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Applied Artificial Intelligence and user satisfaction: Smartwatch usage for healthcare in Bangladesh during COVID-19

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ABSTRACT

The evolution of Artificial Intelligence (AI) has revolutionized many aspects of human life, including healthcare. Amidst the Covid-19 pandemic, AI-enabled smartwatches are being used to help users to self-monitor and self-manage their health. Using a framework based on Stimulus-Organism-Response (S–O-R) theory, this present study aimed to explore the use of AI-enabled smartwatches for health purposes, in particular the effects of product quality, service quality, perceived convenience, and perceived ease of use on user experience, trust and user satisfaction. Based on a purposive survey sample of 486 smartphone users in Bangladesh, data collected was analyzed using SPSS software for elementary analyses and PLS-SEM for hypotheses testing. The findings showed that the predictors, namely product quality, service quality, perceived convenience, and perceived ease of use, significantly affected user experience and trust. Similarly, user experience and trust were influential on user satisfaction and played partial mediating roles between predictors and user satisfaction. Besides, gender and age moderate the relationships of experience and trust with customer satisfaction. These findings support the S–O-R theoretical framework and have practical implications for brand and marketing managers of smartwatches in developing product features and understanding users' attitudes and behaviours.

1. Introduction

Technology infuses each aspect of human lives-individual and group life [1]. Artificial intelligence (AI) is the leatest edition to it. AI has evolved tremendously over the years [2], shaping various disciplines, such as marketing [3] and various sectors, including government sectors like healthcare [4]. AI is "the natural predispositions, genetic inheritance or learned skillsets forming the core of individual personalities" [5]. AI involves the application of machine-taught program(s) built into computer systems to act as a human brain in decision making [6]. In marketing applications, AI closes the gap between markets and marketers [7]. While consumers seek the satisfaction of needs and consumption maximization, marketers attempt to meet consumers' requirements at a profit [8]. AI enhances these interactions between

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businesses and consumers [9] by making the marketing process quick and efficient [10]. As marketing activities coalesce around needs, wants, consumption, and exchange relationships (Murthy 2010), AI allows marketers to understand better and meet consumers' needs, thus maximizing values and returns [10]. Consequently, AI can ensure sustainable and purposive relationships between marketers and customers [11].

AI systems allow machine-based human intelligence characteristics to be integrated into business and marketing functions such as sales, budgetary management, and decision-making to maximize customer benefits [5]. They provide compelling propositions in marketing segmentation [12], detecting customers' preferences, enhancing experiences, and satisfying them [10]. AI machines have been shown to replicate human efforts [13] and even outperform them in learning, tacit judgment, and emotion-sensing [14]. As such, AI's capacity to replace humans holds much promise [15] it is predicted that developments in automation and AI will dramatically affect workers, businesses, nations, economies, and society as a whole [16].

1.1. How AI-enabled devices work

People use various AI-enabled technologies and devices to self-administer multiple benefits according to their requirements [17]. Essentially, an AI system tailors an appropriate response or service to fit users' requirements based on users' inputs into the system. Information inputs, including question-answer sessions, allow AI machines to learn about users' specific requirements and conditions and determine particular features such as size, color, time, measurement and weight, and so on to conform closely to users' needs. AI systems can also recommend suitable products, services, brands, or companies that best suit users' needs. For example, in the context of online clothing purchases, automated systems analyze customer requirements to provide appropriate choices to customers and select the most suitable products or services. It resembles seeking suggestions from a best friend who knows the person well enough to recommend the best product or service. Thus, AI benefits online customers by improving the accuracy of measurements and reducing errors, which have long been a pitfall in the online apparel sector.

1.2. AI in medical science

AI has revolutionized the health sector [18,19] and has led a shift in areas such as health application, data acquisition and processing, reporting, follow-up planning, data storage, data mining, and others [20]. AI has been well applied in medical and health care services all over the world [19]. Watson, a question-answering computer system/-software, can diagnose human heart diseases [21]; Chatbot, a text-to-speech software, can give health advice [22]; while SkinVision software can identify skin cancer [23]. Meanwhile, medical software using AI algorithms can detect eye diseases just as expertly as human physicians (Abramoff et al., 2018), while AI-enabled software for autism treatment is getting popular [24]. One report showed that AI will be incorporated into 80% of hospitals by 2025 and will perform 90% of tasks that physicians are currently doing (Khosla, 2012). Compared to human operators, AI is cost-effective, more accurate, and more reliable [19]. As patients can directly adopt, implement (Israyelyan 2017) and interact with AI at any time and with any frequency (Yu, Beam, and Kohane 2018), the adoption rate of new medical technology equipped with AI has increased rapidly. Patients are now able to purchase medical tools to detect health issues, and to maintain frequent check-ups of their health conditions [21]. The smartwatch is a device that allows patients to check their health conditions, detect illnesses and guide them in maintaining good health [25]. In this regard, the present study focuses on customer satisfaction with their experience and trust in using smartwatches as an AI device.

1.3. The smartwatch as an AI-enabled medical device

A smartwatch is a regular watch with a micro-computer. The latest smartwatches offer a touch-screen-enabled interface that houses various applications for everyday use, including a medical app. A branded, high-end smartwatch has overlapping functions with multi-functional smartphones (Abbasi et al., 2021). Embedded in these devices are AI-enabled health applications that allow people to self-monitor certain important health functions, such as measuring and detecting blood pressure, diabetic conditions, heart rates, and other health concerns. They can also suggest particular medication, diet, and so on, to help the user maintain good health. In Bangladesh, their usage has soared in recent years, with many people using smartwatches as an alternative to wristwatches and mobile phones.

1.4. Patients in bangladeshi and users of AI-enabled smartwatches

This study is conducted in Bangladesh, a low-middle income country (LMIC) [26] but was declared as "digital Bangladesh" [27,28], where the risk of cardiovascular disease (CVD) is high due to the lack of primary treatment [29]. According to one study, Bangladesh is the most exposed in Asia to the prevalence of CVD, with 99.6% of males and 97.9% of females being exposed to at least one risk factor [30]. Meanwhile, the number of heart disease patients has increased, outstripping the number of heart specialists needed to cope with these numbers. Besides, doctors are usually busy having to tend to many patients at a time, leaving them with less time to spend on a single patient. Busy people often have difficulty finding time to meet doctors. Hence, patients place value on convenience and timeliness, and will search for the best alternatives to in-person consultations. These issues can be mitigated with the use of AI-enabled smartwatches, which are easy to use, convenient, and can accurately impart health tests and information. In some cases, AI-enabled devices outperform medical practitioners in offering patients more accurate and precise healthcare information.

Socio-demographic characteristics like age and social status are vital in healthcare [31]. Bangladesh has 166.70 million people [32], of which 21.74 million live in Dhaka city [33]. Elderly people (65+ years old) make up 14.23% of Bangladesh's population, with an additional 6.82% in the 55–64 years old category [34]. Among these age groups, (Chronic Obstructive Pulmonary Disease (7%), Heart Disease (6%), Stroke (5%)), Diabetes (3%), are the most severe illnesses [35] as they cause 18% of total deaths in the country [36]. BP [36] also reported that Bangladeshis tend to catch heart disease 10 years earlier than people in other countries, with 40% of them below 50 years old. These people are aware of health issues [17] and are interdependent [37]. As more developing countries are adopting various telehealth platforms to administer healthcare [38], Bangladeshis are following suit. As a result, a significant portion of the population has adopted smartwatches to monitor their health.

1.5. COVID-19 and usage of AI-Enabled smartwatch

The COVID-19 pandemic outbreak occurred at the end of 2019 in China, spread very quickly all over the world [39,40], and has caused, in addition to a large number of human deaths, ongoing physical and mental trauma [41], including anxiety, depression, fear, nervousness, stress and mental distress (Ann, 2020). New social norms have emerged, including social distancing, using masks and sanitizers, avoiding big gatherings, physical contacts, and so on [42]. As health facilities are devoted to Covid-19 cases, clinics, hospitals, and health centers are unable to provide regular services to other patients (Hasan, 2020). Cancellations or delays in doctor appointments have become common. In addition, in-person medical consultations may expose patients, physicians, and other health service providers to infection. In particular, older people tend to be more fearful as they are in the high-risk category for Covid-19 [43,44].

Nonetheless, they still need to have regular medical check-ups and to keep up with treatments and prescriptions. This problem is magnified in a developing country context such as Bangladesh, where access to medical services is already a prevailing problem for many people, including the elderly (Hamiduzzaman et al., 2018). During the pandemic, access to medicine and routine medical care amongst this demographic group in the country has significantly deteriorated [43, 45]. In such a scenario, smartwatches as a mechanism for self-monitoring of health have become important.

During this critical time technology has increased human-device interaction in various sectors with minimum cost and less effort with more convenience and benefit [46] including human care with smart-devices. Smartwatches as self-monitoring mechanisms allow users to administer quick and frequent self-tests at home, even without an attending physician. It incurs minimum or no additional spending and does not require interaction with other people. Despite these advantages, users' satisfaction with this technology, particularly among elderly users, remains unclear. To date, much of the research in this area has focused on the adoption or acceptance aspects of the technology, while significantly less research has been devoted to studying usage satisfaction. Meanwhile, as many as one-third of all users have reportedly abandoned their wearable smartwatch devices after a period of usage (Gartner, 2016).

A meta-review by Attig and Franke [47] shows several reasons for the abandonment of these devices, including usability, accuracy, data usefulness, design and comfort, loss of motivation, privacy and so on. These problems with attrition raise the issue of user satisfaction and perceptions of product usefulness. Despite their importance, to the best of the authors' knowledge, the issues that impact user satisfaction, particularly elderly users in a developing country context, have not been explicitly addressed in prior research. Thus, this paper aims to fill this gap, namely to investigate the impact of user experience and trust on their satisfaction in using these devices for self-monitoring of health.

Based on this, our research aims to address questions of how product quality, service quality, perceived convenience, and perceived ease of use contribute to user experience and trust. It integrates the three aspects of hardware, software, and technology with consumer orientation and activities [48].

The study applies a stimulus-organism-response (S–O-R) framework to investigate the effects of product quality, service quality, perceived convenience, and ease of use as stimuli on user satisfaction (response). In contrast, t**rust and user experience (internal organism) are hypothesised as mediating factors.**

By situating the study sample on elderly users of smart devices for healthcare purposes in the country of Bangladesh, the study frames how this group of users perceives the benefits of medical technology afforded by product and service quality, ease of use, and convenience. The authors expected the study to extend the S–O-R theory in applied AI discipline and link it with marketing and consumer behavior.

The rest of the paper will review the relevant literature, develop hypotheses based on the literature, and formulate research settings. The latter will be followed by data analysis and a discussion of the findings. The paper concludes with conclusions and implications of the results and future direction.

2. Literature review

This section provides a review of the S–O-R model and the relevant literature supporting the development of this study's hypotheses.

2.1. Stimulus-organism-response (S–O-R) theory

Mehrabian and Russell [49] developed the Stimulus-Organism-Response (S–O-R) model to explain the mediation of an organism to process stimuli in triggering a response or reaction. This model narrates how the outer or external environment affects customer behavior [50]. It envisages customers' responses or feedback to market conditions, marketing effort, and environmental stimuli to understand the complicated internal human processes and their reactions and choices [51]. An environmental or external stimulation induces behavior patterns and reactions in users [51]. In this study, product quality, service quality, perceived convenience, and ease of use constitute the stimuli in the framework. These stimuli follow Jacoby's (2002) examples of products, brands, logos, ads, packages, prices, store and store environments, word-of-mouth communication, newspapers, and television as stimuli agents.

Meanwhile, organism refers to the inner state of users [52] and a psychological or cognitive condition that links stimuli and users' responses (Islam & Rahman, 2017). It consists of affective and cognitive intermediary states and processes mediating the relationship between the stimulus and the individual's responses [53]. This stimuli-internal mechanism induces either a positive response (satisfaction) or an adverse reaction (dissatisfaction). In this study, user experience and trust mediate between stimuli and satisfaction and strengthen these relationships, which are impacted by age and income level. Finally, a response indicates the state of either acceptance or avoidance of the incentives [54], which is a psychological reaction, such as contentment, attitudinal and behavioral reactions [55]. Thus, in this study, the stimuli consist of product quality, service quality, perceived convenience, and ease of use of AI-enabled smartwatches; organism consists of user experience and trust (considering the user's age and social status-income), which mediate between stimuli and user satisfaction, which represents the response, or outcome of the stimuli-organisms interaction.

2.2. Selection of constructs

Construct selection was guided by the literature, suggesting that marketing cues (such as product quality, service quality, ease of use, and convenience) can invoke internal assessments in a subject organism to create an affective state (trust and experience with age and income level) to bring a positive output as satisfaction. The constructs were adopted from Brill et al. [56]; who studied product performance and trust in AI, Prentice et al. [57] for AI-enlabed service quality and customer satisfaction, Naumov [58] for service and service experience in robotics, AI and service automation, Baena-Arroyo et al. [59] for virtual services in terms of service experience and service convenience, Vishnoi et al. [60] for the application of AI in the marketing mix in intelligence information systems, and Etherington [61] who explored automobile user experience of MBUX smart multimedia systems and in-car voice-activated assistants. Hengstler et al. [62] examined artificial intelligence and trust, while Chien et al. [63] and Alhashmi et al. [64] examined AI and perceived ease of use.

2.3. Product quality (PQ)

Product quality, expressed in its functionality and performance, affects the benefits of significant advantages that customers obtain from using or consuming a product [65], determining how well the product can meet their needs. With this, the benefits that consumers receive from using a product are both functional and emotional [65]. Consequently, product quality corresponds to fitness for a reason or "conformance to specification" (Russell and Taylor, 2006). The International Organization for Standardization (ISO) describes product quality as the capacity to appease consumers and markets (Lakhal and Pasin, 2008). Garvin (1984) proposed eight dimensions of quality, consisting of performance, features, reliability, conformance, durability, serviceability, aesthetics, and perceived quality, while more recent research by Kotler and Armstrong (2018), Lin et al. [66]; and Gök et al. [67] focused on commodity consistency.

Hence, with AI-enabled smartwatches, product quality refers to the particular smartwatch device's characteristics, attributes, and features

in satisfying customers' healthcare needs through its speed, accuracy, precision, and accurate rendering of information about the user's health, such as heart rate, diabetes score, and blood pressure. Device quality, functionalities, and performance enhance customers' experiences, develop trust and a positive attitude to the smartwatches. Therefore, the following hypotheses are formulated:

H1. Product quality of a smartwatch has a positive effect on user experience.

H2. Product quality of a smartwatch has a positive effect on trust.

2.4. AI-enabled service quality (SQ)

Service quality is an assessment of the psychological state [68]. Services are intangible goods or "operative activities" [69] that meet customer requirements. According to Parasuraman et al. [70]; service quality is the difference between the expected performance provided by a service and the actual performance of the service. Extensive research on service quality has established its significance on a range of consumer goods and services [71,72], including research on the service quality of AI-enabled machines or devices [73].

In this study, the service quality of AI-enabled devices depends on the extent and amount of a customer's personal information that can be collected and stored [10]**.** Service quality refers to the perceived quality of the service users' experience in using AI-enabled devices, such as providing health information, detecting blood pressure, diabetes, heart rates, and specific ailments. It depicts the reliability and responsiveness of the system in fulfilling user's health needs as and when required [74], which reinforces trust in the device. **As a result, users experience positive and enhanced satisfaction.** Ganguli and Roy [75] supported the effects of technology-based services' quality on customers' satisfaction and loyalty. The service quality signifies users' trust, experience, and contentment during an emergency, such as a pandemic, when human interactions involve risks, even with a doctor in a hospital. **Considering the service quality of smartwatches, the following hypotheses were formulated:**

H3. **Service quality of an AI-enabled smartwatch** has a positive effect on **user experience.**

H4. **Service quality of an AI-enabled smartwatch** has a positive effect on **trust.**

2.5. Perceived convenience (PC)

The concept of convenience considers the time and effort that customers invest in acquiring and using a product or service [76]**. Convenience is one of the main benefits of using AI-enabled devices** [77]**, as it reduces the** *time and effort spent in availing health-related products and services. Morganosky* [78] *refers to service convenience as* "*the ability to accomplish a task in the shortest amount of time with the least expenditure of human energy*." Berry et al. [79] conceptualized service convenience in five dimensions: decision convenience, access convenience; transaction convenience; benefit convenience; and post-benefit convenience.

During the current pandemic, health care services delivered through smartwatches afford great convenience in replacing in-person medical services and avoiding the risk of infection. Ameen et al. [10] illustrated three dimensions of perceived convenience: 24/7 service anywhere [80], real-time information and support [81], and proactive information of the user's lifecycle. Therefore, perceived convenience concerning these three dimensions affects users' technology experience, trust in AI, and overall satisfaction. Thus, the following hypotheses were formulated:

H5. Perceived convenience of a smartwatch has a positive effect on user experience.

H6. Perceived convenience of a smartwatch has a positive effect on trust.

2.6. Perceived ease of use (PEOU)

Perceived ease of use refers to how potential users perceive whether a given application or technology is easy to use. Davis et al. [82] described perceived ease of use as "the degree to which a person believes that using a particular system would be free of effort". Ease of use is the user's impression of the measure of proficiency needed to use technology [82]. If an application is perceived as easier to use compared to others, it is more likely to be accepted by users. Perceived ease of use is a precursor to satisfaction [82,83].

Therefore, it can be inferred that AI-enabled smartwatches are widely adopted because of their ease of use. The latest models offer helpful functionalities that require minimal physical and mental exertion and minimal technical know-how. Their user interfaces are typically designed for broad mainstream usage, usually featuring simple layouts, intuitive navigation, visual elements, typography, animations, and graphical information [84]. This study attempts to measure users' beliefs of the degree to which AI-enabled smartwatches have low, mid, or high ease of use. During this pandemic, it is postulated that the various levels of ease of use of AI-enabled smartwatches affect consumer experience, trust, and satisfaction among older people. Therefore, the following hypotheses were proposed:

H7. Perceived ease of use of a smartwatch has a positive effect on user experience.

H8. Perceived ease of use of a smartwatch has a positive effect on trust.

2.7. User satisfaction (US)

Satisfaction refers to the "perceived discrepancy between prior expectation and perceived performance after consumption, that is, when performance differs from expectation, dissatisfaction occurs" [85]. According to Chitty et al. [86]; customer satisfaction is a psychological assessment and a constructive comparison between the sacrifice they make by paying (cost) for availing services or products and the benefits they receive from the moment of purchase to the end of the life cycle of the product or service. Satisfaction is an aftermath of comprehended value or quality, which consumers assess according to their service skill and anticipation [48]. [85]Satisfaction is a trade-off between pre- and post-consumption or usage of a product [87]. The pursuit of customer satisfaction has become a strategic imperative for most firms that need to survive and remain competitive [88].

Many scholars have attempted to conceptualize and formulate constructs that constitute customer satisfaction, including Mannan et al. [89] and Tandon et al. [90]. Keshavarz and Jamshidi [91] and Thielemann et al. [92] also used customer (user) satisfaction.

Customers spend money to gain pleasure, benefits, or positive experiences from products ([93,94], which leads to customer satisfaction [95,96]. added that customer satisfaction results from better performance of a product and customer usage experience compared to customer expectations ([97]. A customer (user) with a positive experience tends to have positive emotion and mental contentment with the brand [98]. As such, customer satisfaction is a psychological aspect strongly affected by customer experience and their reliability on the brand or product. Considering the significance of experience and trust on satisfaction, the following hypotheses were formulated:

H9. User experience has a positive effect on user satisfaction

H10. Trust has a positive effect on user satisfaction

2.8. AI-enabled user experience

User experience refers to the overall evaluation a customer gains

from purchase to usage time with a retailer, product, or service based on their interactions with and thoughts about the brand or products [99]. User experience results from a series of encounters between a user and a product, a corporation, or a department within that business, causing a reaction that may be positive or negative [100]. It is the internal and subjective reaction consumers have to direct or indirect interactions with a brand or business [101]. Schmitt and Rogers [102] suggested users' experiences of a brand are formed through five ways: sensing, feeling, thinking, acting, and relating.

In recent years, as computer-human interaction has increased [103], the concept of user experience has been researched widely in technology adoption among elderly people [104]. AI-enabled user experience involves highly personal encounters that require the customer's participation on many levels - rational, emotional, sensorial, physical, and spiritual [105]. Ladhari et al. [106] identified four aspects of the user experience when interacting with an AI-enabled tool: cognitive, emotional, physical and sensorial, and social. The cognitive aspect denotes the tool's functionality, speed, and availability (American Psychological Association, 2016). The emotional element refers to feelings of delight, frustration, excitement, outage, or surprise [107]. *Physical and sensorial aspects* of experience refer to online technology-supported user interface features of the AI-enabled tool [107] and offline context of artifacts, lighting, layout and design [108]. Social experience depicts the impact of family and friends, colleagues, neighbours, peer groups and even communities in social media [109]. As AI-enabled devices used in medical services and healthcare can outperform human physicians in making precise measurements to detect diseases [110], customers will more likely have a positive experience. Thus, accuracy and precision of AI technology enhance user experience, confidence and understanding [10].

In this study, it is postulated that interactions with AI-enabled smartwatches produce user experiences in relation to perceived product quality, perceived service quality, perceived convenience and perceived ease of use, which can affect users' overall satisfaction. Interactions that generate good impressions, good feelings, and a strong sense of belonging to a special community can increase users' satisfaction. Therefore, user experience is hypothesised as a mediating factor. In the proposed research framework, the effects of perceived quality, convenience and ease of use on user satisfaction are mediated by user experience. Lin et al. [66] and Gök et al. [67] found that product quality plays an impactful predictor of customer satisfaction. Perceived convenience leads to user satisfaction [111]. Meanwhile, ease of use is a successful predictor of users' psychological contentment, as a user with a positive experience tends to have a positive response and psychological contentment due to using the AI-enabled tool [98]. Therefore, we propose the following hypotheses of user experience as a mediator:

H11a. User experience mediates the effect of product quality on user satisfaction

H11b. User experience mediates the effect of service quality on user satisfaction

H11c. User experience mediates the effect of perceived convenience on user satisfaction

H11d. User experience mediates the effect of perceived ease of use on user satisfaction.

2.9. Trust

The importance of trust on the internet has been consistently argued (Fang et al., 2011; Kim et al., 2009; Palvia, 2009). Trust refers to an attitude of confident expectation of two parties that they keep their promise even when the situation changes [112]. Past studies highlighted the significant role of trust, including its contributions to technology-mediated interactions between customers and products and their companies [113,114]. Trust is crucial in online transaction processes, given the uncertainty presented by the impersonal nature of the online environment and the inability to judge product quality prior to purchase [115]. Thus, trust in technology is often perceived to be difficult, including among older people who tend to be less familiar with the technology. As a fundamental element that determines human-technology relationships, it contributes to the success of AI-enabled services [116,117]. For example, users expect AI-enabled devices to be trustworthy in terms of ensuring their privacy and confidentiality. Trust surfaces on privacy and confidentiality [118]. As such, it mediates the relationships between the various stimuli elements and user satisfaction in an AI context [119,120].

The impersonal nature of healthcare delivered by AI-enabled devices replaces in-person services, disrupts traditional expectations about physician-patient consultations, and can create trust issues. Users may not trust the technology to afford diagnosis and prescriptions effectively and safely properly. As a dynamic and multi-faced construct [121], trust affects customer satisfaction in adopting and using technology [122]. Past studies have examined the trust and satisfaction relationship either as a mediator [123–125] or as a predictor of customer satisfaction [126, 127]. This study postulates that the predictors of customer satisfaction, namely product quality, service quality, perceived convenience and ease of use, are mediated by trust. In other words, the presence of trust strengthens those relationships with customer satisfaction. The product quality of AI-enabled health devices will strongly influence user satisfaction if users trust the functional quality of these tools.

Similarly, each AI-enabled product is associated with service, contributing to user satisfaction where trust is present. Perceived convenience will also affect user satisfaction significantly if trust is present. Lastly, the ease of use in which the technology presents itself to users will improve satisfaction where trust is present. Based on these, the following hypotheses are proposed:

H12a. Trust mediates the effect of product quality on user satisfaction

H12b. Trust mediates the effect of service quality on user satisfaction

H12c. Trust mediates the effect of perceived convenience on user satisfaction

H12d. Trust mediates the effect of perceived ease of use on user satisfaction.

2.10. The role of gender and age

Past research has shown that demographic and country factors can impact trust and behavioral processes in technology usage (Kim et al., 2011; [128]. Sánchez-Franco et al. [129] found that the influence of trust was more robust for females than males. Females were also found to be more tolerant and easier to satisfy than males [130]. They are more materialistic [131], and are more concerned about the environment, whereas males are more concerned with product information (Hwang and Lee [132]; and its functional utilities such as transaction speed, convenience, and efficiency [133]. Sharma et al. [134] found a positive and stronger relationship between service quality and satisfaction in the case of women than men.

Past studies have shown that age is a significant factor in buying and usage behavior, as age is associated with social and environmental cues and information [135]. Hargittai et al. [136] and Sanchiz et al. [137] investigated the relationship between age and technological affinity, while Chien et al. [63] found that positive experiences could help improve older adults' attitudes towards technology. Thus, it is postulated that gender and age have a significant role in creating trust, experience and satisfaction in using smartwatches. Therefore, the following hypotheses were formulated:

H13a. Gender moderates the significance of the direct relationships such that males are different from females.

H13b. Age moderates the significance of the direct relationships such

that the younger are different from the older.

2.11. Proposed model

Based on S–O-R theory, the current study applies the proposed model shown in Fig. 1, where, the antecedent variables, or stimuli, consist of perceived product quality, AI-enabled perceived service quality, convenience, and ease of use. User satisfaction is the dependent variable, while user experience and trust are the mediating variables.

3. Methods

3.1. Measurement scales

The study adopted the measurement items for all constructs from past research, as follows: AI-enabled customer experience was adopted from Refs. [10,138]; product quality from Ref. [139]; AI-enabled service quality from Ref. [140]; trust from Refs. [141,142]; perceived convenience from Ref. [143]; customer satisfaction from Refs. [144,145]; and perceived ease of use from Ref. [82]. Each construct consists of multiple items or indicators and was measured along a 5 point Likert Scale ranging from "1- strongly disagree" to "5- strongly agree". The five-point scale is less confusing, has higher reliability, increases the response rate and response quality, and reduces the "frustration level." As the study conducted research on elderly people, the 5 point Likert scale offers more advantages [146].

3.2. Sampling and data collection

The study's target population consisted of users of smartwatches in Dhaka, Bangladesh, specifically those who use AI-enabled tools to monitor their health. Dhaka is the capital of Bangladesh, a populous city with many open spaces for parks, lakes and other recreation. Respondents were selected purposively from three parks, namely *Ramna Parks, Zia Uddyan* Zia Garden)*, and Dhanmondi Lake Parks*. These are well-known places where people of all ages walk, jog, and do various exercises in the mornings and evenings. Park visitors include many older individuals, and men tend to outnumber women. Many are frequent users of the park facilities and tend to spend a substantial amount of time there daily. As such, they constitute a thriving community consisting of senior retired government employees, business people, writers, editors, doctors, engineers, professors, and other professionals.

The study used the purposive (judgment) sampling technique following [147], where participants were selected based on two criteria: they had to be more than 40 years old, and they had to be able to use an AI-enabled smartwatch. A total of 486 respondents were interviewed in December 2020. To assure the safety of participants, interviewers maintained social distancing and other health guidelines. The interviewing process was conducted carefully to avoid missing values and missing information. A total of 206 respondents (42%) were interviewed in *Ramna* Park, the largest and oldest park in Dhaka, where many people exercise every day. Another 162 (33%) were found in *Zia Uddyan*, located near the National Assembly House of Bangladesh, while 118 (24%) were from *Dhanmondi Lake*.

The questionnaire was accompanied by a cover letter that introduced the researcher and explained the purpose of the study. Participants were assured of confidentiality as names and other personal identifiers were not collected, and the data collected were purely for academic purposes. Their consent was obtained before the interview with a structured questionnaire. A proper sequence in the questionnaire was maintained [148] during the process. To ensure their proficiency in operating their smartwatches, participants were asked to use their smartwatches to check their body temperature, heartbeat, blood pressure, and other health indicators before proceeding to the actual questionnaire. Participants were also informed of the purpose of the study and assured its confidentiality. Table 1 depicts the descriptive profile of the respondents.

3.3. Demographic information of respondents

As shown in Table 1, participants ranged from age 40 to above 80. The largest group was the 60 to 69-year-old category, which represented 41% of the population. This, combined with the 70 to 79-year-old category, accounted for 69% of the sample, highlighting the respondents' relatively older age range. Conversely, respondents aged 59 and below made up only 30% of the sample. In terms of gender, the majority were males (428, 88%), while only 58 (12%) were females.

. Generally, a large proportion of respondents appeared to be relatively experienced users, as 79% indicated that they had been using their smartwatches as a health device for at least six months. A majority (62%) claimed they visited their doctors three to six times a year, while 79% of respondents checked their health with their smartwatches between 11 and 16 times a day, indicating generally high usage.

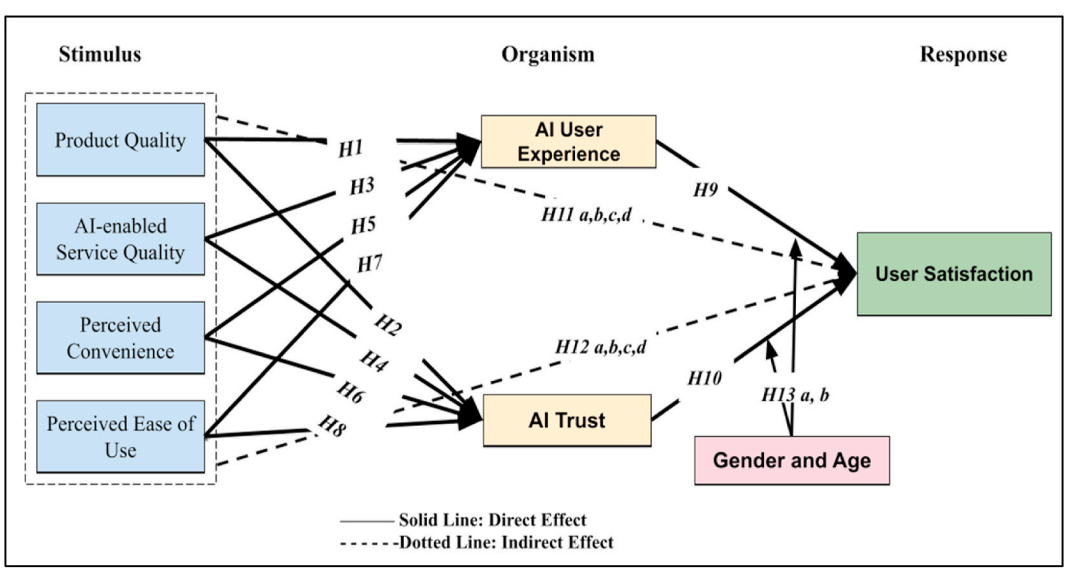

Fig. 1. Conceptual framework.

Table 1
Demographic information of respondents.

Profile	Frequency	Percentage
Age		
40–49 years	17	3%
50–59 years	131	27%
60–69 years	201	41%
70–79 years	135	28%
80 years and above	2	0.40%
Gender		
Male	428	88%
Female	58	12%
Smartwatch Usage		
6 months and below	103	21%
7–12 months	98	20%
13–18 months	144	30%
19–24 months	141	29%
Frequency of Doctor Visits Per Year		
2 times and below	36	7%
3 to 4 times	148	31%
5 to 6 times	150	31%
7 to 8 times	69	14%
9 to 10 times	83	17%
Frequency of Daily Health Checking on Smartwatches		
10 times and below	28	6%
11 to 12 times	124	25%
13 to 14 times	142	29%
15 to 16 times	120	25%
17 to 18 times	66	14%
19 to 20 times	6	1%
Survey Location		
Ramna Park	206	42%
Zia Uddyan	162	33%
Dhanmondi Lake	118	24%

4. Data analysis and results

4.1. Common method variance or bias (CMV or CMB)

In collecting data from respondents in a single questionnaire over a short period, the possibility of an issue of common method variance (CMV) or common method bias (CMB) was acknowledged. Podsakoff and Organ [149] explained common method variance as a concern when data of variables are collected from the same sources. The current study adopted Harman [150] single-factor test proposed by Podsakoff and Organ [149] and an unmeasured latent method construct (ULMC) to examine common method variance. According to Podsakoff et al. [151]; method bias is very powerful in a study where data of both predictors and criteria are collected from the same respondents with the same measures and the same items in the same time frame. Harman's single factor test was done using unrotated principal component factor analysis in SPSS. The result showed that seven distinct factors having eigenvalue 1.00 accounted for 72.793% of variance rather than a single factor. The result also showed that the first factor has 44.759% (largest) variance, which is less than 50% [152], followed by the second factor at 9.471%. Furthermore, the results indicated that no single factor had high covariance in the predictor and criterion variables [153]. This result inferred that common method variance is not a major concern.

In contrast to the single factor test, Guide and Ketokivi [154] illustrated that correlation and single-factor tests are no longer acceptable. Thus, this study applied an unmeasured latent method construct (ULMC) technique that Podsakoff et al. [153] suggested. In this technique, a substantive construct and common method construct were created from all items. Both path coefficients from substantive constructs to single-item constructs and from the common method construct to single-item constructs were considered from the results. For both method constructs and substantive constructs, the square of the loading is interpreted as the percentage of item-explained variance. The method construct loadings are not significant, and the substantive constructs' percentages are substantially higher than those of the method construct; thus CMB is not a critical issue in this study.

4.2. Partial least square structural modeling (PLS-SEM)

The two-step procedure suggested by Anderson and Gerbing [155] was applied to test hypotheses. In the first step, the researcher examined the outer model to check the construct reliability and validity (convergent and discriminant validity). In the second step, with the inner model, the path coefficient and hypotheses were tested. Two-step procedures were analyzed with second-generation structural equation modeling (SEM), specifically, SmartPLS3.3, a popular and widely used data analysis technique in behavioral science [156]. Compared to covariance-based SEM (CB-SEM), PLS-SEM is more robust to multicollinearity and distributional variance in indicator properties [157]. As PLS is nonparametric, it can overcome these two limitations of multiple regression. Its flexibly supports a variety of research variables [158], and is suitable when the data is non-normal [159]. Additionally, PLS-SEM is more suitable for explaining complex relationships as it eliminates two key issues: inadmissible solutions and factor indeterminacy [158]. It simultaneously analyses how well the measures relate to each construct and whether the proposed hypotheses are supported. It is suitable for theory-testing and handling small sample sizes [160]. The hypothesised model was estimated using SmartPLS3 with a bootstrap re-sampling procedure, where 5000 sub-samples were randomly generated [160]. To test for mediating effects, the bootstrapping method of Preacher and Hayes [161] was followed.

The use of PLS-SEM and SmartPLS was necessary to analyze data on users' behavior and psychological state, such as trust, user experience and user satisfaction, along with their perceived quality of the product and service, its usage convenience and ease of use for elderly people. The data had a chance to be non-normal and the conceptual model was complex as it included dual mediating relationships and dual moderation relationships. The study also intended to check the model's prediction through R-square for its strength, to assess effect size (f-square) for determining the variables' roles in the model and predictive prevalence (Q-square) for future reference, and to find the important variable and its significant performance through IPMA analysis.

4.3. Assessment of the inner (measurement) model

Through the inner model, the study evaluated the reliability and validity of indicators and constructs [160]. Cronbach's alpha (CA) and composite reliability (CR) was done for internal consistency of indicators (construct reliability). Construct validity was done through convergent validity and discriminant validity. Average variance extracted (AVE) was used for checking convergent validity [160]. [162] defined discriminant validity as "the degree to which a construct is distinct from other constructs". In discriminant validity, the Fornell-Larcker criterion, cross-loadings, and the HTMT ratio of correlations are checked. Ramayah et al. [163] suggested several guidelines to appraise the validity of the measurement model: internal consistency via composite reliability (CR) > 0.7; indicator reliability via indicator loadings> 0.7 and significant at least at the 0.05 level; convergent validity via AVE >0.50; discriminant validity via cross-loading and the Fornell and Larcker correlation where the square root of the AVE of a variable should be greater than the correlations between the variable and other variables in the model. Henseler et al. [116] proposed Heterotrait-Monotrait Ratio (HTMT) to handle discriminant validity issues. HTMT threshold value is 0.85 [164] or 0.90 [165,166].

Table 2 shows that Cronbach's Alpha and Composite Reliability (CR) were more than the threshold value of 0.70 that indicated the internal consistency of the items. For convergent validity, the average variance extracted (AVE) was more than 0.50, which also indicated convergent validity. In the case of discriminant validity assessment, Fornell-Larcker criteria (Table 3) and cross-loading of indicators met the required conditions. The other way to assess discriminant validity, using HTMT-ratio

Table 2
Descriptive statistics, reliability, and convergent validity.

Construct	Items	Source	Loading	CA	CR	AVE
Customer Experience	The smartwatch's service is memorable (CEx_1)	[10,138]	0.858	0.930	0.947	0.780
	The smartwatch's service is entertaining (CEx_2)		0.895			
	The smartwatch's service is exciting (CEx_3)		0.860			
	The smartwatch's service is sense of comfort (CEx_4)		0.896			
	The smartwatch's service is an educational (CEx_5)		0.906			
Customer Satisfaction	The smartwatch meets my expectations. (CS_1)	[144,145]	0.899	0.952	0.962	0.808
	The smartwatch is my only choice for purchase and usage. (CS_2)		0.887			
	I have had a pleasurable experience with this device. (CS_3)		0.868			
	It is wise of me to choose this device. (CS_4)		0.893			
	I get satisfaction in my decision to use this device. (CS_5)		0.916			
	I am very satisfied using this device. (CS_6)		0.929			
Perceived Convenience	The smartwatch allows me to use the service whenever I choose. (PC_1)	[143]	0.908	0.909	0.943	0.846
	The smartwatch allows me to use the service at a convenient time. (PC_2)		0.924			
	I value the ability to use the device from the comfort of home. (PC_3)		0.928			
Perceived Ease of Use	I find the device easy to use. (PEU_1)	[82]	0.881	0.914	0.936	0.744
	I find this device easy to do what I want. (PEU_2)		0.858			
	The smartwatch is flexible to interact with me. (PEU_3)		0.859			
	It is easy for to remember to how to perform tasks using this device. (PEU_4)		0.871			
	Interaction with this device requires less mental effort. (PEU_5)		0.844			
Product Quality	The materials used in this device are genuine. (PQ_1)	[139]	0.908	0.928	0.949	0.822
	The smartwatch has good functioning qualities. (PQ_2)		0.901			
	This is a durable electronic device. (PQ_3)		0.914			
	The smartwatch shows consistent results. (PQ_4)		0.905			
Service Quality	The smartwatch is well designed. (SQ_1)	[140]	0.865	0.877	0.915	0.730
	The smartwatch is reliable. (SQ_2)		0.850			
	The smartwatch is secure. (SQ_3)		0.863			
	The smartwatch's service team is helpful. (SQ_4)		0.839			
AI-Trust	The performance of smartwatch always meets my expectations. (Tr_1)	[141,142]	0.878	0.948	0.958	0.794
	The smartwatch has good features. (Tr_2)		0.902			
	The smartwatch introduced is reliable. (Tr_3)		0.874			
	The smartwatch has authentication. (Tr_4)		0.882			
	I trust this device. (Tr_5)		0.885			
	The device shows interest in me as a customer/user. (Tr_6)		0.923			

Table 3
Discriminant validity (fornell and larker criterion, and HTMT ratio).

	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1. CEx	0.883													
2. CS	0.795	0.899						**0.845**						
3. PC	0.693	0.684	0.920					**0.754**	**0.734**					
4. PEU	0.667	0.627	0.664	0.863				**0.723**	**0.671**	**0.728**				
5. PQ	0.708	0.687	0.673	0.602	0.907			**0.761**	**0.731**	**0.733**	**0.653**			
6. SQ	0.604	0.587	0.603	0.510	0.596	0.854		**0.667**	**0.640**	**0.673**	**0.568**	**0.658**		

shown in Table 3 was less than 0.90. Thus, discriminant validity was achieved. Fig. 2 shows the various parameters of the inner (measurement) model.

4.4. Structural (inner) model and hypothesis test

For hypothesis testing, the structural model was assessed after the measurement model was found to be valid and reliable. The hypotheses were examined through the structural model to answer research questions and associated research objectives [167]. Hair et al. [160] affirmed that the structural model in PLS-SEM is assessed in critical criteria, such as the significance of the path coefficients, coefficient determination (R^2), the effect size (f^2) and predictive relevance (Q^2).

Multicollinearity assessment of exogenous variables was checked before testing hypotheses through variance inflation factors (VIFs). The result showed that VIFs were less than 3.33, which indicated no multicollinearity issue prevailed in this dataset (Table 4).

4.4.1. Path coefficient

The structural model was evaluated using standardized path coefficients (β-value), significance level (*t* statistic) and R^2 estimates. The path loadings, interpreted as standardized regression coefficients, indicate the strength of the relationship between independent and dependent variables [160]. Table 5 and Fig. 3 show that all direct relationships were significant except delivery service quality and consumer perceived value relationship. Therefore, all hypotheses were accepted as p-values were less than 0.05 (close to zero).

Table 5 and Fig. 3 show that all hypotheses were accepted as t-values (>1.96) and p-values (<0.05) met the recommended condition. Besides, the lower bound and upper bound of the bias-corrected confidence interval did not contain a zero value. Therefore, these relationships were significant. The strongest and most significant relationship was between trust and user satisfaction (beta value = 0.518), followed by user experience and user satisfaction (beta value = 0.430); and the least significant relationship was service quality and trust (beta value = 0.145).

4.4.2. Coefficient of determinant

According to Chin [168]; a value of R^2 value of 0.19 is considered weak, 0.33 is average, and a value of 0.50 R^2 is considered substantial. The study found R^2 for UEx was 0.641 [substantial]; for Trust, R^2 was 0.638 [substantial], and for US, the R^2 was 0.767 [substantial] (Table 4). Besides, for model validity, path coefficients must be at least 0.100 at least 0.05 significance.

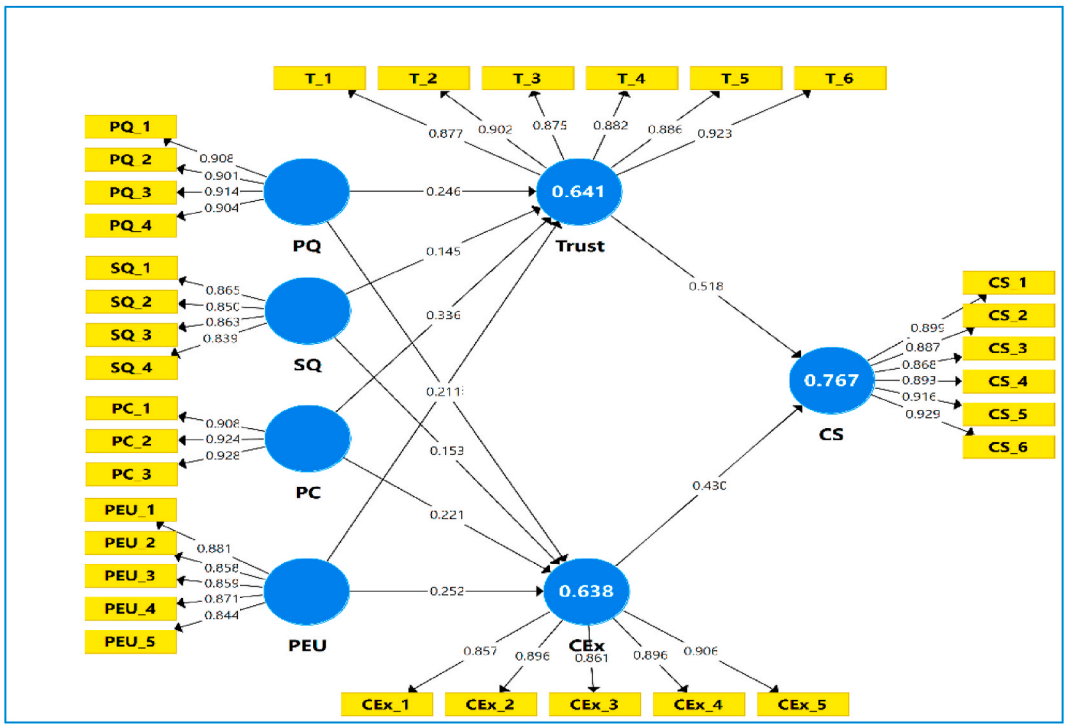

Fig. 2. Measurement Model of the study.

Table 4
VIF, R Square, f Square and Q Square.

Construct	VIF			R Square	f Square (Effect Size)			Q^2
	CEx	CS	Trust		CEx	CS	Trust	
CEx		1.986		0.638 (Substantial)		0.400 (Strong)		0.492
CS				0.767 (Substantial)				0.615
PC	2.440		2.440		0.055 (Small)		0.129 (Small)	
PEU	1.963		1.963		0.089 (Small)		0.063 (Small)	
PQ	2.165		2.165		0.127 (Small)		0.078 (Small)	
SQ	1.772		1.772		0.037 (Small)		0.033 (Small)	
Trust		1.986		0.641 (Substantial)		0.579 (Strong)		0.505

Table 5
Path Co-efficient and hypothesis.

Hypothesis	Paths	Beta	T Statistics	P Values	Lower	Upper	Decision
H1	**PQ → UEx**	0.316	4.549	**0.000**	0.177	0.448	Supported
H2	**PQ → Trust**	0.246	4.273	**0.000**	0.129	0.354	Supported
H3	**SQ → UEx**	0.153	3.165	**0.002**	0.052	0.242	Supported
H4	**SQ → Trust**	0.145	2.893	**0.004**	0.048	0.243	Supported
H5	**PC → UEx**	0.222	3.322	**0.001**	0.084	0.343	Supported
H6	**PC → Trust**	0.337	5.385	**0.000**	0.209	0.455	Supported
H7	**PEU → UEx**	0.251	4.129	**0.000**	0.138	0.379	Supported
H8	**PEU → Trust**	0.211	3.879	**0.000**	0.108	0.319	Supported
H9	**UEx → US**	0.430	10.318	**0.000**	0.347	0.513	Supported
H10	**Trust → US**	0.518	11.739	**0.000**	0.417	0.595	Supported

4.4.3. Assessment of effect size (f^2)

The assessment of effect size (f^2) is the third criterion to evaluate a structural model through the assessment of R^2 values of the independent variable. Cohen [169] stated that the f^2 value of 0.02, 0.15, and 0.35 as weak, moderate, and strong effects, respectively. In the case of both user experience and trust, perceived convenience had an effect size of 0.055 and 0.129, perceived ease of use had 0.089 and 0.063, product quality had 0.127 and 0.078, and service quality had 0.037 and 0.033, indicating their respective small effects (Table 4). As also shown in Table 4, user experience (effect size = 0.40) and trust (effect size = 0.579) had a strong effect on user satisfaction.

4.4.4. Predictive relevance (Q^2)

The predictive relevance technique was tested using the blindfolding analysis [162]. The redundant communality was more than zero for the exogenous variable [170], and the cross-validated redundancy estimates (Q^2) was presented to probe the predictive relevance [171,172]. The cross-validated redundancy for the endogenous variables, customer experience, trust, and consumer satisfaction, were 0.492, 0.505, and 0.615, respectively (Table 4). These values indicated sufficient

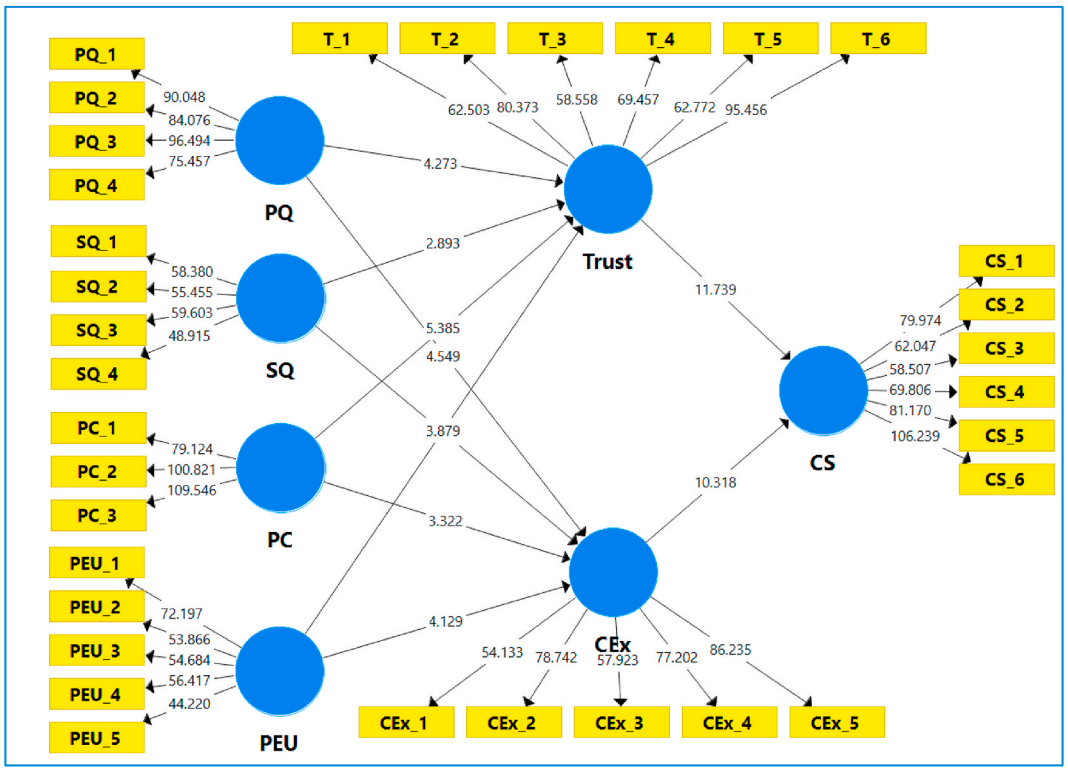

Fig. 3. Structural model.

predictive capability of the model based on Fornell and Cha's [173] standards, which required these values to be larger than zero.

4.4.5. Mediation effect

The objective of this study was to examine the mediating effect of trust and user experience on the relationships of product quality, service quality, perceived convenience, and ease of use on user satisfaction. Mediation analysis enables the investigation of mediators that intervene in the relationships between endogenous predictors and an exogenous construct ([174]. The strength of effect of a predictor on exogenous constructs varies with the presence of the mediator if the mediator has a mediating effect; otherwise, no variation occurs [175]. The bootstrapping method suggested by Ref. [175] was used to assess the mediation effects of user experience and trust. The criteria were bias-corrected at 95% confidence intervals and 5000 iterations to check the significance of the indirect impacts. If the indirect effect is significant and the confidence interval is not zero, mediation is supported [176]. The findings of mediation are depicted in Table 6. It was found that mediating effects existed as the indirect effect was significant (p-value <0.05) and bias-corrected confidence intervals had no zeros. In accordance with Hair et al. [177]; the strength of the mediating effect was tested by measuring the variance account for (VAF), where a VAF of less than 20% would indicate no mediation; a VAF of between 20% and 80% would indicate partial mediation, and a VAF of more than 80% would indicate full mediation. The VAFs in this study were within the range of 35% to 65%. As shown in Table 6, the lowest VAF was in the PC → UEx → US relationship, while the highest VAF was in the PC → Trust → US relationship. Since the VAFs were in between the 20% to 80% range, the mediation effects were considered partial [178].

4.4.6. Moderation effects of gender and age

In investigating the role of gender and age in users' satisfaction with AI-enabled smartwatches, Table 7 shows that the significance of the direct relationship between product quality and user experience and between perceived convenience and user experience differ according to age groups but not according to gender. Again, the significance of the direct relationship between service quality and user experience, between perceived convenience and trust, between perceived ease of use and user experience, and between perceived ease of use and trust varied in both demographic characteristics (gender and age groups). On the other hand, other direct relationships (PQ→Trust, SQ→Trust, UEx→US, and Trust→US) were not influenced by gender and age of the respondents.

Table 6
Mediation effect of user experience and trust.

Hypothesis	Path	Specific Indirect Effect				Total Effect	Mediation	
		Beta	P Values	Lower	Upper	Beta	VAF	Status
H11a	**PQ → UEx → US**	0.136	**0.000**	0.073	0.208	0.263	52%	Partial
H11b	**SQ → UEx → US**	0.066	**0.005**	0.022	0.110	0.141	47%	Partial
H11c	**PC → UEx → US**	0.095	**0.001**	0.041	0.156	0.270	35%	Partial
H11d	**PEU → UEx → US**	0.108	**0.000**	0.062	0.164	0.217	50%	Partial
H12a	**PQ → Trust → US**	0.127	**0.000**	0.063	0.183	0.263	48%	Partial
H12b	**SQ → Trust → US**	0.075	**0.007**	0.026	0.128	0.141	53%	Partial
H12c	**PC → Trust → US**	0.174	**0.000**	0.099	0.253	0.270	65%	Partial
H12d	**PEU → Trust → US**	0.109	**0.001**	0.053	0.178	0.217	50%	Partial

Table 7
Moderation role of Gender and Age.

Paths	Gender				Age							
	Female		Male		Age Group 1		Age Group 2		Age Group 3		Age Group 4	
	Beta	P-Value	Beta	P Values	Beta	P Values	Beta	P Values	Beta	P Values	Beta	P Values
PQ→UEx	0.609	0.000	0.269	0.000	0.448	0.000	0.278	0.051	0.239	0.073	0.324	0.003
PQ→Trust	0.625	0.000	0.201	0.000	0.019	0.751	0.132	0.035	0.098	0.000	0.266	0.004
SQ→UEx	−0.016	0.889	0.169	0.001	0.101	0.037	0.309	0.003	0.269	0.055	0.069	0.484
SQ→Trust	0.255	0.030	0.134	0.009	0.563	0.000	0.722	0.000	0.822	0.000	0.376	0.000
PC→UEx	0.330	0.031	0.199	0.008	0.414	0.000	0.155	0.198	0.148	0.220	0.193	0.070
PC→Trust	0.047	0.795	0.360	0.000	0.067	0.481	0.121	0.033	0.101	0.000	−0.082	0.373
PEU→UEx	0.005	0.962	0.308	0.000	0.132	0.010	0.201	0.098	0.232	0.039	0.384	0.000
PEU→Trust	−0.010	0.933	0.239	0.000	0.158	0.000	0.059	0.145	−0.004	0.876	0.304	0.004
UEx→US	0.413	0.001	0.438	0.000	0.448	0.000	0.388	0.000	0.386	0.000	0.584	0.000
Trust→US	0.499	0.001	0.515	0.000	0.581	0.000	0.560	0.000	0.516	0.000	0.223	0.023

Note: Shaded region indicated moderation effects.

4.4.7. PLS-prediction for prognosis of data

Shmueli et al. [179] and Hair et al. [160] suggested a state-of-the-art prediction approach in PLS-SEM through PLSpredict. The PLSpredict approach is a holdout sample-based process that prognoses new data. This present research utilized the PLS predict approach to generate a case-level prognosis on the dependent construct level. Table 8 shows that all endogenous items of fear of business loss and mental distress indicate strong prediction power. The Q^2, in particular, predicted values in the PLS-model to outperform those from Linear Model (LM) (Q^2 values > 0). Conversely, all values of Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) for the PLS model are less compared to those of LM [160]. Thus, it is concluded that this conceptual framework has strong predictability.

4.4.8. Importance-Performance Map Analysis (IPMA)

The study utilized the Importance-Performance Map Analysis (IPMA) for assessing further the structural model [180]. IPMA is an advanced mechanism to evaluate user satisfaction, which is the dependent variable. Pisitsankkhakarn and Vassanadumrongdee [181] stated that the objective of IPMA is to detect the more significant construct having an impact with a lower average score. The result of IPMA analysis, following the process of Hair et al. [160] and Pisitsankkhakarn and Vassanadumrongdee [181] showed that trust influenced user satisfaction with 0.535 at the performance level of 64.175, while user experience influenced user satisfaction with 0.463 at the performance level of 62.870. (Fig. 4).

In summary, satisfaction among users of AI-enabled smartwatches for the purposes of self-monitoring of health can be improved by building better user experience and trust.

5. Discussion

This study aimed to explore the use of AI-enabled smartwatches for self-monitoring of health and the impact of user experience and trust on their satisfaction. Using a proposed model based on S–O-R theory, the data analysis showed that the effects of product quality, service quality, perceived convenience, and perceived ease of use on user experience, trust and user satisfaction were significant. Again, trust and experience significantly influenced user satisfaction. The study also supported the contributory mediating roles of user experience and trust on user satisfaction.

While previous research has emphasized the value of user experience and trust in maximizing the utilization of AI-enabled services (e.g. Davenport et al. [12]; neither aspect, to our knowledge, has been empirically validated as part of a holistic theoretical model. This gap has been addressed in the present research which introduces a novel theoretical framework that combines user experience and trust with intervening effects on user satisfaction in relation to product quality, service quality, perceived convenience, and ease of use.

Product quality and service quality were found to significantly affect user experience, users' trust and user satisfaction. It supports previous findings on the importance of product and service quality in ensuring

Table 8
Assessment of the PLSPredict.

	PLS-SEM				LM				PLS-LM				Predictive Power
Indicators	RMSE	MAE	MAPE	Q^2_predict	RMSE	MAE	MAPE	Q^2_predict	RMSE	MAE	MAPE	Q^2_predict	
CEx_1	0.786	0.626	22.310	0.455	0.790	0.634	23.142	0.432	−0.004	−0.008	−0.832	0.023	
CEx_2	0.710	0.579	20.649	0.497	0.724	0.588	21.022	0.477	−0.014	−0.009	−0.372	0.020	Moderate
CEx_3	0.719	0.586	21.142	0.501	0.720	0.598	21.431	0.495	−0.001	−0.012	−0.289	0.006	
CEx_4	0.679	0.543	19.695	0.527	0.695	0.553	19.948	0.485	−0.016	−0.011	−0.253	0.042	
CEx_5	0.689	0.540	20.279	0.500	0.690	0.543	21.160	0.481	−0.001	−0.003	−0.881	0.019	
CEx_6	0.710	0.531	19.863	0.267	0.718	0.541	20.156	0.261	−0.008	−0.010	−0.293	0.006	
CS_1	0.825	0.640	23.425	0.469	0.830	0.657	23.562	0.455	−0.005	−0.017	−0.137	0.014	
CS_2	0.825	0.622	24.794	0.449	0.839	0.649	25.328	0.431	−0.014	−0.028	−0.535	0.019	
CS_3	0.784	0.625	23.223	0.462	0.780	0.631	23.328	0.448	0.004	−0.006	−0.105	0.014	Moderate
CS_4	0.755	0.575	22.167	0.495	0.770	0.586	22.791	0.456	−0.014	−0.011	−0.624	0.039	
CS_5	0.720	0.539	21.202	0.503	0.732	0.541	20.919	0.486	−0.012	−0.003	0.283	0.017	
CS_6	0.722	0.530	20.676	0.497	0.737	0.538	20.783	0.476	−0.014	−0.008	−0.107	0.020	
T_1	0.802	0.623	23.513	0.468	0.810	0.664	24.163	0.438	−0.008	−0.041	−0.650	0.031	
T_2	0.763	0.590	21.948	0.493	0.770	0.599	22.523	0.481	−0.007	−0.009	−0.574	0.013	
T_3	0.759	0.597	22.300	0.465	0.770	0.643	22.581	0.449	−0.011	−0.046	−0.281	0.016	Moderate
T_4	0.735	0.589	22.277	0.490	0.747	0.602	22.578	0.473	−0.012	−0.013	−0.301	0.017	
T_5	0.706	0.550	21.637	0.515	0.710	0.554	21.995	0.487	−0.004	−0.004	−0.358	0.028	
T_6	0.680	0.509	20.357	0.549	0.685	0.517	20.495	0.543	−0.005	−0.008	−0.138	0.006	

Notes: PLS-SEM= Partial Least Squares Structural Equation Modeling, LM = Linear Regression Model, RMSE = Root Mean Squared Error, MAE = Mean Absolute Error.

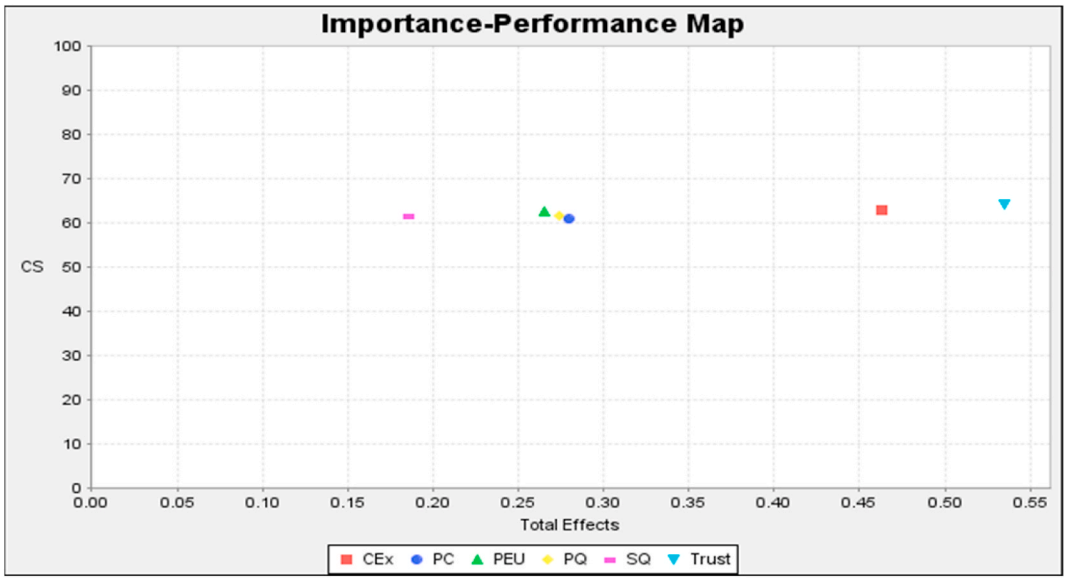

Fig. 4. Importance-performance map analysis.

positive user experiences, trust and satisfaction in using these devices [74,182–184].

Gök et al. [67] showed that the quality of the product minimizes the gap between the product received and the product expected. Product quality is encapsulated in the devices' functionalities and performance, such as the ability to provide personalized content, real-time support, real-time information and real-time interaction with users [74,185, 186].

Service quality is indicated by how reliably smartwatches are designed to manage users' personal and health information, detect blood pressure, diabetes, heart rates and other ailments in a safe manner [10].

In this study, smartwatch users indicated satisfaction with using the device for health management purposes as their level of responsiveness and reliability were consistent with their expectations. The performance and reliability of these devices were shown to improve user satisfaction, which is consistent with findings by Ganguli and Roy [75]; Lin et al. [66] and Gök et al. [67]. Consistent with Suhaily and Darmoyo [184]; the reliability of AI technology in helping users monitor and manage their health was also found to affect development of trust among users who use these devices for health purposes. Trust has been shown to develop through collaborative engagements between the user and the device [187,188] and is accumulated when the technology is demonstrated to be reliable through repeated usage [10]. **Moreover**, the finding in this current study that overall service quality of AI-enabled technology offers a memorable experience supports findings in past studies, such as Cai et al. [189]; Gursoy et al. [190]; Lin et al. [191]; Lu et al. [192,193], that AI-enabled services create positive attitudes and behaviours among customers through influencing customer experiences.

In this study, perceived convenience in terms of reduced time and effort of usage [79] was found to have a significant effect on user experience, trust and satisfaction, which aligns with findings by Payne et al. [77] and Pham et al. [76]. Other studies have indicated user satisfaction with the convenience of medical information and service that is constantly available [80], access to real time information and assistance [81] and advanced guidance [10]. This anytime, anywhere availability can be critical in emergency situations such as the current pandemic. In developing countries like Bangladesh where health services have been hampered by the crisis [194], smartwatch users have been able to rely on their devices to access health care services in place of visits to doctors [195].

Time saving convenience [196], self-service convenience [80], and real-time convenience [81] have an impact on user experience. Similarly, service convenience motivates the users to engage with the products (smartwatches) in gaining a beneficial experience [196,197]. Besides ensuring a positive and memorable experience, the perceived convenience of the AI-enabled smartwatch builds trust among the users. Removing barriers [198], ensuring a good feeling among the users [199], and assessing service utility [76] develop user trust to use AI-enabled device tools such as smartwatches.

In terms of perceived ease of use, the findings confirmed that perceived ease of use is significant with user trust, user experience and their satisfaction. This finding is consistent with studies by Jarrahi [84] and Tandon et al. [200]. **As perceived ease of use is arguably most important for older users who tend to be less proficient with technology, users are more comfortable in operating and managing these devices if they are easy to use, easy to handle and easy to maintain** [201]**. Well-designed layouts, navigation and aesthetics that emphasize simplicity and user-friendliness afford minimal physical effort and less mental exertion, and will likely result in positive experiences** [63,202]**. Repeated use will reinforce familiarity with the technology, increase user confidence and build trust among users** [202].

Our data analysis confirmed the mediating effects of trust and experience on user satisfaction. The effects of product quality, service quality, perceived convenience, and perceived ease of use on trust, experience and user satisfaction were found to be significant. In addition, the indirect effects of predictors were also significant in the presence of both mediators (user experience and trust). In other words, trust and experience played partial mediating roles in these relationships. In terms of user experience, a positive experience in using AI-enabled smartwatches will strengthen the direct relationships between the predictors, namely product quality and services, perceived convenience and ease of use, and user satisfaction. This supports other empirical studies that have found this construct to be an impactful mediator [203–207]. In the health care context, previous experience is empirically significant in strengthening the relationships among various factors [208], including their satisfaction in utilizing AI-enabled devices [209]. In practical terms, previous positive experiences in using smartwatch technology to manage health issues coupled with approvals by medical doctors on the use of these devices will likely result in higher levels of satisfaction among users.

In empirical studies in the social sciences, especially marketing and management, trust has been established as a successful and influential

mediator [210–212]. In studies of technology adoption and usage, trust has also been found to be a significant mediator [213,214]. In healthcare, trust in technology is vital [214,215]. In this study, trust in the use of AI-enabled smartwatches for health purposes was found to play an important role in mediating the relationship between the antecedent constructs, namely product quality, AI-enabled service quality, perceived convenience, and perceived ease of use, with user satisfaction, which is in line with previous research (see De Kerviler et al. [216] Shin and Lin [217]. Supporting this, Hengstler et al. [62] emphasized the role of trust as a mediator between humans and technology. This study also suggests that uncertainties associated with AI-enabled technology, such as issues of security, reliability, privacy and ethics that have been previously highlighted [218–220], can be overcome by emphasizing product and service quality, convenience, and ease of use inherent in these devices. Hence, AI-enabled products and services that feature simplicity of design, functionality, reliability and security will generate familiarity and trust in users [81,142,221] and, subsequently, overall service satisfaction.

As this technology offers increasing convenience, ease of use and personalized services, the value of substituting traditional human-to-human interactions with technology that prioritises human-technology interactions will continue to gain acceptance [10,72,193]. In particular, this form of human-technology interaction has proven its significance during the current pandemic where people-people interactions are frowned upon [10], highlighting the importance of cultivating trust in AI-systems for the health-care market.

The findings also showed that gender and age had significant effect on the direct relationships. Product quality, service quality, convenience and ease of use are significant determinants of customer satisfaction, mediated through experience and trust, for both gender and age. These findings e correspond with past studies on gender differences by Chen et al. [128]; Hwang and Lee [132] and Atulkar and Kesari [131]. They also correspond with past studies on age differences, by, Stephan et al. [135] and Chien et al. [63].

6. Contributions and implication

6.1. Theoretical contributions

This current study contributes to the existing body of knowledge in wearable health technology in several ways. First, it offers and validates a theoretical framework that integrates a number of critical factors that affect user satisfaction in utilizing these devices. In this framework, user trust and their experience are shown to mediate between the predictor constructs and user satisfaction. Where trust has previously been used as a mediator [218], the addition of experience as a mediator in this study represents a theoretical contribution to understanding the use of wearable health devices. The inclusion of perceived ease of use and perceived convenience in the same framework strengthens the findings and has added theoretical value in the literature. The study confirms the assumptions of the S–O-R model, that perceived quality (product and service), perceived convenience and ease of use are a successful stimulus and trust and experience of users are internal assessments of stimuli (organism). Trust is found to be a successful mediator in explaining S–O-R theory. The results show that S–O-R theory contributes to the understanding of user responses to AI-based technology. While the impact of technology-based devices on user satisfaction in health care service has been examined in different contexts [10,138], this current study provides insights into one of the more complex technologies, that is artificial intelligence, in automating the provision of a critical services to users. The outcomes of the study will support efforts to integrate artificial intelligence into wearable smart devices to allow users to be self-dependent in managing their health. In addition, the finding that users are satisfied using these devices to access health services is considered significant, and confirms how users are becoming accustomed to personalized technology and the digital environment [138].

6.2. Managerial implications

The findings of this study have implications for Bangladesh and other less developed economy contexts. As the number of patients, especially those with diabetes, cardiovascular diseases, and high blood pressure, is increasing rapidly in Bangladesh, managing and attending to health issues immediately and efficiently has become very important. In particular, where the current pandemic has caused many people to be reluctant to visit doctors or seek medical services in person, AI-enabled smartwatches have become a useful alternative to assure continued access to health care.

While the impact of technology-based devices on user satisfaction in health care service has been examined in different contexts [10,138], this current study provides insights into one of the more complex technologies, that is AI, in automating the provision of critical health services to users. The outcomes of this study will support efforts to integrate artificial intelligence into wearable smart devices to allow users to be self-dependent in managing their health.

Furthermore, the finding that users are satisfied and accustomed with 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 [138].

Based on these findings, smartwatch brands should continue to improve upon their products' functionalities such as customized size, suitable color, lucrative model, easy button, longer battery duration, inter-watch connectivity, result sharing, etc.; healthcare features such as automatic temperature signature, blood pressure signal, etc., and ease of use feature such as an easy button in order to appeal to important user groups. Besides, these features and functionalities brands should highlight result reliability and privacy through self-management of the healthcare services.

6.3. Limitations and future study

As with any research, this study has 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 just three zones in Dhaka city. A broader coverage would assure better representation. Thus, future studies could apply random sampling and cover locations outside Dhaka, or other developing countries. Other studies should also include a significant number of female respondents. Second, future work should utilize other theories such as TAM, UTAUT, TBP and so on. Third, CB-SEM can be utilized to test adoption theories.

Furthermore, in a developing context such as Bangladesh, price could be a significant factor to be investigated, as a predictor (stimulus) in the existing model. Lastly, future models can consider various types of diseases and personalisation of devices.

7. Conclusion

This study is significant in understanding the usage of AI-enabled smartwatches as a *device doctor* or *electronic doctor (e-doctor)*. This finding contributes to understanding user satisfaction, specifically older people, in maximizing their use of AI-enabled technology for healthcare and other related issues. As AI technology continues to proliferate and essential services such as health are increasingly democratized, the ability to self-manage healthcare will become indispensable. Brands should find ways to make their products and services more malleable by understanding user behaviours and usage patterns to ensure effective usage and user satisfaction.

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