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# Applied artificial intelligence: Acceptance-intention-purchase and satisfaction on smartwatch usage in a Ghanaian context

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ABSTRACT

Technology and its continuous advancement facilitate human beings to get rid of their criticality and limitation. Applied artificial intelligence (AAI) is one of the latest forms that delimited the

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limitation of human beings. Smartwatch acts as an applied artificial intelligence to assist various patients to check medical care without going to hospital and physicians. This (three) multiple-study research focused on the intention to use, purchase, and their satisfaction and spread positive word of mouth among others in the Ghanaian. To investigate these issues two renowned theories were underpinned- TAM theory and the Stimulus-Organism-Response (*S–O*-R). Total 550, 320, and 170 respondents were interviewed with Google forms due to COVID-19 using social media. AI-enabled smartwatch considering Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Perceived Credibility (PC), Perceived Self-Efficacy (PSE), and Perceived Financial Cost (PFC) were significant on intention to adoption and adoption intention on actual purchase. The final study showed device quality, its service level, their usage experience, perceived value, and the extent to which the satisfied customers made positive word of mouth to their friends and family, colleagues and followers. This research is significant in understanding the usage of AI-enabled smartwatches as a device doctor or electronic doctor (e-doctor).

## 1. Introduction

Technology has reached every aspect of our lives, both individually and collectively [1], including real world and virtual world [2]. One of its most significant impact is how it has elevated human well-being in ways that have never been possible before. Artificial intelligence (AI) has been one of the most significant technological advancements [3]. Its applications has revolutionized broad sectors of society, including automotive, transportation and logistics, pharmaceuticals, agriculture, and manufacturing [4]. AI has been defined as "*the natural predispositions, genetic inheritance or learned skillsets forming the core of individual personalities*" [5], which works like a human brain in a decision-making process, and is based on computers' predefined programs and algorithms [6]. AI-embedded devices advancements have touched every aspect of the health sector [7] and health applications [8]. Abràmoff and Lavin [9] showed that AI applications can detect diseases more efficiently than human physicians can. At the same time, in view of its accuracy, reliability, and cost-effectiveness, AI is getting more popular among the general public [7].

AI technology embedded in a smartwatch can turn it into a medical tool that can deliver various benefits for medical patients [10], such as allowing them to check on their health, detect diseases and get instant guidance [11]. As a micro-computer, the smartwatch has multiple functionalities (smartphone, watch, music tool, etc.), including functionalities that allow patients to detect blood pressure, diabetic conditions, heart rates, and other health concerns [12]. Within this context, it should be noted that new technology, especially those assocated with medical and health care, are likely to be well accepted if they are easy to use, low cost, reliable, convenient and beneficial [13]. The necessity of using this device was during the COVID19 pandemic [10] when the restriction and lack of access to normal healthcare existed [12,14–16]. Especially, elderly people would get benefit from this technology, thoguh they are sometimes reluctant to adopt these technologies [17]. Ajzen and Fishbein [18] mentioned that a person's attitude or behaviour towards a system or device is determined by their reaction and perception of this tool, and emphasizes the importance of how people perceive the usage benefits, usefulness, credibility and ease of use associated with a technology. Another theory, Technology Acceptance Model (TAM) depicts that user behaviour (to ease of use and usefulness) determined by the intention to use a particular technological system or device [19]. Besides, the intention to use those devices is also backed by abilities such as monetary resources, time, and expertise [20]. The intended person behaves as per their intention when they feel the necessity of using the particular device or system [21].

Ghana represents a suitable context for this research for a number of reasons. First, the ageing population is growing rapidly in low-middle income countries [22], especially in sub-Saharan Africa including Ghana [23,24]. In 2021, older adults constituted approximately 2 million (6.5%) of Ghana's population of 30.9 million [25]. For the last 60 years, the number of ageing people in Ghana has increased seven times (Ghanaian Census, 2010). Second, a majority of older people die of non-communicable diseases (NCDs) such as heart disease, cancer, stroke and diabetes, rather than from infectious and parasitic diseases [23]. Stroke is a major issue for elderly Ghanaians. Third, while the older people in urban Ghana are a dependent population and need care, their children are not able to provide such care as they do not have the time [26]. Therefore, elder care has become a commercial service purchased by those who can afford it. Fourth, Ghana has been greatly affected by the Covid19 crisis. From January 3, 2020 till July 8, 2022, there have been 166,546 confirmed cases of COVID-19 with 1452 deaths in Ghana, as reported by WHO. As of June 26, 2022, a total of 18, 643, 437 vaccine doses have been administered. Lastly, studies have observed that a high proportion of older Ghanaians live in poverty, lack housing and access to quality health care [25].

AI is now a critical research area in the 21st century in nearly every field [27]. In marketing, the study of AI applications can contribute to better optimization of effectiveness and efficiency marketing activities, and better satisfaction of customer needs. In practice, AI remains underutilized at the marketing though companies have recognized its significance in marketing analytics. The AI revolution continues to introduce transformative applications such as AI assistants and chatbots, it is the challenge for marketing managers to keep pace [28]. Nevertheless, AI development and applications in developing countries continue to lag behind the more developed countries [29] and have become potential drivers of demand and growth for this technology. It is important for academic scholarship on AI to incorporate more perspectives from developing countries to ensure greater inclusivity. Thus, studies that focus on understanding the factors and conditions for adoption AI-enabled healthcare technology are needed to better realize its effective application in the marketing process.

Past studies have shown that intention is the main factor in committing any behaviour [30]. According to Ajzen and Fishbein [18], attitudes, assessments, and internal psychological operations lead to an intention to behave in a particular way. This particular behaviour is regarded as buying behaviour in the marketing discipline [31]. In the case of a smartwatch for healthcare purposes, a purchase is the outcome of an intention to adopt or use this watch. This purchase decision is influenced by various factors e.g. percived quality, their experience, cost-benefit comparison, etc.- which may result in a multi-stage decision process on consumer choice [32]. In the case of a device, the intention to leads to repeated or multiple usage over a certain period of time and the users gather experience from the device. This experience results in satisfaction and subsequently an inclination to recommend others, generally via word-of-mouth (WOM). WOM, including electronic word-of-mouth (eWOM), is a prominent construct in the marketing discipline as an ability to influence customers' buying intentions. Bhatt and Sankhla [33] studied customer purchasing behaviour and discovered that consistency is the most significant motivator for preferring one brand over another. Consumers might be likely to spread positive WOM about the experience once they feel committed to a brand and have widely engaged in the actual purchase behaviour [34]. Similarly, loyal customers are willing to share positive WOM as a form of loyal behaviour [35].

Customers also prefer the best quality product at any price [36]. Prior studies on the marketing of conventional products have demonstrated that the values customers derive from products or services positively affect their level of satisfaction with the specific offer [37]. Previous studies [38] have considered positive WOM as being a part of customer loyalty. Satisfaction is strongly and positively related to brand loyalty [39]. It has been described as an influential predictor of loyalty [40], a pivotal driver of loyalty [41] and a determinant of the success of loyalty [42]. Thus, the aim of the present research is to investigate the factors that affect the intentions and actual purchase of AI-enabled smartwatches among the elderly for medical purposes during the Covid19 pandemic, and the effects of satisfaction as a result of using these devices on WOM. Thus, this research is composed of three studies that investigate (1) a set of factors that affect purchase intentions and usage of smartwatches among an elderly population for health care purposes, (2) the actual purchase of these devices and (3) the usage satisfaction and positive attitude in the form of word-of-mouth (WOM) that may result from the use of these devices post-purchase. Specifically, this research attempted to answer the following questions in the three studies.

1. What drives elderly consumers' intention to purchase and use smartwatches for their healthcare? {Intention to buy}
2. What factors actively influence the intended customers to actually purchase and use smartwatches for their healthcare? {an actual buy and use by the intended people}
3. To what extent does this device satisfy these customers and do they share positive WOM with others? {actual use and their satisfaction level}

To address these questions this research conducted longitudinal studies in three stages: 1) intention, 2) actual buy and use, and 3) usage satisfaction and loyalty. Multiple theories were utilized in the three studies. In the first two studies that investigated the adoption intention of smartwatch and its purchase, two constructs "perceived self-efficacy" and "perceived financial cost" in the TAM theory were adopted along with the construct "perceived behavioural control" in the Theory of Planned Behaviour (TPB). Stimulus-Organism-Response (*S*–*O*-R) theory was also utilized to examine the impact of perceived quality, perceived value, and user experience as stimuli on user satisfaction (organism) [43]. A user's positive WOM is hypothesized as a response or reaction to the stimulus of the predictor. The testing of three frameworks, represented in Study 1, Study 2 and Study 3, align with the three research questions.

To implement the research, a sample of elderly users of smart devices for healthcare purposes in Ghana [44], was obtained from a patient database from government sources, where participants were selected regardless of gender, income, social status, and occupation. Practically these multiple studies will provide the marketing people to develop a marketing strategy and plan to create customer demand for new technology devices, convince them to purchase, and assess their satisfaction for a long-term relationship.

The rest of the paper provides a review of the relevant literature, hypotheses development based on the literature, and a formulation of research settings. It is followed by data analysis and a discussion of the study findings. The paper concludes with conclusions and implications of the results and future research direction.

## 2. Literature and conceptual frameworks

As AI-poweredmachines are capable of replicating human efforts [45,46] it has a potential to dramatically affect workers, businesses, nations, economies, and society as a whole [44]. AI has been examined in various disciplines and industries [47], including marketing [48] and healthcare [49]. Studies on AI in the marketing field has shown its application in wide ranging functions and processes, such as analyzing customer habits, behaviors, preferences, purchasing patterns [50], identifying profitable customer segments for planning and strategy development [51], customizing products and other offerings to align with customer needs [51], managing and adjusting prices in real time in response to actions of customers, competitors and supply chains [51], personalization of promotional messages [52] and links marketers and the market (buyers) [53]. These applications encapsulate the capabilities of AI-enabled tools to meet user requirements, detect their preference, enhance the better experience and finally satisfy them [54]. Similarly, AI is utilized in the health sector [55] in a number of ways. It provides greater convenience as it allows self-medication and frequent usage [56]. Benefits such as these can be delivered via an AI-enabled smartwatch that is used for persoal healthcare [57]. A smartwatch is a micro-computer and a touch-screen-enabled interface [58] that allows users to detect blood pressure, measure diabetic conditions, count heart rates, and perform other healthcare functions. This device is wearable and easily maintainable. It is a self-monitoring mechanism for administering quick and frequent self-tests at home in absence of a physician [12,58].

The outbreak of the pandemic in China at the end of 2019 and its rapid spread across the globe has brought much psychological and physical trauma [59], including unprecedented distruptions to normal functioning of business and society. As medical resources and attention were diverted to COVID-19 patients in clinics, hospitals, and health centres [60], common and regular health services such as routine checkups became unavailable or difficult to access in many places [61] due to the unavailability of physicians and nurses, and rules for social distance [62]. In addition, rules on lockdowns, movement restrictions, social distancing, minimizing of doctor-patient interactions and movements in clinics and hospitals have compounded the problem [63,64]. At the height of the crisis, a simple visit to a medical facility for a simple or routine check up would mean taking a risk of exposure to the virus. All these have impacted elderly patients in particular, as access to medicine and routine medical care amongst this demographic group has significantly deteriorated [65]. In such a scenario, technological solutions delivered through human-device interactions has filled the gap, in applications such as contactless payments and online purchasing which have come to the fore during this time. Such systems promise minimum cost and less effort, with added convenience and benefits [13].

Attig and Franke [66] outlined several reasons for using these devices, including accuracy, data usefulness, design and comfort, motivation, privacy and so on. However, the high rate of usage attrition raises the issue of user satisfaction and perceptions of product usefulness for these devices. Various research on user satisfaction among elderly users in a developing country context have indicated its impact on WOM [26]. In the case of a medical device such as AI-embedded smartwatch, the fear of Covid19 will moderate its adoption, use, satisfaction and the likelihood of positive recommendation to other people. Thus, in the third stage, this paper attempts to fill this gap, namely to investigate the impact of perceived quality, perceived value and user experience on their satisfaction in using these devices.

### 2.1. *Technology adoption intention and actual behaviour*

Many researchers [67] investigated the intention to adoption new technologies Technology Acceptance Model (TAM) is a widely used and influential model to investigate acceptance of a technology by users [68]. Chatterjee, Kar [17] mentioned two main factors among others that affect an individual's intention to use a new technology: perceived ease of use and perceived usefulness, which are adopted into the framework for this study.

### 2.2. *Selection of constructs and their measurement items*

This study focused on technology (applied artificial intelligence device) adoption (intention to adopt and actual use) and its post usage behaviour (satisfaction and behavioural loyalty). In technology adoption few factors are significant such its usefulness (benefits), easy to use (easiness), credibility (reliability on performance), users' confidence on the device, and price to pay for acquiring this device, which are correlated with intention to start using. Once the users keeping this AAI device, they assess the quality of it on the basis of service quality and physical quality. They compare cost-benefits of the device and gain experience from usage, those all shape overall assessment of the device in either happy, unhappy or neutral state. Satisfied and dissatisfied both users showed their post-usage behaviour in spreading positively or negatively towards their colleagues, family members and friends.

#### 2.2.1. *Perceived ease of use (PEU)*

Davis [69] was concerned about the resistance of users to accept and use technologies (devices or tools). This resistance is minimised once the user perceive that a particular device is easy to use. Thus, the construct Ease of use refers to the degree in which individuals believe or perceive how easy or effortless it is to use a particular technology. An intention to purchase will increase if a potential user finds it relatively easy to use a new device, thereby reducing the learning curve [70].

#### 2.2.2. *Perceived usefulness (PU)*

The construct Perceived usefulness (PU) is a cognitive factor-which determines the acceptance or intention towards an innovation or device [71]. PU is defined as a belief that a person has about the improvement in performance and productivity that will be achieved by using a new technology [72]. Davis [69] illustrated that people will show an interest to adopt new technology or device if they believe that the device will perform in a useful way. Peña-García, Gil-Saura [31] and Santoro, Bertoldi [73] found that PU is an influential factor in inspiring people to adopt new technology.

#### 2.2.3. *Perceived self-efficacy*

Self-efficacy is a "cognitive perceptions of the consumer [74] and a belief about their ability to perform a behaviour [75]. Peña-García, Gil-Saura [31] showed in their study that self-efficacy is a strong influencer of intention to use or purchase an electronic device. Thus, it is expected that consumers who indicate stronger perceptions of self-efficacy will exhibit greater purchase intentions.

#### 2.2.4. *Perceived credibility*

AI raises questions about privacy, security, legality, and fairness [53], which are critical in affecting users' adoption of a new technology [76]. These issues amount to a concern with credibility, which is a dimension of trust [77] and is defined as "the extent to which a person considers the believability level of information or data provided by a device [78]. Since an AI-enabled smartwatch provides information about a user's health conditions, it is vital for users to be able to ascertain -the validity and accuracy of the information provided [12]. Wang, Li [79] found that perceived credibility had a significant positive influence on the behavioural intention.

#### 2.2.5. *Perceived financial cost*

Perceived financial cost is an amount incurred to acquire a device [76]. Luarn and Lin [19] found that financial cost considerations might influence the customer behavioural intention. Cost has also been found to be a major barrier to adoption [80].

Based on the discussion, several hypotheses were formulated as follows.

**H1**. Perceived ease of use is positively correlated with purchase intention.

**H2.** Perceived usefulness is positively correlated with purchase intention.

**H3**. Perceived credibility is positively correlated with purchase intention.

**H4**. Perceived self-efficacy is positively correlated with purchase intention.

**H5**. Perceived financial cost is **NEGATIVELY** correlated with purchase intention.

### *2.3. Purchase intention and actual purchase behaviour*

Purchase (behavoir) intention refers to whether an individual or organization implements or adopts new technology, innovation or device [31]. Several scholars [30,69] consider intention to be a key predictor of actual behaviour or purchase. In other words, consumers who express an intention to buy a certain product is more likely to actually buy the product, compared to those who have no intentions of buying [32]. From a loyalty aspect, intention is related to attitudes, while purchase or action is related to behaviour loyalty [81]. To predict consumer behaviour, it is necessary to know the attitudes, assessments, and internal factors that ultimately generate the purchase intent [18]. In accordance with Pavlou, Liang [82], this research considers a purchase intention as the degree to which a consumer is willing to buy an AI-enabled smartwatch. A purchase intention does not necessarily translate into an actual purchase. Research such as Niessen and Hamm [83] showed that only a small percentage of consumer who indicated an intention to buy something will actually make the purchase. Based on the above, the first research hypothesis for this study explores the effect of online purchase intention on consumer purchase behaviour.

**H6**. Perceived ease of use is positively correlated with purchase intention.

**H7**. Perceived usefulness is positively correlated with purchase intention.

**H8**. Perceived credibility is positively correlated with purchase intention.

**H9**. Perceived self-efficacy is positively correlated with purchase intention.

**H10**. Perceived financial cost is **NEGATIVELY** correlated with purchase intention.

**H11**. Purchase (behaviour) intention is positively correlated with purchase (actual) behaviour.

### *2.4. Device use, user satisfaction and positive word of mouth through S–O-R theory*

A consumer or user usually purchases a product (device) or service based on some stimuli such the product quality, past experience (their own or of that of others), and previous usage benefit (their own or that of others). These stimuli help to develop a mind-set among consumers or users regarding a product or service such as a smartwatch device, which produce a positive or negative behavioural response. These series of steps were conceptualised by Mehrabian and Russell [84], who established stimulus organism response (*S*–*O*-R) theory as a model with three layers: stimulus, organism and response, and its application. This model explains the links between stimulus, organism, and response regarding consumer or user behaviour [43]. Originally and widely used in environmental psychology [72], *S*–*O*-R theory has also been popularly used in consumer behaviour studies [85]. From the *S*–*O*-R model, Schreuder, van Erp [86] showed how a certain stimulus or activity can organize a consumer's thinking to effect certain a reactions and behaviours. Consumers and users may respond differently to the given cues, depending on their internal emotional response mechanisms [81]. In this research, perceived (product and service) quality, perceived value and experience are the stimuli that develops a degree of satisfaction or dissatisfaction in the customers' minds. This state of positive or negative satisfaction stimulates a customer or user to react positively or negatively to the stimuli. A positive response can take the form of a positive word of mouth, which indicates positive loyalty behaviour. Conversely, a negative response can manifest in acts of negative WOM regarding the product or service. Thus, brand loyalty or brand avoidance behaviours constitute final outcomes of a customer's response to the stimuli.

Products or services, company's logos, advertisement, prices, packages, symbol, in consumer behaviour and marketing context [87], which are motivators in purchase and in use a device [81]. Elnagar, Alnazzawi [88] mentioned that satisfaction as organism in recent studies has been tested.

Response behaviors in *S*–*O*-R have been assessed in many studies recently, including positive word of mouth [89], loyalty [90], and impulse buying behaviour [81] which reinforces the significance of WOM in understanding consumer behaviour [43].

#### *2.4.1. Perceived quality*

Technology adoption has been widely discussed at both individual and organizational levels [47]. At the individual level, technology adoption depends on the benefits that a particular technology offers or facilitates the users. These benefits are, in whole or in part, related to product quality. Where a product is designed to satisfy an individual's needs [91], its particular set of attributes or functionalities and corresponding services are able to construe its perceived quality [43]. For an AI smartwatch, its quality can be seen in terms of its durability, performance, accuracy, weight, reliability, responsiveness and so on. Product quality is also often assessed in terms of a service dimension, especially an after-sales service, after-sales support, or technical support [92]. After-sales services can include supplementary service components that service-oriented company renders [93] or 'operative activities' in the case of sales of tangible goods [94], which can include transportation or delivery to clients, installation, product-related training, a help hotline, repairing services and even a recycling process [37]. These two quality dimensions of products and services are vital factors in selecting a smart device.

#### 2.4.2. Perceived value

A perceived value is 'what a customer desires from products and services' [95]. For examples, Solakis, Peña-Vinces [96] presented four types of perceived value in– a) "value as low price" [97] "value as whatever a customer want in a product" [95], c) "value as the quality the customer gets for the price s/he pays" [36]; and d) "value as what the customer gets for what s/he gives" [98]. When customers believe that a purchase will return a value or feels that the transaction will result in a 'win', they are more likely to proceed with the purchase.

#### 2.4.3. User experience

Users experience is defined as "subjective, internal consumer responses (sensation, feelings, and cognitions, and behavioural responses), evoked by the stimuli (product or advertisement) that are part of a product's design and identity, packaging, communications, and environments" [99]. A positive experience is formed if a product fulfils the self-image of consumers and gives satisfaction to their self-expressive need [69]. In the case of an AI-enabled smartwatch, interactions with the device will produce certain user experiences such as enjoyment, feeling assured, being productive, and so on, and can lead to a sense of satisfaction with using the product.

#### 2.4.4. Customer satisfaction

Customer satisfaction refers to a "customer's psychological response to his/her or her positive evaluation of the consumption outcome in relation to his/her expectation" and customers' evaluation between desired and actual performance of a product [100]. Satisfaction results from consumption of product or service, when actual performance exceeds expected/desired performance [101]. In this study, satisfaction occurs when the performance of an AI-embedded smartwatch, in terms of its perceived quality, perceived value and user experience exceeds the user's expectations.

#### 2.4.5. Word-of-mouth

WOM refers to an informal communication between customers concerning the evaluation of goods and services [43] and has been considered to be one of the most powerful forces in the market place [91]. Positive WOM helps in increasing the sale of products [102] and has long been associated with loyalty [103]. There is consensus that satisfied customers will engage in positive behavioural intentions [104], including positive WOM [105]. The link between satisfaction and positive WOM intention is supported by empirical research in the literature [106], and in a meta-analytic review by Ref. [74]. In this study, it is postulated that satisfaction, as a result of favourable perceived quality, perceived value, and user experiences will lead to positive WOM.

#### 2.4.6. Fear of the pandemic

A pandemic refers to a new disease that has an exponential rate of growth, has spread on a global scale and has affected a large number of people [23]. The toll brought about by the COVID-19 pandemic has raised public fears about the contagion, which has become an issue as it impacts consumer purchases and usage [107]. A bludgeoning literature on the impact of a fear of the pandemic on user or buyer behaviors has emerged since 2020, where a fear of the pandemic has been studied as a moderator in the adoption of a number of technological tools and processes, including educational technologies [108], banking [109], mobile payments [106], and e-commerce [110] among others. In the health arena, a response to the fear of COVID-19 has been the move towards 'telehealth', or the delivery of health services at a distance rather than in-person [11], which commensurate with the capabilities afforded by an AI-enabled smartwatch that is examined in this present study. Thus, in this study, a fear of the pandemic is taken as the negative or worrisome effects caused by the COVID-19 pandemic [111], which influences consumers' buyer behaviors, and is postulated to moderate the relationship between satisfaction and WOM.

**H12.** Perceived quality is positively correlated with user satisfaction.

**H13.** Perceived value is positively correlated with user satisfaction.

**H14.** User experience is positively correlated with user satisfaction.

**H15.** Satisfied users will spread positive word of mouth regarding smartwatch in physical and virtual community.

**H16.** To what extent a satisfied user will spread a positive word of mouth regarding smartwatch will depend on to what extent s/he is scared of a pandemic (a higher-level fear of pandemic, a higher level of positive word of mouth regarding use of smartwatch.

### 2.5. Proposed research framework

Upon the extent discussion, the study proposed the following research framework which shows three levels of study to understand their intention to use (buy), actual use (buy) and finally their satisfaction and loyalty level (Fig. 1).

## 3. Research methodology

### 3.1. Data collection and measurements

In this study, an online survey technique was used for data collection, which was conducted for over a year, and consisting of three studies using three separate structured. Due to the lockdown imposed by the Ghanaian government during the COVID-19 pandemic, an online survey method was used to collect data. The survey instrument was hosted on Google Forms. To implement the data collection, more than 1500 email addresses were sourced from different government sources, such as government websites, hospital websites, and so on, and various social media groups, such as WhatsApp, Facebook, FB Messenger, LinkedIn, and so on, so that participants could be invited to respond to the survey instrument on the Google Form through those email addresses [78]. The Google Form was also shared in social media groups with a cover letter, mentioning the purpose of the study and the usage of data. For the first study, a total of 550 responses were received in two months after two soft reminders were given (March and April 2021).

In the second study, from September to November 2021, a second questionnaire was sent to the previous 550 respondents, out of which 320 data responses were collected using a second questionnaire. A total of 170 respondents from the previous 320 respondents of the second study were interviewed for further data collection. These three studies adapted the measurements of questionnaires from previous research, with slight modifications to suit the current context [112].

### Ethical approval

Researchers conduct studies involving human participants per institutional and national research committee's ethical standards and the 1964 Helsinki declaration and its later amendments or comparable ethical standards. The questionnaire with cover letter stated the purpose of the survey assuring the confidentiality and sought the consent of respondents. The study confirmed that informed consent was obtained from all patients/participants for experiments. Besides, the ethical approval was taken from **Barakah Research Consultancy and Digital Marketing (BRCDM)** with the reference number: **BRCDM/2021/Res/01** dated **February 15, 2021**. The competent authority headed by Professor Dr. Md. Rakibul Hoque, Department of MIS, University Dhaka and head of ethical committee of BRCDM. However, the questionnaire quality was internally checked before data collection.

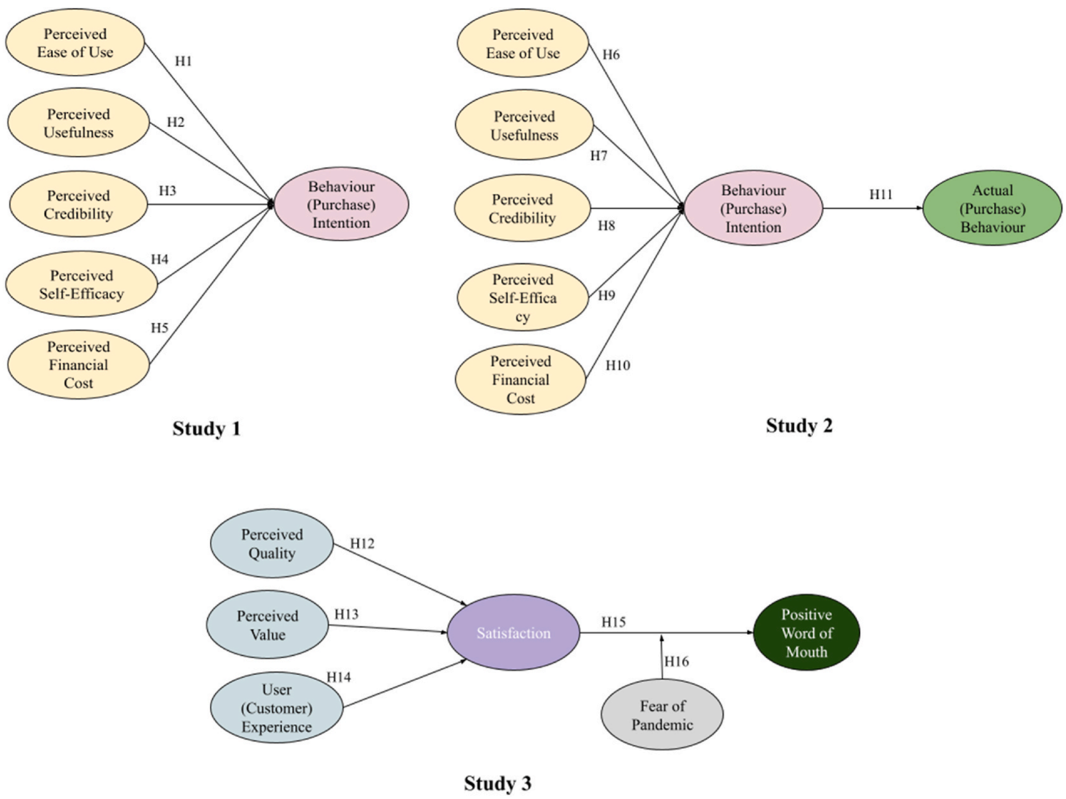


**Fig. 1.** Research models.

**Table 1**
Measurement of Constructs and their sources.

| Items | Statement | Sources and reasons for using the items | |
|---|---|---|---|
| | | Source and its relevance | Item relevance |
| Perceived Ease of Use (PEOU) | | | |
| PEOU1 | I think that it's easy to use this smartwatch. | [113]. The indicators of these constructs were adapted from the study of Stal and Paliwoda-Pękosz [113]. The study focused on the adoption of mobile technology or mobile device. The measurement scale of constructs in that study illustrate a portable, pocket-size, handheld, and wireless device (mobile device). How easily, comfortably, reliably the mobile device is being used for personal use and social use. The similar perspective is applicable for illustrating the measurement scale of this current study regarding using intention and usage of smartwatch for personal healthcare used by elderly people. This smartwatch is convenience, portable, handheld, wireless device. Corresponding the similar pattern of investigation, this current study adapted and utilized those measurement scale to investigate user' intention, purchase, and usage. The smartwatch is an applied AI which is being used for healthcare service to check diabetes, heartbeat, and blood-pressure. | These three items illustrate how easily an elderly people can use this smartwatch for their physical check-up. |
| PEOU2 | I think it would be easy for me to use this smartwatch to get health information | | |
| PEOU3 | The user interface of this app is clear and intuitive. | | |
| **Perceived Usefulness (PU)** | | | |
| PU1 | I believe that I can get health information using this smartwatch at a critical time. | | These indicators for measuring perceived usefulness illustrate that to what extent an elderly people can benefit from using smartwatch. |
| PU2 | I believe that using this smartwatch to obtain health information can increase my health consciousness. | | |
| PU3 | I think that I get useful health information from this smartwatch. | | |
| **Perceived Credibility (PC)** | | | |
| PC1 | Using this smartwatch will not leak my personal information. | | There are two indicators adapted for perceived credibility. In this study as the device will be used for healthcare by checking hear-beat, diabetes, blood pressure, thus, it is significant for the elderly people to get accurate measurement or checking value. |
| PC2 | I will find this smartwatch secure in my actual health information. | | |
| **Perceived Self-Efficacy (PSE)** | | | |
| PSE1 | I will use a smartwatch if I have just the built-in help facility for assistance. | | Perceived self-efficacy consists of three indicators illustrating how much confidently an elderly people can use this device. |
| PSE2 | I will use a smartwatch if I have seen someone else using it before trying it myself. | | |
| PSE3 | I will use a smartwatch if someone showed me how to use it first. | | |
| **Perceived Financial Cost (PFC)** | | | |
| PFC1 | It will not cost a lot to purchase this smartwatch. | | Perceived financial cost (price or value for gaining the device) includes two items illustrating how much an elderly people from a developing country can afford the device. |
| PFC2 | There are no financial barriers e.g., having to pay for this smartwatch and installation. | | |
| **Purchase Intention (PI)** | | | |
| PI1 | I intend to purchase this smartwatch to get health information. | | Purchase intention consists of three items illustrate to what extent an elderly people show their interest in using this device. |
| PI2 | I intend to purchase this smartwatch to maintain my health. | | |
| PI3 | I intend to purchase this smartwatch to obtain health information to support physicians. | | |
| **Actual Purchase (AP)** | | | |
| AP1 | I purchased this smartwatch to get health information very recently. | | Actual purchase construct has three indicators that explain whether the elderly people purchased it for themselves and for others and started using it. |
| AP2 | I am using this smartwatch to get health information. | | |
| AP3 | I purchase this smartwatch for my colleagues | | |
| **Fear of Pandemic (FoP)** | | | |
| FoP1 | I am most afraid of COVID-19. | [114]. This construct is being used in various discipline since it was propounded. | Fear of pandemic consists of four items that illustrate how much an elderly people get frightened due any pandemic such as SARS, MARS, COVID-19, Earthquake, Flood, or other natural and manmade calamities. |
| FoP2 | It makes me uncomfortable to think about COVID-19. | | |
| FoP3 | I am afraid of losing my life because of COVID-19. | | |
| FoP4 | When I watch news and stories about COVID-19on social media, I become nervous or anxious. | | |
| **Product Quality (PQ)** | | | |

(*continued on next page*)

**Table 1** (*continued*)

| Items | Statement | Sources and reasons for using the items | |
|---|---|---|---|
| | | Source and its relevance | Item relevance |
| Perceived Ease of Use (PEOU) | | | |
| PQ1 | This device has good functioning qualities. | [92]. This construct was adapted from a well-established and widely used measurement. | Product quality illustrates the functionality, durability and consistency attributes of smartwatch. |
| PQ2 | This is a durable electronic device. | | |
| PQ3 | This device shows consistent results. | | |
| **AI-enabled Service Quality (SQ)** | | | |
| SQ1 | The smartwatch is well designed. | [115]. The authors establish the dimensions of the experience, and develop a reliable and valid scale for the measurement of quality. | These measurement illustrates AI device and this service capability. |
| SQ2 | The smartwatch is reliable. | | |
| SQ3 | The smartwatch is secure. | | |
| **User Experience (UE)** | | | |
| UE1 | This device's service is memorable. | [54]. This construct was adapted the study which focused on customer experience in the age of artificial intelligence. | The three items of user experience construct illustrate the extent to which an elderly people find the device as memorable, educational, entertaining and comfortable. |
| UE2 | This device's service is entertaining and educational. | | |
| UE3 | This device's service is a sense of comfort. | | |
| **User Perceived Value (UPV)** | | | |
| UPV1 | I think the price of this smartwatch is equivalent to its quality. | [116,117]. User perceived value and user satisfaction were adapted from well-established measurements which were widely used. | Three indicators illustrate the cost and benefit assessment of buying and using AI device such as smartwatch. |
| UPV2 | The price of this smartwatch is reasonable and competitive. | | |
| UPV3 | This brand offers good value for money. | | |
| **User Satisfaction (US)** | | | |
| US1 | This device meets my expectations. | | Four items of user satisfaction illustrate the extent to which an elderly people are happy and satisfied from their internal assessment in using smartwatch. |
| US2 | This device is my one of choice for purchase and usage. | | |
| US3 | It is wise of me to choose this device. | | |
| US4 | I am very satisfied with using this device. | | |
| **Positive Word-of-Mouth (PWoM)** | | | |
| PWoM 1 | I speak positively of this smartwatch's good side to others. | [91]. The measurement scale for word of mouth (e-WOM scale) in the context of electronic service was derived. | These four items illustrate the WOM construct encompasses the dimensions of intensity, valence, and content. |
| PWoM 2 | I am proud to say to others that I am a user of this smartwatch. | | |
| PWoM 3 | I strongly recommend people to buy this smartwatch for a health issues. | | |
| PWoM 4 | I mostly share positive postings on social media about this smartwatch. | | |

### 3.2. Measurement of constructs

Table 1 displays the measurement of the construct employed in this study with source and items (indicators) relevance.

A panel of experts were invited to validate the measurement items in the questionnaire and modifications were made based on their suggestions. Since Ghanaians speak the standard English language, translation was not necessary. The survey instrument featured a five-point Likert scale with endpoints for "1-strongly disagree" and "5-strongly agree" and a seven-point Likert scale for positive WOM with endpoints for "strongly agree" as "7" as an endogenous construct. All measurements of the instrument were first order except perceived quality (product quality and AI-enabled service quality) which was reflective-reflective second order (see Table 3). This endogenous construct, positive WOM had a seven-point Likert scale to avoid systematic error in respondents' responses.

## 4. Data analysis and results

### 4.1. Pilot study

They study conducted pilot study to check the construct reliability. The result of the pilot study showed that the reliability of Cronbach's alpha of all constructs was within the threshold (>0.70).

### 4.2. Descriptive statistics (respondent profile)

Demographic information of respondents included gender, age (years), marital status, number of family members, education, occupation, monthly income (salary), religion, and major diseases. In this study, 41% of respondents were female, and 59% were male. In the age category, the youngest respondent was 48 years old and the most senior was 79 years old. The collected data showed that the most frequent age group lies in 51–55 years old (29%). In the fifth decade, only 18% of respondents and only 6% were most senior

**Table 2**
Descriptive statistics of constructs.

| Items | Descriptive | | | |
|---|---|---|---|---|
| Perceived Ease of Use (PEOU) | *Mean* | *Standard deviation* | Kurtosis | Skewness |
| PEOU1 | 4.24 | 0.94 | −0.38 | −0.91 |
| PEOU2 | 4.17 | 1.25 | 0.67 | −1.42 |
| PEOU3 | 3.88 | 0.76 | 0.39 | −0.61 |
| **Perceived Usefulness (PU)** | | | | |
| PU1 | 4.01 | 0.89 | −0.48 | −0.49 |
| PU2 | 3.86 | 1.25 | −0.46 | −0.80 |
| PU3 | 3.89 | 0.87 | −0.10 | −0.54 |
| **Perceived Credibility (PC)** | | | | |
| PC1 | 3.42 | 0.82 | −0.35 | 0.49 |
| PC2 | 3.29 | 0.94 | −0.75 | 0.32 |
| **Perceived Self-Efficacy (PSE)** | | | | |
| PSE1 | 3.76 | 0.81 | −0.42 | −0.23 |
| PSE2 | 3.77 | 1.08 | −1.24 | −0.26 |
| PSE3 | 3.92 | 1.01 | −1.34 | −0.24 |
| **Perceived Financial Cost (PFC)** | | | | |
| PFC1 | 3.07 | 1.14 | −0.77 | −0.54 |
| PFC2 | 3.15 | 1.00 | −0.27 | −0.11 |
| **Purchase Intention (PI)** | | | | |
| PI1 | 3.79 | 0.86 | −0.17 | −0.57 |
| PI2 | 3.49 | 1.09 | −1.30 | 0.03 |
| PI3 | 3.55 | 1.08 | −1.25 | −0.09 |
| **Actual Purchase (AP)** | | | | |
| AP1 | 3.62 | 0.90 | −0.77 | −0.08 |
| AP2 | 3.50 | 0.85 | −0.61 | −0.05 |
| AP3 | 3.76 | 0.95 | −0.89 | −0.25 |
| **Fear of Pandemic (FoP)** | | | | |
| FoP1 | 3.24 | 1.40 | −0.96 | −0.56 |
| FoP2 | 3.35 | 1.28 | −0.46 | −0.69 |
| FoP3 | 3.12 | 1.37 | −1.06 | −0.08 |
| FoP4 | 3.24 | 1.00 | −0.70 | 0.58 |
| **Product Quality (PQ)** | | | | |
| PQ1 | 3.91 | 0.81 | 0.64 | −0.51 |
| PQ2 | 3.87 | 1.02 | −0.71 | −0.42 |
| PQ3 | 3.49 | 0.97 | −0.63 | −0.02 |
| **AI-enabled Service Quality (SQ)** | | | | |
| SQ1 | 3.88 | 0.90 | −0.04 | −0.74 |
| SQ2 | 3.41 | 1.03 | −0.09 | −0.57 |
| SQ3 | 3.53 | 1.09 | −0.21 | −0.62 |
| **User Experience (UE)** | | | | |
| UE1 | 4.18 | 0.79 | −1.32 | −0.32 |
| UE2 | 3.71 | 0.96 | −0.56 | −0.60 |
| UE3 | 3.88 | 1.02 | −1.01 | −0.43 |
| **User Perceived Value (UPV)** | | | | |
| UPV1 | 3.88 | 0.83 | −0.37 | −0.39 |
| UPV2 | 3.71 | 0.96 | −0.92 | −0.20 |
| UPV3 | 3.94 | 1.00 | −0.72 | −0.60 |
| **User Satisfaction (US)** | | | | |
| US1 | 3.77 | 0.94 | −0.73 | −0.37 |
| US2 | 3.71 | 0.82 | −0.63 | −0.04 |
| US3 | 3.94 | 0.94 | −0.21 | −0.75 |
| US4 | 3.47 | 1.09 | −0.33 | −0.47 |
| **Positive Word-of-Mouth (PWoM)** | | | | |
| PWoM 1 | 5.35 | 1.41 | −0.04 | −0.65 |
| PWoM 2 | 4.59 | 1.88 | −0.65 | −0.57 |
| PWoM 3 | 5.29 | 1.49 | −0.43 | −0.73 |
| PWoM 4 | 4.18 | 2.12 | −1.45 | −0.27 |

(76–80 years old). All respondents have their families. Since it is necessary for senior citizens, to meet their doctors regularly, respondents were asked how many times they meet their doctors. Most of the respondents (59%) indicated that they meet their doctors more than five times a year. Only 12% meet their doctors or go to the hospital three times a year, while 29% of them meet five times a year. In terms of education categories, the majority were highly educated, with 53% of all participants having either a master's or doctoral degree. In terms of occupation, most respondents (59%) were engaged in various businesses or self-employment. 24% were government servants, while 18% were in the private sector. In terms of monthly income, 59% of the respondents earned more than six thousand Cedis, 12% earned between four to six thousand Cedis, another 12% earned between two to four thousand Cedis and the rest (18%) earned below two thousand Cedis. In the religious aspect, 41% were Muslims and 59% were Christians. Respondents were also

**Table 3**
Non-response test via independent sample test.

| Independent Samples Test | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Levene's Test for Equality of Variances | | *t*-test for Equality of Means | | | | | | |
| | | F | Sig. | t | df | Sig. (2-tailed) | Mean Difference | Std. Error Difference | 95% Confidence Interval of the Difference | |
| | | | | | | | | | Lower | Upper |
| PQ | Equal variances assumed | 0.347 | 0.557 | −0.460 | 168 | 00.646 | −0.05490 | 0.11942 | −0.29066 | 0.18085 |
| | Equal variances not assumed | | | −0.460 | 164.505 | 0.646 | −0.05490 | 0.11942 | −0.29069 | 0.18089 |
| SQ | Equal variances assumed | 0.000 | 1.000 | 0.000 | 168 | 10.000 | 0.00000 | 0.13230 | −0.26118 | 0.26118 |
| | Equal variances not assumed | | | 0.000 | 168.000 | 10.000 | 0.00000 | 0.13230 | −0.26118 | 0.26118 |
| CPV | Equal variances assumed | 0.034 | 0.854 | 0.257 | 168 | 0.798 | 0.03529 | 0.13745 | −0.23607 | 0.30666 |
| | Equal variances not assumed | | | 0.257 | 167.883 | 0.798 | 0.03529 | 0.13745 | −0.23607 | 0.30666 |
| UE | Equal variances assumed | 0.002 | 0.964 | −0.030 | 168 | 0.976 | −0.00392 | 0.13214 | −0.26479 | 0.25695 |
| | Equal variances not assumed | | | −0.030 | 167.868 | 0.976 | −0.00392 | 0.13214 | −0.26479 | 0.25695 |
| Sat | Equal variances assumed | 0.000 | 1.000 | 0.000 | 168 | 10.000 | 0.00000 | 0.12691 | −0.25055 | 0.25055 |
| | Equal variances not assumed | | | 0.000 | 168.000 | 10.000 | 0.00000 | 0.12691 | −0.25055 | 0.25055 |
| PWoM | Equal variances assumed | 0.122 | 0.727 | 0.622 | 168 | 0.535 | 0.12941 | 0.20794 | −0.28111 | 0.53993 |
| | Equal variances not assumed | | | 0.622 | 167.783 | 0.535 | 0.12941 | 0.20794 | −0.28111 | 0.53993 |
| FoP | Equal variances assumed | 2.463 | 0.118 | −0.103 | 168 | 0.918 | −0.01176 | 0.11458 | −0.23796 | 0.21443 |
| | Equal variances not assumed | | | −0.103 | 165.463 | 0.918 | −0.01176 | 0.11458 | −0.23799 | 0.21446 |

asked to indicate their health conditions, in terms of heart disease, blood pressure and/or diabetes. A large proportion (50%) revealed that they had heart disease, 25% had blood pressure and another 25% had diabetes. A relatively high proportion (40%) had both blood pressure and heart diseases, 35% had both diabetes and heart diseases, while 10% had these three diseases. Demographic statistics also showed that diabetes patients were mostly female and heart disease was largely in the male group. Besides, high blood pressure was reported in both cases.

### 4.3. Common method bias analysis

The current research collected three sets of data from separate surveys. For these data, common method bias (CMB) was checked through four techniques that are widely used: Harman's single factor procedure [118], useful correlation matrix [119], full collinearity assessment [120] and Unmeasured Latent Marker Variables-ULMV [118]. The correlation matrix result showed that the maximum R-value was 0.756 (<0.90). Harman's single factor test showed the first and largest factor with 36.65% variance (<50%) [121]. However, as these two techniques are no longer sufficient for testing CMB [122], this study checked a third approach, full collinearity assessment, as suggested by Kock [120], and a fourth approach which is ULVM. Collinearity checking results showed that maximum VIF values were less than 3.3 [120] and a few had less than 5.0 [120]. For ULVM, the SmartPLS algorithm analysis showed that with and without unmeasured marker variable R square varies less than 10% [123]. The results of these last two assessments indicated no significant concern regarding CMB/CMV in the current study.

### 4.4. Descriptive statistics of constructs and their items

This section showed the descriptive statistics of construct and their items with mean value, standard deviation, kurtosis and skewness. Mean value (average) indicates the central tendency of data, which were more than mid value of 3.00 (as all constructs ranged from 1 to 5, except positive word of mouth with 1–7 range). The standard deviation value (the dispersion of value is distant from mean) with 0.80–1.40 which also indicate data are not more much more orphan from central value. The data shape from skewness and kurtosis showed that the data were in normal distribution (within ±1.96 for both cases). It is to be noted that partial least square method is not vulnerable with data distribution (Table 2).

### 4.5. Non-bias response test

The research also checked a non-response bias test. In conducting non-response bias test, the study split the cases into early response and late response category and conducted independent sample *t*-test. The findings showed that Levene's equality variance of all constructs are insignificant (F value < 3.00 and p-value >0.05 at 95% confidence interval). And equality of means test for all variables are found insignificant. It implies that early response and late response are similar, no significant difference (Table 3).

### 4.6. Structural equation modelling (SEM) assessment

The two-step data analysis procedure [124] SEM is a popular and widely used data analysis technique in behavioural science [94]. In the first step, the research examined the outer model (measurement model) to check construct reliability and validity (convergent and discriminant). The second step performed the testing of the hypotheses through a structural model (inner model). In both cases, partial least square structural equation modelling (PLS-SEM) was used, namely the SmartPLS 3.3 version. Cassell and Bickmore [125] reported that variance-based PLS-SEM is superior to covariance-based SEM due to having robustness to collinearity and data distribution. As PLS is nonparametric, it can overcome these two limitations of multiple regression. According to Fornell [126], PLS support a variety of constructs and explains complex relationship model and eliminates inadmissible solutions and factor indeterminacy. Moreover, data non-normality is a vital issue in multiple regression. Hair and Ringle [127] assured that PLS-SEM is also reliable with non-normal data. Moreover, Ashraf and Ilyas [128] mentioned that PLS-SEM explains multiple statistical relationships simultaneously the wellness of the relationship among each construct and the hypotheses.

#### 4.6.1. Analysis of measurement model

In the first step, an assessment of the outer model (measurement model) was performed through a reliability test and a validity test. Construct reliability test was checked through indicator reliability (loading >0.70), Cronbach's alpha ($\alpha > 0.70$) and composite reliability (CR > 0.70). Convergent validity was checked with average variance extract (AVE >0.50) and discriminant validity was checked with the Fornell-Larcker criterion (diagonal square root of AVE) (is greater), and with hetero-trait and mono-trait (HTMT <0.85 0r 0.90) in these three studies.

A. Study One

The findings showed that construct reliability e.g. loading, α, CR met the recommended threshold (Table 4); convergent validity e. g. AVE and discriminant validity e.g. Fornell-Larcker Criterion and HTMT also met the suggested value to be validated in Table 5 [129, 130]. The square root of AVE is higher than that of other values in the matrix (Fornell-Larcker criterion). That means diagonal values are greater than off-diagonal values [131]. Henseler and Ringle [132] warned that Fornell and Larcker criterion method is traditional and less reliable to determine discriminant validity. Thus, Heterotrait-Monotrait Ratio (HTMT) approach was adopted as it is more reliable. Henseler and Ringle [132] recommended that HTMT's cut-off point is 0.85 and 0.90 for reflective measurement. $HTMT_{0.85}$ is

**Table 4**
Reliability and Convergent Validity, R2, f2 for study One.

| | Loading | α | CR | AVE | $R^2$ | $f^2$ |
|---|---|---|---|---|---|---|
| *Behaviour Intention (BI)* | | **0.750** | **0.858** | **0.668** | **0.693** | |
| BI1← BI | 0.758 | | | | | |
| BI2 ← BI | 0.870 | | | | | |
| BI3 ← BI | 0.842 | | | | | |
| *Perceived Credibility (PC)* | | **0.925** | **0.962** | **0.926** | | 0.063 |
| PC1 ← PC | 0.950 | | | | | |
| PC2 ← PC | 0.979 | | | | | |
| *Perceived Ease of Use (PEU)* | | **0.921** | **0.950** | **0.865** | | **0.277** |
| PEU1 ← PEU | 0.940 | | | | | |
| PEU2 ← PEU | 0.964 | | | | | |
| PEU3 ← PEU | 0.883 | | | | | |
| *Perceived Financial Cost (PFC)* | | **0.824** | **0.918** | **0.848** | | 0.020 |
| PFC1 ← PFC | 0.856 | | | | | |
| PFC2 ← PFC | 0.822 | | | | | |
| *Perceived Self-Efficacy (PSE)* | | **0.903** | **0.939** | **0.838** | | 0.078 |
| PSE1 ← PSE | 0.896 | | | | | |
| PSE2 ← PSE | 0.909 | | | | | |
| PSE3 ← PSE | 0.938 | | | | | |
| *Perceived Usefulness (PU)* | | **0.831** | **0.899** | **0.748** | | 0.087 |
| PU1 ← PU | 0.901 | | | | | |
| PU2 ← PU | 0.839 | | | | | |
| PU3 ←PU | 0.818 | | | | | |

**Table 5**
Fornell-Larcker Criterion and Heterotrait-Monotrait Ratio (HTMT) for study One.

| | 1 | 2 | 3 | 4 | 5 | 6 | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. BI | **0.817** | | | | | | | | | | | |
| 2. PC | 0.587 | **0.963** | | | | | **0.665** | | | | | |
| 3. PEU | 0.744 | 0.495 | **0.930** | | | | 0.893 | **0.515** | | | | |
| 4. PFC | 0.425 | 0.458 | 0.403 | 0.921 | | | **0.532** | **0.517** | **0.463** | | | |
| 5. PSE | 0.665 | 0.483 | 0.589 | 0.400 | **0.915** | | **0.809** | **0.499** | **0.644** | **0.436** | | |
| 6. PU | 0.546 | 0.331 | 0.463 | 0.013 | 0.468 | **0.865** | **0.692** | **0.355** | **0.523** | **0.125** | **0.537** | |

more conservative [133] and $HTMT_{0.90}$ is also admissible [134]. Thus, the measurement model for study one fits better and is suitable for the structural model and hypothesis test (Fig. 2).

B. Study Two

The findings from study two showed that construct reliability e.g. loading, α, CR met the recommended threshold (Table 6); convergent validity e.g. AVE and discriminant validity e.g. Fornell-Larcker Criterion and HTMT also met the suggested value to be validated in Table 7. Thus, the measurement model for study two also fitted better and was suitable for the structural model and hypothesis test (Fig. 3).

C. Study Three

The findings from study three showed that construct reliability e.g. loading, α, CR met the recommended threshold (Table 8); convergent validity e.g. AVE and discriminant validity e.g. Fornell-Larcker Criterion and HTMT also met the suggested value to be validated in Table 9 (Ramayah et al., 2018; [130]. Thus, the measurement model for study two also fitted better and was suitable for the structural model and hypothesis test (Fig. 4).

*4.6.2. Analysis of the structural model*

The multi-collinearity assessment was done for the suitability of the structural model. As shown in Table 10, the variance inflation factors (VIFs) from three studies found that no collinearity issues were prevalent in these studies.

The study confirmed the psychometric properties of the reflective measures [135]. The following stage examined the structural model (Fig. 5, Fig. 6, Fig. 7) intending to assess the explanatory power of the model and the significance of the hypothesized paths

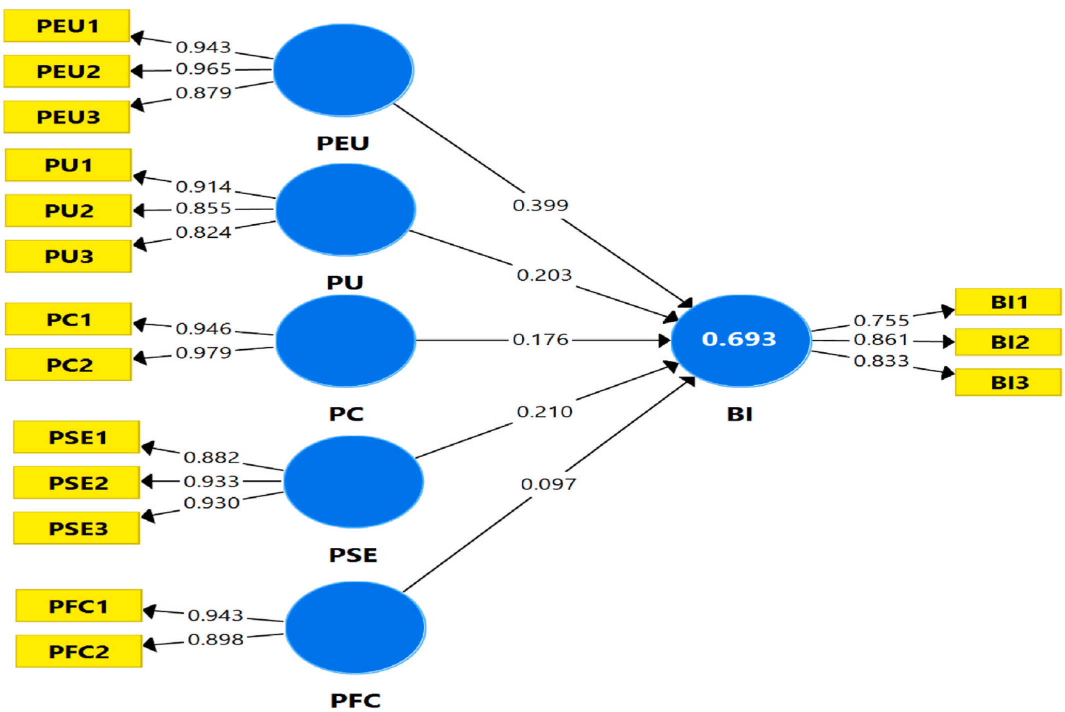


**Fig. 2.** Measurement model: Study one.

**Table 6**
Reliability and Convergent Validity, R2, f2 for study Two.

| | Loading | α | CR | AVE | $R^2$ | $f^2$ |
|---|---|---|---|---|---|---|
| *Actual Purchase (AP)* | | **0.965** | **0.977** | **0.935** | **0.520** | |
| AP1 ← AP | 0.979 | | | | | |
| AP2 ← AP | 0.957 | | | | | |
| AP3 ← AP | 0.965 | | | | | |
| *Behaviour Intention (BI)* | | **0.744** | **0.855** | **0.664** | **0.683** | **1.085** |
| BI1 ← BI | 0.727 | | | | | |
| BI2 ← BI | 0.876 | | | | | |
| BI3 ← BI | 0.833 | | | | | |
| *Perceived Credibility (PC)* | | **0.923** | **0.961** | **0.925** | | 0.066 |
| PC1 ←PC | 0.944 | | | | | |
| PC2 ← PC | 0.979 | | | | | |
| *Perceived Ease of Use (PEU)* | | **0.921** | **0.950** | **0.864** | | **0.274** |
| PEU1 ← PEU | 0.942 | | | | | |
| PEU2 ← PEU | 0.965 | | | | | |
| PEU3 ← PEU | 0.879 | | | | | |
| *Perceived Financial Cost (PFC)* | | **0.815** | **0.914** | **0.841** | | **0.018** |
| PFC1 ←PFC | 0.940 | | | | | |
| PFC2 ← PFC | 0.893 | | | | | |
| *Perceived Self-Efficacy (PSE)* | | **0.901** | **0.938** | **0.835** | | 0.066 |
| PSE1 ← PSE | 0.880 | | | | | |
| PSE2 ← PSE | 0.931 | | | | | |
| PSE3 ← PSE | 0.929 | | | | | |
| *Perceived Usefulness (PU)* | | **0.835** | **0.901** | **0.752** | | 0.097 |
| PU1 ← PU | 0.915 | | | | | |
| PU2 ← PU | 0.860 | | | | | |
| PU3 ← PU | 0.825 | | | | | |

**Table 7**
Fornell-Larcker Criterion and Heterotrait-Monotrait Ratio (HTMT) for study Two.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. AP | 0.967 | | | | | | | | | | | | | |
| 2. BI | 0.721 | 0.815 | | | | | | **0.839** | | | | | | |
| 3. PC | 0.660 | 0.587 | 0.962 | | | | | **0.695** | **0.661** | | | | | |
| 4. PEU | 0.576 | 0.737 | 0.497 | 0.930 | | | | **0.613** | 0.887 | **0.516** | | | | |
| 5. PFC | 0.298 | 0.413 | 0.466 | 0.395 | 0.917 | | | **0.343** | **0.521** | **0.529** | **0.457** | | | |
| 6. PSE | 0.326 | 0.653 | 0.495 | 0.583 | 0.401 | 0.914 | | **0.341** | **0.804** | **0.510** | **0.638** | **0.438** | | |
| 7. PU | 0.515 | 0.535 | 0.301 | 0.446 | −0.006 | 0.448 | 0.867 | **0.570** | **0.680** | **0.319** | **0.502** | **0.125** | **0.514** | |

[136]. As suggested by Hair and Sarstedt [137], the Bootstrap resampling procedure was utilized. The assumed significance of hypotheses assumes of 5000 resampling bootstrapping procedures, 95% confidence interval, 0.05 significance level, beta value above 0.10, t-value above 1.96 (two-tailed), p-value less than 0.05 and bias-corrected confidence interval lower limit and upper limit do not possess zero-value. In a special case at a 90% confidence interval and 10% significant level a hypothesis was accepted while a t-value >1.56 and p-value <0.10. In assessing the moderation effect, the product indicator method was applied in low and high interaction.

All five hypotheses of study one were supported. Perceived ease of use, perceived usefulness, perceived credibility, perceived self-efficacy and perceived financial cost had positive correlation with behavioural intention (purchase intention of smartwatches). These hypothesized paths complied with the recommended statistical requirements (Table 11). Similarly, all hypotheses in study two except perceived financial cost to behaviour intention were accepted. These findings indicated that perceived ease of use, perceived usefulness, perceived credibility, perceived self-efficacy had positive correlation with behavioural intention (purchase intention of smartwatches) and behavioural intention to purchase and use was also correlated with actual purchase. Only financial cost was found insignificant with behavioural intention to buy in second study due to the perception that when they actually purchased financial cost e.g. price of smartwatch was affordable for them to buy.

In the study three all hypotheses were found significant, indicating that showed perceived quality (Product and AI service), perceived value, and user experience were positively correlated with satisfaction whereas, similarly, satisfaction had also positive relationship with positive word of mouth. Customer satisfaction had the strongest effect on repurchase intention (beta = 0.521, T-value = 9.595 and *P*-value <0.001). The lowest accepted negative effect was found in between fear of pandemic and repurchase intention (beta = −0.334, T-value = 6.445 and *P*-value <0.001). Quality of service had no significant effect on customer satisfaction (beta = 0.038, T-value = 0.516 and *P*-value = 0.607). It is found that product quality ((beta = 0.345, T-value = 4.585 and *P*-value <0.001), customer perceived value (beta = 0.378, T-value = 6.696 and *P*-value <0.001) and social media (beta = 0.301, T-value = 6.445 and *P*-value <0.001) had significant and positive effect on customer satisfaction (Table 11).

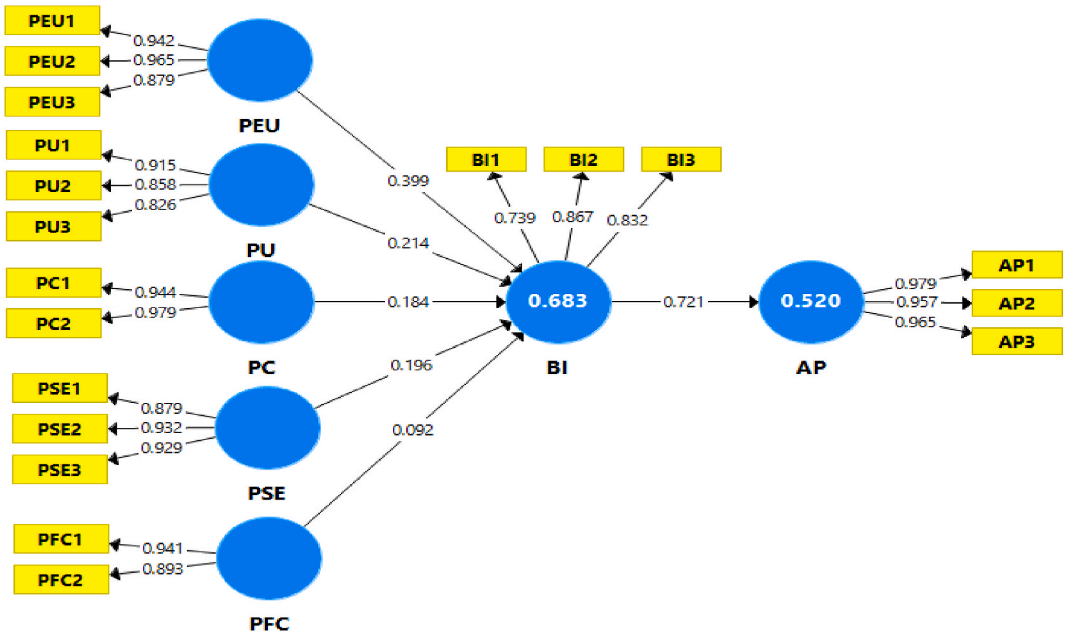


**Fig. 3.** Measurement model: Study two.

**Table 8**
Reliability and Convergent Validity, R2, f2 for study Three.

| | Loading | α | CR | AVE | $R^2$ | $f^2$ |
|---|---|---|---|---|---|---|
| *Customer Perceived Value (CPV)* | | 0.869 | 0.920 | 0.794 | | **0.353 (on SAT)** |
| CPV1 | 0.829 | | | | | |
| CPV2 | 0.933 | | | | | |
| CPV3 | 0.908 | | | | | |
| *Fear of Pandemic (FoP)* | | 0.900 | 0.937 | 0.833 | | 0.741 **(on PWoM)** |
| FoP1 | 0.895 | | | | | |
| FoP3 | 0.911 | | | | | |
| FoP4 | 0.932 | | | | | |
| *Product Quality (PQ)* | | 0.787 | 0.876 | 0.703 | | 0.078 (on SAT) |
| PQ1 | 0.886 | | | | | |
| PQ2 | 0.788 | | | | | |
| PQ3 | 0.837 | | | | | |
| *Positive Word-of-Mouth (PWoM)* | | 0.822 | 0.893 | 0.736 | 0.723 | |
| PWoM1 | 0.901 | | | | | |
| PWoM2 | 0.794 | | | | | |
| PWoM3 | 0.875 | | | | | |
| *Satisfaction (SAT)* | | 0.931 | 0.951 | 0.829 | 0.716 | **0.257 (on PWoM)** |
| SAT1 | 0.912 | | | | | |
| SAT2 | 0.915 | | | | | |
| SAT3 | 0.915 | | | | | |
| SAT4 | 0.901 | | | | | |
| *AI-enabled Service Quality (SQ)* | | 0.803 | 0.885 | 0.720 | | 0.078 (on SAT) |
| SQ1 | 0.787 | | | | | |
| SQ2 | 0.911 | | | | | |
| SQ3 | 0.842 | | | | | |
| *User Experience (UE)* | | 0.903 | 0.940 | 0.839 | | **0.230 (on SAT)** |
| UE1 | 0.884 | | | | | |
| UE2 | 0.966 | | | | | |
| UE3 | 0.896 | | | | | |

#### *4.6.3. Moderating effect of fear of pandemic via product indicator approach*

As fear of pandemic is continuous data, product indicator interaction of the construct fear of pandemic on the relationship between customer satisfaction and positive WOM was applied. The result showed that the interaction effect was significant ($\beta = 0.264$, $p = 0.001$), indicating that fear of pandemic had a moderation effect on this relationship (Table 11). It meant that the lower level of fear a customer had regarding the pandemic the less customer satisfaction had an effect on positive WOM. In contrast, the more customer

**Table 9**
Fornell-Larcker Criterion and Heterotrait-Monotrait Ratio (HTMT) for study Three.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. CPV | 0.891 | | | | | | | | | | | | | |
| 2. FoP | 0.460 | 0.913 | | | | | | 0.489 | | | | | | |
| 3. PQ | 0.584 | 0.094 | 0.838 | | | | | 0.719 | 0.205 | | | | | |
| 4. PWoM | 0.503 | 0.702 | 0.333 | 0.858 | | | | 0.591 | 0.785 | 0.46 | | | | |
| 5. SAT | 0.752 | 0.518 | 0.468 | 0.707 | 0.910 | | | 0.832 | 0.556 | 0.542 | 0.789 | | | |
| 6. SQ | 0.419 | 0.032 | 0.680 | 0.322 | 0.609 | 0.848 | | 0.511 | 0.176 | 0.839 | 0.386 | 0.698 | | |
| 7. UE | 0.625 | 0.476 | 0.474 | 0.569 | 0.750 | 0.612 | 0.916 | 0.695 | 0.53 | 0.55 | 0.638 | 0.808 | 0.703 | |

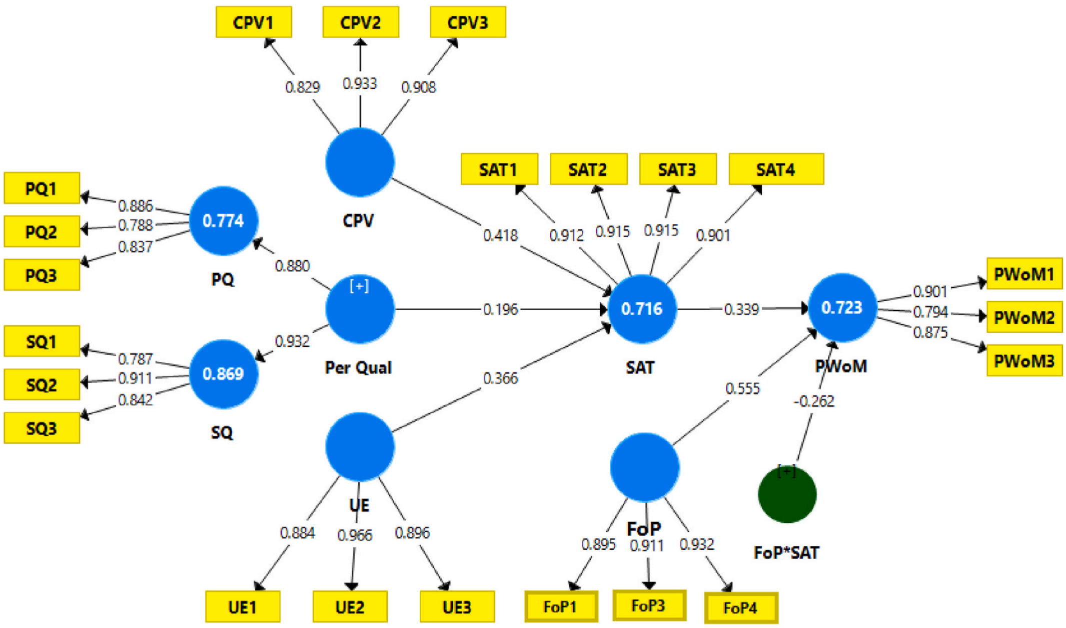


**Fig. 4.** Measurement model: Study three.

**Table 10**
Multi-collinearity (VIF).

| Study One | | Study Two | | | Study Three | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | BI | | AP | BI | | PQ | PWoM | SAT | SQ |
| PC | 1.594 | BI | 1.000 | | CPV | | | 1.74 | |
| PEU | 1.870 | PC | | 1.611 | FoP | | 1.50 | | |
| PFC | 1.522 | PEU | | 1.840 | SAT | 1.76 | 1.61 | | 1.76 |
| PSE | 1.859 | PFC | | 1.522 | UE | | | 2.05 | |
| PU | 1.541 | PSE | | 1.851 | UE | | | 2.05 | |
| | | PU | | 1.492 | | | | | |

fears the pandemic, the higher customer satisfaction had an effect on positive WOM. For a better understanding of moderation effects, the graphical presentation is illustrated in Fig. 8.

#### 4.6.4. *Assessment of coefficient determinant ($R^2$), effect size ($f^2$) and PLSPredict*

Hair and Sarstedt [137] posited that the $R^2$ value represents the amount of variance in the dependent variable by independent variables linked to it. According to Cohen [138], the rule of thumb for acceptable $R^2$ is 0.02, 0.13 and 0.26, respectively, describing weak, moderate and substantial levels of predictive accuracy. In study one, as shown in Table 4, the $R^2$ value for behaviour intention (purchase intention) was 0.693 (69.3%), indicating strong predictive accuracy. Similarly, in study two, as shown in Table 6, that the $R^2$ value for behaviour intention (purchase intention) was 0.663 (66.3%), indicating strong predictive accuracy, while for actual behaviour (actual purchase), the $R^2$ value was 0.520 (52%), also indicating strong predictive accuracy. If it was concentrated on study three, the $R^2$ value for both satisfaction and positive WOM would show strong predictive accuracy (0.716; 71.6% and 0.723; 72.3%, respectively) shown in Table 8.

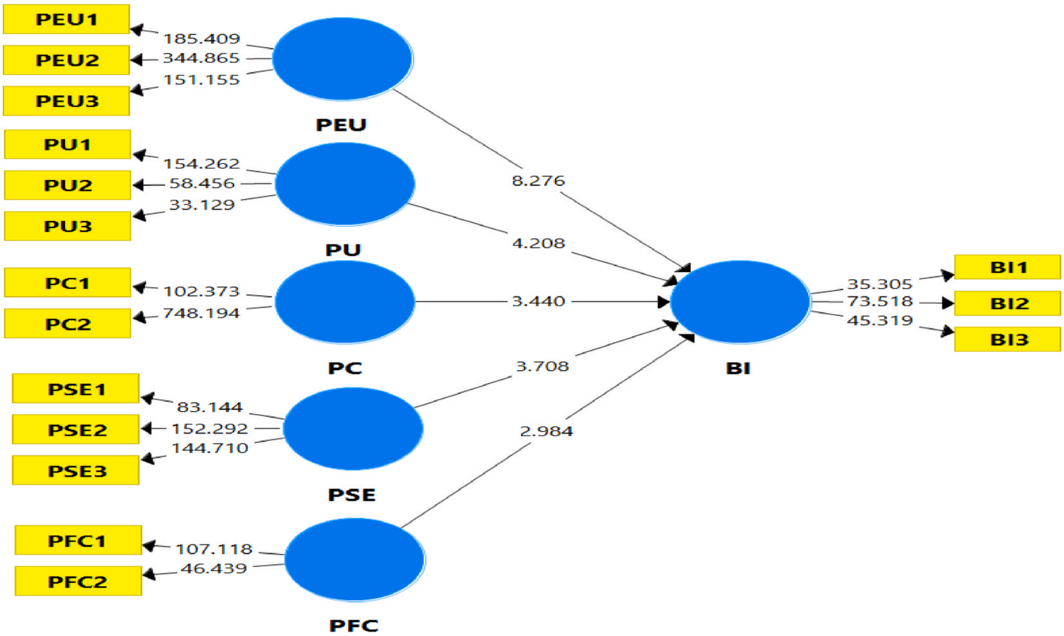


**Fig. 5.** Structural model: Study one.

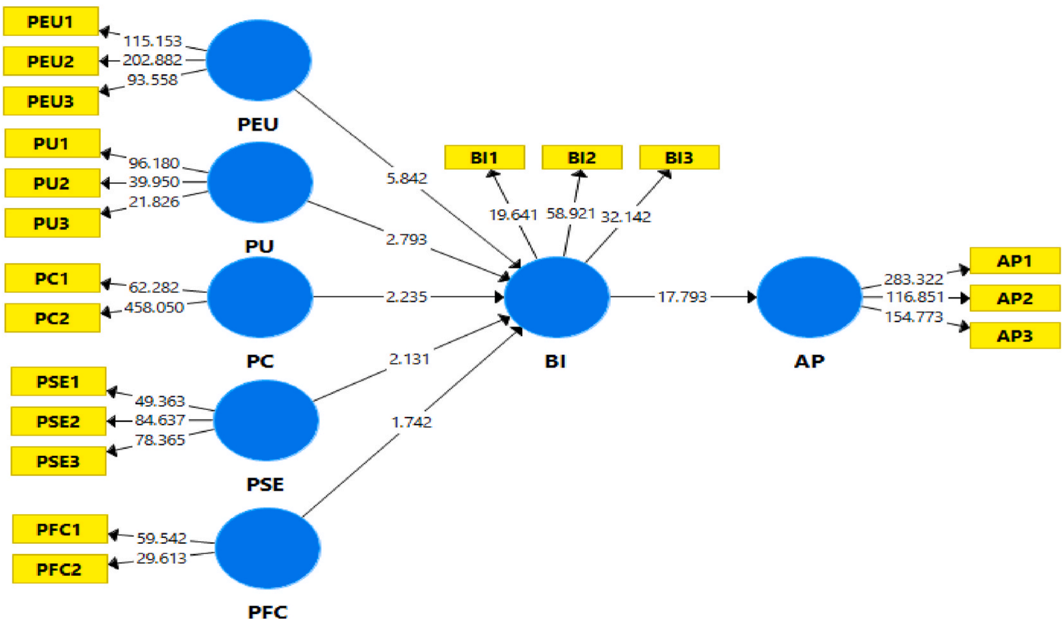


**Fig. 6.** Structural model: Study two.

Effect size ($f^2$) assessment of a structural model indicates the impact of the exogenous construct on the endogenous construct through changes in $R^2$ [139]. According to Cohen [140], $f^2$ values of 0.02, 0.15, and 0.35 are referred to as weak, moderate, and strong effects, respectively. Study one and study two showed that perceived credibility, perceived financial cost, perceived self-efficacy, and perceived usefulness had a weak effect (Tables 4 and 6). On the other hand, perceived ease of use had a moderate effect on behavioural intention and actual behaviour (Tables 4 and 6). In study three, product quality and service quality had a weak effect; however, user experience had a moderate effect while customer perceived value had a strong effect on customer satisfaction. In the second level, customer satisfaction had a moderate effect while fear of the pandemic had a strong effect on positive WOM (Table 8).

This third study also applied PLSPredict technique to measure out-of-sample predict power by using 10 folds and one repetition [107]. Comparing the values of RMSE, MAE, and MAPE of PLS-SEM and Linear Model, it is found that the PLS-SEM analysis produces

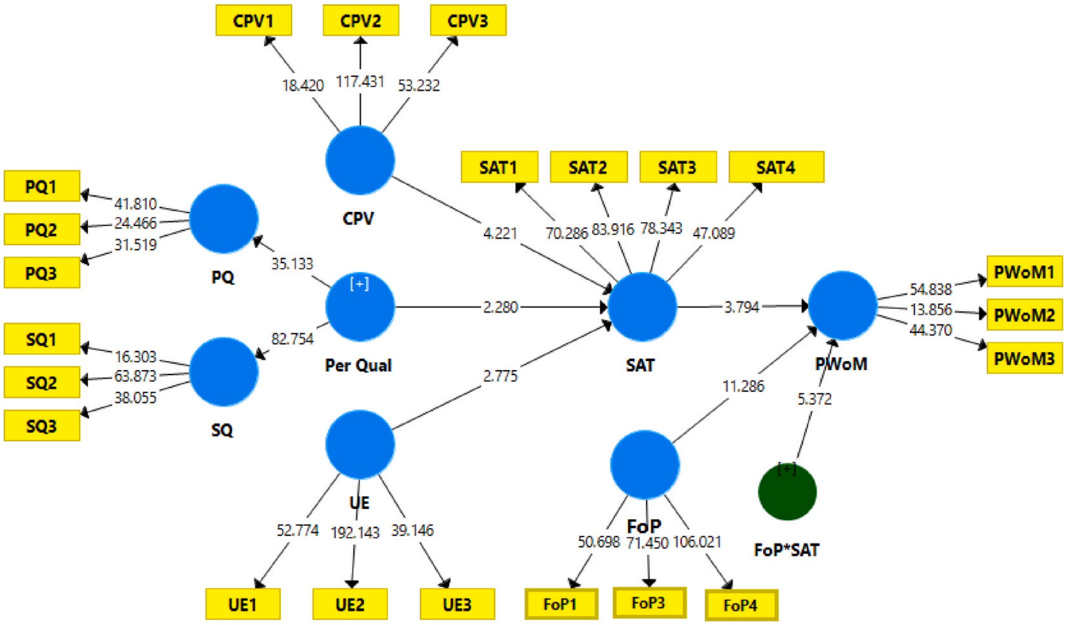


**Fig. 7.** Structural model: Study three.

**Table 11**
Path coefficient and hypotheses.

| Hypo | Path | Beta | Std. Error | t-value | p-value | 95% BC CI | | Result |
|---|---|---|---|---|---|---|---|---|
| | | | | | | Lower Level | Upper Level | |
| *Study One* | | | | | | | | |
| H1 | PEU → BI | 0.400 | 0.048 | 8.276 | 0.000 | 0.319 | 0.511 | Supported |
| H2 | PU → BI | 0.203 | 0.048 | 4.208 | 0.000 | 0.114 | 0.300 | Supported |
| H3 | PC → BI | 0.177 | 0.051 | 3.440 | 0.001 | 0.069 | 0.271 | Supported |
| H4 | PSE →BI | 0.209 | 0.056 | 3.708 | 0.000 | 0.091 | 0.316 | Supported |
| H5 | PFC → BI | 0.097 | 0.032 | 2.984 | 0.003 | 0.037 | 0.161 | Supported |
| *Study Two* | | | | | | | | |
| H6 | PEU → BI | 0.402 | 0.069 | 5.842 | 0.000 | 0.286 | 0.537 | Supported |
| H7 | PU → BI | 0.215 | 0.077 | 2.793 | 0.005 | 0.081 | 0.372 | Supported |
| H8 | PC → BI | 0.188 | 0.084 | 2.235 | 0.026 | 0.023 | 0.352 | Supported |
| H9 | PSE → BI | 0.186 | 0.087 | 2.131 | 0.034 | 0.010 | 0.346 | Supported |
| H10 | PFC → BI | 0.096 | 0.055 | 1.742 | 0.082 | −0.002 | 0.206 | Not-Supported |
| H11 | BI → AP | 0.726 | 0.041 | 17.793 | 0.000 | 0.637 | 0.796 | Supported |
| *Study Three* | | | | | | | | |
| H12 | CPV → SAT | 0.418 | 0.099 | 4.221 | 0.000 | 0.203 | 0.566 | Supported |
| H13 | Per Qual → SAT | 0.195 | 0.086 | 2.28 | 0.023 | 0.049 | 0.354 | Supported |
| H14 | UE → SAT | 0.365 | 0.132 | 2.775 | 0.006 | 0.173 | 0.655 | Supported |
| H15 | SAT → PWoM | 0.338 | 0.089 | 3.794 | 0.000 | 0.162 | 0.49 | Supported |
| **Moderation of Fear of Pandemic** | | | | | | | | |
| H16 | FoP → PWoM | 0.554 | 0.049 | 11.286 | 0.000 | 0.462 | 0.651 | Supported |
| | FoP × SAT → PWoM | 0.264 | 0.049 | 5.372 | 0.000 | 0.333 | 0.185 | Supported |

lower prediction error for all indicators of endogenous constructs (here, satisfaction- SAT and positive word of mouth-PWoM) (Table 12). Table 12 showed that the all items of endogenous constructs have predictive relevance since their $Q^2$ values are greater than zero [131].

## 5. Discussion

The current investigation empirically explores the viability of the adoption of smartwatches for elderly healthcare. A combined model that includes concepts from the TAM model and *S*–*O*-R theory was employed to verify the usage of smartwatches involving three seriatim studies. In the first study, perceived ease of use, perceived usefulness, perceived credibility, and perceived self-efficacy were found to be positively significant in determining the interest of customers to purchase and smartwatches for their healthcare service. These findings are similar to many past studies [141,142]. On the other hand, perceived financial cost is not found negatively

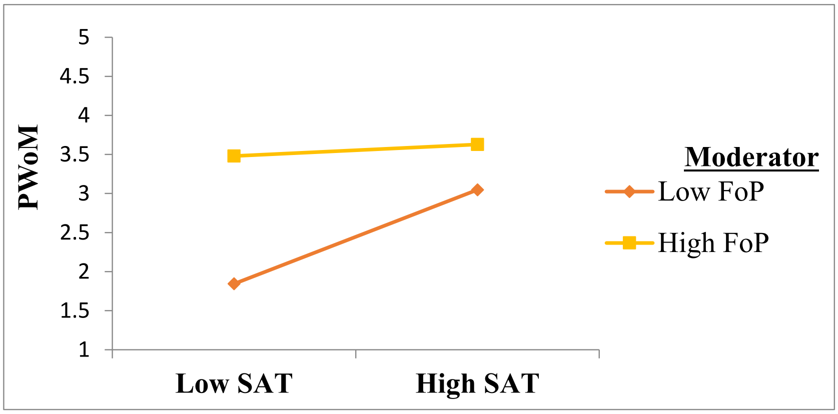


**Fig. 8.** Moderating Effect of FoP on SAT and PWoM relationship.

**Table 12**
Assessment of PLSPredict.

| | PLS | | | | LM | | | PLS-SEM - LM | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | RMSE | MAE | MAPE | $Q^2$ predict | RMSE | MAE | MAPE | RMSE | MAE | MAPE |
| **PWoM1** | 1.162 | 0.171 | 10.227 | 0.375 | 1.515 | 0.986 | 24.155 | −0.353 | −0.815 | −13.928 |
| **PWoM3** | 1.118 | 0.135 | 7.041 | 0.472 | 1.178 | 0.908 | 23.705 | −0.060 | −0.773 | −16.664 |
| **PWoM2** | 1.734 | 0.215 | 11.685 | 0.070 | 1.827 | 1.303 | 56.298 | −0.093 | −1.088 | −44.613 |
| **SAT1** | 0.607 | 0.049 | 1.431 | 0.588 | 0.929 | 0.450 | 13.137 | −0.322 | −0.401 | −11.706 |
| **SAT3** | 0.589 | 0.011 | 0.330 | 0.610 | 0.710 | 0.460 | 12.948 | −0.121 | −0.449 | −12.618 |
| **SAT2** | 0.556 | 0.036 | 1.050 | 0.550 | 0.847 | 0.465 | 13.424 | −0.292 | −0.429 | −12.374 |
| **SAT4** | 1.002 | 0.031 | 0.921 | 0.166 | 1.170 | 0.697 | 32.653 | −0.168 | −0.665 | −31.732 |

associated with intention to purchase and use of smartwatches [19]. These findings suggest that elderly customers are more likely to develop purchasing intentions for a smartwatch device if they find that the device is useful and easy to use, reliable and credible. Furthermore, their interest in purchasing and using this device is strengthened if it corresponds with their status and lifestyles. It is also argued that significant financial cost or cost of acquiring this smartwatch does not necessarily impede the intention to purchase and use this product. While lower prices can encourage a purchase intention, higher prices do not necessarily impede a purchase intention if its cost is not excessive compared to the costs associated with conventional treatment or physician visits. Any type of disasters or calamities like War, Pandemic, Earthquake, flood, etc. When people have less to option to meet the doctors, go to clinics, hospitals or healthcare services are rare to avail. These critical times smartwatch could be a vital solution.

In the second study, this research investigated the extent to which elderly peoples' purchasing intentions for smartwatches was translated into actual purchase behaviour. Like study one, similar findings were extracted in this second study that perceived ease of use, perceived usefulness, perceived credibility, and perceived self-efficacy were also found to be positively significant in the intended purchase and use of smartwatches. Additionally, the intended customers actually purchased and started to use this device which was accorded by previous studies [143,144]. This finding implies that customers with purchase intentions actually purchase this device so that they could check their health conditions by themselves and avoid going to doctors frequently. During the COVID-19 pandemic when physical dimensions and social distancing rules were imposed. The finding is also applicable to other pandemics and crisis situations where people will be restricted from meeting their physicians or vesting clinics.

The third study investigated the extent of user satisfaction based on quality of the device, their experiences, and their perception on cost-benefit. The findings that device quality, its usage value, and usage experience satisfy the users were supported in the earlier research [145]. As this device serves healthcare, this device reliable, shows accurate readings, and able to deliver timely information about users' health conditions. These qualities can assure the elderly people and they can handle it easily. The findings in this study suggests that elderly users who were satisfied with this device showed loyalty by sharing positive WOM with others. These findings implied that customers felt that the cost-benefit ratio of using their smartwatches was positive e.g., they are getting more benefits than they are spending for this device. They also implied that physical product quality, functionality, colour, design, and manufacturing elements were pleasantly perceived by users. Intangible services such as reliability, result reading, convenience, accuracy, battery-life, and customer service from the company were perceived to be favourable. Using this device created a positive impression among the users. The accuracy and precision of AI technology are thus found to enhance user understanding and satisfaction [54].

Satisfied customers or users who shared their experiences with others (family members, friends, colleagues, etc.), can be construed as an act of customer attitudinal loyalty in the form of positive word of mouth. The findings also showed that the effect of customer satisfaction on positive WOM is moderated by a fear of the pandemic. Thus, the more customers fear the effects of the pandemic, the more likely they will purchase and use this device and subsequently share it in a way through WOM among their family members, friends, colleagues, and others.

## 6. Contributions and implications

### 6.1. Theoretical contribution

This research offered multiple frameworks which contribute to the existing body of knowledge in wearable AI in healthcare in a few ways. First, it offers and validates three theoretical frameworks that integrate several critical factors of intention to adopt innovation or technology, actual behaviour to purchase and use it and finally user satisfaction and loyalty utilizing these devices. Second, fear of pandemic was incorporated in this research which is very relevant to the present COVID-19 pandemic and other similar crisis situations. Where a crisis or pandemic interrupts regular life, AI-enabled smartwatches can help customers, especially elderly customers, in managing their health issues. The moderating effect of fear of pandemic indicates that a high level of fear will instigate people to adopt AI-enabled healthcare devices, which can be used easily, and conveniently at an affordable price. Third, the study confirms the assumptions of TAM models for the first two studies as well as the assumptions of the *S*–*O*-R model. The results show that the TAM model and *S*–*O*-R theory contribute to the understanding of user intention, actual behaviour and their responses to AI-based technology.

While the impact of technology-based devices on user satisfaction in health care services has been examined in different contexts [146], This study sheds light on the challenges of implementing AI technology to automate the delivery of essential health services to users. The results of the study will aid in the integration of AI technology into wearable smart devices, empowering users to manage their health independently. Furthermore, the finding that users, including older individuals, are content with utilizing these devices to access healthcare services is noteworthy and affirms how users are increasingly comfortable with personalized technology and the digital world [147].

### 6.2. Managerial implications

This study has implications for Ghana, a low income country [22] and other developing economies. As the population of elderly people are increasing in developing countries like Ghana and other sub-Saharan Africa [24], the number of non-communicable diseases is also increasing, especially diabetes, cardiovascular diseases and high blood pressure. Thus, there is a high potential demand among older individuals who desire to manage their healthcare independently and quickly for the use of AI-enabled smartwatches. The desire to use and actual usage of this device is likely to be strong among the general elderly population. The findings of these studies will aid in the integration of AI into wearable smart devices, enabling users to manage their health autonomously. Besides, AI has the potential to improve living and working conditions [47]. Furthermore, the finding that users are satisfied and accustomed to using these devices to access health services is considered significant and affirms that users are becoming accustomed to personalized technology and the evolving digital environment [147].

According to these results, it is recommended that manufacturers of smartwatches should enhance the features of their products, such as providing personalized sizes and colors, making them more user-friendly, extending the battery life, improving inter-device connectivity, allowing for result sharing, and so forth. It is important for healthcare features like automatic temperature sensing, blood pressure monitoring, and ease of use to be integrated into these smartwatches. In addition, brands should prioritize ensuring the reliability of the results and the privacy of the data by implementing self-management of healthcare services through these devices.

Furthermore, wearable technology developers can benefit from this study when creating new wearable technology, such as smartwatches, specifically for the medical industry. The use of wearable technology should be advantageous for patients, healthcare professionals, and the healthcare sector in general. It is crucial for developers to consider the features that doctors require in wearable technology to encourage doctors to voluntarily adopt new technology. Doctors should be informed about the features that wearable technology must possess to make it useable. Technology developers need to be cautious when incorporating features that have important and time-sensitive functions. Users' decisions to accept and use technology are heavily influenced by how well these critical processes work [148].

Thus, users tend to utilize technology more frequently when it effectively performs specific tasks that they require. Medical professionals can play a significant role in promoting the adoption of these devices by acknowledging their capabilities and integrating them into the healthcare process, thereby convincing patients to accept and utilize these devices [12]. When the capabilities of smartwatch fully meet each user's specific demands, wearable technology can be used effectively by both doctors and patients [149].

For wearable technology managers, it is crucial to create and adjust the features of smartwatches based on the preferences and needs of their users. This is important for enhancing user acceptance and meeting the demands of the medical field. Both sides will need this compatibility in technology design in order to achieve the core goal of these gadgets [150].

Hospital managers ought to support this technology by encouraging doctors and patients to adopt its usage, and coordinating its applications across various sections of hospitals. This needs careful integration of the capabilities of smartwatches with standard processes and procedures in medical facilities, while coordinating efforts among medical advisors, doctors, and other medical professionals to ensure it is effectively used for diverse medical applications. Although the usage of various smart watches devices with phone-based functions is mainly driven by individuals, its adoption is a huge gain for medical professionals and patients alike [151].

### 6.3. Limitations and future study

As with any other research, these studies have a few limitations. First, the purposive sampling technique utilized for this study has limited the generalizability of the findings to those users who are 40 years old and above, with males dominating the sample respondents. In addition, respondents were sourced from online. Thus, future studies could apply probabilistic sampling and cover diversified respondents, or other developing countries. Other studies should also include a significant number of female respondents. On the top of that, future research is encouraged to employ different data collection methods or data triangulation techniques, such as interviews and observations, to give healthcare professionals a much more thorough picture of smartwatch adoption. The research concentrated on pertinent outside factors that improve smartwatch visibility. The external variables (e.g., content richness and personal innovativeness) to be considered in future studies may differ from the ones currently used due to the constantly changing features and applications of smartwatches. Second, future work should utilize other theories such as, UTAUT, TBP and so on. Third, CB-SEM can be utilized to test the adoption theories. Fourth, future models can consider various types of diseases and the personalization of devices. This research was also limited to the domain of medicine, so upcoming research might comprise further surroundings, whether academic or non-academic. Lastly, in the present investigation, no consideration was given to gender differences. Thus, future research may fill in the gap and examine possible differences in the study results due to gender.

## Author contribution statement

Md. Uzir Hossain Uzir: Conceived and designed the analysis; Analyzed and interpreted the data; Contributed analysis tools or data; Wrote the paper.

Zakari Bukari: Conceived and designed the analysis; Analyzed and interpreted the data; Contributed analysis tools or data; Wrote the paper.

Hussam Al Halbusi: Conceived and designed the analysis; Analyzed and interpreted the data; Wrote the paper.

Rodney Lim Thiam Hock: Conceived and designed the analysis; Analyzed and interpreted the data; Wrote the paper.

Siti Norida Wahab: Conceived and designed the analysis; Analyzed and interpreted the data; Wrote the paper.

Tareq Rasul: Conceived and designed the analysis; Analyzed and interpreted the data; Wrote the paper.

Ramayah Thurasamy: Conceived and designed the analysis; Analyzed and interpreted the data; Wrote the paper.

Ishraq Jerin: Conceived and designed the analysis; Analyzed and interpreted the data; Wrote the paper.

Rezaul Karim Chowdhury: Conceived and designed the analysis; Analyzed and interpreted the data; Wrote the paper.

Arun Kumar: Conceived and designed the analysis; Analyzed and interpreted the data; Wrote the paper.

Azizul Yadi Yaakop: Conceived and designed the analysis; Analyzed and interpreted the data; Wrote the paper.

Abu Bakar Abdul Hamid: Conceived and designed the analysis; Analyzed and interpreted the data; Wrote the paper.

Ahasanul Haque: Conceived and designed the analysis; Analyzed and interpreted the data; Wrote the paper.

Abdur Rauf: Conceived and designed the analysis; Analyzed and interpreted the data; Wrote the paper.

Bilal Eneizan: Conceived and designed the analysis; Analyzed and interpreted the data; Wrote the paper.

## Data availability statement

Data will be made available on request.

## Additional information

Supplementary content related to this article has been publish online at [URL].

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2023.e18666.

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