers' intention to use wearable healthcare devices highlighted that compatibility with users' health management practices and personal preferences was a key determinant of adoption (Schaarup et al., 2023). In summary, compatibility as an independent variable is a strong predictor of wearable health device adoption. It influences users' perceptions of usefulness and ease of use by ensuring the technology aligns with their lifestyle, values, and social context. Understanding compatibility enables developers and marketers to design wearable devices that better meet user expectations and cultural requirements, thereby improving adoption rates and promoting sustained use.

H1: Compatibility has a positive and significant effect on the adoption of AI-driven wearable technology in the Malaysian manufacturing industry.

2.6.2 Relative Advantage

Relative advantage is a core construct of Rogers' Diffusion of Innovations (DOI) theory, referring to the degree to which an innovation is perceived as superior to the idea, product, or technology it supersedes (Rogers, 2003). It captures the perceived benefits and improvements that a new technology offers over existing alternatives, influencing users' motivation to adopt it. In the context of wearable health devices, relative advantage refers to how users perceive these devices as offering superior health monitoring, convenience, or lifestyle enhancement compared to traditional health management methods or other technologies (Şehbenderoğlu, 2019; Chen et al., 2022). Empirical research consistently demonstrates that relative advantage is a significant predictor of users' intention to adopt wearable technologies. For instance, studies have shown that consumers who perceive wearables as providing meaningful benefits, such as real-time health tracking, early detection of medical conditions, or personalized fitness guidance, are more likely to adopt these devices (Kim & Shin, 2015; Chen et al., 2022). Relative advantage encompasses not only functional benefits but also social and psychological gains, including increased social image, novelty, and ease of integrating the device into daily life (Jeong & Choi, 2022). This multifaceted advantage makes relative advantage a powerful motivator in adoption decisions.

In practical terms, emphasizing the relative advantages of wearable health devices — such as superior health insights, convenience, and seamless integration with smartphones or health platforms — can enhance user acceptance and market penetration. Manufacturers and marketers should communicate clear, tangible benefits and continuously improve device functionalities to maintain a competitive advantage (Şehbenderoğlu, 2019; Chen et al., 2022). In summary, relative advantage as an independent variable plays a pivotal role in predicting the adoption of wearable health technologies. It encapsulates the perceived superior benefits of wearables over existing solutions and mediates the influence of perceived usefulness and ease of use on adoption intention. Recognizing its moderating relationship with personal innovativeness further refines strategies for promoting the adoption of wearable technology.

H2: Relative advantage has a positive effect on the adoption of AI-driven wearable technology among employees in the Malaysian manufacturing sector.

2.6.3 Trialability

Trialability, one of the key attributes in Rogers' Diffusion of Innovations (DOI) theory, refers to the degree to which an innovation can be experimented with on a limited basis before making a full commitment to adoption (Rogers, 2003). It allows potential users to test the technology, reducing the uncertainty and perceived risk associated with adopting new devices. In the context of wearable health technology, trialability enables users to experience the device's features, usability, and benefits firsthand, which can significantly influence their intention to adopt the technology (Choe & Noh, 2018; Kruger & Steyn, 2024). Research indicates that trialability positively impacts the adoption of wearable devices, as it allows users to evaluate compatibility with their lifestyle and assess ease of use without a full investment (Kruger & Steyn, 2024; Şehbenderoğlu, 2019).

For example, consumers who can try smartwatches or fitness trackers before purchasing are more likely to perceive the devices as less complex and more useful, which increases their likelihood of adoption (Jeong & Choi, 2022). This hands-on experience helps alleviate concerns about functionality, comfort, and data privacy, which are common barriers to the adoption of wearable technology (Kruger & Steyn, 2024). Trialability as an independent variable is a significant predictor of wearable health device adoption. By enabling limited experimentation, it reduces uncertainty, enhances perceived ease of use, and increases user confidence. For manufacturers and healthcare providers, facilitating trial opportunities such as free trials, demos, or pilot programs can effectively accelerate the adoption and diffusion of wearable technologies.

H3: Trialability has a positive influence on the adoption of AI-driven wearable technology in the Malaysian manufacturing context.

2.6.4 Complexity

Complexity, as defined in Rogers' Diffusion of Innovations (DOI) theory, refers to the degree to which an innovation is perceived as difficult to understand and use (Rogers, 2003). It is a critical factor influencing the adoption of wearable health devices, as higher perceived complexity tends to discourage potential users from embracing new technologies (Marshall & Byrd, 1998; Thompson et al., 1991). In the context of wearable technology, complexity encompasses both the operational difficulty users experience when interacting with the device (input complexity) and the challenge of interpreting the data output by the device (output complexity) (Khan et al., 2020). For example, older adults often perceive wearable devices as complex due to difficulties in entering personal data or understanding the health metrics displayed, which can reduce their intention to use such devices (Kruger & Steyn, 2024).

Empirical studies have consistently shown that perceived complexity negatively impacts adoption intention. A mixed-methods study on seniors' adoption of wearables found that complexity acts as a significant barrier, as users with limited technical skills or cognitive capacity are less inclined to adopt devices (Khan et al., 2020). Similarly, research conducted in Malaysia identified complexity as a deterrent to the adoption of wearable healthcare devices, emphasizing that users prefer technologies that are intuitive and easy to use (Choo, 2022). These results align with findings from a Turkish market study, where complexity was found to have a negative relationship with adoption, confirming that users tend to reject wearable health tracking devices perceived as difficult (Şehbenderoğlu, 2019). Complexity as an independent variable plays a pivotal role in wearable health device adoption. High perceived complexity discourages use by increasing cognitive load and reducing perceived ease of use, especially among older or less tech-savvy users. Addressing complexity through user-centered design and education is crucial for facilitating the broader adoption of wearable technologies.

H4: Complexity negatively affects the adoption of AI-driven wearable technology in the Malaysian manufacturing industry.

2.6.5 Observability

Observability, as defined in Rogers' Diffusion of Innovations (DOI) theory, refers to the degree to which the results or benefits of an innovation are visible and easily perceived by potential adopters (Rogers, 2003). It plays a crucial role in influencing the adoption of wearable health devices, as users are more likely to adopt and continue using a technology when they can observe its advantages or outcomes, as evidenced by Bø et al. (2023) and Zhang et al. (2022). In the context of wearable technology, observability refers to how easily users or their social circles can notice improvements in health metrics, physical activity, or overall well-being that are attributable to the device's usage. Research indicates that higher observability enhances users' awareness and understanding of the value provided by wearable devices, thereby reducing uncertainty and promoting positive attitudes toward adoption (Taib et al., 2016; Bø et al., 2023).

For example, if a wearable device displays heart rate trends, sleep quality improvements, or step counts in an understandable and visually appealing manner, users are more likely to recognize its benefits and maintain engagement. Furthermore, observability extends beyond the individual user; when others in a user's social network observe the device's positive effects, social influence can further accelerate adoption (Zhang et al., 2022). Observability as an independent variable significantly influences the adoption of wearable health technologies by making the benefits of the innovation visible and understandable to users and their social environment. Enhancing observability through clear data presentation, social visibility, and an appealing design can increase adoption rates and sustain the use of wearable devices.

H5: Observability has a positive effect on the adoption of AI-driven wearable technology among employees in Malaysia's manufacturing industry.

2.7 Categories of Adopters

Rogers (1962) classified adopters into five groups based on their rate of adoption of innovations. For example, Innovators (2.5%), who are risk-takers that adopt innovations first and influence others as shown in Figure 1. At the same time, early adopters (13.5%) are opinion leaders who assess and validate innovations before the majority follows. The early majority (34%) are thoughtful adopters who accept innovations after observing their success. The late majority (34%) are skeptical individuals who adopt once the innovation is widely accepted. Lastly, the laggards (16%) are the last group to adopt, often resistant to change and preferring traditional methods. Rogers (1995) further classifies adopters into five segments: innovators, early adopters, early majority, late majority, and laggards. Each group demonstrates varying levels of openness to innovation. For instance, innovators quickly adopt novel solutions and influence others, while laggards tend to resist change due to their comfort with traditional methods (Rogers, 1962). In healthcare, early adopters may include tech-savvy medical professionals or urban health institutions, whereas rural hospitals or older practitioners may represent the late majority or laggards (Dearing & Cox, 2018).

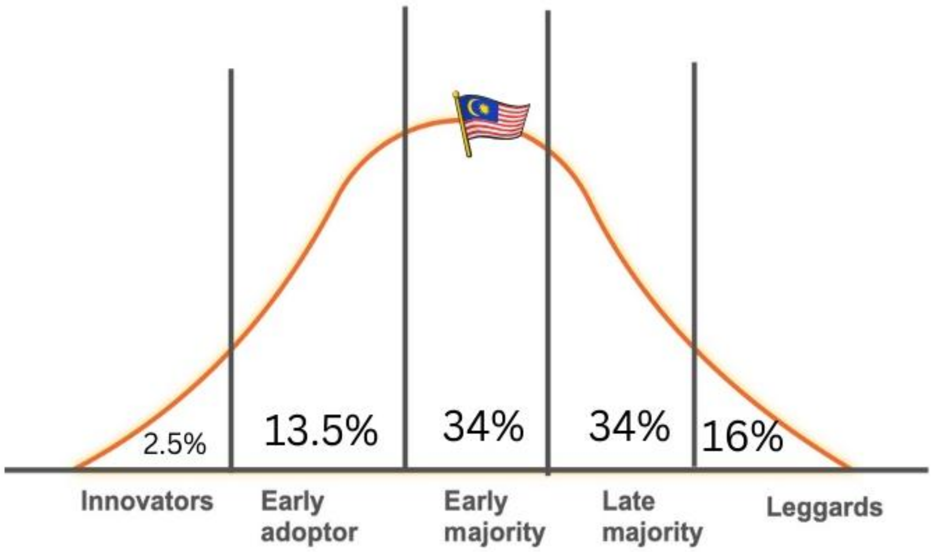

Figure 1: Diffusion of Innovation Model for Wearable Technology and Artificial Intelligence in Developing Countries such as Malaysia

2.7.1 Factors Influencing Adoption

The above-mentioned studies have indicated that the speed and extent of innovation diffusion depend on five key attributes, namely, Relative Advantage, which refers to the degree to which the innovation is superior to existing solutions. Compatibility refers to how well the innovation aligns with users' values, experiences, and needs. Complexity, along with easier-to-use innovations, is adopted faster. Trialability, the ability to experiment with the innovation before making a full commitment, and observability, which refers to the visibility of the innovation's benefits to potential adopters. The successful diffusion of AI-driven wearable technology hinges on how users perceive its utility and usability. For instance, Davis et al. (1989) and Venkatesh et al. (2003) emphasized that perceived usefulness and ease of use are significant determinants of technology acceptance. This is particularly relevant in healthcare, where clinicians prioritize patient safety, workflow efficiency, and adherence to regulatory compliance.

2.7.2 The Human Side of Innovation Diffusion

Beyond technical features, innovation in adoption involves complex human emotions and social dynamics. Drawing parallels from consumer technologies like smartphones or streaming platforms, initial scepticism is common but can be mitigated through exposure, peer validation, and evidence of benefits. Similar behavioral patterns are observed in the medical field, as demonstrated during the transition from paper-based records to electronic medical records (Greenhalgh et al., 2004). Adoption was gradual but accelerated as more practitioners witnessed efficiency gains and institutional support increased. Considering the categories of adopters defined by Rogers (1995), the adoption of new ideas is not merely a technical or logical process; it is a deeply human phenomenon. People adopt innovations based on personal experiences, societal influences, and emotional connections. For instance, the adoption of smartphones was not just about improved communication but also about convenience, social status, and staying connected with loved ones.

Considering how streaming services like Netflix have revolutionized the entertainment industry. The early adopters were tech-savvy individuals who appreciated on-demand content. As people began to recognize the convenience and diverse content available through streaming services, an increasing number of users joined in. Initially, the early majority adopted it, and before long, streaming became the norm. Even the late majority eventually followed, especially as traditional cable TV lost its relevance, and finally, the laggards made the switch as well. This pattern of adoption isn't unique to entertainment; it's also evident in healthcare. For instance, when electronic medical records (EMRs) were first introduced, many doctors resisted the change, favouring familiar paper-based systems. However, as more hospitals and clinics demonstrated the efficiency and practicality of digital solutions, EMRs gradually became the standard way of managing patient information (Dearing & Cox, 2018).

2.7.3 Overcoming Barriers to Adoption

Even with innovations that bring obvious benefits, resistance is still unavoidable most of the time. Individuals may feel uncomfortable about technology they are not familiar with, worrying about the associated costs. Or they prefer sticking to what they are already familiar with. For this very reason, understanding human psychology is essential when introducing new thoughts and ideas. It’s significant for companies and innovators to address these concerns openly, offer their expertise, and transparently showcase the real-time benefits to encourage and promote widespread acceptance. Awareness and education are equally pivotal in this process. For instance, the early adoption of electric vehicles (EVs). Initially, the majority of consumers were hesitant due to a lack of clarity about battery life and the availability of charging infrastructure. Although more charging stations are being installed and governments are introducing incentives, the adoption rate has increased significantly. In the context of healthcare in Malaysia, tackling these factors can help shift perceptions to a more positive paradigm among patients and healthcare providers. Research indicates that user friendliness and perceived usefulness play crucial roles in determining whether new health technologies are readily accepted (Davis et al., 1989; Venkatesh et al., 2003).

Moreover, understanding the social systems within which these technologies are introduced, such as organizational culture and peer pressure and influence, can significantly enhance communication strategies aimed at building awareness and knowledge about AI-driven wearables (Greenhalgh et al., 2004; Dearing & Cox, 2018). Drawing on insights from the Diffusion of Innovations theory can help stakeholders tackle challenges more effectively while adopting new technologies within healthcare settings. In summary, this study aims to explore the adoption of AI-powered wearable technology in the Malaysian healthcare sector through the lens of the Diffusion of Innovation (DOI) theory. By focusing on how innovations are perceived, DOI helps us understand the factors influencing their spread. Specifically, the study examines the impact of perceived usefulness and ease of use on shaping user acceptance. The proposed framework will highlight key barriers to adoption and offer strategies to overcome them, ultimately contributing to better healthcare outcomes.

2.8 Conceptual Framework

Figure 2 below presents the proposed study framework, which is grounded in the theoretical foundations and literature previously discussed. The framework outlines all key variables and illustrates their relationships with the factors influencing the adoption of AI-driven wearable technology. The specific components are as follows:

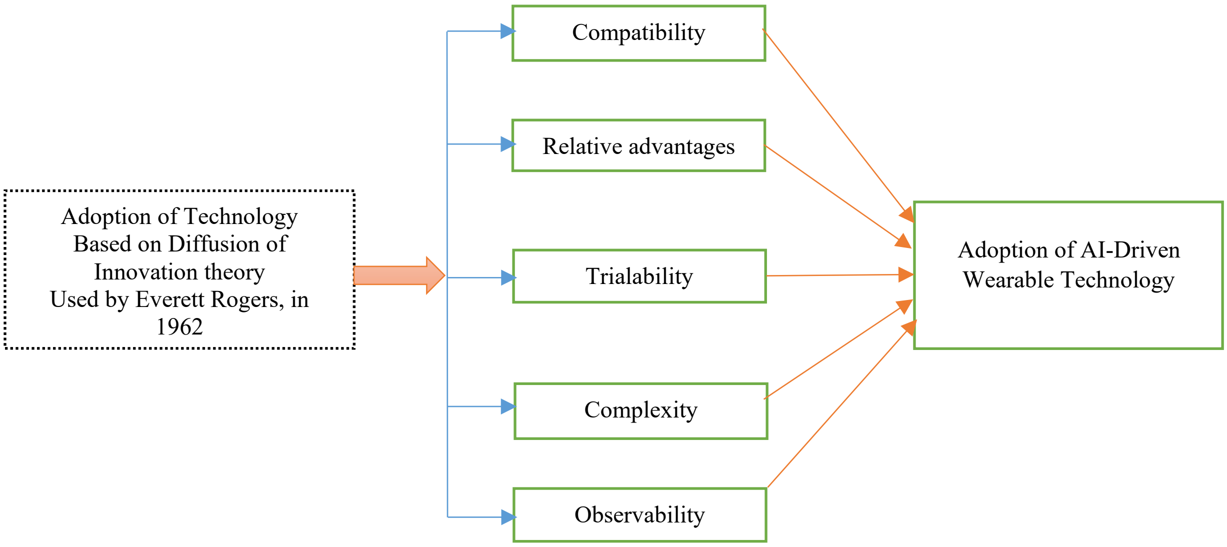

Figure 2: Proposed Conceptual Framework

3.0 Methodology

While this study is primarily conceptual, focusing on the development of a theoretical framework to explore the relationship between all factors affecting the adoption of artificial intelligence-driven wearable technology in the Malaysian healthcare sector, this section proposes a detailed research methodology for the empirical validation of the proposed framework. A robust research design is essential for ensuring the validity and reliability of findings, as it provides a structured approach to coordinating research activities, optimizing resource allocation, and adhering to rigorous methodological standards (Creswell & Creswell, 2018). Consequently, a comprehensive research plan must be meticulously outlined before data collection to ensure systematic execution and alignment with the study's objectives. This section elaborates on the proposed methodology, including the research design, data collection, and analysis techniques, as well as preliminary analysis and data analysis, to facilitate future empirical testing of the theoretical model. The research process underlying this study consists of 11 stages, and an overview is presented in Figure 3.

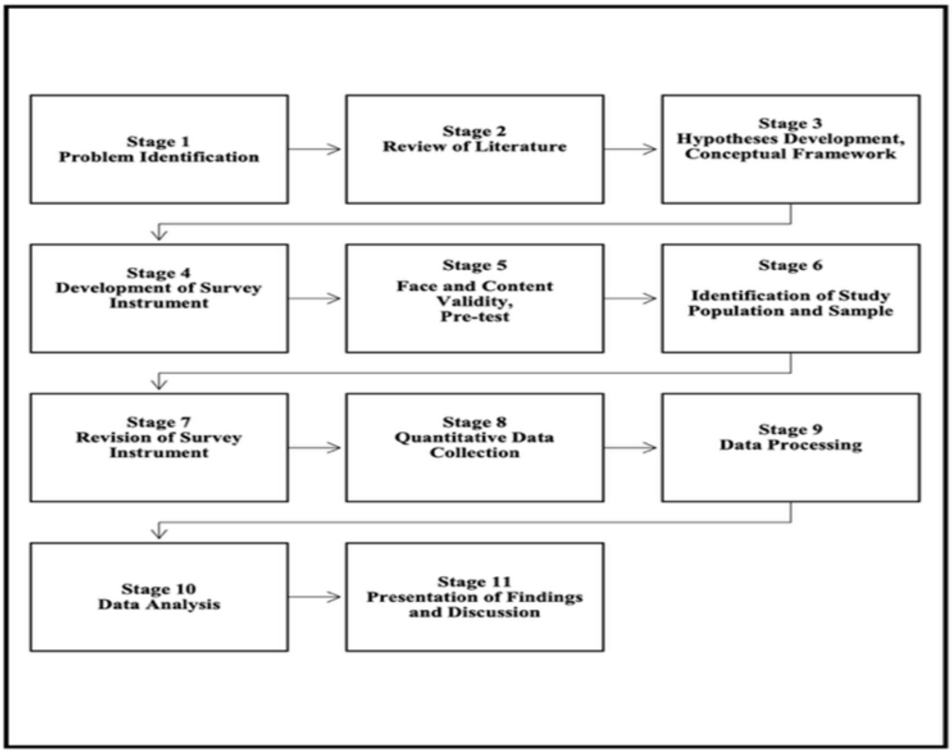

Figure 3: Stages of Research

3.1 Research Design

This study employs a quantitative research approach to investigate the barriers to the adoption of AI-driven wearable technologies in the Malaysian healthcare industry, drawing on the key constructs of the Diffusion of Innovation (DOI) theory: compatibility, relative advantage, complexity, trialability, and observability (Rogers, 2003). A cross-sectional survey design will be employed to collect data from a target population of 300 medical professionals in Malaysia. Data collection will be conducted using an adopted questionnaire, comprising four questions for each construct, sourced from established and reliable previous studies.

Purposive sampling will be employed to ensure the inclusion of respondents who have either interacted with or intend to use AI-driven wearable health technologies in the future. To determine the minimum required sample size and ensure sufficient statistical power, *G*Power analysis will be conducted. G*Power* is a widely recognized tool for computing statistical power analyses for various tests commonly used in social and behavioral sciences (Faul et al., 2009). In this study, the analysis will be based on anticipated effect size, desired statistical significance level (commonly set at $\alpha = 0.05$), and the number of predictors included in the research model. By applying G*Power analysis, the study aims to ensure that the sample size is adequate to detect meaningful effects and support the generalizability and validity of the findings.

3.2 Data Collection and Analysis Techniques

The Primary data for this research will be collected using a structured questionnaire distributed through online survey platforms. A five-point Likert scale (ranging from "strongly disagree" to "strongly agree") will be utilized to measure the constructs. Validated scales from prior research with similar theoretical foundations will be adopted and adapted to ensure the reliability and validity of the questionnaire. A pilot study will also be conducted to assess the feasibility of the proposed research design. It will serve as a technique to identify potential issues with data collection methods, refine research instruments, evaluate feasibility, and practice procedures before proceeding with the in-depth study.

3.3 Preliminary Analysis

A preliminary analysis will also be conducted to assess the quality, accuracy, and reliability of the data and the results. This process will involve inspecting and cleaning the data, identifying missing values, outliers, and errors, before conducting the primary analysis (Leong et al., 2024). Data filtering will be applied to enhance data accuracy by focusing on data that meets specific criteria while removing irrelevant information. Missing Value Analysis (MVA) will be used to detect and address incomplete or erroneous data, hence maintaining data integrity. In addition, Common Method Variance (CMV) analysis will also be employed to identify and assess potential biases within the obtained dataset. Normality assessment, using Mardia's coefficient, will determine whether the data follows a normal distribution, as many statistical procedures assume data normality. Lastly, an outlier analysis will be conducted to identify and exclude extreme values that may discrepant the results and lead to inaccurate findings.

3.4 Data Analysis

SPSS (Statistical Package for the Social Sciences) version 25 and SmartPLS 4.0 will be employed for data analysis in this study. SPSS, a first-generation software, will be used to key in each respondent's response and to perform data cleaning to prepare the data for analysis. Descriptive statistics will be generated using SPSS. First-generation statistical software is suitable for straightforward research models. However, it is only capable of analyzing single relationships between the independent and dependent constructs. Thus, for the path coefficient, Structural Equation Modelling (SEM) will use partial least squares, and SmartPLS 3.0 software will be employed.

4.0 Expected Contribution to Future Government Policies

The government of Malaysia has been actively involved in promoting digital health initiatives as part of its National Health Policy, aiming to improve healthcare accessibility and quality through technology (Ministry of Health Malaysia, 2023). Understanding the perceptions of the Malaysian population about using AI-driven wearable technology aligns with these objectives, providing critical insights for policymakers to develop effective regulations and support systems that foster technology adoption in healthcare. This study will significantly contribute to the Malaysian

Government in addressing health-related challenges and achieving Malaysia's Shared Prosperity Vision (SPV2030) and the 10-10 My STIE framework within the national plan, aligning with SDG Goal 3 of achieving good health and well-being for all, as outlined by the World Health Organization (2021).

5.0 Recommendation and Conclusion

This research intends to provide a foundation for future innovations and policy development by identifying the critical factors that influence technology adoption in the Malaysian healthcare context. It will support the creation of a roadmap for the effective and sustainable integration of AI-driven wearable health technology, one that enhances patient outcomes, boosts healthcare system efficiency, and strengthens public confidence in digital health solutions.

6.0 Conclusion

This proposed research will play a pivotal role in addressing key barriers to the adoption of AI-driven wearable technology within Malaysia's healthcare landscape. By investigating public perceptions, trust levels, and the socio-cultural factors that shape technology acceptance, the study aims to generate insights that will inform the design of more effective and inclusive adoption strategies. In doing so, the research will seek to bridge the existing gap between technological innovation and practical healthcare implementation, ultimately supporting Malaysia's transition toward a digitally advanced healthcare system. Framed within the Diffusion of Innovation (DOI) Theory, this study will provide a systematic approach to understanding how AI-powered wearable technologies are perceived and adopted by various segments of the Malaysian population. The DOI framework, emphasizing attributes such as relative advantage, compatibility, complexity, trialability, and observability, will guide the analysis of user behavior and adoption patterns. Through this lens, the research will aim to uncover both the motivators and deterrents that influence technology uptake, providing a nuanced understanding of the human and contextual factors at play.

In alignment with Malaysia's Shared Prosperity Vision 2030, the study aims to contribute to the national goals of equitable access to healthcare and inclusive digital transformation. By exploring how wearable technologies can support more personalized, real-time care, the research will propose recommendations to enhance trust, improve accessibility, and inform evidence-based policymaking around digital health tools. The anticipated societal contributions of this research will be far-reaching. By addressing concerns around data privacy, cost, ease of use, and awareness, the study will help empower underserved populations to engage with emerging healthcare technologies. It will also provide guidance for stakeholders, including healthcare providers, developers, and regulators, on how to align their efforts with public needs and expectations. In summary, by highlighting both ethical and practical considerations, the study will advocate for a responsible and people-centred approach to AI integration in the Malaysian healthcare sector, successfully overcoming the existing barriers to adoption.

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