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Abstract: There have been many attempts to predict new markets, including a new market for internet of things (IoT)-based healthcare and the IoT platform's ability to offer a variety of applications. It is anticipated that the market for these devices will continue to grow as the healthcare sector undergoes fast expansion. IoT can measure a user's kinetic data (calorie consumption, distance, number of steps, etc.) using wearable healthcare equipment. Most of the recent top research on IoT-based healthcare wearable devices (IWHDs) has, up to this point, concentrated on potential users. The medical industry and healthcare are being quickly changed by the use and adoption of wearable healthcare devices. This study intended to uncover the mediating impacts of "perceived ease of use", "perceived usefulness", and "community immersion" on the interactions between influencing factors (personalization, service convenience, interactivity), and the intention to utilize IHWDs. The moderating role of a consumer's innovativeness in the influence link between IHWD features on perceived ease of use and perceived usefulness was also examined. The study found that personalization has a direct (+) impact on usage intention. Through this, it would be feasible to raise the intention of wearable medical devices being accepted if customized benefits that are thoroughly examined just for individuals are supplied. The association between personalization and continued use intention was shown to be partially mediated by perceived utility and community immersion. Additionally, the association between interactivity and continued use intention, was fully mediated by perceived usefulness and community immersion. By analyzing the elements influencing the usage intention of wearable healthcare devices, this study offers a marketing plan to increase the number of users. The internet of medical things (IoMT) sector has had compound growth of approximately 26% from 2018 to 2021, which is a remarkable accomplishment. The effectiveness of factors affecting IoT usage was examined in this study when applied to the actual IoT industry. First, patients with diabetes who previously had to check their blood sugar levels through a blood test can now check it through lifestyle management and steady glucose monitoring through IoMT glucose monitoring when the convenience and individuality of the service are improved. So far, 10% of all Americans have benefited from this device. Second, as an illustration of interactivity, an IoMT-connected inhaler used to assist asthma sufferers with breathing, notifies the user when the inhaler is left at home and reminds them of appropriate times to use the device. This subsequently resulted in saving 1 life out of every 3 deaths. In addition, the findings of this study may also provide a turning point for the design and development of cutting-edge IoT-based healthcare goods and services.

**Keywords:** wearable healthcare devices; personalization; service convenience; interactivity; perceived ease of use; perceived usefulness; innovativeness

# 1. Introduction

One of the most crucial topics in the study of new technologies has been to comprehend why individuals accept or reject new information technology [1]. The Internet of Things (IoT) refers to a network of physical objects (things) that incorporate sensors, software, and



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**Copyright:** © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). other technologies to connect and exchange data with other devices and systems over the Internet. [2]. IoT enables formerly "dumb" devices to become "smarter" by allowing them to transfer data via the internet, enabling devices to interact with people and other IoT-enabled objects. Wearable technology, was crucial to the healthcare sector when it came to diagnosis during the COVID-19 outbreak [3]. IoT refers to a device that is online and connected to an IoT application or network, as well as a number of 'things' that may exchange data with other objects, including commercial machinery. Built-in sensors are used by internetconnected gadgets to gather data and, in some situations, respond appropriately. Machines and devices that are IoT-connected help us live and work better. Wearable healthcare devices are quickly becoming commonplace as IoT devices and healthcare technology intersect, and the wearable healthcare device industry is still expanding. Wearable healthcare devices use Near Field Communication (NFC) technology to detect, measure, collect, and transmit health biological information that occurs in the body. These devices are characterized as wearable devices that perform healthcare-related functions. Doctors may continuously obtain crucial patient information thanks to wearables, such as VitalConnect's HealthPatch MD. These instances demonstrate how wearable technology significantly affects the health industry [4]. The internet of medical things (IoMT) is the technology that connects personalized information, devices, and systems by digitizing data, such as an individual's lifestyle, disease history, medical use information, genetic information, etc. Through ultimate integration of internet-based devices, IoMT creates a feasible service network that allows all available healthcare resources and various healthcare services to be interconnected. IoMT's main purpose is to use smart devices equipped with sensors, actuators, monitors, detectors, video systems, and other components to keep track of a patient's condition. These devices and sensors capture data in analog form, which is then transformed into digital form for processing [5]. The "Quantified Self" concept, which conveniently monitors health problems, such as meals, blood pressure, and exercise in daily life, is gaining traction thanks to smart devices and sensor technology. Research and Market (globalnewswire.com (https://www.globenewswire.com/en/news-release/2021/06/14/2246369 /28124/en/Global-Wearable-Medical-Devices-Markets-Report-2021-Market-is-Expectedto-Reach-24-38-Billion-in-2025-at-a-CAGR-of-24-Long-term-Forecast-to-2030.html)) (accessed on 5 June 2022). claims at a compound annual growth rate (CAGR) of 23.1%, the market for wearable medical devices will increase from \$8.35 billion in 2020 to \$10.28 billion in 2021. Along with the growth of the IoMT market, it is necessary to inform consumers of the understanding and necessity of IoMT products.

The purpose of this study was to present factors that may affect a user's intention to use wearable healthcare devices. In order to achieve continuous development and growth in the wearable healthcare device industry, a greater understanding of a user's behaviors must first be studied. This is because in order to ensure that consumers continue to use wearable devices, wearable devices must be designed to stimulate consumers' needs based on users' experiences. The market for wearable healthcare is expected to expand as smart devices, healthcare, IoT capabilities, and the activation of each person's quantified self-movement all come together. The term "digital healthcare" refers to an integrated healthcare service that offers personal care services using information and communications technology (ICT) platform-based devices [6]. According to Martin, et al. [7], the service measures each person's health status, among other things, using digital devices that together include the service provided by healthcare organizations or related professionals to improve human health. This study focused on the qualities of the product and user that may influence a user's intention to use a wearable healthcare device. IoT is a technology that uses sensors to transmit and receive data over the internet in real-time. IoT may gather and process data without human interaction by connecting to wired and wireless networks. The term "healthcare" refers to a comprehensive healthcare initiative that integrates established medical services, such as remote examinations or in-person health advising, with concepts for managing and preventing disease. Medical devices that monitor vital signs, such as

patients' respiration, body temperature, heart rate, blood pressure, and electrocardiogram (ECG), are separated from healthcare equipment for healthcare and lifestyle development.

Additionally, when a specialized diagnosis is required, treatment can be freely received online without being limited by time or space. Therefore, the requirement of intelligent healthcare is crucial, especially in developed nations like the United States, Japan, and Korea which have already embraced an aging society.

While wearables have shown promise in the entertainment, gaming, and fitness sectors, the effectiveness of the healthcare sector, including health care service areas, diagnosis, surgery, and treatment sectors, was not quantitatively presented [8]. The majority of wearables on the market have a narrow focus, tracking only one or two health-related variables, and have not yet produced accurate measures for a number of the health markers, including heart rate variability, diet, and mood [9]. The most effective digital health systems, per a prior study, include health behavior models and customized coaching [10]. However, there is a lack of understanding of the factors that affect how well wearable technology is used in a hospital setting [9].

The technical aspects of the product (personalization, service convenience, interactivity), as well as a user's personal qualities (innovativeness), were the main focus of this study's analysis. This study attempted to confirm the statistical significance of the variables ('perceived use', 'perceived utility', and 'community immersion') that mediate the relationship between the components that influence the intention to use the wearable device and the intention to use it. For an empirical examination, a survey of wearable device users was conducted. Smart Pls 3.0 was used to analyze the data gathered. SmartPLS is software with a graphical user interface and is intended for variance-based structural equation modeling (SEM) using partial least squares (PLS) path modeling methods. SmartPLS is provided by SmartPLS GmbH, headquartered in Germany.

In order to set up an empirical research model on the factors influencing the use of IoTbased wearable devices, this study evaluated earlier studies based on Davis's Technology Acceptance Model (TAM) [11]. This study sought to determine whether the attributes of wearable IoT devices directly influenced users' intentions to use them, as well as the impact of perceived usability, the ease of use, and community immersion. This study also found that innovativeness acted as a moderator between independent components and the dependent variable.

#### 2. Literature Review

#### 2.1. IoT-Based Wearable Healthcare Device

Large volumes of processing data and sensor data can be efficiently sorted, categorized, and handled thanks to deep learning technology. The way that healthcare is provided has radically changed because of IoT and deep learning technologies [12]. IoT-based wearables are used to monitor and record a patient's vital signs and health problems while they are isolated [13]. Wearable technology is utilized to monitor possibly infected individuals' health problems, spot physiological changes periodically throughout quarantine, and warn users of the risk of infection [13].

The core of the IoT is to connect people, things, and things without boundaries. It is a new communication environment that can be connected to anything at anytime, anywhere. The IoT provides a multitude of answers in healthcare, making it one of today's hottest subjects. IoT is utilized in a variety of healthcare settings, such as disease monitoring to aid healing, disease treatment, and disease detection as a prevention. Wearable technology has been developed as a component of the IoT to help patients discover the right treatment. For individuals to properly monitor, manage, recognize, and act on information received from the system and to successfully reduce healthcare costs, the IoT in healthcare is essential. An IoT device is a computer equipped with sensors, microcontrollers, and transceivers. To provide the user with meaningful information, IoT components connect with one another [3].

An IoT healthcare service refers to a service that effectively manages patient health, utilizing IoT devices to measure and diagnose a patient's biometric data. By integrating IoT

services into a hospital system and offering medical services, an IoT healthcare service seeks to lower medical costs and improve services. Beyond the current medical service paradigm change and future healthcare service domains, IoT healthcare services can be expanded to include diagnosis, surgery, and therapy. When providing healthcare services, wearable IoT devices can assess a user's activity data (calorie consumption, distance, number of steps, etc.), footprint data (movement, foot pressure, etc.), ECG, and calories. Wearable IoT devices in particular offer a range of services in association with IoT platforms for the healthcare industry.

People who work in the field of wearable healthcare devices will soon be able to detect biosignals using cutting-edge sensors, collect real-time body data with algorithmic processing, identify individual patterns, and gain in-depth insights. They will also need to equip users with personalized smart healthcare systems so they can make critical decisions about their future health and care. When it comes to healthcare, fitness trackers such as smart watches read and record a user's movements and verify their unnoticed exercise pattern and volume [14].

IoT devices are a significant contribution to big data in healthcare since they generate a constant stream of data while tracking the health of individuals (or patients). Such resources can connect numerous technologies to offer the elderly and patients with chronic illnesses a trustworthy, efficient, and intelligent healthcare service. A wearable healthcare device refers to a medical device that is equipped with sensors and can be worn by humans. In addition, it detects and monitors body changes in various areas, providing customized health information to each individual, and allowing them to predict, prevent, and treat diseases [15]. Looking at the recent trends, device-oriented technology is developing to collect important and difficult personal health-related information, such as breathing, electrocardiogram, body composition, etc. Furthermore, relatively precise wearable devices are being developed capable of tracking the amount of exercise, the status of sleeping and stress, and food intake. For example, wearable devices worn on the wrist like watches for 24 h can measure, collect, and store information pertaining to a user's sleeping hours while sleeping, and these collected data can be utilized later. Wearable products have been released in various forms, including watches, bands, glasses, goggles, necklaces, shoes, badges, and clothing. Particularly, watch-type products can provide health information with accordance to the wearers' motion through a small liquid crystal display. Recently, manufacturers have been producing products that implement, not only the basic functions of a smartphone but also collect biometric information, such as pulse, respiratory rate, body temperature, and blood pressure.

Continuous glucose monitoring (CGM), developed by Medtronic in the U.S., can measure blood glucose for three consecutive days and measure concentrations of glucose in subcutaneous tissue every 10 s to alert a patient in advance. Nutromics' smart patch, which is the world's first wearable device that monitors the body's response to food, transmits changing biological indicators after eating to an app, accurately tracking how the body responds to various foods. Through these collected data, a diet that suits a respective individual can be provided. Sun Safety Sensor tracks the user's real-time location and measures how much ultraviolet rays the skin has absorbed for 24 h. It is possible to select skin types by connecting ultraviolet detection sensors to the app of the user's mobile phone, which sends a notification when it exceeds the customized safety standards. In addition, brand-new equipment is being produced by various companies related to blood pressure monitors, body fat monitors, blood glucose monitors, patient monitoring devices, and portable ultrasound diagnostic devices.

IoT essentially facilitates real-time data transfer, layered integration, and analytics of data recorded by intelligent embedded devices (data streams). These will, among other things, raise the standard of living, promote urbanization, make it easier to administer effective healthcare, and deal with natural disasters. Computing services can now be housed at the network's edge rather than on servers in old datacenters thanks to the data plane of the fog layer in layered integration. The integration framework in context

stresses being close to end users for application goals. It facilitates edge stream processing, distributes local resources in a seven-fold manner, and lowers latency for Quality of service (QoS). The main advantages are redundancy, resilience, and integrated user experience. This makes the Internet of Everything (IoE) paradigm's application widely accepted and used in real-time [15].

# 2.2. Technology Acceptance Model (TAM)

A TAM was introduced by Davis [9] to describe the aspects that influence how information technologies are used by people. According to Davis [11], perceived usability and ease of use are the key motivators for people to use technology [16].

In the technology acceptance model of the TAM model, perceived ease of use and perceived usefulness are explained as important variables that allow consumers to accept information technology and determine attitudes [11]. The TAM, which is based on consumer sentiments, is intended to gauge the acceptance of new technology. Perceived usefulness and perceived ease of use are derived as predictors of a user's attitude by TAM, which proposes attitude as a critical variable that predicts the recipient's desire to adopt a technology. An individual's attitude is a factor that directly affects their behavioral intentions and conveys their thoughts and feelings regarding their action. The use attitude and the perceived ease of use and usefulness of the recipient, which are developed under the impact of external variables, are causally related. The use attitude influences the behavioral intention, which influences the behavior [11,16,17].

According to Venkatesh and Davis [17], perceived usefulness refers to the degree to which it is believed that using a specific system can improve the user's ability to perform tasks. While perceived ease of use refers to the perception of the degree to which a user can use a particular system without extra effort. According to Venkatesh and Davis [17], perceived utility is influenced by perceived ease of use. Perceived ease of use has an impact on perceived usefulness because consumers perceive a system to be more useful the more convenient it is for them to use it, and the more useful they perceive a system to be the more favorable their attitude is toward that system, leading to an increased use of that system [11]. The degree to which it is thought that using a specific system will require less physical and mental effort is referred to as perceived ease. Enhancing usability can result in less effort and better results with the same amount of work [18].

#### 3. Theoretical Background, Research Hypotheses, and Model

The research model is shown in Figure 1. Figure 1 describes the relationship between the characteristic (personalization, service convenience, interactivity) variables and mediating variables (perceived use of use, community commitment) that affect the intention to use an IWHD.



Figure 1. Research model.

#### 3.1. The Personalization and the Continuous Intention to Use a IWHD

In order to collect individual patterns captured from real-time data through algorithm processors and to gain a comprehensive insight, personal customized healthcare devices are required. This is achieved by devices detecting biometric signals through high-tech sensors based on the IoT.

When customization reflects individual preferences in detail, satisfaction increases [19]. Utilizing specific client information to offer personalized solutions is known as personalization [20]. The capability of an entity to offer a product or a product purchasing experience is dependent on an individual consumer's personal or preference information [21]. According to Tam and Ho [22], the availability of more personalization services is positively impacted by information about items that are tailored to user preferences. Future uses of personalization strategies in digital health technologies have the potential to minimize stress and boost the effectiveness of digital instruments. By increasing user interest, personalization may help minimize the acknowledged tendency to stop using wearables after 3–6 months because they become "weary."

IoT, big data, cloud computing, and artificial intelligence are just a few of the cuttingedge IT tools that smart healthcare makes use of to improve existing medical systems in all directions, boost patient comfort and efficiency, and offer individualized care [23]. Thanks to technological improvements, top organizations have been able to modify and customize their goods and services to better meet the needs of their clients [24]. On mobile devices, personalization is possible in a number of ways [25]. Mobile devices are now more efficient in receiving, transmitting, and consuming information than desktop and laptop computers. They are more seamlessly integrated into a person's daily routine and present a more organic way for a consumer to use digital services (e.g., mobile news). However, there is currently a dearth of studies on the advantages of personalization in a mobile context.

The intention to continue using something is defined as an action that is related to the user's happiness after acquiring or reusing a service or product [26]. Whether a user has the intention to continue using a system after giving it a try is referred to as consistent usage intention [27]. The intention to continue using the present service as a sign of loyalty to the service provider" is the definition of continuous usage [27].

Personalization often results in positive customer evaluations [28,29] because it can help customers manage information overload [30] and control aimless browsing behavior. If personalization is not applied, customers may become overwhelmed by the amount of product information provided to them [31]. The objective of continuous use is "a condition in which people place full value on the computer to produce inherent business value by assisting the business to run faster, more effectively, and personally", according to Merikivi and Mantymaki [32]. The likelihood of continued usage and the desire to suggest or recommend the product or service to others are both higher the more satisfied the consumer is with the product or service [33].

Thus, the hypothesis is given below:

**Hypothesis 1:** *Personalization has a significant positive impact on the continuous intention to use IoT-based wearable healthcare devices.* 

#### 3.2. The Perceived Service Convenience and the Continuous Intention to Use IWHDs

The ability for mobile apps to rapidly and conveniently use applications of the needed functionalities was termed as convenience by Colwell et al. [34]. In the dictionary, the word "convenience" denotes "convenient and easy to use or utilize", as well as "convenient and good qualities in terms of circumstances or conditions". For tangible and intangible goods generated by an entity, such as products or services, this relates to user convenience [35]. According to Kim et al. [36], convenience, particularly in online settings, promotes value by saving customers money by requiring them to spend less time and effort, which in turn affects customer satisfaction.

The world's population is projected to grow by 2.3 billion people by 2050. Their medical care will be far more challenging to deliver. Better preparation is necessary for this as the current healthcare sector is experiencing an upheaval. The industry is shifting away from a reactive approach to health concerns and toward a more proactive one in terms of early sickness detection, prevention, and long-term health and wellness management [37].

To achieve this goal, monitoring and managing individual well-being must be given high priority. Naturally, the objectives of bettering healthcare services and residents' quality of life are what motivate us to consider IoT technology. They will play a crucial role in the creation, adoption, and upkeep of connected, intelligent, and personalized healthcare services and solutions [38].

Continuous physical condition monitoring and automated processing may be made possible by these services. As a result, processed events are created, which may reveal issues like high blood pressure, stress, and other issues [39]. The development of sufficient storage techniques to preserve the processed events comes before the advent of electronic health records (EHR) [40]. A review of factors influencing technology adoption rates reveals that ease of use and a positive user experience are crucial. Clinical staff and patient users must be taken into consideration when developing apps and devices for wearables in digital health interventions [9]. Health management, including illness prevention and diagnosis, biosignal assessment, and health and medical services employing various technologies, including wearable devices, are all referred to as IoT-based healthcare services. Currently, international businesses are offering IoT-based healthcare services by identifying the demand for independent healthcare service platforms and creating their own healthcare service platforms. As a result, the following is the hypothesis:

**Hypothesis 2:** The perceived service convenience has a significant positive impact on the continuous intention to use IoT-based wearable healthcare devices.

#### 3.3. The Interactivity and the Continuous Intention to Use IWHDs

Interactions are divided into interactions in the process of exchanging and processing information or messages, interactions in the technical/functional characteristics of a system or media, interactions at the user's perceived level, and interactions in a mixture of processes, characteristics, and cognitive perspectives [41]. According to Csikszentmihalyi [42], immersion is a phenomenon when a skilled individual becomes engaged in action in a natural and calm attitude as if they were absorbed. According to Alba et al. [43], interaction is characterized as constant two-way communication between two users. The degree to which senders and receivers accommodate and respond to one another's desires for communication was defined by Ha and James [44].

Customers prefer communication that is frictionless between app users, other app users, and app developers. Pfeil, Arjan, and Zaphiris [45] describe the degree of engagement that users can engage in as a factor that realizes the sensibility they experience in virtual space. Users can adjust the content and shape of the medium environment in a way that people approach.

Future service research in the healthcare sector may focus on topics, including service delivery and technological improvements [46]. Leveraging technology is the practice of utilizing technology to bring about a major change. In the context of the healthcare industry, the usage of wearable technology has the potential to both enhance services and draw the attention of academics. It is an anomaly that people buy and use wearable fitness trackers in big numbers, and then stop using them after a while [47]. Therefore, ensuring the long-term value of service through strong value propositions is a crucial issue.

For instance, it has been demonstrated that patients who actively engage in a doctordesigned treatment plan, seek information online, and join local support groups experience better outcomes. On the one hand, the process of introducing IT technologies such as IoMT can be explained in relation to the sociotechnical system. A sociotechnical system is developed through the interaction between human, social, and technological factors [48], and this system later serves as the basis for a service system [49]. This idea was translated in the study into how a user engages with game dynamics or third-party add-on services provided by a device utilizing a user's self and social perception (human factors) (technical factors). Wearable technology enables users to integrate resources with both the service provider and other customers during service contacts (user-device interactions) [50]. The value provided to the user is increased via interactivity, which enables an interactive information flow between the user and the device.

Each individual integrates information sources through interactions with various users (friends, family etc.) in the service network to better manage his or her healthcare [51]. A user might, for instance, acquire more motivation through peer and group support.

**Hypothesis 3:** Interactivity has a significant positive impact on the continuous intention to use IoT-based wearable healthcare devices.

#### 3.4. Mediation Effect of Perceived Ease of Use on the Continuous Intention to Use IWHDs

Perceived ease of use is described as having no special difficulty utilizing a certain system and refers to the extent to which users expect to use certain information technologies and systems without excessive mental and physical effort [11].

The degree to which potential users think that using a specific information technology or system will require less physical or mental exertion is how Davis [11] characterized perceived ease of use. According to Yang and Yoo [52], the user's mindset determines the intention to accept novel technology based on perceived usability and significantly influences actual use.

Perceived ease of use has a large positive impact on perceived usefulness [53], a belief variable that influences behavioral theory in the process of users accepting new technology. In other words, if consumers believe new technologies and systems are simple to use, they will be properly aware of the value of those technologies and systems. The evaluation of informative and practical features as cognitive attributes to technology is closely related to perceived utility and perceived ease of use [54]. In a study based on the TAM, Bhattacherjee [27] showed that perceived ease of use for e-commerce had a favorable effect on the desire to continue using e-commerce. Vijayasarathy [55] defined "perceived ease of use" as the degree to which consumers believe that online purchases are possible without much effort.

**Hypothesis 4:** *Perceived ease of use has a significant mediating effect of the characteristics of* IoT*based wearable healthcare devices on the continuous use intention.* 

#### 3.5. Mediation Effect of Perceived Usefulness on the Continuous Intention to Use IWHDs

The TAM model was employed in this study to determine the variables influencing the adoption of IoT-based wearable healthcare devices. The TAM model was chosen because it is straightforward, has a strong theoretical underpinning, is simple to modify and extend, and appropriate for dealing with the variety of information technology acceptance phenomena. As one of the cutting-edge technologies of the time, information technology was also developed to explain the determining factors to predict its use and acceptance. The TAM model was created for this purpose and has a strong foundation to explain end user behavior for a variety of technologies. Meanwhile, perceived usefulness refers to the amount to which past users' use of a particular system has improved their work [11]. Perceived usefulness, according to Davis [11], is the degree to which potential users think that utilizing a specific information technology or system will enhance their ability to accomplish their job duties. This is seen as combining the efficiency of the task with the caliber of the information technology used in the work. This represents an aspect of individual work productivity improvement when users of information technology perform specific technologies. New items might be deemed to be extremely beneficial when

they offer consumers benefits that cannot be obtained from existing products in terms of performance or function.

According to Bhattaccherjee [56], user contentment and their willingness to use repeatedly are influenced by perceived utility. Since user experience in the technical model has lessened the impact of ease of use on intention, variables like perceived usability have been eliminated [56].

Perceived usefulness, which is defined as "the degree to which a person believes that using a given system will boost his or her job performance" [11], is one of the most potent markers of IT adoption. According to Park and Chen [57], users' propensity to use mobile phones was influenced by how beneficial they viewed the devices to be. In their study on user acceptance of long-term evolution (LTE) services, Park and Kim [58] discovered that users' intentions to use a service were positively impacted by their perception of the LTE services' value. The intention to use a short messaging service that offered utilitarian benefits to users looking for efficient communication was influenced by perceived usefulness, according to Kim et al. [59].

**Hypothesis 5:** *Perceived usefulness has a significant mediating effect of the characteristics of IoTbased wearable healthcare devices on the continuous use intention.* 

#### 3.6. Mediation Effect of Virtual Community Immersion on the Continuous Intention to Use IWHDs

It has been demonstrated that a user's continuous use is influenced by consistency and satisfaction between expectations and outcomes [60]. This is known as an online community because it engages in cyberspace for shared interests, creating a space where opinions and information are exchanged to establish and sustain relationships [61]. The community is defined as a group of people who share a common interest. Users can communicate with others and learn new things by participating in online communities [62]. Hagel [63] provided evidence that the intention behind real service purchases is significantly influenced by online community loyalty.

This was true for every digital health program that the workgroup evaluated during the development and testing stages. Clinicians desire better patient outcomes, seamless integration of the digital platform into the clinical workflow, and quick access to key clinical data. Wearables are more likely to be purchased by those who already lead healthy lifestyles and want to monitor their progress [2]. The majority of wearable device producers (including Fitbit, Jawbone, and Nike) highlight how their products may work as a "all-inone" platform for improving physical performance and creating healthy habits. Wearable device producers use a range of digital persuasion techniques and social influence strategies, such as the gamification of activity through challenges and competitions, the publication of visible performance feedback based on social influence principles, or reinforcements in the form of virtual rewards for achievements, to increase user engagement. In order to appear respectable to their peers, people frequently conform to normative social norms [64]. The phrase "degree to which users may receive respect and appreciation from peers in their social network as a result of their usage of technology" was coined by Lin and Bhattacherjee [65]. Social image is more important in communication and social interaction systems, which can serve as a symbolic medium for the portrayal of users' social images within their community [66]. According to potential consumers, wearable technology is more practical.

Surgeons can monitor and respond to changes in a patient's vital signs using virtual reality and head-mounted wearable technology without having to look away from the patient. By mimicking intense environments like an operating room, a sports field, or outer space, wearable technology could be employed in schools to improve higher education. In order to increase new consumers' readiness to adopt wearable technology, it's imperative to make sure that both existing and new users are having more fun with it.

**Hypothesis 6:** *Virtual community immersion has a significant mediating effect of the characteristics of IoT-based wearable healthcare devices on the continuous use intention.* 

## 3.7. Sequential Mediating Effect

**Hypothesis 7:** Perceived ease of use and perceived usefulness sequentially mediate the relationship between the characteristics of IoT-based wearable healthcare devices (the personalization, the service convenience, the interactivity) and the continuous intention to useIoT-based wearable healthcare device. (i.e., the personalization  $\rightarrow$  perceived ease of use  $\rightarrow$  perceived usefulness  $\rightarrow$  the continuous intention to useIoT-based wearable healthcare device).

**Hypothesis 8:** Perceived ease of use and virtual community immersion sequentially mediate the relationship between the characteristics of IoT-based wearable healthcare devices (the personalization, the service convenience, the interactivity) and the continuous intention to useIoT-based wearable healthcare device. (i.e., the personalization  $\rightarrow$  perceived ease of use  $\rightarrow$  virtual community immersion  $\rightarrow$  the continuous intention to useIoT-based hearable healthcare device).

## 3.8. Moderation Role of Innovativeness

According to Rogers [67], an innovation is an idea, activity, or object that people who embrace it regard as being novel. Innovation is the propensity to accept novel ideas significantly more quickly than other individuals within the same social system [67]. According to Foxwal and Goldsmith [68], consumers with innovative tendencies have cognitive traits, including being highly resistant to uncertain circumstances, having high flexibility and self-esteem in accepting newness, having a lot of experience, and having a tendency to influence public opinion and not being reluctant to change. Innovation is the extent to which consumers wish to adopt a lifestyle, a product, or a consumption pattern comparatively earlier than other members, according to Ogawa and Pongtanalert [69].

Consumers that are very inventive look for unique experiences through mental exercises that inspire them to make new decisions or experience unusual things, examine difficulties, and find solutions [70]. The innovative consumer group is expected to use IoT-based wearable devices actively and at low risk.

**Hypothesis 9:** Innovativeness moderates the relationship between the characteristics of IoT-based wearable healthcare devices and the continuous use intention f a IoT-based wearable healthcare device.

## 4. Empirical Analysis

# 4.1. Variables

Table 1 describes the definition of variables. Personalization was referred to in Kalyanaraman and Sundar [19], convenience of service was referred to from Colwell et al. [34], and interactivity was referred to from Ulrike, Raj, and Panayiotis [45]. The 'perceived use of' is referred to by Davis [11] and Vijayasarathy [55], 'perceived usefulness' is referred to by Thong, Hong, and Tam [71], and 'virtual community image' is referred to by Tsai and Pai [72]. The intensity of continuing use was referred to by Bhattacherjee [28], and 'innovativeness' was referred to by Ailawadi et al. [73].

 Table 1. Definition of variables and researchers.

Composition Concept	Criteria	Researchers
Personalization	IoT-based healthcare wearable devices know what I need. IoT-based healthcare wearable devices know what I like. IoT-based healthcare wearable devices provide content that suit my interests.	Kalyanaraman and Sundar [19]
Service convenience	It is convenient to use IoT-based wearable healthcare devices. The menu design of IoT-based wearable healthcare devices is simple. I can use IoT-based wearable healthcare devices immediately when I want to.	Colwell et al. [36]

Composition Concept	Criteria	Researchers
Interactivity	IoT-based wearable healthcare devices can share information with multiple people. Information exchanges between each other can be frequent in IoT-based wearable healthcare devices. The community in IoT-based wearable healthcare devices is active A IoT-based healthcare wearable device is a product that I need.	Ulrike, Raj, and Panayiotis [45]
Perceived ease of use	It is convenient for me to use IoT-based healthcare wearable devices. The menu configuration of IoT-based healthcare wearable devices is simple. I can use IoT-based healthcare wearable devices immediately when I want.	Davis [11] Vijayasarathy [55]
Perceived usefulness	Using a healthcare wearable device is useful in everyday life. Using healthcare wearable devices can increase the effectiveness of my work. Using a healthcare wearable device helps you accomplish my work goals faster.	Thong, Hong, and Tam [71]
Virtual community immersion	I have a sense of belonging to the community related to wearable healthcare devices. I have a psychological attachment to the community related to wearable healthcare devices. I exchange views with other members of the community with wearable healthcare devices. I participate in wearable healthcare device community activities.	Tsai and Pai [72]
Intention of continued use	I will regularly use IoT-based healthcare wearable devices in the future. I will recommend IoT-based healthcare wearable devices to people around me. I will continue to use short video IoT-based healthcare wearable devices.	Bhattacherjee [27]
Innovativeness	I'm used to using new products and tend to learn how to use them quickly. I am curious about new products or services such as IoT-based healthcare wearable devices, so I can't wait to use them. I tend to want to know the latest information on new media or technologies. I like to tell people around me about new media or technologies.	Ailawadi et al. [73]

#### Table 1. Cont.

#### 4.2. Data Collection

The subjects filled out the survey using a self-written method. Of the 170, 163 (excluding unfaithful respondents) questionnaires were used in this study. Those surveyed were living in the United States. All respondents used IHWDs. Specifically, the types of healthcare wearable devices were classified into bands, smart glasses, clothing, smart watches, lenses, patches, and tablets. On average, the number of wearable devices in use was 1.45. There were 107 people (65.6%) who owed one, 43 people (26.4%) who owed two, 9 people (5.5%) who owed three, and 4 people (2.5%) who owed four or more devices. The average time respondents used IOT wearable healthcare services was 2.35 years. There were 11 people (6.7%) who used IWHDs for one year, 79 people (48.5%) who used

IWHDs for two years, 41 people (25.1%) who used IWHDs for three years, and 32 people (19.6%) who used IWHDs for four years. Of the total respondents, 89 people (54.6%) used smartwatches the most as IoT wearable devices, with 51 people (31.3%) using bands, and 20 people (12.3%) using glasses. The rest responded otherwise. This data is available at https://github.com/777minjungkang/IOThealthcare (accessed on 1 September 2022).

## 4.3. Method of Analysis

Analysis of the findings involved the use of structural equation modeling (SEM) in the form of the partial least squares (PSL) method. Structural equation model analysis is a multivariate statistical framework analysis method that verifies the complex causal relationship between directly observed variables and indirectly observed (potential) variables through the model. For PLS, it is recommended to analyze 10 times more samples than the number of independent variables in the setting of the sample [74]; however, the number of independent variables in this study was six. This meant that there was no problem in conducting the sample analysis.

PLS-SEM is widely used in marketing research and is known as a suitable method for research aimed at forecasting [75]. PLS has the advantage of being able to analyze the relationships between different variables regardless of the complexity of the model. Since PLS-SEM is a regression-based approach that maximizes explanatory power by minimizing the error term variance of endogenous variables, strict application is not required in data construction such as sample number constraints because the covariance of each variable is not considered.

#### 4.4. Measurement Items

Personalization was referenced in Kalyanaraman and Sundar [19]. Interaction was referred to in the paper by Urlike [45]. Service convenience means the degree of ease with which a perceived wearable healthcare device is available. The question was created by referring to Colwell et al. [34]. The perceived usefulness was defined as operationally so that healthcare wearable devices are considered useful for their intended use. Measurement questions were referred by Thong, Hong, and Tam [71]. Community immersion was defined as "the extent to which we would like to have a continuous relationship with members of wearable healthcare devices", and the measurement items were composed of three categories based on a study by Tsai and Pai [72]. Lastly, the intention of continuing use was modified for this study, referring to the question in the preceding study [27].

#### 4.5. Reliability Assessment

Reliability is a question of which measurement tool is repeatedly applied to the same object, and it is the concept of finding out whether the measurement tool used is accurate. In other words, it means the accuracy and precision of a measurement tool, and the more consistent results are derived, the higher the reliability of the measure. To verify the internal consistency of the research model, the Cronbach's alpha coefficient, Dijkstra-Henseler's rho, and the composite reliability were confirmed. The reliability of an external model can be evaluated by the internal consistency reliability and the indicator reliability, which suggests that observational variables achieve internal reliability if the Cronbach's alpha coefficient meets or exceeds the reference value of 0.7 [76]. Composite reliability is also a verification value that evaluates reliability by considering different loads at the Dillon-Goldstein's rho values, with a reference value of 0.7 or higher [77]. Composite reliability is referred to in the analysis of structural equation models as a more appropriate reliability assessment than the Crohnbach's alpha coefficient [78]. The average variance extracted (AVE) value which is also an indicator of internal consistency refers to the magnitude of the variance that measurement variables can explain the latent variable. All AVE values are 0.05 or higher to confirm internal consistency [77]. The intrinsic inertia reliability of the observations in this study were analyzed. As a result, all the variables were above the reference values, and

thus the internal inertia reliability of the metrics was obtained. The results of the internal inertia reliability assessment are as follows (see Table 2).

Latent Variables	Factor Loadings	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Personalization	0.852 0.921 0.930	0.884	0.887	0.929	0.813
Service Convenience	0.940 0.940 0.847	0.895	0.899	0.935	0.828
Interactivity	0.900 0.912 0.907	0.891	0.892	0.932	0.822
Perceived Usefulness	0.939 0.954 0.914	0.929	0.930	0.955	0.876
Community Immersion	0.888 0.897 0.930 0.892	0.923	0.925	0.946	0.813
Continuous Use Intention	0.894 0.940 0.929	0.911	0.911	0.944	0.849

Table 2. Internal consistency reliability assessment results.

#### 4.6. Discriminant Validity

In the PLS structured equation model, the validity of the external model is evaluated with convergent validity and discriminant validity. Convergent validity can be considered to be achieved when the average variance extracted (AVE) value of the latent variables is greater than 0.5 of the reference value. As shown in Table 2, the AVE values for all latent variables are all above the value of 0.5 and thus provide a high degree of validity [74]. Discriminant validity can be achieved when the square root of the AVE values of each variable is higher than the square value between that latent variable and other latent variables [79]. As shown in Table 3, the discriminant validity has been confirmed.

Table 3. Discriminant validity results.

	PI	SC	INT	PU	CI	CUI
PI	0.902					
SC	0.732	0.910				
INT	0.733	0.775	0.906			
PU	0.751	0.826	0.802	0.936		
CI	0.739	0.783	0.791	0.758	0.902	
CUI	0.765	0.776	0.794	0.798	0.832	0.921

PI = Personalization, SC = Service Convenience, INT = Interactivity, PU = Perceived Usefulness, CI = Community Immersion, CUI = Continuous Use Intention.

## 4.7. Structural Model and Hypotheses Tests

#### 4.7.1. Direct Effects

The PLS method analyzes the path using a non-parametric evaluation method based on bootstrapping so that the path factor is statistically significant [80]. In order to evaluate the internal model in the PLS-SEM model,  $R^2$  was analyzed.  $R^2$  stands for the explanatory power of endogenous potentials.  $R^2$  can be seen as the sum of the variances described by the extrusive potential variables associated with the endogenous potential [80]. A model whose  $R^2$  value means less than 0.19 indicates a low explanatory power; a  $R^2$  value of more than 0.19 and less than 0.33 means that the model has moderate explanatory power; and a  $\mathbb{R}^2$  value greater than 0.67 indicates that the model has a significant level of explanatory power [74]. The percentage of explained variance  $(R^2)$  for perceived usefulness is 0.767, the percentage of explained variance ( $\mathbb{R}^2$ ) for virtual community immersion is 0.763 and the percentage of explained variance  $(R^2)$  for continuous use intention is 0.782. This means that the structural model has a predictive association [80]. The PLS Structural Equation Model analyzes the causality of the variables in the path analysis, where the path factor is a method of bootstrap sampling, in which samples of the same size are randomly restored and extracted from the sample [80]. The results of the study hypothesis were determined by standardized regression weights. Thresholds were cut-off values used to indicate the beginning of areas where test statistics obtained from hypothesis tests were not applicable. In thypothesis tests, the threshold was compared to the test statistics obtained to determine whether the null hypothesis should be rejected. The t-value was an observation of the *t*-test statistic that measured the difference between the observed sample statistic and the population parameter in the null hypothesis in standard error units. The null hypothesis were rejected if the absolute value of the t-value was greater than the threshold. The standard for t value was 1.96. Adopting a hypothesis was based on the criteria in critical ration (CR). Hypotheses were accepted if the threshold value of t was greater than 1.96 or the value of p, a significant level, was less than 0.05. The results for direct effects are shown in Table 4. The *p*-value was used as an alternative to the reject point to provide the least significance to which the null hypothesis was rejected. The smaller the *p*-value, the stronger the evidence supports the alternative hypothesis. The t-value measured the size of the difference relative to the variation in the sample data. The standard error (SE) of statistics referred to the approximate standard deviation of the statistical sample population.

Table 4. Direct effect results.

Hypot	heses	Coefficient	Std. Error	<b>T-Statistics</b>	<i>p</i> -Value	Adoption
H1: PL -	$\rightarrow$ CUI	0.157	0.068	2.297	0.022	Supported
H2: SC -	$\rightarrow$ CUI	0.066	0.066	1.022	0.317	Unsupported
H3: INT	$\rightarrow$ CUI	0.149	0.077	1.949	0.052	Unsupported

PL = Personalization, SC = Service Convenience, INT = Interactivity, CUI = Continuous Use Intention.

H1, suggested that the personalization of wearable health devices had a positive effect on consumers' continuous use intention was supported ( $\beta = 0.157$ , p = 0.022 < 0.05). H2 was not supported ( $\beta = 0.066$ , p = 0.317 > 0.05), suggesting that the service convenience of wearable health devices did not have a significant direct effect on consumers' continuous use intention. The interactivity of wearable health device had no significant direct effect on consumers' continuous use intentions is significant was not supported ( $\beta = 0.149$ , p = 0.052 > 0.05).

## 4.7.2. Mediation Tests

Bootstrapping was performed to verify the significance of indirect effects. This is a method of estimating the standard error of indirect effects, in which a confidence interval for the measurement of indirect effects is presented and the indirect effects are considered significant if the interval does not include zero [81]. To verify the mediating effect, two parts must be verified: the significance of the indirect effect and the significance of the direct effect [82]. For hypothesis verification, an analysis was conducted on the indirect effects of each mediating path using the individual indirect effect significance verification method proposed by Chan [83]. The effect of an independent variable on a dependent variable in a mediation effect study model was divided into direct and indirect effects. Direct effects referred to direct causality between independent and dependent variable through

the mediation variable. Therefore, a significant indirect effect was interpreted as having a mediated effect. Table 5 below shows an analysis of the mediation effects hypothesis.

Hypotheses	Std.	Std.	T-Statistics	95% Boo	ot CI BC	Decision	
51	Beta Eri		1 0 00000	LL	UL		
$PL \rightarrow PEU \rightarrow CUI$	0.029	0.020	1.423	-0.001	0.078	Unsupported	
$SC \rightarrow PEU \rightarrow CUI$	0.043	0.025	1.679	-0.002	0.101	Unsupported	
$INT \rightarrow PEU \rightarrow CUI$	0.046	0.029	0.590	-0.001	0.110	Unsupported	
$PL \rightarrow PU \rightarrow CUI$	0.042	0.023	1.833	0.007	0.098	Supported	
$SC \rightarrow PU \rightarrow CUI$	0.012	0.021	0.590	-0.019	0.061	Unsupported	
$\text{INT} \rightarrow \text{PU} \rightarrow \text{CUI}$	0.069	0.027	2.575	0.021	0.124	Supported	
$PL \rightarrow CI \rightarrow CUI$	0.100	0.033	3.013	0.036	0.161	Supported	
$SC \rightarrow CI \rightarrow CUI$	-0.040	0.037	1.075	-0.114	0.030	Unsupported	
$INT \to CI \to CUI$	0.157	0.044	3.603	0.077	0.251	Supported	

Table 5. Hypotheses testing on Mediation.

Note: CI BC = Confidence Interval Bias Corrected; LL = Lower Level; UL = Upper Level; PL = Personalization, SC = Service Convenience, INT = Interactivity, PEU = Perceived Ease of Use, PU = Perceived Usefulness, CI = Community Immersion, CUI = Continuous Use Intention.

In a 95% confidence interval, the indirect effect could not be interpreted as significant because there was a zero between the upper and lower values of the coefficient for the estimate of the effect [84]. Therefore, it can be seen that perceived usefulness does not mediate the relationship between the characteristics of healthcare wearable devices and continuous use intention on healthcare wearable devices.

Based on the results from bootstrapping analysis (Table 5), both of the hypotheses were significant,  $PL \rightarrow PU \rightarrow CUI \ (\beta = 0.042)$  with t-values of 1.833 and INT  $\rightarrow PU \rightarrow CUI \ (\beta = 0.069)$  with t-values of 2.575. Both of the indirect effects, 95% Boot CI BC with the values of (LL = 0.007; UL = 0.098) (PL  $\rightarrow$  PU  $\rightarrow$  CUI) and (LL = 0.021; UL = 0.124) (INT  $\rightarrow$  PU  $\rightarrow$  CUI). Therefore, PL  $\rightarrow$  PU  $\rightarrow$  CUI and INT  $\rightarrow$  PU  $\rightarrow$  CUI, were supported, in which perceived usefulness mediated the relationship between PL and CUI, and INT and CUI. Meanwhile, both of the hypotheses were significant, H6-1 ( $\beta$  = 0.100) with t-values of 3.013 and H6-3 ( $\beta$  = 0.157) with t-values of 3.603. Both of the indirect effects, 95% Boot CI BC with the value of (LL = 0.036; UL = 0.161) (PL  $\rightarrow$  CUI) and (LL = 0.036; UL = 0.161) (INT  $\rightarrow$  CI  $\rightarrow$  CUI). Therefore, H6-1 and H6-3, were supported, in which perceived community immersion mediated the relationship between PL and CUI, and INT and CUI.

Table 6 below shows an analysis of the mediation type. PU and CI partially mediated the relationship between PL and CUI. Also, PU and CI fully mediated the relationship between INT and CUI. Table 6 presents the mediation type.

Table 6. Mediation types for indirect effects.
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Indirect Path	Std. Beta	<b>Direct Path</b>	РС	Mediation Type
$PL \rightarrow PU \rightarrow CUI$	0.042	$\text{PL} \rightarrow \text{CUI}$	0.157	Partially Mediated
$\mathrm{INT} \to \mathrm{PU} \to \mathrm{CUI:}  \mathrm{PL} \to$	0.069	$\text{INT} \rightarrow \text{CUI}$	not significant	Fully Mediated
$CI \rightarrow CUI$	0.100	$\text{PL} \rightarrow \text{CUI}$	0.157	Partially Mediated
$\text{INT} \rightarrow \text{CI} \rightarrow \text{CUI}$	0.157	$\text{INT} \rightarrow \text{CUI}$	not significant	Fully Mediated

Note: PC = Path Coefficient. PL = Personalization, SC = Service Convenience, INT = Interactivity, PU = Perceived Usefulness, CI = Community Immersion, CUI = Continuous Use Intention.

#### 4.7.3. Serial Mediation

This study employed a bootstrapping method to check the serial mediation of perceived usefulness and community immersion through the serial path of perceived ease of use with the continuous use intention of healthcare wearable devices. The findings in Table 7 exhibit that perceived usefulness and community immersion had a positive and significant mediating influence between the characteristics of healthcare wearable devices, for instance, the personalization, the service convenience, the interactivity, and the continuous use intention through serial mediation of perceived ease of use. Hence, it is finally concluded that hypotheses H7 to H8 were accepted and retained because T >  $\pm$ 1.96, *p* < 0.01, and a value of zero did not exist between the lower and upper interval of BCCI [85]. Table 7 shows the results of serial mediation analysis.

Table 7. Serial mediation analysis.

Serial Mediation Path Analyses	Path Coefficient	(Boot) S.E.	<b>T-Statistics</b>	<i>p</i> -Values	LLCI	ULCI	Decision
$\mathrm{PL} \to \mathrm{PEU} \to \mathrm{PU} \to \mathrm{CUI}$	0.021	0.011	1.977	0.049	0.007	0.051	Supported
$SC \rightarrow PEU \rightarrow PU \rightarrow CUI$	0.031	0.015	2.085	0.038	0.009	0.065	Supported
$\text{INT} \rightarrow \text{PEU} \rightarrow \text{PU} \rightarrow \text{CUI}$	0.033	0.014	2.444	0.015	0.013	0.074	Supported
$\mathrm{PL} \to \mathrm{PEU} \to \mathrm{CI} \to \mathrm{CUI}$	0.032	0.013	2.418	0.016	0.013	0.064	Supported
$SC \to PEU \to CI \to CUI$	0.047	0.020	2.334	0.020	0.015	0.096	Supported
$\mathrm{INT} \to \mathrm{PEU} \to \mathrm{CI} \to \mathrm{CUI}$	0.051	0.017	2.926	0.004	0.024	0.092	Supported

PL = Personalization, SC = Service Convenience, INT = Interactivity, PEU = Perceived Ease of Use, PU = Perceived Usefulness, CI = Community Immersion, CUI = Continuous Use Intention.

## 4.7.4. Moderation Analysis

Tables 8–10 present the results of the moderating effect of innovativeness in the relationship between the characteristics of IoT-based wearable healthcare devices and the user's intention. H9 predicted that innovativeness would moderate association between the characteristics of healthcare wearable devices and the continuous use intention. For hypothesis 9 of the study, Hayes' 13 macro PROCESS was done to test moderation [86] (See Tables 8-10). This technique is best as a moderating effect technique because it is based on the R-square and the slope test value can also be checked [86]. The interaction term of the personalization and the innovativeness produced significant values ( $\beta = 0.204$ , p < 0.01, CI [0.072, 0.335],  $\Delta R^2 = 0.022$ ). Slope test values showed the effect of personalization on the intention to use at low levels ( $\beta = 0.507$ , p < 0.01, CI [0.308, 0.706], at moderate levels  $(\beta = 0.670, p < 0.01, CI [0.533, 0.807])$ , and high levels ( $\beta = 0.833, p < 0.01, CI [0.691, 0.974]$  as significant in all levels of moderation i.e., the innovativeness. The interaction plots shown in Figure 2 show that the interaction for personalization rated use intention as stronger when the innovativeness was high (i.e.,  $\beta = 1.83$ , p < 0.001) than when it was low ( $\beta = 0.52$ , p < 0.05). The interaction term of the service convenience and the innovativeness produced significant values ( $\beta = 0.222$ , p < 0.01, CI [0.07, 0.38],  $\Delta R^2 = 0.021$ ). Slope test values showed the effect of the service convenience on intention to use at low levels ( $\beta = 0.342$ , p < 0.05, CI [0.11, 0.57]), at moderate levels ( $\beta = 0.519$ , p < 0.01, CI [0.38, 0.66], and high levels  $(\beta = 0.696, p < 0.01, CI [0.57, 0.82]$  as significant in all levels of moderation i.e., the innovativeness. The interaction plots shown in Figure 3 illustrate the positive effect of service convenience on the use intention was stronger the more innovative the respondents are. The result of Process Model 1, using 5000 bootstrap samples and a 95% confidence interval, revealed the combined outcome of interactivity and innovativeness as significant  $(\beta = 0.150 < 0.01, CI [0.005.29, \Delta R^2 = 0.009])$ . Slope test values showed that the effect of the interactivity on intention to use at low levels ( $\beta = 0.590$ , p < 0.01, CI [0.39, 0.79], at moderate levels ( $\beta$  = 0.71, *p* < 0.01, CI [0.59, 0.83], and high levels ( $\beta$  = 0.829, *p* < 0.01, CI [0.70, 0.96] as significant in all levels of moderation i.e., the innovativeness. The interaction plots shown in Figure 4 illustrate the positive effect of interactivity on the use intention was stronger the more innovative the respondents are, which supports H9-3. Thus, the increase in the size of the effect (beta) indicates that the relationship between the characteristics of healthcare wearable devices and the continuous use intention were being strengthened with increasing innovativeness. Figures 2–4 show the results of the moderating effect of innovativeness.

Parameters	Dependent R <sup>2</sup>	F	р	Coef	SE	t	LLCI	ULCI
Constant				3.149	0.761	4.140	1.647	4.652
PL IN	CUI 0.614	84.414	0.000	-0.176 -0.817	0.196	-3.420	-0.209 -1.289	-0.345
PL * IN				0.204	0.066	3.062	0.072	0.335
	Conditiona	l Effect f	rom X t	o Y at Valı	ues of Mc	derator		
	PL	Effect	SE	t	LLCI	ULCI		
	1.619	0.507	0.101	5.032	0.308	0.706		
	2.419 3.219	0.670 0.833	0.070 0.072	9.644 11.605	0.533 0.691	0.807 0.974		

Table 8. Moderation effect of innovativeness between personalization and use intention.

PL = Personalization, CUI = Continuous Use Intention, Innovativeness = IN, PL \* IN = the interaction term between IN and PL.

Table 9. Moderation effect of innovativeness between service convenience and use intention.

Parameters	Dependent	<b>R</b> <sup>2</sup>	F	р	Coef	SE	t	LLCI	ULCI
Constant SC	~~~~				$4.369 \\ -0.017$	0.910 0.235	$4.799 \\ -0.073$	$2.571 \\ -0.480$	$6.166 \\ 0.446$
IN SC * IN	CUI	0.587	75.180	0.000	-1.114 0.222	0.294 0.079	-3.792 2.817	$-1.694 \\ 0.066$	$-0.534 \\ 0.377$
			Conditional E	ffect from X	to Y at Values	of Moderato	r		
		SC	Effect	SE	t	LLCI	ULCI		
		1.619	0.342	0.112	2.949	0.113	0.570		
		2.419	0.519	0.070	7.451	0.381	0.656		
		5.219	0.696	0.065	10.745	0.358	0.824		

SC = Service Convenience, CUI = Continuous Use Intention, Innovativeness = IN, SC \* IN = the interaction term between SC and IN.

 Table 10. Moderation effect of innovativeness between interactivity and use intention.

Parameters	Dependent	<b>R</b> <sup>2</sup>	F	р	Coef	SE	t	LLCI	ULCI
Constant INT					2.853 0.348	0.777 0.209	3.670 1.667	$1.318 \\ -0.064$	4.388 0.760
IN INT * IN	CUI	0.668	106.430	0.000	$-0.752 \\ 0.150$	0.258 0.072	-2.916 2.053	$-1.261 \\ 0.006$	-0.243 0.293
			Conditional E	ffect from X	to Y at Values	of Moderato	r		
		SC	Effect	SE	t	LLCI	ULCI		
		1.619 2.419 3.219	0.590 0.709 0.829	0.100 0.062 0.066	5.882 11.528 12.630	0.392 0.588 0.699	0.790 0.831 0.959		

INT = Interactivity, CUI = Continuous Use Intention, Innovativeness = IN, INT \* IN = the interaction term between INT and IN.



Figure 2. Interactive effect of personalization and innovativeness on continuous use intention.



Figure 3. Interactive effect of service convenience and innovativeness on continuous use intention.



Figure 4. Interactive effect of interactivity and innovativeness on continuous use intention.

## 5. General Discussion

This study found that the wearable healthcare device market can only expand and develop if research into potential users' attitudes toward the technology and related behaviors is conducted. As a result, the factors influencing potential users' acceptance of wearable healthcare devices were identified. This study's theoretical significance comes from combining basic TAM models to present a model that takes into account the parameters that encourage potential users' acceptance intentions for IoT wearable healthcare devices. This model helps to explain how consumers come to accept IoT wearable healthcare devices. Additionally, from a practical perspective, it is significant as it discusses key implications for how to convince potential users to accept IoT wearable healthcare devices in the future by highlighting factors that have a large impact on acceptable healthcare devices, as the market is still developing in its early stages. Table 11 presents an example of the relationship between efficiency and the hypothesis of this study based on IoT healthcare-based applications.

**Table 11.** An example of the relationship between efficiency and the hypothesis of this study based on IoT healthcare-based applications.

Examples of IoT Healthcare-Based Applications	Association with the Research Hypothesis
Glucose Monitoring: The IoT glucose monitoring device is an IoT device that can notify patients when the level is higher than normal by monitoring blood sugar levels without undergoing an invasive procedure. Using these monitoring devices, doctors can remotely track the patient's condition.	Personalization, service convenience $\rightarrow$ perceived ease of use $\rightarrow$ perceived usefulness $\rightarrow$ use intention
Connected Inhalers: The IoMT-connected inhaler tracks the patient's data and helps them live a normal life, confirming that the respiratory patient is using the device in the right way. For example, the device is connected to a smartphone so that patients do not leave their inhalers at home.	Interactivity $\rightarrow$ perceived ease of use $\rightarrow$ perceived usefulness/virtual community immersion $\rightarrow$ use intention
Remote patient monitoring device: Remote patient monitoring is a device that can monitor heart rate, blood pressure, temperature, glucose level, and oxygen level. Since this can automatically collect health measurements the patient does not need to collect them directly.	Personalization, service convenience, interactivity $\rightarrow$ perceived ease of use $\rightarrow$ perceived usefulness/virtual community immersion $\rightarrow$ use intention

#### Table 11. Cont.

Examples of IoT Healthcare-Based Applications	Association with the Research Hypothesis
Hand hygiene monitoring: Hand hygiene monitoring is an IoT device that reminds people to sanitize their hands when entering a hospital room. Compliance with hand hygiene was important during the coronavirus pandemic. The IoT device, which detects the hygiene component of the hand, causes the service provider to sound an alarm to wash the hand when it comes close to the patient's bed.	Personalization, service convenience $\rightarrow$ perceived ease of use $\rightarrow$ perceived usefulness $\rightarrow$ use intention

This study experimentally investigated the relationship between wearable healthcare device acceptability characteristics, usefulness, community immersion, and usage intentions based on research on the adoption of healthcare equipment. Results indicated that personalization has a considerable direct impact on its intended use. The findings of this study support the idea that personalization services are a crucial element in determining whether smart wearables are used continuously. Data and individually tailored services are the foundation of personalization services. Smart wearable devices give data on users' physical changes while donning them, as well as data on the environment in which they are used. For instance, weight, sweat, blood pressure, pulse, body temperature, and sugar level. Users will modify their environment or behavior appropriately based on the information provided by smart wearable devices.

Through community immersion and perceived utility, service interaction and convenience have encouraged continued use. According to McMillan and Hwang [41], the process of inter-user communication is more involved the higher the interaction. Because Wearable technology has to perform various smart functions by increasing mobility while being attached to the human "perceived usefulness" is crucial. Finding a solution to simultaneously boost perceived easiness and usefulness is required to promote interactivity. Devices should be equipped with a real-time tracking system to reduce the time it takes to locate medical supplies and give emergency first aid. Additionally, IoT-based technologies' connectivity needs to be improved in order to comprehend the complex user environment and their characteristics.

It was also confirmed that among the features of wearable healthcare, personalization, service convenience, and interaction all impacted perceived usefulness, which in turn impacted the intention to use through perceived usefulness (or community immersion). It can be observed from this that wearable healthcare devices are perceived as being convenient and simple to use by consumers to a greater extent the more personalization, service convenience, and interactivity they perceive.

Furthermore, it was discovered that perceived ease had a positive (+) impact on perceived usefulness. These findings confirmed those of earlier research in which perceived ease of a new system or service had an impact on perceived usefulness.

Additionally, it was discovered that perceived ease of use had a favorable (+) impact on community immersion, serving as a pre-variable for the parameters of perceived usefulness and community immersion. It was proven that the perceived usefulness and level of community integration of wearable exercise equipment increased with perceived convenience. All attributes of wearable medical devices have an impact on the desire to use them continuously, which is supported by the dual mediating effect of perceived ease and perceived usefulness/perceived ease of use and community immersion.

Focusing on the three characteristic factors (personification, service convenience, and interaction) that affect the use of wearable health devices, this study derives practical implications for the wearable device market in the future.

First, the wearable device market has rapidly become popularized because "personalization" in which individuals directly manage their biometric information through smart devices eliminates information asymmetry and allows them to choose various medical and healthcare services. By monitoring and analyzing personal information in real time, smart healthcare managers can provide various healthcare services, such as counting calorie intake and daily walking steps, and measuring heart rate and blood pressure according to the functions provided by smartphones. In addition, now that it seems apparent that the need for personal healthcare will gradually increase in modern society due to aging, the size of the personalized wearable device market is expected to continue to expand.

Second, one of the important factors concerning wearable device acceptance in this study is 'service convenience', which allows healthcare service providers to monitor the health status of chronically ill patients using measured data and provide remote services, such as education for therapeutic purposes related to exercise, diet, and medication. On the one hand, as various healthcare-related applications enhance service convenience, the demand for wearable healthcare devices that allow individuals to easily measure and manage health information is increasing rapidly.

Third, wearable devices should be freely used even when consumers move. Recently, due to the low weight and miniaturization of wearable devices, they can be located close to the body and remotely controlled or bio transplanted, which increases the level of 'interaction' with consumers. The development and spread of networks following the popularization of smart devices enabled people to interact with and exchange medical-related knowledge, information, and services, and laid the foundation for providing new healthcare services outside the traditional medical industry.

As a result of these market changes, the findings from Gartner suggest that in 2020, the overall market size of global wearable devices was \$69 billion, and speaking by item, earwares such as Air Pods and Galaxy Buds had the highest share and growth rate of \$32.7 billion.

The majority of research on wearable technology is based on studies looking at domestic and international market trends or related technologies. Numerous people, such as early adopters, are the focus of research into user behavior related to technology and devices, and empirical studies of wearable device users are still lacking [87,88]. Businesses and consumers in a wide range of industries are becoming more interested in wearable technology. However, the majority of research is carried out from a technological standpoint and only concentrates on evaluating outcomes on goods worn by humans. Although it examines the key elements that influence customers' practical intentions of continued usage of healthcare wearable devices, this study is theoretical in nature. Additionally, this study focuses on the technical aspects of wearable technology and the individual user characteristics. Moreover, the work has theoretical value in that it uses empirical analyses to confirm correlations between variables. Wearables represent a hyperconnected civilization where there is connectivity between humans, machines, and other machines. Therefore, research is required to understand and track the proliferation of wearable technology from the standpoint of consumers.

It has been proven that the features of wearable technology, such as personalization, service convenience, and interactivity, have a significant impact on long-term usage intentions when innovation is high. This suggests that as a result of attempting to learn more about innovative products, innovative consumers have more information and knowledge about innovation than others and are better equipped to handle challenging circumstances and issues that arise during the acceptance of innovation [67]. Consumers that respect innovation tend to be explorers who intentionally choose risky and creative products because they value different experiences [89]. A smart marketing plan that targets highly creative consumers with strong curiosities and daring impulses is therefore required. Consumer innovation has a significant impact on how consumers accept new items and how quickly, [68]. Therefore, the study's findings indicate that consumers who value innovation place a high value on interaction. This can have significant practical ramifications for wearable device marketing strategies. Consumers that are highly inventive favor cognitive planning and procedures, which concentrate on gathering a lot of new information from many sources, processing it, applying it to solve problems, and learning new decisionmaking techniques [90]. As a result, it is assumed that interactivity matters when choosing IoT-based wearable technology.

Future growth of eHealth technology options should increase access to healthcare's flexibility. With the potential to instantly offer health advice, smartphones are becoming more used as healthcare tools. A smartphone app can be used to order and deliver medications to patients' homes. Evidence for the appropriate balance in the use of these developing technologies is needed going forward.

The majority of wearable technologies are still in their infancy. Challenges including user acceptance, security, ethics, and big data issues in wearable technology must be addressed in order to enhance the usability and functionality of these devices for practical deployment. Researchers should be pushed to take user preferences into account while creating wearable sensing systems [91]. One area of worry regarding older persons' adoption of wearable device applications is their acceptance and desire to use consumer-wearable devices for personal health objectives. Over 60% of seniors are interested in employing wearable technology to improve their physical and mental health in the future, according to a recent analysis of 31 studies by Kekade and colleagues [92]. Despite advancements in monitoring devices and the wearable sector, widespread adoption of this technology in medical practice is still a long way off.

As a way to cope with senile diseases caused by aging, the ICT digital healthcare industry, including wearable devices, is growing in the medical field. Additionally, it would enhance healthcare and living conditions for the aging population. Future devel-

opments in device design will take into account user goals, design comfort and usability issues, physician/healthcare professional performance and utility, among other things. As information technology develops, mobile devices become more intelligent and have taken the place of traditional communication tools [93]. There many different types of mobile devices, including smartphones, tablet computers, and wearable technology.

The significance of big data analysis and utilization is growing as the paradigm in the healthcare sector evolves from diagnosis and treatment to prevention. The findings of this study suggest that improving personalization, service convenience, and interaction can encourage customers to use wearable healthcare devices, which will increase the collection of healthcare data. By offering tailored precision medical services including chronic illness management and disease prediction based on big data such as health record data and hospital clinical data obtained through wearable devices, the quality of medical services will be improved.

#### 6. Limitations and Future Research

Davis [11] emphasized that perceived ease of use and perceived usefulness are important variables that influence the acceptance process of information technology. Perceived ease of use refers to the degree to which a particular system use is believed to make it easy for an individual to acquire a task. Perceived usefulness refers to the degree to which a particular system is believed to improve an individual's work performance. The perceived accessibility of new technologies is measured by their perceived ease of use. The idea that new technology can be employed to increase productivity at work is known as perceived usefulness. This study only looked at perceived usefulness as a model mediating variable. Future research will be useful in determining how perceived ease of use affects the use of IoT wearable healthcare devices.

Depending on how familiar consumers are with the device, if they have had a comparable experience, and what demographic traits they associate with the associated technology, the outcomes of this model may differ. Therefore, in future studies, it will be meaningful to reveal the differences in the influencing factors on the acceptance of IWHD according to the characteristics of each user (health interest, cultural background, age, use experience, etc.). Additionally, wearable devices consist of a variety of products, ranging from ear wear such as wireless earphones to smartwatches, activity wearables, and smart patches. Therefore, in future studies, it will be necessary to present an acceptance model of wearable healthcare devices in consideration of more various products, services, and influencing factors.

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