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Investigating User-Centric Factors Influencing Smartwatch Adoption and User Experience in the Philippines

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Abstract: Smartwatches enable users to easily monitor their health, self-quantify, and track various activities. However, manufacturers and researchers in the field of smartwatches must explore and improve perceived usability to enhance the user experience of consumers and increase the device's adoption rate. Therefore, this study investigates the factors influencing the adoption of smartwatches among Filipinos, focusing on usability and demographic influences. This is performed by utilizing the UTAUT2 model to examine key factors. External variables are explored, including perceived usability and privacy. To analyze the data acquired, partial least squares structural equation modeling (PLS-SEM) was conducted. The results indicated that performance expectancy, effort expectancy, social influence, hedonic motivation, price value, habit, and behavioral intention significantly influence smartwatch adoption. Habit emerged as positively affecting intention to use and usage behavior. However, facilitating conditions were found not to be significant in influencing intention to use and usage behavior, and privacy was perceived as having an insignificant relationship with the intention to use smartwatches. These findings offer theoretical and practical implications for enhancing smartwatch design and usability, addressing the diverse needs of users, and expanding inclusivity in the market.

Keywords: smartwatch adoption; UTAUT2; perceived usability; system usability scale (SUS)



Citation: Gumasing, M.J.J.; Carrillo, G.Z.D.V.; De Guzman, M.A.A.; Suñga, C.A.R.; Tan, S.Y.B.; Mascariola, M.M.; Ong, A.K.S.. Investigating User-Centric Factors Influencing Smartwatch Adoption and User Experience in the Philippines. *Sustainability* **2024**, *16*, 5401. <https://doi.org/10.3390/su16135401>

Academic Editor: Flavio Boccia

Received: 11 April 2024

Revised: 14 June 2024

Accepted: 21 June 2024

Published: 25 June 2024



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1. Introduction

Smartwatches have been commercially launched since 2000, showing great potential as a revolutionary technology in health-related fields [1]. Smartwatches are wearable devices that contain sensors and screens that can wirelessly connect to various applications and allow smartphones to be a proprietary medium [2]. Various users prefer the usability of wearable devices such as smartwatches that track aggressive or non-aggressive human motions where users can quickly determine the progress of their activity, i.e., health monitoring, self-quantification, and activity tracking. Individuals with high health goal-pursuit motivation greatly value the use of smartwatches due to their ability to provide feedback that tends to motivate the users to maintain their healthy lifestyle consistently [3]. This result implies the continuous intention of users to use the smartwatch as a daily tool to regulate their lifestyle [2]. The smartwatch has been a great tool for cycling due to its portability. In the past, cyclists have used a physically installed bike computer, which needs to be more accurate in capturing data. The capability of a smartwatch as an activity tracker to capture accurate data while being portable has greatly benefited cyclists, with

one instance of them changing bikes while in a competition. It also benefits athletes; e.g., smartwatches can store accurate sleep quality, health status, heart rate, and stress level [4]. Cyclists from the Philippines have slowly adapted to smartwatches in their cycling routines. However, the demand for and popularity of smartwatches have been constantly increasing in the Philippines [5].

Smartwatches have become increasingly relevant in the Philippines due to health consciousness, technological advancements, convenience, and lifestyle trends. The rising awareness of health and fitness has driven many Filipinos to adopt smartwatches for their health monitoring features, such as heart rate tracking and sleep analysis, which are crucial in a country where lifestyle diseases are prevalent. A study by Pandey et al. [6] highlighted that the increasing incidence of lifestyle diseases in the Philippines has led to a greater emphasis on preventive health measures, with many Filipinos turning to wearable technology to monitor their health parameters. According to the Philippine Heart Association [7], cardiovascular diseases remain a leading cause of mortality in the country, prompting more people to use devices that help track and improve heart health. Technological advancements and enhanced internet connectivity have also made smartwatches more accessible and multifunctional, with features like notifications, GPS, and mobile payments enhancing their appeal. According to a report by the International Data Corporation (IDC) Philippines [8], the introduction of more affordable and feature-rich smartwatches from companies like Xiaomi, Huawei, and Realme has driven a steady increase in the wearable technology market in the Philippines. The improvement in smartphone penetration and internet connectivity has also facilitated the integration of smartwatches into daily life, making them an essential gadget for tech-savvy Filipinos [9]. Many Filipinos value the convenience that smartwatches provide by allowing users to manage daily tasks without constantly accessing their smartphones. Additionally, smartwatches have become a fashion statement, especially among youth and young professionals, who view them as trendy accessories that complement their modern lifestyle [10]. The COVID-19 pandemic further underscored the importance of health monitoring, leading to a surge in smartwatch adoption as people sought ways to track their health amidst lockdowns and restricted movements [11]. With this, smartwatches have integrated into the daily lives of Filipinos, blending functionality, style, and connectivity to meet their evolving needs and preferences.

Smartwatch brands like Apple, Samsung, and Huawei have expressed interest in selling their wearable smartwatch products in the Philippines because of the rapidly increasing demand in the fourth quarter of 2022 [12]. According to the International Data Corporation (IDC) [13], smartwatch year-over-year data reached 102.9% based on years 2021 and 2022 in the third quarter. More specifically, the market share in the last 3Q21 was 15.8%, compared to the market share in the last 3Q22, where it garnered 25.9%, which is about a 10.1% difference. It rapidly increases yearly because of fashion trends and health benefits such as calorie counting and counting steps to monitor heart rate and blood pressure, which have some excellent benefits. However, many users, especially older adults, find smartwatches a disadvantage because they are expensive and require help exploring the device's features [14]. More importantly, one of its unfortunate disadvantages is its privacy risk. According to the study by Ernst [15], its perceived privacy risk negatively influences smartwatch usage. There are no definite and clear policies regarding privacy. The manufacturer just sets the default option for privacy, and the consumers are required to adjust the privacy setting themselves. This factor may affect the privacy of users, as some are not knowledgeable enough to explore the features of a smartwatch. According to the National Privacy Commission (NPC) [16], 94% of Filipino adults wanted to know more about how the personal data they provided during transactions would be used.

Smartwatches must also consider usability, which is accessible to and used by people with various needs, including those who are disabled. According to Beldad and Hegner [17], enhancing inclusivity and expanding the user base can be achieved through improving perceived usability. The user's demands, preferences, and capabilities need to be considered while designing products, which is encouraged by an emphasis on perceived usability [18].

This may result in more user-friendly and better-designed smartwatches. A smartwatch's adoption rates and market success will undoubtedly increase if consumers view it as simple to use and user-friendly [19]. Therefore, both producers and researchers in the field of smartwatches must explore and improve perceived usability.

Recent years have seen a substantial increase in the use of smartwatches, motivated by both technological breakthroughs and shifting customer demands. Manufacturers and researchers must both comprehend the factors that affect the acceptance and usage of smartwatches. The Unified Theory of Acceptance and Use of Technology (UTAUT) Model is a theoretical framework that offers important insights into the adoption of new technologies. Venkatesh et al. developed the UTAUT model in 2003 to understand and predict the acceptance and use of various digital technologies in a consumer context. It touches on performance expectancy, effort expectancy, social influence, and facilitating conditions [20]. However, this theoretical framework is revealed to have its limitations. Past studies that have used this model have shown an excessive emphasis on topics and assignments, insufficient sample sizes in certain studies, and a deficiency in longitudinal investigations. These factors collectively suggest potential areas for further exploration by researchers and the need for further development of the UTAUT model [21].

Subsequently, Venkatesh et al. [21] proposed the UTAUT2 model, which incorporates the four standard constructs of the original UTAUT model. This framework extends to the hedonic motivation, price value, and habit of the topic involved. The impacts of these dimensions on behavioral intention and technology usage are hypothesized to be moderated by individual characteristics, including age, gender, and experience. The extensions recommended in the UTAUT2 model greatly enhanced the variation described in behavioral intention (from 56 percent to 74 percent) and technology usage (from 40 percent to 52 percent) [22]. In the study, it was concluded that consumers' routine behavior greatly influences how they use personal technology, especially in situations that are dynamic and continually changing. Habit serves as a pre-established intention pathway that impacts behavior and has a direct and automatic impact on how we use technology. To reinforce both the established intention and its link to behavior, marketing communication efforts must be strengthened. Thus, the UTAUT model was developed into the current UTAUT2 framework.

Most studies relating to the adoption of smartwatches rely on structural equation modeling (SEM) using the UTAUT2 framework, which covers various types of statistical models and methods to verify hypotheses [12]. The UTAUT2 framework is a more significant framework for the conceptualization of the adaptation of smartwatches. It considers consumer identification, behaviors, experiences, and age as it analyzes the usage of new technologies. The connection of the UTAUT2 framework with the adoption of smartwatches is incredibly significant, such that the UTAUT2 framework can cover all factors related to user experiences.

2. Review of Related Literature

2.1. Encounters of Manufacturers in Smartwatches

Numerous well-known and unknown smartwatch brands have emerged to capture market share in this expanding industry of wearable tech products, as the use of smartwatches has been steadily rising [23]. By 2023, the sales of global smartwatches will reach 109 million [24]. However, since the 2010s, various companies have begun to manufacture wearable smartwatch devices, even though the current sales of these products are not impressive [25]. So, manufacturers need something diverse in their marketing strategy to seek consumers' attention and engagement with smartwatches. According to Gopinath et al. [26], they are expecting an increased product strategy exercise undertaken by smartwatch manufacturers. Strategies like improving people's smartwatch use by providing easy-to-understand manuals, being active in answering questions, providing a detailed frequently asked questions (FAQ) list, managing users' experience, and regularly

upgrading the operating system can boost the users' attention [27]. Also, these strategies may have a positive impact on solving problems and keeping users connected.

Manufacturers' design aesthetics of products are a determinant of market success or failure [28]. Aesthetics are an important consideration in fashion design, and since some smartwatches are used in fashion, smartwatch manufacturers should join the trend. Aesthetic diversity generates order and price differentiation [29]. With increased consumer influence, the device will be well-known, and apps will collaborate with smartwatch manufacturers. According to Chuah [30], different social and communication applications can be used with smartwatches. However, this collaboration can be difficult because consumers are searching for the right technical or functional features, and the growth of smartwatches can cause security risks, technology stress, and digital addiction [31]. Even though most smartwatch manufacturers have not yet been linked to significant privacy flaws, adding various new tracking and location features to their accelerometer and Bluetooth technologies creates the possibility of a wide range of privacy violations, including eavesdropping, data aggregation, and user harm. Smartwatches typically contain multiple sensors to perform data detection based on motion and physical activity and to ensure social network interactions [32]. At this point, smartwatch manufacturers should cooperate with other manufacturers of Internet of Things (IoT) devices and improve the ability of smartwatches to connect with other IoT devices [27].

Manufacturers should also consider their smartwatch price because it is one of the most common influences on consumers in terms of perception. From a financial feasibility standpoint, current prices for smartwatches start at less than USD 100 or PHP 5691 for the Pebble Classic [33]. This is another reason why nonconsumers purchase the smartwatch. However, many consumers pay more attention to the features and brand of the smartwatches than their price because they think they are reasonably priced based on their quality [34,35].

2.2. Usability of Smartwatches

A smartwatch was deemed the first commercialized wearable device for consumers and is perceived as one of the most outstanding wearable devices [14,36]. In the current generation, it is referred to as a high-technology product due to its advanced features and capabilities, which greatly benefit its users [37]. Primarily, it can track health information, physical activity, and sleep quality. In addition, a smartwatch has the potential to evaluate health care in the everyday lives of consumers through the continuous real-time monitoring of health information by sensor-based measures [33]. However, it has negative impacts that concern privacy risks, performance depreciation, and safety risks [22].

Activity trackers, one of the most prominent features of smartwatches, greatly benefit older people with dementia as they can detect the aggressive movements of their users. People with dementia tend to project aggressive behaviors; smartwatches can detect these behaviors through human activity recognition [38]. In addition, these activity trackers can also be beneficial to cyclists, as the data can be transmitted from the device. Furthermore, cyclists continuously monitor their cycling activities utilizing the Global Positioning System (GPS); thus, they are considered an effective tool in cycling. Activity trackers also track fitness levels, primarily focusing on heart rate and sleep quality [5]. Another prominent feature of the smartwatch is transport mode detection, which can be a crucial solution to solve the conflict of heavy traffic in the Philippines [37].

Concerning the rapid development of the Internet of Things (IoT), smartwatches allow users to access information without time and location restrictions [22]. In comparison to other devices concerning IoT, such as smartphones, tablets, and computers, smartwatches are more accessible due to their significant portability and practicality, wherein a user can access relevant information on short notice [37]. Also, smartwatches can be connected to other devices through a wireless connection, promoting convenience and accessibility. Users may use their smartwatches for calls, messages, and real-time tracking; this connection allows them to view various notifications and information from the smartphone [38].

2.3. Perception of Consumers Regarding Smartwatches

Smartwatches are one of the critical drivers of wearable technology and are being used by a large population of consumers [39]. There are two kinds of smartwatch consumer behaviors: consumer consumption and nonconsumption. Consumer consumption increases with continued smartwatch use because it is a novelty technology. To further elaborate, it pertains to when a consumer consistently uses the technology; it becomes prominent, and the user can determine how it fits into their lives. This phenomenon is not always immediate; they can purchase it for the novelty factor, with an appreciation for effective marketing, or just because they are early adopters. However, this does not guarantee that consumers will immediately find a use for the smartwatch [40].

Excellent product design further attracts consumers' attention and enhances the user experience to improve the perceived value of products [28]. A study by Jung et al. [34] states that consumers tend to appreciate the features of the smartwatch rather than its brand, image, and price. On the contrary, Indonesian consumers are heavily influenced by brands and prices. As a result, Indonesian consumers tend to be less aware due to their perception of the smartwatches' usability [41]. The capability of a smartwatch to collect various data concerning physical activity can be a determinant of privacy risk as it negatively influences the behavioral intentions of its consumers [42].

Conversely, nonconsumption is a phenomenon in marketing research that occurs at the time of a product's nactment [31]. It is considered a reason against consuming a product [43]. The survey conducted by Gerhart et al. [44] found that privacy concern is not a primary factor for disidentifying. Thus, smartwatch nonconsumption is strongly related to disidentification due to intrusiveness, dissimilarity, disrepute, and indistinctiveness. Additional findings show that features specific to ubiquitous products show different results in smartwatch misidentification. These findings have critical implications for consumer brand identification and marketers.

On the other hand, consumers' attitudes, such as enjoyment or pleasure toward smartwatches, are presumed to be essential in their perception of hedonic motivation. According to Krey et al. [45], functional ads evoke higher hedonic values than ergonomic ones, while emotional ads produce higher functional values. Extraversion is responsible for the symbolic value–attitude relationship, while personal innovativeness negatively influences the functional value–attitude relationship.

2.4. Research Gap

The related literature on the adoption of smartwatches offers valuable insights into various factors influencing consumer behavior in adopting wearable technology. However, there are notable gaps that highlight the need for further research, particularly concerning usability and privacy concerns. For instance, while the study by Dutot et al. [46] provides a comprehensive overview of the adoption determinants of smartwatches, it tends to overlook the nuanced interplay between factors such as perceived usefulness, ease of use, and design aesthetics. This oversight suggests a need for more in-depth exploration of specific usability aspects like interface design and navigation, which significantly impact user experience and adoption rates.

Similarly, the study by Chuah et al. [30] on wearable technologies offers valuable insights into adoption factors but does not thoroughly examine privacy concerns. Given the growing concerns over data security and personal information protection, it is crucial to understand how privacy issues influence consumer attitudes towards wearable technology. This gap underscores the necessity of incorporating privacy considerations into future research to capture the increasing importance of data security in shaping consumer behavior.

Furthermore, the study by Gunduz et al. [47] on the acceptance of smartwatch usage highlights the significance of health beliefs and trust. However, it does not adequately address the role of usability and privacy in building trust and fostering adoption. This limitation indicates a need for more comprehensive analyses that integrate usability and privacy concerns with factors like health beliefs and trust.

Despite numerous studies on smartwatch adoption using the UTAUT2 model, significant gaps remain, particularly concerning the unique socio-cultural context of the Philippines, usability, and privacy concerns. Previous research has often overlooked specific usability aspects such as interface design and navigation, which are crucial for the user experience, as well as the growing importance of privacy in technology adoption. Additionally, the influence of demographic variables such as age, gender, income, and education level has not been comprehensively explored within the UTAUT2 framework. This study aims to fill these gaps by extending the UTAUT2 model to include perceived usability and privacy and by applying partial least squares structural equation modeling (PLS-SEM) to capture the nuanced relationships between these variables. By focusing on the Filipino context and addressing these overlooked factors, the study provides both theoretical insights and practical recommendations for enhancing smartwatch design and adoption.

3. Conceptual and Theoretical Framework

As illustrated in Figure 1, the study's framework offers an integrated approach to evaluating smartwatch adoption among the Gen Z population in the Philippines. This framework draws upon the extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) Model, incorporating perceived usability and privacy concerns as additional factors. It represents an evolution from the original UTATUT framework, offering a more comprehensive understanding of technology adoption behavior, particularly in the context of smartwatches. While the original UTAUT model focuses on factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions, the extended model recognizes the critical roles of perceived usability and privacy concerns in shaping user attitudes and behaviors towards technology adoption. Perceived usability encompasses factors related to the ease of use, interface design, and overall user experience of smartwatches, influencing users' perceptions of their utility and value. On the other hand, privacy concerns address users' apprehensions about data security, personal information protection, and the potential risks associated with using smartwatches, impacting trust and willingness to adopt. By integrating these additional factors into the UTAUT2 model, the extended framework offers a more comprehensive understanding of the factors driving smartwatch adoption, enhancing its predictive power and explanatory capabilities. Overall, these combined approaches will allow the study to delve deeply into users' inclinations and willingness to adopt smartwatches, offering a thorough analysis of their usability within the technological landscape of the Philippines.

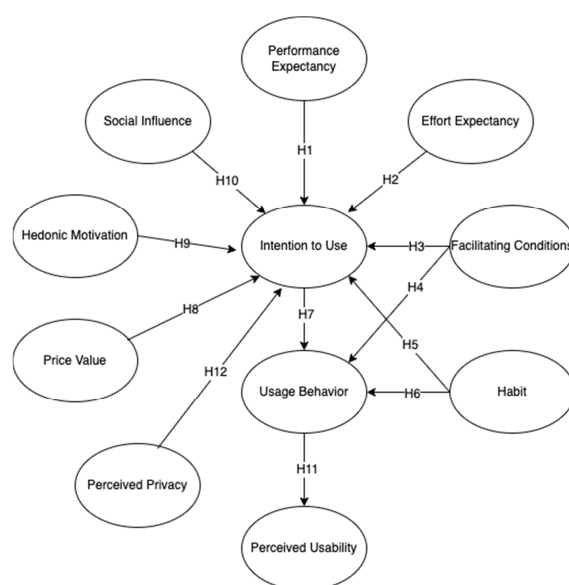


Figure 1. Proposed conceptual framework.

Determinants of Smartwatch Adoption and Usability

Performance expectancy (PE) in the context of smartwatches refers to users' belief or expectation that wearing a smartwatch will improve their performance or enhance their quality of life. Performance expectancy is the user's expectation that a smartwatch will offer them useful and advantageous functionality or features. This can include functions like receiving notifications, monitoring fitness and health statistics, instantly accessing information, or making daily tasks easier [48]. According to Reeder and David [33], there is a larger scale of technological perceptions regarding the performance of smartwatches—hence, smartwatches have been rapidly developing health and wellness uses. These features were found to play a crucial role in the intention of usage towards smartwatches, for the benefits of the device are valued in said field. Along with this, from the results of previous studies, it was determined that performance expectancy was one of the main predictors of smartwatch acceptance [49]. In view of this, it was hypothesized that:

Hypothesis 1 (H1). *Performance expectancy (PE) positively affects the intention to use smartwatches.*

Effort expectancy (EE) is the perceived level of effort required for users to learn and use the smartwatch [50]. The perceived ease of interacting with and utilizing a smartwatch is the focus of this dimension. It considers factors like how easy-to-use the smartwatch's user interface is, how natural it is to operate, and how much work people anticipate having to spend on figuring out how to use the device [51]. In the UTAUT model, the expectation of effort has a direct impact on the intention to use technology. People are more likely to have positive intentions to use smartwatches if they believe that using one will only involve a small amount of work [52]. Moreover, it was found that consumers are more likely to consider EE before the intention of using a smartwatch. In view of this, it was hypothesized that:

Hypothesis 2 (H2). *Effort expectancy (EE) positively influences the intention to use smartwatches.*

Facilitating conditions (FC) represent the circumstances in which consumers perceive the availability of resources and assistance that enable them to engage in a specific behavior, such as smartwatches and technology adoptions [53]. These circumstances greatly influence the ease with which smartwatches are incorporated into consumers' daily lives. Users' attitudes, past experiences, and degree of familiarity with technology hold considerable sway in shaping their willingness to embrace and employ technological adoptions [54]. Included in this dimension is smartphone compatibility. According to Kim and Shin [52], more people will likely choose smartwatches if they can effortlessly connect with various smartphone types and operating systems. Bhoover et al. [54] mentioned that dependable internet connectivity, through Wi-Fi and mobile networks, is required for some smartwatch functionalities. Users who have access to a reliable and quick internet connection are more inclined to adopt smartwatches. In view of this, it was hypothesized that:

Hypothesis 3 (H3). *Facilitating conditions (FC) positively influence the intention to use smartwatches.*

In the context of facilitating conditions in smartwatch use, Chen and Chen [55] concluded from their paper that this predictor positively affects the usage behavior of consumers towards "LINE TODAY," which is a technological product. Despite not having significance, it was still found to have a reasonable impact on consumers' use. In view of this, it was hypothesized that:

Hypothesis 4 (H4). *Facilitating conditions (FC) positively influence the usage behavior of consumers of smartwatches.*

The adoption and continued usage of smartwatches can be significantly influenced by the development of habits [56]. Habit (HB) can be defined as the extent to which individuals engage in actions automatically, almost instinctively, as a result of their previous learning or accumulated experience [57]. When consumers develop patterns for using their smartwatches, it becomes an essential component of their daily activities and way of life. This behavioral pattern reflects the ingrained responses that people develop over time. In a noteworthy research study by Escobar-Rodriguez and Carvajal-Trujillo in 2013 [58], they conducted a comprehensive examination of the role of habituated behavior in influencing consumers' intentions to take specific actions. Their study shed light on the pivotal role that established habits play in shaping the way individuals choose to act in particular situations. It was demonstrated that these ingrained habits hold significant sway over individuals' decision-making processes, ultimately influencing their behavioral intentions and choices. Once habits are formed, users may find it challenging to stop using smartwatches, turning them into ardent supporters of the technology [59]. This finding underscores the enduring impact of habituation on consumer behavior and decision-making. In accordance with Bölen [60], consumers' intention to continue using smartwatches is heavily associated with habit. In view of this, it was hypothesized that:

Hypothesis 5 (H5). *Habit (HB) positively influences the intention to use smartwatches.*

According to Tamilmani et al. [61], the predictor "Habit" was also one of the main factors in the UTAUT2 model for usage behavior. The article recommended this variable for further introduction of a technological product as it heavily influences "intrinsic" motivation. In view of this, it was hypothesized that:

Hypothesis 6 (H6). *Habit (HB) positively influences the usage behavior of consumers of smartwatches.*

In the context of smartwatches, behavioral intention (BI) describes a person's subjective willingness to engage in particular actions or behaviors connected to the adoption and usage of smartwatches [62]. Based on their attitudes, beliefs, and perceptions, it shows the person's intention or plan to use a smartwatch in the future. In technology adoption models like the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) Model, behavioral intention is crucial. Behavioral intention often precedes the actual adoption of a smartwatch. It displays an individual's decision-making process, including whether, when, and how they intend to purchase a smartwatch. According to Malhi et al. [63], individual attitudes and beliefs toward smartwatches impact behavioral intention. Positive attitudes are more likely to produce a positive intention to use a smartwatch, such as perceiving a smartwatch as pleasant and beneficial. Loo [64] also revealed that behavioral intention encompasses the user's conscious and purposeful plan to adopt or engage with a newly introduced technology or device, such as a smartwatch. Previous research consistently highlights the central role of behavioral intention in influencing how consumers use technology, especially regarding new devices and innovations. This strong link between what people intend to do and what they ultimately do has been the subject of exploration and confirmation in numerous studies by leading experts in the field [65]. In view of this, it was hypothesized that:

Hypothesis 7 (H7). *Behavioral intention (BI) positively influences the usage behavior of consumers of smartwatches.*

Price value (PV) signifies the balance that users strike between the advantages derived from employing technology and the financial cost associated with the use of wearable devices such as smartwatches. Canhoto and Arp [19] stated that users weigh the costs and advantages of owning and using a smartwatch. Convenience, fitness and health tracking, notifications, style, and entertainment features are a few of these advantages. Saheb et al. [66] suggested that potential adopters frequently balance the expense of the

smartwatch against the benefits they believe it to provide as part of a cost–benefit analysis. Adoption is likely to be stimulated by a favorable evaluation of this balance. The cost of a smartwatch in relation to the disposable income of an individual or target market is also important, according to Cecchinato et al. [67]. Smartwatches are more likely to be embraced if they are seen as inexpensive within a specific budget. This suggests that users are more inclined to adopt smartwatches when they perceive them to offer a favorable perceived value in relation to their cost. In a study conducted in Korea regarding the use of wearable devices, price value was identified as one of the main factors for use [68]. In view of this, it was hypothesized that:

Hypothesis 8 (H8). *Price value (PV) positively influences the intention to use smartwatches.*

Hedonic motivation (HM) denotes the joy or satisfaction experienced when using wearable devices such as a smartwatch. It embraces the notion that individuals use smartwatches for a variety of reasons, including the simple enjoyment and happiness they bring as well as their useful functionality [69]. As per Brown and Venkatesh’s research in 2005 [65], the key drivers that encourage people to embrace and make use of new technology are the elements of amusement and pleasure. Various entertainment options, including music playing, games, and multimedia content, are frequently available on smartwatches. Thus, people who like and find entertainment in these activities may be encouraged to use smartwatches [70]. A consumer’s hedonic motivation may shape their attitude towards the use of smartwatches, especially for entertainment and enjoyment [45]. In view of this, it was hypothesized that:

Hypothesis 9 (H9). *Hedonic motivation (HM) positively influences the intention to use smartwatches.*

In the context of technology adoption and the use of smartwatches, social influence (SI) refers to how an individual’s perception of the impact of others, including family, friends, and colleagues, influences their adoption and usage of a particular technology or product. Social influence has a significant effect on how people feel and act towards adopting smartwatches [44]. In a study by Ernst et al. [15], it was discovered that one of the main antecedents of football players using smartwatches is their social influence. According to Dawi et al. [71], even in Malaysia, social influence is heavily related to the factors associated with using smartwatches. In view of this, it was hypothesized that:

Hypothesis 10 (H10). *Social influence (SI) positively influences the intention to use smartwatches.*

Perceived usability (PU) in smartwatch adoption refers to a person’s subjective assessment of how simple it is to use a technology or product, focusing on its learnability and utility. It includes how the user feels about the user interface, interaction patterns, and overall user experience [72]. A person’s decision to acquire and use a smartwatch is greatly influenced by its perceived usability [52]. The ease with which users may use the smartwatch’s features and functions is evaluated by users. According to Seong [73], perceived usability is improved by a user-friendly interface and a short learning curve. Another critical aspect is how simple it is for people to understand how to utilize the smartwatch. A steep learning curve may put off potential users, whereas a shallow one promotes adoption [74]. In addition, how quickly users can complete tasks and obtain information on the smartwatch also impacts perceived usefulness. Swift and effective interactions influence positive perceptions [75] and effectively showed that users’ perceptions of a particular technology’s overall usability were significantly influenced by their desire to use it and their actual usage behavior. This study highlights the intricate interplay of variables that affect the user experience, illuminating the dynamic link between users’ goals, their actual encounters with the technology, and their perception of its usability. In view of this, it was hypothesized that:

Hypothesis 11 (H11). *Usage behavior (US) positively influences the perceived usability of smartwatches.*

In the context of smartwatch adoption, perceived privacy refers to a person's individualized evaluation of the privacy and security risks related to using a smartwatch. It includes the user's opinions and worries about how the smartwatch and its related services collect, store, and share their personal data [76]. According to prior studies, a person's decision to acquire and utilize a smartwatch might be strongly influenced by how they feel about privacy [77]. Concerns regarding the security of the data kept on the smartwatch are also part of perceived privacy [78]. If the device is lost or stolen, users can be concerned about the possibility of data breaches, unauthorized access, or data loss. In a study by Ernst [15], perceived privacy was determined to be a significant factor positively affecting the behavioral intention to use smartwatches. Along with this is the risk that is anticipated; the higher the risk, the less likely they are to use smartwatches. In view of this, it was hypothesized that:

Hypothesis 12 (H12). *Perceived privacy (PS) negatively influences the behavioral intentions of consumers of smartwatches.*

4. Materials and Methods

4.1. Setting

This study gathered participants from urbanized cities in the Philippines. Urbanized cities are characterized by having a population of at least 200,000, as verified by the Philippine Statistics Authority in accordance with the Local Government Code of 1991 (PHI). Examples of these cities include Manila, Zamboanga, Cagayan de Oro, 16 cities in Metro Manila, and other cities that also have a total annual income of at least 50,000,000 PHP. Though this captures a very broad setting, it is necessary to gain a proper data set with minimal variation yet valid results. Using this setting, this study may cover the gap found in studies such as Jorge et al. [79] that lack the capacity to apply the findings to a general population. Moreover, using urbanized cities as the specific setting in procedures, there are more smartwatch users present in this setting, which coincides with the objective of this study as opposed to using a general population such as the entirety of the country [80]. Therefore, it is critical that this setting be used in the study for optimized efficiency and relevance to the topic of the adoption of smartwatches.

4.2. Participants and Sampling Technique

The scope of this study focused on people in the Philippines. Since the objective of this study was to study the connection between certain factors and the adoption of smartwatches, each participant had to be familiar with the use of smartwatches. Therefore, it is evident that the most suitable sampling technique for the study was purposive sampling.

The study used purposive sampling to ensure that participants possessed pertinent experience and information regarding smartwatch usage, which is crucial for investigating the factors influencing their adoption. Purposive sampling, as described by Asiamah et al. [81], is a beneficial method for gathering information from a targeted population with first-hand experience and expertise about the subject being studied. This sampling strategy is especially appropriate as it focuses on specific individuals who can offer valuable and comprehensive data, improving the study's validity. Prior research conducted by Naderifar et al. [82] and Nordhoff et al. [83] has shown that purposive sampling effectively targets specific user groups and collects valuable and pertinent information. In urban locations characterized by various populations, purposive sampling facilitates efficient data collection from those most likely to utilize smartwatches, ensuring the effective achievement of research objectives. Campbell et al. [84] highlighted that purposive sampling is advantageous when the researcher aims to guarantee the representation of specified population characteristics in the sample. Purposive sampling enables the gathering of comprehensive and detailed data, which can provide a profound understanding of the

elements that influence the adoption of smartwatches. This methodology facilitates comprehending intricate actions and attitudes unique to smartwatch users, which may not be accurately represented through random sampling. Lopez and Whitehead [85] also emphasized that purposive sampling is particularly suitable for qualitative research, as it prioritizes obtaining in-depth information rather than a wide range of data.

The setting dictated that the study be conducted in urban cities in the Philippines. The study utilized a margin of error of 10% for valid results based on previous studies such as that of Nordhoff et al. [83]. Participants had to be adults, so guardian consent was not necessary when collecting their data. With this setting, there are no previous statistics that determine an estimate for the number of legally aged smartwatch users in urbanized cities. Given the target population of the study, following the foundations of statistics written by Yamane et al. [86], there is no feasible manner to determine the exact population; therefore, the number of participants should be a minimum of 300 for valid results accounting for error and variation.

4.3. Data Gathering Tools

The self-administered online survey was distributed via a Google Form. The questionnaire contained multiple cross-sectional designs, and the survey link was sent to the target respondents for two months. The questionnaire was presented in the English language. The survey questionnaire consisted of three (3) major parts: the demographic profile and the indicators based on the UTAUT2 model and SUS. The first page displayed the Data Privacy Act of 2012 under Republic Act 10173, which was agreed on before the survey; otherwise, participation in the data gathering was forfeited. The survey consisted of 50-item questions. The respondent's demographics were determined in the first section of the questionnaire using 6-item questions, including age, gender, civil status, area of residence, and how long they have been using a smartwatch.

Previous papers have already used these questions, proving they can be used in future research. However, it is better to do pilot testing with our well-structured questions for the chosen pilot participants. These participants had to meet the criteria from the actual survey, and in addition, they had to be well-versed in research so that their judgment could be used to improve the questions.

The second part of the questionnaire consisted of the indicators based on the extended UTAUT2 model: performance expectancy, effort expectancy, facilitating conditions, habit, social influence, hedonic motivation, price value, perceived privacy, and perceived usability. This measured users' perceived intention to use smartwatches. The survey consisted of item-based questions where all answers were on a 5-point Likert scale ranging from "strongly disagree" to "strongly agree." An answer of five (5) would correspond to "strongly agree," an answer of four (4) would correspond to "agree," an answer of three (3) would correspond to "neutral," an answer of two (2) would correspond to "disagree," and an answer of one (1) would correspond to "strongly disagree." Eleven (11) latents were used in the survey. The summary of measures and constructs is shown in Table 1. The items for the constructs were adopted from existing studies.

Table 1. The construct and measurement items.

Construct	Items	Measure	Research Title of Supporting Reference
Performance Expectancy	PE1	Using a smartwatch enhances my daily activities and tasks.	Mobile Shopping Apps Adoption and Perceived Risks: A Cross-Country Perspective Utilizing the Unified Theory of Acceptance and Use of Technology [87]; Adoption and Usage of E-Grocery Shopping: A Context-Specific UTAUT2 Model [88]
	PE2	Using a smartwatch makes my life more convenient and efficient.	
	PE3	Using a smartwatch helps me stay connected and organized in my daily life.	
	PE4	Using a smartwatch enhances my overall experience and engagement with technology.	

Table 1. Cont.

Construct	Items	Measure	Research Title of Supporting Reference
Effort Expectancy	EE1	I find a smartwatch easy to use.	Adoption and Usage of E-Grocery Shopping: A Context-Specific UTAUT2 Model [88]
	EE2	I find it effortless to navigate and operate the features of a smartwatch.	
	EE3	I believe that using a smartwatch requires minimal mental and physical effort.	
	EE4	I find the smartwatch's interface intuitive.	
Social Influence	SI1	Members of my family think that it is a good idea to use a smartwatch.	Adoption and Usage of E-Grocery Shopping: A Context-Specific UTAUT2 Model [88]; Determining Factors Affecting the Acceptance of Medical Education ELearning Platforms during the COVID-19 Pandemic in the Philippines: UTAUT2 Approach [89]
	SI2	People around me consider it appropriate to use a smartwatch.	
	SI3	The use of a smartwatch is a status symbol in my environment.	
	SI4	People who influence my behavior think that I should use a smartwatch.	
Facilitating Conditions	FC1	I have the resources necessary to use a smartwatch.	Adoption and Usage of E-Grocery Shopping: A Context-Specific UTAUT2 Model [88]; Determining Factors Affecting the Acceptance of Medical Education ELearning Platforms during the COVID-19 Pandemic in the Philippines: UTAUT2 Approach [89]
	FC2	I have the knowledge necessary to use a smartwatch.	
	FC3	A specific person (or group) is available to assist me when difficulties arise with using a smartwatch.	
	FC4	The smartwatch is compatible with other technologies I use.	
Hedonic Motivation	HM1	Using a smartwatch is fun.	Keep Using My Health Apps: Discover Users' Perception of Health and Fitness Apps with the UTAUT2 Model [90]; Online Grocery Shopping in Thailand: Consumer Acceptance and Usage Behavior [91]
	HM2	Using a smartwatch is enjoyable.	
	HM3	Using a smartwatch is very entertaining.	
	HM4	The use of a smartwatch makes me feel good.	
Habit	HB1	I use my smartwatch without consciously thinking about it because it has become a routine part of my daily life.	Assessing preventive health behaviors from COVID-19: a cross sectional study with health belief model in Golestan Province, Northern of Iran [92]; Factors Influencing Autonomous Vehicle Adoption: An Application of the Technology Acceptance Model and Innovation Diffusion Theory [93]
	HB2	Using a smartwatch is something I do automatically, almost without realizing it.	
	HB3	I find that I use my smartwatch consistently because it has become a habit for me.	
	HB4	Using a smartwatch is something I do automatically as part of my daily routine, without much thought.	
Price Value	PV1	I strongly believe that the price I paid for my smartwatch is justified by the value it provides in my daily life.	Acceptance of the COVID-19 Vaccine Based on the Health Belief Model: A Population-Based Survey in Hong Kong [94]; Using the Health Belief Model to Understand Age Differences in Perceptions and Responses to the COVID-19 Pandemic [95]; Examining Factors Influencing Adoption of M-Payment: Extending UTAUT2 with Perceived Value [96]
	PV2	I perceive that the cost of my smartwatch is reasonable considering the benefits and features it offers.	
	PV3	I think the price of my smartwatch is a good value for the functionality and convenience it provides.	
	PV4	I consider my smartwatch to be a cost-effective investment in terms of its impact on my daily performance.	
Perceived Usability	PU1	I think the use of a smartwatch is not unnecessarily complex.	Assessing preventive health behaviors from COVID-19: a cross sectional study with health belief model in Golestan Province, Northern of Iran [92]
	PU2	I think a smartwatch is easy to use.	
	PU3	I think the various functions of a smartwatch are well integrated.	
	PU4	I think there is not much inconsistency in the design of a smartwatch.	

Table 1. Cont.

Construct	Items	Measure	Research Title of Supporting Reference
Perceived Privacy	PP1	I strongly believe that using a smartwatch does not compromise the privacy of my personal information and data.	Assessing preventive health behaviors from COVID-19: a cross sectional study with health belief model in Golestan Province, Northern of Iran [92]; Elderly and internet banking: An application of UTAUT2 [97]
	PP2	I perceive that the smartwatch I use has robust privacy features in place to protect my sensitive information.	
	PP3	I feel confident that my smartwatch ensures the security and confidentiality of my personal data.	
	PP4	I believe that the use of my smartwatch is in line with my privacy preferences and concerns.	
Behavioral Intention	BI1	I strongly intend to continue using my smartwatch in the future.	Online Grocery Shopping in Thailand: Consumer Acceptance and Usage Behavior [91]; The Reviewer's Guide to Quantitative Methods in the Social Sciences [98]
	BI2	I have a clear intention to use a smartwatch for an extended period and incorporate it into my daily routine.	
	BI3	I am committed to using a smartwatch in the long term and expect it to be a regular part of my life.	
	BI4	I strongly plan to maintain my use of a smartwatch for various tasks and activities.	
Usage Behavior	UB1	I consistently use my smartwatch for various tasks and activities.	Mobile Shopping Apps Adoption and Perceived Risks: A Cross-Country Perspective Utilizing the Unified Theory of Acceptance and Use of Technology [87]
	UB2	I frequently rely on my smartwatch to perform the functions it is designed for.	
	UB3	I use my smartwatch as part of my regular routine and daily life.	
	UB4	I make a conscious effort to use my smartwatch consistently for work and personal tasks.	

4.4. Research Procedures

Due to specific considerations, the data gathering process was conducted virtually. This was because of the possibility of facing limitations in gathering the targeted number of participants and deploying the survey in a face-to-face setup. Despite the decline in COVID-19 cases and the fact that the government put safety protocols to a minimum, there were still risks that could not be taken. Therefore, the survey was handed out via Google Forms and on social media platforms like Facebook, Instagram, and Twitter. The researchers earnestly observed and monitored the progress of the data gathering using Microsoft Excel, as the data was exported there. The data collection for this study spanned three months, from November 2022 to January 2023. This approach facilitated remote participation, prioritizing safety and convenience for both researchers and respondents. The self-administered survey meant that participants completed the questionnaire independently, without direct researcher interaction. Employing multiple cross-sectional designs, data were gathered simultaneously from distinct respondent groups, enhancing the study's comprehensiveness. Geographically, the study targeted the Gen Z population residing in the National Capital Region (NCR) and outside the NCR, narrowing down the participant pool to ensure relevance and specificity to these areas of interest. Overall, these meticulous methodological choices aimed to capture a diverse range of perspectives while navigating the challenges posed by the pandemic and ensuring the study's validity and applicability to the designated regions.

4.5. Data Analysis

With the utilization of surveys, the researchers thoroughly analyzed the data that were obtained through multivariate analysis. In this study, the researchers utilized the structural equation model (SEM), a commonly known tool to study non-experimental and experimental data. It can impose flexibility and generality, which have become massively popular among numerous disciplines [98]. Initially, the researchers utilized a structural equation model (SEM), particularly partial least squares SEM (PLS-SEM), because of its

variance-based relationship. According to the study of Hair et al. [99], PLS-SEM is conceptually similar to multiple regression analysis as its main objective is to maximize variances from dependent variables, from which independent variables were evaluated. PLS-SEM is a model that was utilized to evaluate the quality of data based on the properties of the model. It aided the researchers in further analyzing the complex relationships of the data in terms of evaluating how each variable influenced one another and how the gathered data constructed the model. Dash and Paul [100] state that PLS-SEM has been a great tool due to its reliability in terms of prediction regarding the complex construction of models with an advanced level of abstraction.

Additionally, there have been comparisons between covariance-based structural equation modeling (CB-SEM) and partial least squares-based structural equation modeling (PLS-SEM). The difference is that covariance-based structural models are used in order to evaluate theory testing and confirmations [99]. Another comparison with PLS-SEM is with one of its aspects, known as partial least squares consistent-SEM (PLSc-SEM). However, various authors state that the SEM must be precisely defined as PLS-SEM or CB-SEM to prevent debate regarding reflective or formative aspects of the relationships in the SEM [101].

Various fit indices, such as standardized root mean square residual (SRMR), normal fit index (NFI), and chi-square, were used to prove that PLS-SEM is the model that fits the study. Firstly, SRMR considers a model a good fit if it has a value of less than 0.08 [102]. Secondly, NFI considers a model an acceptable fit if it has a value of more than 0.90. Lastly, chi-square considers a model as well-fitting if it has a value below 5.0 [103].

4.6. Ethical Considerations

The questionnaire that the researchers provided was given to the respondents concisely and with caution, resulting in a process of gathering valuable pieces of information via written consent that prevented ethical violations and promoted transparency. Upon evaluating the ethical considerations of this paper, the researchers proficiently applied Republic Act No. 10173 in the Philippines, known as the Data Privacy Act. The researchers also formally signed a consent form stating that all the information and data they gathered would only be used for research and academic purposes to ensure the paper's confidentiality. Furthermore, permission was granted to the researchers by Mapúa University before data collection.

5. Results

In accordance with the demographic data gathered from the respondents, the majority of smartwatch users are male, accounting for 64% of the whole sample. A study conducted by Singh et al. [104] showed that most males prefer the utilization of smartwatches to women who prefer fitness trackers through targeted advertising on Facebook, wherein they consider gender a prominent demographic variable for advertisements. As such, it can be concluded that the performance expectancy derived from the advertisements entertains more males than females. In terms of the age and civil status of the smartwatch users, it can be seen in Table 2 that ages ranging from eighteen (18) to twenty-four (24) years old account for 77% of the total sample, which the researchers conclude are likely students in senior high school or college. Koutromanos and Kazakou [105] concluded that students use smartwatches because they enhance their performance in education and increase their motivation and attitude toward learning. In accordance with the ages, the researchers concluded that 90% of the respondents' civil status is single and students. According to a study conducted by Howard [106], the results revolved around the self-efficacy of college students in relation to demographics. The study showed that students are more likely to strategize to achieve their financial wants innovatively. Regarding the area of residences, most smartwatch users reside outside of the National Capital Region (NCR), so it can be stated that smartwatches have greater influence in less urbanized areas. It can also be concluded from the data that some people have yet to discover smartwatches,

extrapolating from the results that show most smartwatch users utilize smartwatches for one (1) to two (2) years, while smartwatches are designed for long-term usage [4]. Therefore, demographic factors such as gender, age, civil status, area of residence, and duration of usage of smartwatches are vital for the acceptance and adoption of smartwatches.

Table 2. Respondents' descriptive statistics ($n = 414$).

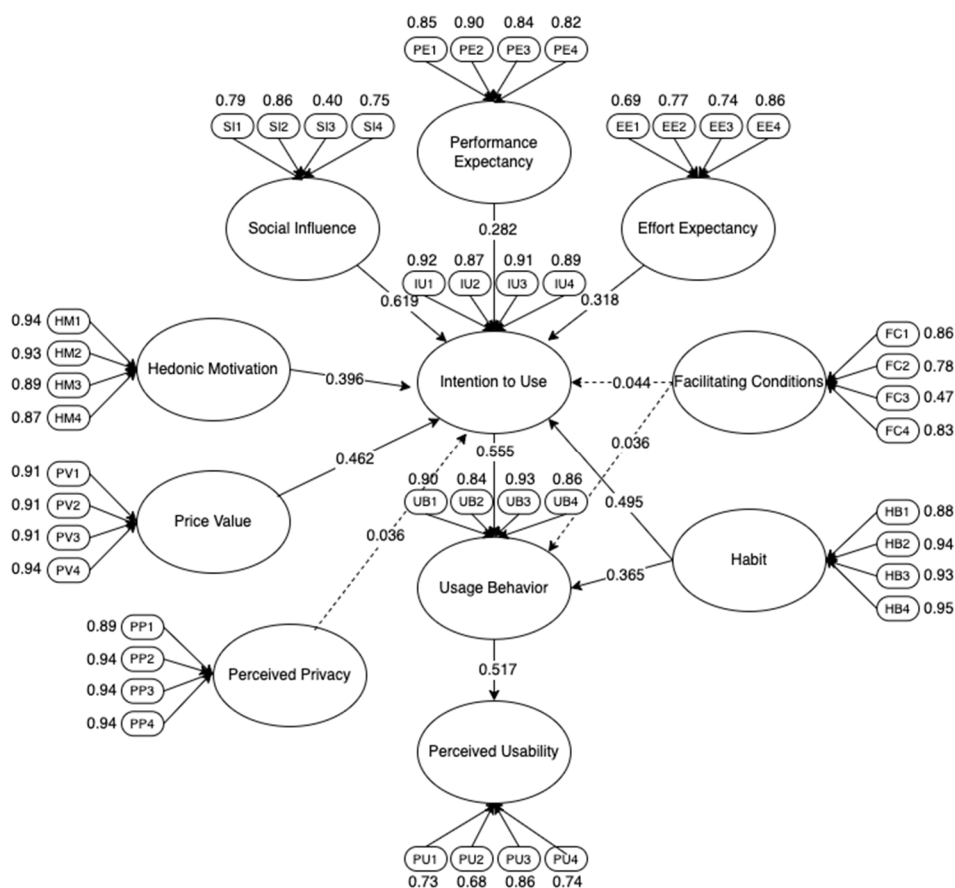
Characteristics	Category	<i>n</i>	%
Gender	Male	264	64%
	Female	138	33%
	Prefer not to say	12	3%
Age	18–24	318	77%
	25–34	42	10%
	35–44	33	8%
	45–54	12	3%
	55–64	6	1%
	65–75	3	1%
	75 or older	0	0%
Civil Status	Single	372	90%
	Married	42	10%
	Divorced	0	0%
	Widowed	0	0%
Area of Residence	NCR	201	49%
	Outside the NCR	213	51%
Duration as a Smartwatch User	Less than a year	90	22%
	1 year–2 years	189	45%
	3 years–4 years	99	24%
	5 years–6 years	33	8%
	7 years–8 years	3	1%
	9 years–10 years	0	0%
	10 years and above	0	0%

The initial model used for exploring the factors influencing smartwatch adoption by Filipinos can be found in Figure 2. The model is composed of eleven (11) latent variables with forty-four (44) indicators following the UTAUT2 framework. The reliability and validity of this approach were tested prior to data collection according to the recommendations of Kimberlin et al. [107]. The study utilized Cronbach's alpha, composite reliability, and the average variance extracted test to determine the validity of the statistical tool. Based on the study of Hamid et al. [108], the desired value for composite reliability and Cronbach's alpha was at least 0.70. Following this, the target value for the average variance extracted was to be at least 0.50 [109]. The results of the validity testing can be found in Table 3. Based on the table, all values satisfied the conditions, thus making the model valid and reliable.

In testing the proposed hypotheses of this study, partial least squares structural equation modeling (PLS-SEM) was performed using SmartPLS v4.1.0.0. According to Hair et al. [110], PLS-SEM software has become a standard approach for analyzing complex inter-relationships between observed and latent variables. Due to the software's capacity to estimate complex models and its flexibility regarding data requirements and measurement specifications, PLS-SEM was used [111]. The results of the hypothesis test are presented in Table 4. Out of twelve proposed hypotheses, nine were proven to affect the adoption and user experience of smartwatches significantly. Furthermore, all nine accepted hypotheses have a positive influence on intention to use, usage behavior, and perceived usability.

The proposed hypotheses were tested using the UTAUT2 framework with PLS-SEM, and the variable results, whether significant or not, are shown in Table 4. The results imply that performance expectancy ($\beta = 0.291, p = 0.001$), effort expectancy ($\beta = 0.318, p < 0.001$), social influence ($\beta = 0.631, p < 0.001$), hedonic motivation ($\beta = 0.399, p < 0.001$), price value ($\beta = 0.465, p < 0.001$), habit ($\beta = 0.495, p < 0.001$), and perceived privacy ($\beta = 0.036, p < 0.001$) significantly influence intention to use smartwatches, with a positive result leading to their acceptance. Moreover, another notable relationship where habit ($\beta = 0.368, p < 0.001$) significantly influences usage behavior can be seen in Table 4. Additionally, intention to

use smartwatches ($\beta = 0.557, p < 0.001$) significantly influences behavioral intention. Lastly, behavioral intention ($\beta = 0.520, p < 0.001$) significantly influences perceived usability. This study provides various significant factors that affect the adoption of smartwatches. Despite the significant positive relations between each variable, the theoretical and practical implementation of insignificant relations, such as facilitating conditions influencing intention to use smartwatches and usage behavior, perceived privacy influencing intention to use smartwatches, and behavioral intention influencing perceived usability, requires a better implementation of relationships to reach maximum satisfaction from smartwatch users.



Legends:

----- insignificant effect
 _____ significant effect

Figure 2. Initial SEM model.

In significant accordance with the recommendation of Henseler et al. [112], the researchers utilized the performance of the Fornell–Larcker criterion and heterotrait-monotrait ratio of correlation to significantly demonstrate the correlation of the variables discussed in this study. To further elaborate, discriminant validity is a means to measure certain degrees of difference within the overlapping constructs [110], and the heterotrait-monotrait ratio of correlation (HTMT) has the ability to achieve higher specificity and sensitivity rates in terms of undermining discriminant validity, following the Fornell–Larcker criterion. As seen in Tables 5 and 6, the values were within the desired range, with an inclusion for discriminant validity and satisfaction, leading to the overall results being valid.

Table 3. Reliability and convergent validity results.

Construct	Items	Mean	S.D.	FL (≥ 0.7)	α (≥ 0.7)	CR (≥ 0.7)	AVE (≥ 0.5)
Performance Expectancy	PE1	3.51	1.03	0.854	0.875	0.914	0.727
	PE2	3.43	1.07	0.899			
	PE3	3.21	1.07	0.840			
	PE4	3.60	0.99	0.816			
Effort Expectancy	EE1	3.68	1.04	0.694	0.768	0.851	0.589
	EE2	3.54	1.09	0.770			
	EE3	3.56	1.11	0.742			
	EE4	3.85	1.11	0.855			
Social Influence	SI1	3.47	1.00	0.785	0.701	0.802	0.518
	SI2	3.37	0.96	0.858			
	SI3	3.46	0.94	0.404			
	SI4	3.40	1.07	0.747			
Facilitating Conditions	FC1	3.60	1.07	0.860	0.723	0.832	0.563
	FC2	3.63	1.06	0.777			
	FC3	3.62	1.03	0.468			
	FC4	3.65	1.05	0.831			
Hedonic Motivation	HM1	3.30	1.06	0.942	0.929	0.949	0.824
	HM2	3.33	1.05	0.925			
	HM3	3.64	1.07	0.891			
	HM4	3.67	0.97	0.871			
Price Value	PV1	3.41	1.11	0.908	0.937	0.943	0.842
	PV2	3.30	1.11	0.913			
	PV3	3.51	1.11	0.911			
	PV4	3.45	1.06	0.939			
Habit	HB1	3.41	1.11	0.882	0.944	0.960	0.856
	HB2	3.30	1.11	0.940			
	HB3	3.51	1.11	0.932			
	HB4	3.45	1.06	0.946			
Perceived Privacy	PP1	3.41	1.11	0.887	0.945	0.961	0.859
	PP2	3.30	1.11	0.938			
	PP3	3.51	1.11	0.941			
	PP4	3.45	1.06	0.940			
Behavioral Intention	BI1	3.41	1.11	0.918	0.919	0.943	0.805
	BI2	3.30	1.11	0.867			
	BI3	3.51	1.11	0.910			
	BI4	3.45	1.06	0.892			
Usage Behavior	UB1	3.41	1.11	0.903	0.907	0.935	0.783
	UB2	3.30	1.11	0.839			
	UB3	3.51	1.11	0.933			
	UB4	3.45	1.06	0.862			
Perceived Usability	PU1	3.41	1.11	0.725	0.753	0.838	0.565
	PU2	3.30	1.11	0.675			
	PU3	3.51	1.11	0.856			
	PU4	3.45	1.06	0.740			

Table 4. Hypothesis test.

No	Relationship	Beta Coefficient	p-Value	Result	Significance	Hypothesis
1	PE→IU	0.291	0.001	Positive	Significant	Accept
2	EE→IU	0.318	<0.001	Positive	Significant	Accept
3	SI→IU	0.631	<0.001	Positive	Significant	Accept
4	HM→IU	0.399	<0.001	Positive	Significant	Accept
5	FC→IU	0.044	0.341	Positive	Not Significant	Reject
6	FC→UB	0.036	0.246	Positive	Not Significant	Reject
7	PV→IU	0.465	<0.001	Positive	Significant	Accept
8	HB→IU	0.495	<0.001	Positive	Significant	Accept

Table 4. *Cont.*

No	Relationship	Beta Coefficient	p-Value	Result	Significance	Hypothesis
9	HB→UB	0.368	0.001	Positive	Significant	Accept
10	PP→IU	0.036	0.260	Positive	Not Significant	Reject
11	IU→BI	0.557	<0.001	Positive	Significant	Accept
12	BI→PU	0.520	<0.001	Positive	Significant	Accept

Table 5. Discriminant validity: the Fornell–Larker criterion.

	BI	EE	FC	HB	HM	PP	PU	PE	PV	SI	UB
BI	0.897										
EE	0.587	0.768									
FC	0.600	0.710	0.751								
HB	0.663	0.623	0.654	0.925							
HM	0.437	0.531	0.565	0.653	0.908						
PP	0.667	0.656	0.640	0.673	0.497	0.927					
PU	0.448	0.611	0.527	0.446	0.329	0.585	0.752				
PE	0.716	0.720	0.608	0.698	0.526	0.676	0.575	0.853			
PV	0.487	0.690	0.681	0.675	0.600	0.657	0.473	0.600	0.917		
SI	0.567	0.596	0.716	0.673	0.346	0.642	0.563	0.816	0.615	0.820	
UB	0.761	0.459	0.651	0.598	0.657	0.457	0.678	0.677	0.590	0.718	0.885

Table 6. Discriminant validity: the heterotrait-monotrait ratio.

	BI	EE	FC	HB	HM	PP	PU	PE	PV	SI	UB
BI											
EE	0.623										
FC	0.648	0.771									
HB	0.723	0.679	0.726								
HM	0.496	0.591	0.652	0.762							
PP	0.733	0.723	0.720	0.759	0.579						
PU	0.426	0.752	0.558	0.446	0.347	0.663					
PE	0.770	0.769	0.661	0.758	0.595	0.747	0.588				
PV	0.551	0.792	0.791	0.789	0.738	0.676	0.533	0.690			
SI	0.617	0.713	0.719	0.710	0.437	0.531	0.456	0.561	0.715		
UB	0.671	0.610	0.711	0.789	0.562	0.450	0.513	0.610	0.659	0.594	

To demonstrate the validity of the proposed model, a model fit study was utilized. This included SRMR, chi-square, and NFI, applying as a reference the model fit parameters from previous studies. As seen in Table 7, the results indicate that every parameter estimate has a sufficient number for its corresponding model and the minimum cut-off, with SRMR and chi-square/dF being rightfully less and NFI presenting a greater number, proving the validity of the suggested model fit.

Table 7. Model fit.

Model Fit for SEM	Parameter Estimates	Minimum Cut-Off	Recommended by
SRMR	0.062	<0.08	Hu and Bentler [102]
(Adjusted) Chi-square/dF	4.03	<5.0	Henseler [112]
Normal Fit Index (NFI)	0.921	>0.90	Baumgartner [103]

The study's final SEM model, an expanded UTAUT2 model, is shown in Figure 3. While the broken lines imply a negligible specific association between the two, the solid lines demonstrate a considerable positive relationship between one construct and the other. Consequently, the model allots a 49.1% variance in the smartwatches' perceived usability.

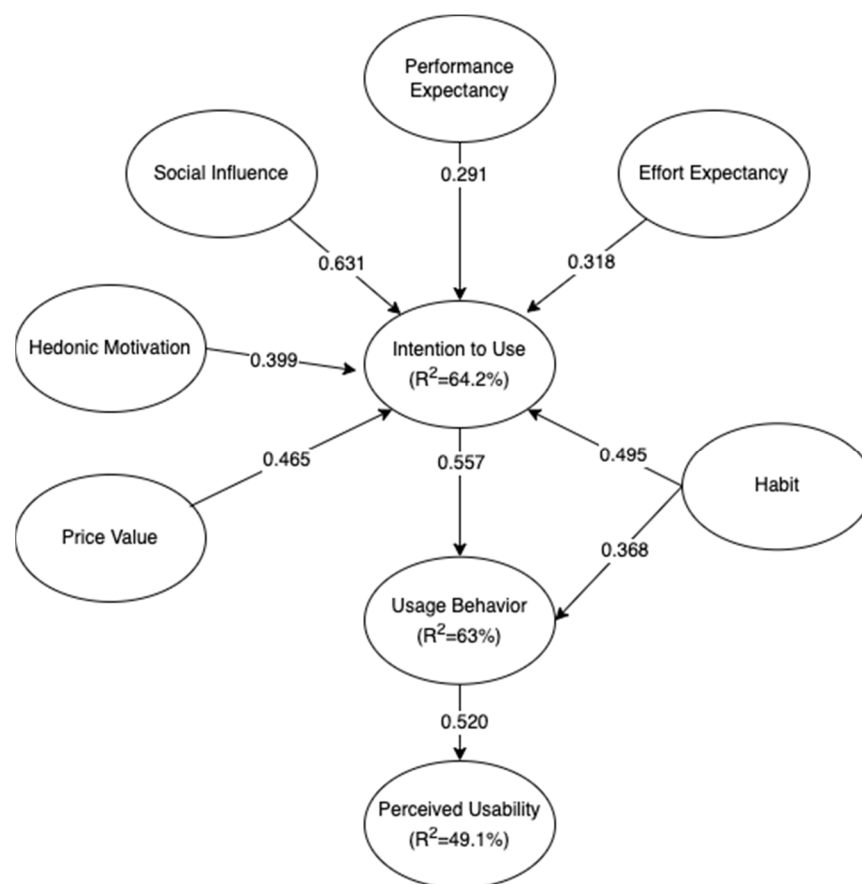


Figure 3. Final SEM model.

6. Discussion

Upon evaluation of the hypotheses, it was determined that not only do the factors in the UTAUT2 model affect the intention to use smartwatches but also the activity of the smartwatch user. Based on the indicators under the factors of effort expectancy and performance expectancy, the use of smartwatches in different fields of work, such as health, fitness, entertainment, and others, poses a significant relationship with the intent to use or buy a smartwatch. Heavily supported by studies such as Beh et al. [48], the sentiment that the purpose of the smartwatch coincides with the activities of the user is a critical factor in determining consumption.

This study's range of target population is general; therefore, the demographics attained through the respondents are an overall interpretation. As stated by Cristescu et al. [113], the elderly population is particularly appreciative of the use of smartwatches, and many studies have concluded that smartwatches provide a larger benefit to the older population. However, according to the results from the general population, the greatest number of respondents came from ages 18–24, for a total of 78.6%. It has been argued that smartwatches are more marketable to the younger generation—adoption, awareness, and implementation are the key factors for the device (Smart Watch Market Size, Share, Trends, and Growth Report, 2033, 2022). Furthermore, the results show that males are more inclined to use smartwatches than females—as males were 63.8% of the respondents, females were 33.3%, and the 2.9% left preferred not to indicate their gender. Males lean more toward the technological aspect of the device, whereas females prefer the aesthetics of it [30].

According to these findings, it is recommended that manufacturers add features that capitalize on the activities of the common smartwatch user to further encourage interest. On the other hand, this study bears the implication that users adopt smartwatches depending on their activity. Thus, consumers considering smartwatches should also be knowledgeable and consider their activity when choosing to purchase this piece of wearable technology.

As seen in Table 7, there are nine (9) total hypotheses accepted after the utilization of the statistical tool. The factors that have a significant positive effect on the intention to use smartwatches are performance expectancy, effort expectancy, social influence, hedonic motivation, price value, habit, and behavioral intention. It was also determined that using smartwatches positively affects behavioral intention. Lastly, habit has a significant positive relationship with usage behavior.

From the results, it can be seen that performance expectancy positively affects the intention to use smartwatches. Performance expectancy refers to the perception that a tool of technology will be proficient in doing a certain task [65]. This suggests that individuals' expectations regarding the performance or functionality of smartwatches influence their intention or willingness to use them. In other words, if people believe that smartwatches will effectively perform the tasks and functions they desire, they are more likely to intend to use them.

Multiple studies have studied this specific factor, such as that of Chang and Wu [114], where it was determined that the relative advantage provided by the smartwatch played a key role in its acceptance within the community. This proposition is also supported by Cristescu et al. [113], where the elderly appreciated the use of this technology when it benefited them. Newer studies utilizing the UTAUT and UTAUT2 models have found similar results when using the framework with other applications of technology. It is recommended that smartwatch features and functionalities be improved to better meet customers' needs and expectations. This could entail expanding connectivity options, enhancing battery life, integrating new sensors, and boosting compatibility with a broader range of devices and apps.

Effort expectancy was found to have a significant positive relationship with the intention to use smartwatches. This implies that the perceived ease or difficulty of using smartwatches influences individuals' intentions or willingness to use them. People are likely to use smartwatches if they think utilizing them is simple and involves little effort. In a study conducted by Beh et al. [48], smartwatches were studied from the perspective of fitness and health monitoring. It was determined that the overall convenience of the smartwatch was a significant factor in having a pleasant experience utilizing it for fitness-related tasks. Supporting the determined relationship, Cristescu et al. [113] studied the acceptance of smartwatches by the elderly. Here, it was also found that usability and simplicity were key factors for their acceptance and daily usage. Thus, effort expectancy having a significant positive relationship with intention to use smartwatches coincides with the conclusions found in previous studies. It is therefore suggested that smartwatches be made easier to use and more intuitive by streamlining their user interface. Navigation should be simple, uncluttered, and have clear instructions to lessen the cognitive load needed for engagement.

Social influence was found to have a significant positive relationship with the intention to use smartwatches. This means that the social context in which smartwatches are used may impact people's intentions or desire to use them. In other words, people are more likely to use a smartwatch themselves if they believe their friends, relatives, or other members of their social circle use and recommend them. Several studies support this finding. In Malaysia, since there is a rapid advancement in the use of smartwatches to track the health of Malaysians, a study by Dawi et al. [71] concluded that social influence is one of the latent factors associated with the intention to use the smartwatch. According to another study by Rekha [115], social influence is one of the deciding factors that makes people continue to use the smartwatch. Therefore, smartwatch developers and marketers should actively promote the adoption of smartwatches by leveraging social influence strategies. This entails fostering a sense of community among users, encouraging peer recommendations, and showcasing real-life success stories.

Hedonic motivation (HM) has also proved to have a significant positive relationship with consumers' intention to use smartwatches, resulting in their acceptance. Furthermore, a study conducted by Dehgani et al. [116] states the relevance of factors, e.g., hedonic

motivation, in driving the intention of consumers to use smartwatches, where it results in positive emotional reactions. In relation to this, there is a probability that consumers' intention to use smartwatches is due to their enjoyment of the smartwatch along with its functionality, leading to a strong correlation with hedonic motivation [29]. Based on this implication, for smartwatches to be adopted, they must appeal to a certain demographic by leveraging their functionality or overall enjoyment. Therefore, manufacturers would benefit from considering the hedonic factor of adoption by integrating recreational features or even leisurely applications.

Price value was found to have a significant positive relationship with the intention to use smartwatches. Price value is the cost of technology and the benefit of consuming that technology [98]. According to Ramkumar and Liang [23], price value is a significant factor in the perception of consumers. Its affordability can correspond to the perceived worth of the product as well as its quality. Inexpensive smartwatches may be perceived as poorly made by the general consumer. In contrast, expensive smartwatches may make consumers question the worth of purchasing a smartwatch. Since a certain demographic of smartwatch consumers are adults or even other people with income, it is advisable that the price be kept to a reasonable degree so it will be bought for its functionality and not be seen as a luxury.

Habit (HB) was revealed to have a positive significance for consumers' intention to use a smartwatch. According to Tarhini et al. [57], habit can be defined as the extent to which individuals engage in actions automatically, due to their previous learning or acquired experience. Moreover, once habits are established, consumers may find it challenging to stop using a device, turning them into strong supporters of the technology [59]. Though habit is a significant factor in the adoption of smartwatches, it may prove difficult for manufacturers to integrate this factor into the technology itself. Therefore, outside strategies concerning the consumer themselves, such as marketing tactics, are highly recommended for aiding the consumption of smartwatches so that consumers have an interest in integrating a smartwatch into their habits.

Behavioral intention (BI) shows a positive significance for the perceived usability of smartwatches. This result comes in line with the prior finding by Al-Emran [117], which concluded that perceived usability has a positive impact on students' behavior and intention to adopt smartwatches. Since this study gathered respondents from a general population, this implication can be applied to a larger demographic. With this finding, manufacturers may also consider having a more generic approach to the development of a smartwatch to cater to a larger audience that may consider adopting the technology, in contrast to focusing on a specific niche with a high likelihood of purchasing the technology.

The intention to use (IU) was also shown to positively influence the usage behavior of smartwatch consumers. Based on Loo [64], behavioral intention also includes a user's deliberate and intentional strategy for how they will adopt or engage with a newly introduced technology or device, such as smartwatches. As stated before, usage behavior alone was not a significant factor in the intent to use smartwatches. However, the reverse was observed to be true. This implies that the initial intent to use smartwatches affects the usage behavior of a consumer concerning technology. Simply put, when a consumer intends to use a smartwatch, the integration of the device into their daily use will be a likely scenario. Therefore, developers should naturally encourage the interest of consumers since their initial intent to use the smartwatch will be a factor in the integration of the device into their daily lives.

Lastly, habit (HB) was also proven to have a significant positive impact on the usage behavior of smartwatch consumers, resulting in its acceptance. According to the study conducted by Tamilmani et al. [61], one of the main factors that greatly influence usage behavior, such as habit, also heavily influences intrinsic motivation. Habit has been proven to affect both usage behavior and intent to use; therefore, marketers or even developers must consider this factor when creating strategies or developing technology. This implication not

only shows that habit has a positive relationship with intent to use but is also a relatively large factor in overall smartwatch adoption.

6.1. Theoretical Contribution

This study uses the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) Model to explore what influences the adoption of smartwatches among Filipinos, focusing on usability and demographics. The UTAUT2 model looks at key factors like performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit, and behavioral intention. Additionally, it considers external factors such as perceived usability and privacy. Using partial least squares structural equation modeling (PLS-SEM) for analysis, the study finds that performance expectancy, effort expectancy, social influence, hedonic motivation, price value, and habit significantly influence the intention to use smartwatches. Habit also directly impacts actual usage. However, facilitating conditions and perceived privacy do not significantly affect the intention to use or actual usage behavior. This theoretical framework provides a structured approach to understanding the multifaceted factors influencing smartwatch adoption. The findings offer valuable insights for manufacturers and researchers aiming to enhance the design and usability of smartwatches, address user needs, and improve market inclusivity by considering demographic variables and user-centric factors.

6.2. Practical Contribution

This study provides several practical contributions for manufacturers and researchers in the field of smartwatches. By identifying key factors such as performance expectancy, effort expectancy, social influence, hedonic motivation, price value, and habit that significantly influence the adoption of smartwatches among Filipinos, the study offers actionable insights into enhancing smartwatch design and usability. Understanding that habit strongly affects both the intention to use and actual usage behavior suggests that manufacturers should focus on creating user-friendly and engaging experiences that seamlessly integrate into daily routines. Additionally, the findings highlight the need to prioritize usability features, as perceived usability positively influences adoption rates. Addressing these factors can help tailor marketing strategies and product designs to better meet user expectations and preferences. Furthermore, the study's insights into the insignificance of facilitating conditions and perceived privacy in influencing adoption suggest that resources might be better allocated towards improving core functionality and user experience rather than overemphasizing these aspects. Overall, these practical implications can help drive higher adoption rates, improve user satisfaction, and expand the market reach of smartwatches, particularly in diverse and rapidly urbanizing regions like the Philippines.

6.3. Limitations and Future Research

Although the study yielded a good outcome, it was necessary to consider many limitations. Because of time limitations and a limited social network, the study could only collect a moderate number of participants from the urban region of the Philippines. Therefore, expanding the survey range may enhance the study's results. Moreover, the demographic figures revealed that most respondents fall into the younger age bracket (below 30 years old). The particular demographic makeup of this group raises questions regarding the generalizability of our findings to a broader population. The uniformity of our sample indicates that specific subgroups, such as the elderly, individuals residing in rural areas, or those with diverse educational or socio-economic backgrounds, were either underrepresented or completely absent. The findings could be more robust in generalizability due to a lack of representativeness. Our participants' behaviors and attitudes, as well as the study's consequences, may not represent a broader, more heterogeneous population. Therefore, it is advisable to incorporate more participants who fall into the older age group (30 years and older). Furthermore, the study did not consider the influence of gender, educational level, religion, culture, and income as potential characteristics that could affect usage be-

havior. This omission was due to the possible bias that could arise from using an online survey. Therefore, it is suggested that future researchers incorporate these aspects into their studies to validate the hypotheses presented in this study. Further research could explore these topics to gain a more comprehensive understanding of the factors that influence the adoption of smartwatches in the Philippines.

7. Conclusions

While this study provides valuable insights into the adoption of smartwatches among the Gen Z population in the Philippines, it is important to consider the unique cultural, historical, and geographical aspects of the country that may affect the generalizability of the findings to other regions. The strong community ties, religious influences, and logistical complexities specific to the Philippines are significant factors that might not hold the same relevance or influence in other contexts.

The cultural emphasis on communal relationships and social conformity in the Philippines may shape the preferences and adoption behaviors of the Gen Z population in ways that differ from their counterparts in other countries. Additionally, the prominent role of religion can influence lifestyle choices, including the adoption of new technologies. Moreover, logistical challenges such as varying levels of internet connectivity and access to technology across different regions can impact the adoption rates and usage patterns of smartwatches.

Therefore, while this study enhances our understanding of smartwatch adoption among the Gen Z population in the Philippines, its findings should be interpreted with caution when applying them to other national contexts. Future research should consider these unique factors and potentially conduct comparative studies across different countries to better understand the global trends in smartwatch adoption among the Gen Z population.

In addition, this study, although extensive, predominantly employs conventional methodologies and participants, which may restrict the range and relevance of its conclusions. Many enhancements can be implemented to bolster the durability and significance of future studies. First and foremost, integrating contemporary technologies like data analytics and machine learning can yield more profound insights and enhance the accuracy of the outcomes. Expanding the diversity of research subjects is essential. Incorporating a broader range of demographics will guarantee that the findings are more representative and applicable to a broader population. Engaging with a broader range of stakeholders, such as industry experts and policymakers, is essential to ensuring the study remains relevant and influential. In addition, revising ethical guidelines to correspond with current practices will enhance the study's credibility and integrity. Finally, comparing data across several locations or countries, including from a global perspective, can enhance the overall comprehension of the research issue. By using these methodologies, future studies can surpass the constraints of conventional methods and subjects, leading to more groundbreaking, pertinent, and influential research findings.

Author Contributions: Conceptualization, M.J.J.G.; methodology, M.A.A.D.G., G.Z.D.V.C., C.A.R.S. and S.Y.B.T.; software, M.J.J.G.; validation, M.A.A.D.G., G.Z.D.V.C., C.A.R.S. and S.Y.B.T.; formal analysis, M.J.J.G.; investigation, M.J.J.G.; resources, M.J.J.G., M.M.M. and A.K.S.O.; data curation, M.A.A.D.G., G.Z.D.V.C., C.A.R.S. and S.Y.B.T.; writing—original draft preparation, M.A.A.D.G., G.Z.D.V.C., C.A.R.S. and S.Y.B.T.; writing—review and editing, M.J.J.G., M.A.A.D.G., G.Z.D.V.C., C.A.R.S. and S.Y.B.T.; visualization, M.J.J.G.; supervision, M.J.J.G., M.M.M. and A.K.S.O.; project administration, M.J.J.G., M.M.M. and A.K.S.O.; funding acquisition, M.J.J.G., M.M.M. and A.K.S.O.; All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Mapua University Directed Research for Innovation and Value Enhancement (DRIVE).

Institutional Review Board Statement: This study was approved by the Mapúa University Research Ethics Committee.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflict of interest.

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