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Customer adoption of smartwatches – a privacy calculus perspective

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Abstract

Purpose – This study tries to explain the customer adoption of smartwatches by considering the perceived benefits and perceived costs. Through this study, the authors aim to determine the factors affecting behavioural intentions towards smartwatches.

Design/methodology/approach – The authors applied the survey method to collect data to validate the conceptual model related to the research objectives. The authors collected 310 responses using a structured questionnaire; after data cleaning, 270 responses were used for data analysis. Structural equation modelling (SEM) was performed using Smart PLS to test the proposed hypotheses.

Findings – The results established creepiness, privacy concerns, perceived expectancy and performance effort expectancy as factors affecting behavioural intentions related to customer adoption of smartwatches.

Originality/value – This study has incorporated the concept of creepiness into the factors inhibiting factors affecting behavioural intentions in the context of smartwatches.

Keywords Smartwatches, Creepiness, Privacy concerns, Adoption, SEM, Consumer behaviour

Paper type Research paper

1. Introduction

Over the past decade, there has been a significant surge in consumer engagement with technology and artificial intelligence (AI) (Ameen *et al*., 2021, 2022). This growth, enabled by advanced computational capabilities and AI, has empowered technology leaders to create multifunctional smart wearable devices. Smart wearable devices are intelligent computers incorporated into different accessories like fashion accessories, clothing and other items worn by individuals (Ferreira *et al*., 2021; Wright and Keith, 2014). Activity trackers and smartwatches are just a few examples of intelligent wearable devices. Smartwatches demonstrate the versatility of such devices, serving various functions ranging from fashion, health and wellness to multimedia capabilities. They have driven the wearable technology market's rapid growth and commercial success. Users turn to smartwatches for tracking activities and monitoring vital health statistics, signifying a growing interest in these innovative information technology (IT) devices (Choi and Kim, 2016). People also employ smartwatches as connected accessories to their smartphones, enabling individuals to control their mobile devices through these wearable gadgets. Smartwatches efficiently manage phone calls, messages and other notifications from smartphones. These devices have become ubiquitous daily as one of the most used wearable smart technologies (Cecchinato *et al*., 2015). Smartwatches represent high-tech consumer durables frequently embraced by end consumers.

Academic scholars of marketing and management have directed their attention towards understanding customer adoption and behavioural intention regarding smartwatches. Numerous studies have delved into customer acceptance and purchase intention within this realm, particularly emphasizing the technological facets (Bölen, 2020; Choi and Kim, 2016;

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Chuah *et al.*, 2016; Wu *et al.*, 2016). Factors such as usefulness, ease of use, privacy concerns, benefits and risks have traditionally influenced consumer decisions concerning smartwatches (Bölen, 2020). Almuraqab (2021) determined smartwatch purchase intentions using the core constructs of the technology acceptance model (TAM). Kamal Basha *et al.* (2022) applied the stimulus-organism-response (SOR) theory to determine the usage continuation of smartwatches. Beh *et al.* (2021) found performance and effort expectancy predictors of behavioural intention in the context of smartwatches. Bölen (2020) identified perceived usefulness as one of the significant determinants of customer acceptance of smartwatches. As previously mentioned, smartwatches belong to the technology-enabled consumer durables category; thus, their market dynamics intertwine technology factors with marketing elements like brands. Han *et al.* (2021) identified and categorized several factors, such as ease of use, tracking and monitoring of activities, collection of personal information, usefulness, etc. significantly associated with customer adoption of smartwatches. Saheb *et al.* (2022) determined the behavioural intentions of smartwatch customers based on TAM.

Existing studies have generally focussed on either the benefit or psychological cost perspective while determining the customer adoption of smartwatches. Through this study, we are trying to integrate the expected benefits and psychological costs to determine customer adoption of smartwatches. A smartwatch, being a high-technology consumer durable, provides personalized services based on the personal data provided by the users. We have taken perceived expectancy and perceived effort expectancy as the proxy of perceived benefits and privacy concern and creepiness as the proxy of psychological cost associated with the personal data provided by the individuals. Rajaobelina *et al.* (2021) empirically validated the negative role of creepiness in the context of chatbots, which are relatively similar to smartwatches since both are based on AI-enabled technologies. The collection of personal information and tracking of activities create privacy concerns and creepiness in the context of human interaction with smartwatches (Han *et al.*, 2021; Rajaobelina *et al.*, 2021).

Although the broad objective of the study is to determine the customer adoption of smartwatches and provide a better presentation of the work, we have arrived at some precise objectives of the study. These objectives are as follows:

(1) Investigate the impact of privacy concerns on the perceived creepiness of customers who are related to smartwatches.

(2) To examine the effect of creepiness on customer adoption of smartwatches.

(3) The investigation of the combined effect of perceived costs and perceived benefits on customer adoption of smartwatches.

The study's objectives motivated us to develop a conceptual model based on existing theories, literature and logical arguments. Four research hypotheses have been developed to study the research objectives. Primary data were collected using a structured questionnaire to validate the proposed conceptual model. Existing scales were adapted for the development of the questionnaire. The proposed hypotheses were tested using structural equation modelling (SEM). The data were analysed through Smart PLS.

2. Theoretical background

Technology adoption models have systematically evolved over the period. Academic researchers have extensively used theories related to consumer psychology and consumer behaviour to determine consumers' behavioural intention and purchase intention toward technology-enabled products and services. The theory of reasoned action (TRA) (Fishbein and Ajzen, 1975) is one of the oldest technology adoption theories. The theory of planned behaviour (TPB) (Ajzen, 1991) is another popular theory that extends TRA and helps determine factors affecting purchase intentions. The TAM (Davis, 1989) is the most popular theory of study of human acceptance of technology. The unified theory of acceptance and use of technology (UTAUT) (Venkatesh *et al.*, 2003) combines eight technology acceptance and behavioural science theories, including TAM and TPB. It is currently one of the most comprehensive technology adoption theories. UTAUT states that performance expectancy, effort expectancy, social influence and facilitating conditions influence behavioural intentions in the context of information systems.

Apart from the technology adoption models, some other influential human behaviour theories will be used to develop the conceptual framework. Two such theories are briefly explained below.

Privacy calculus theory: This theory states that individuals perform a psychological cost-benefit analysis before accepting a technology or system. In digital technology, personalized service is the perceived benefit and privacy concerns are the perceived cost (Culnan and Armstrong, 1999; Laufer and Wolfe, 1977).

Stimulus-organism-response (SOR) theory: SOR is one of the most essential theories used in studying consumer decision-making. Individuals typically make decisions based on three factors: stimulus factors (for example, cues, etc.), organism factors (for example, feelings, impressions, etc.) and response factors (for example, usage, etc.) (Jacoby, 2002).

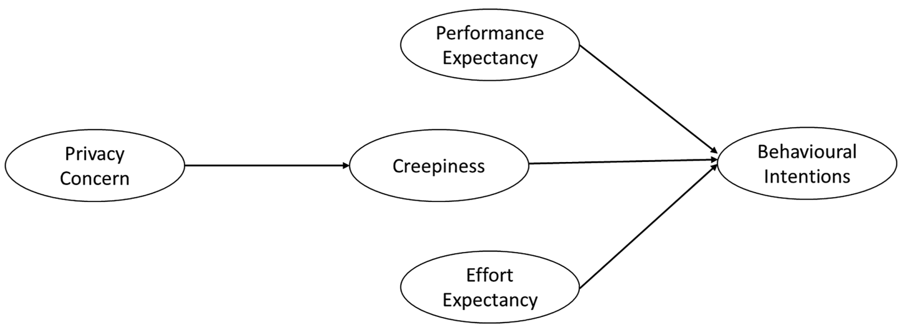
3. Conceptual framework and hypotheses development

The conceptual framework (see Figure 1) of the current study is primarily based on the premise of UTAUT, privacy calculus theory and SOR theory.

3.1 Creepiness and privacy concerns

Creepiness can be defined as an unpleasant response to uncertain situations, unknown people and new technology (Rajaobelina *et al.*, 2021). Creepiness can not only be experienced in an interpersonal situation, like interacting with a stranger, but also while interacting with a new technology (Langer and König, 2018). In the context of technology, creepiness comes into the picture when the behaviour of technology contradicts socially acceptable norms or if it is perceived beyond the control of an individual. Smartwatches provide personalized services like activity tracking, critical vital tracking, etc (Beh *et al.*, 2021). To deliver personalized services, smartwatches collect a lot of personal information, and that collection of personal information creates privacy concerns among smartwatch users. Creepiness has been developed as an essential construct in psychology and marketing literature. Rajaobelina *et al.* (2021) have studied the impact of creepiness on brand loyalty in the context of chatbots.

Privacy concern is a set of beliefs of individuals regarding the risks and potential adverse outcomes affiliated with the collection, utilization and sharing of personal data (Malhotra



Source(s): Authors' own work

Fig. 1. Conceptual framework

et al., 2004). Collections of personal information by AI-based personal intelligent assistants are of primary concern for users (Manikonda *et al.*, 2018). A smartwatch is a device that is called smart only because it provides personalized services based on personalized data collected through itself. It is inevitable to avoid privacy concerns in the case of smartwatches.

The social norm in any civilized society is that individuals have their private space, and no one is allowed to invade the privacy of individuals. However, in the case of a smartwatch, it collects a significant amount of personal data.

Therefore, we propose the following hypothesis:

H1. Privacy concerns increase creepiness in the case of smartwatches.

3.2 Creepiness and behavioural intentions

Behavioural intention is the individual's perceived likelihood or subjective probability that they will engage in a given behaviour. Behavioural intention is the intention to perform a particular task or behaviour (Ajzen, 1985; George and Sahadevan, 2023). In the case of smartwatches, behavioural intention can be an intention to use or purchase.

As defined earlier, creepiness is a negative feeling that is bound to influence the behavioural intention to buy or use smartwatches negatively. If we take SOR theory into perspective, creepiness can be considered an organism factor, while behavioural intention can be an example of a response factor.

Therefore, we propose the following hypothesis:

H2. Creepiness negatively influences behavioural intentions in the context of smartwatches.

3.3 Performance expectancy, effort expectancy and behavioural intention

Performance expectancy is the extent to which people think that employing the system will enable them to improve their performance at work. Performance expectancy is the level of belief of an individual as to how technology will help them in productivity. It stems from perceived usefulness, extrinsic motivation, the relative advantage, outcome expectancy, etc (Venkatesh *et al.*, 2003).

Performance expectancy is one of the influential predictors of behavioural intention in the context of technology adoption, as per UTAUT. In the case of smartwatches, the characteristics of performance expectancy, for example, perceived usefulness and relative advantage, etc. are very much applicable.

Effort expectancy is the level of ease associated with using a device (Venkatesh *et al.*, 2003). Effort expectancy is also an important construct of UTAUT. Effort expectancy combines the perceived ease of use construct of TAM and the construct of complexity. Several studies have used effort expectancy as a critical determinant of behavioural intention in the context of technology adoption. Since smartwatches are AI-enabled, technology-based, consumer durable, performance expectancy and effort expectancy can be used as predictors of behavioural intention.

Behavioural intentions have been the response variable of several significant technology adoption theories like TAM, TPB and TAM.

By referring to UTAUT, TAM, TPB and other literature, we propose the following hypotheses for our study.

H3. Performance expectancy positively influences behavioural intentions in the context of customer acceptance of smartwatches.

H4. Effort expectancy positively influences behavioural intentions in the context of customer acceptance of smartwatches.

4. Methodology

4.1 Context and data collection

To achieve our research objectives, we chose to conduct a survey. Our survey specifically targeted individuals with a basic understanding of smartwatches. This ensured that our respondents possessed the necessary knowledge to provide meaningful insights through our questionnaire. We have used a convenience sampling technique due to our limited resource availability. We have developed a questionnaire by adapting existing scales (see Appendix) from the literature. The scale for the privacy concern construct was adapted from Malhotra *et al.* (2004). The scale for the creepiness construct was adapted by Langer and König (2018). The scales for performance expectancy, effort expectancy and behavioural intentions were adapted from Venkatesh *et al.* (2003). We have circulated the questionnaire among our peers and close circles to check the wording and connotations and whether the prospective respondents will be able to understand the context in which the words are phrased. After a few alterations based on the initial respondents' feedback, we circulated the questionnaire to the prospective respondents. Data collection occurred in India from October 2023 to November 2023; on average, respondents took approximately seven minutes to complete the questionnaire. Before filling out the questionnaire, participants received introductory information about smartwatches. To reach our intended audience, we utilized social media platforms, leveraging our connections and engaging in various groups on platforms such as Facebook, Instagram and LinkedIn. The reliability of our data was confirmed using Cronbach's alpha values, all of which exceeded 0.7, indicating a high degree of consistency. In total, we received 310 responses, and after thorough data cleaning, we retained 270 usable responses for our subsequent analysis.

This study follows a cross-sectional and descriptive research approach. Using Microsoft Excel, descriptive analysis is performed to get demographic information on participants' behavioural intentions. Additionally, we employed SEM to assess the data when adopting smartwatches, a well-established and statistically reliable method across various disciplines Hair *et al.* (2012). There are two robust methodologies for conducting SEM: partial least squares (PLS-SEM) and covariance-based SEM (CB-SEM). Research by Reinartz *et al.* (2009) and Wetzels *et al.* (2009) suggests that PLS-SEM may offer greater statistical power than CB-SEM.

To examine the adoption of smartwatches and behavioural intentions, we utilized the PLS-SEM approach with the help of SMART-PLS 4.0, following the methodology outlined by Hair *et al.* (2019). To address potential common method bias (CMB), we applied attention retention questions as suggested by Podsakoff *et al.* (2003). These questions helped filter out incorrect responses to the data.

Our study's sample comprised 55% male and 45% female respondents. Most participants fall into two age categories of 20–30 and 30–40 years, i.e. 71 and 16%, respectively, followed by 40 above and 20 below age groups, i.e. 8 and 4%, respectively. Furthermore, a significant number of respondents held postgraduate degrees as their highest educational qualification, i.e. 56%, followed by graduates 21%, Ph.D. 19% and below intermediate 9%, respectively. For a concise overview of the demographic characteristics of respondents, please refer to Table 1.

5. Analyses and results

5.1 Assessment of measurement model

We adhered to the guidelines Hair *et al.* (2019) outlined for assessing the quality of our measurements. This involved evaluating the construct's reliability, convergent validity and discriminant validity. In Table 2, we will find a comprehensive summary of our measurement model assessment results. This includes both Cronbach's alpha and composite reliability values, all surpassing the threshold of 0.7, signifying strong construct reliability. However, the effects of age, gender and educational qualification were found to be insignificant.

Table 1. Demographic profile

Demographic variable		Responses	Percentage (%)
Gender	female	121	44.81
	male	149	55.19
Age	below 20	13	4.81
	20–30	192	71.11
	30–40	43	15.93
	40 above	22	8.15
Educational qualification	below intermediate	7	2.59
	graduation	58	21.48
	post-graduation	153	56.67
	Ph.D. and above	52	19.26

Source(s): Authors' own work

Table 2. Reliability and validity

Constructs	Items	Loadings	VIF	α	CR	AVE
Behavioural intention (BINT)	BINT1	0.881	2.117	0.881	0.882	0.808
	BINT2	0.911	2.901			
	BINT3	0.903	2.665			
Creepiness (CR)	CR2	0.844	2.578	0.853	0.861	0.694
	CR3	0.884	2.859			
	CR5	0.822	1.730			
	CR6	0.779	1.652			
Effort expectancy (EE)	EE11	0.66	1.589	0.78	0.788	0.534
	EE12	0.788	1.763			
	EE13	0.644	1.485			
	EE14	0.785	2.213			
	EE15	0.762	2.204			
Privacy concern (PC)	PC1	0.914	2.476	0.865	0.884	0.787
	PC2	0.903	2.546			
	PC4	0.842	1.937			
Performance expectancy (PE1)	PE11	0.815	1.291	0.757	0.779	0.666
	PE12	0.846	2.005			
	PE13	0.787	1.863			

Note(s): *Indicates the indicator was removed due to low loading
α: Cronbach's Alpha, CR: Composite Reliability, AVE: Average Variance Extracted and VIF: Variance Inflation Factor
Source(s): Authors' own work

We ensured convergent validity as indicated by all loadings and average variance extracted (AVE) values exceeding 0.7 and 0.5, respectively. Items with loadings between 0.4 and 0.7 were retained if their AVE values remained above 0.5. We examined the variance inflation factor (VIF) for all constructs and indicators to address multi-collinearity. The VIF values were below 3.0, signifying the absence of multicollinearity (Table 2) (Hair *et al.*, 2019). However, a few items that have trouble in AVE and discriminant validity, i.e. CR1, CR4 and PC3, are dropped due to low loadings.

Discriminant validity was established through Heterotrait-Monotrait (HTMT) and the Fornell–Larcker criterion; diagonal values were less than 0.9 (Henseler *et al.*, 2015). Table 3 confirm discriminant validity. In conclusion, our measurement model is acceptable, allowing us to proceed with the structural model examination (see Table 4).

Table 3. Discriminant validity; HTMT

	BINT	CR	EE	PC	PE1
BINT					
CR	0.253				
EE	0.806	0.304			
PC	0.091	0.455	0.082		
PE1	0.507	0.117	0.523	0.058	0.507

Source(s): Authors' own work

Table 4. Discriminant validity; Fornell–Larker

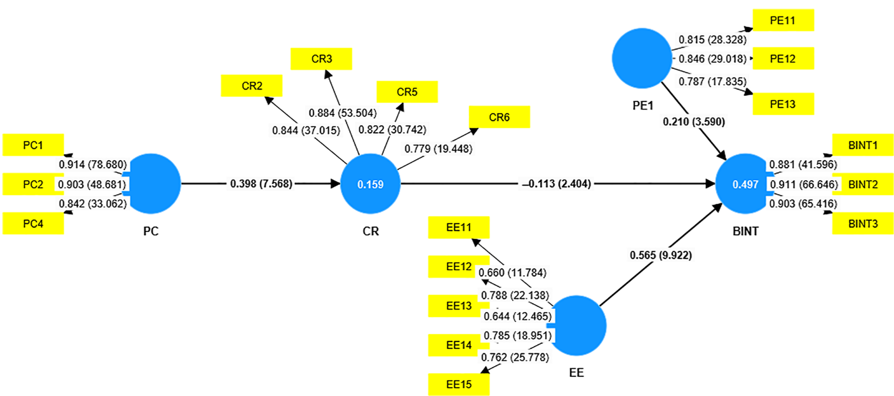
	BINT	CR	EE	PC	PE1
BINT	0.899				
CR	−0.224	0.833			
EE	0.675	−0.222	0.731		
PC	−0.077	0.398	0.042	0.887	
PE1	0.430	0.072	0.404	−0.038	0.816

Source(s): Authors' own work

5.2 Structural model and hypotheses test

Using the PLS technique's bootstrapping (10,000 samples), the t-values, significance levels and path coefficients (standardized beta) were examined. The structural model is presented in Figure 2. Four hypotheses were established, and all are supported based on the results (see Table 5). *PC* ($\beta = 0.398$, $p < 0.05$) was observed to exert a significant positive impact on CR (H1). Also, it was found that the effect of CR on BINT (H2) was significant ($\beta = -0.113$, $p < 0.05$).

The effects of PE and CE on BINT (H3 and H4) are positive and found to be significant ($\beta = 0.210, 0.565$, $p < 0.05$), respectively.



Source(s): Authors' own work

Fig. 2. Structural model

Table 5. Structural measurements

Relationships	Hypotheses	Original sample (O)	Standard deviation (STDEV)	(|O/STDEV|)	*p*-values	Results
PC → CR	H1	0.398	0.053	7.568	0.000	Supported
CR → BINT	H2	−0.113	0.047	2.404	0.008	Supported
PE1 → BINT	H3	0.210	0.059	3.590	0.000	Supported
EE → BINT	H4	0.565	0.057	9.922	0.000	Supported

Source(s): Authors' own work

6. Discussion and conclusion

As discussed in the previous sections of the manuscript. We tried to explain the customer adoption of smartwatches by using privacy calculus theory, SOR theory and UTAUT. We have developed four hypotheses to fulfil the research objective of this study. All the hypotheses were supported after the analysis of the collected data. The relationship between privacy concerns and creepiness was significant, consistent with the outcome of Rajaobelina *et al.* (2021). Rajaobelina *et al.* (2021) have studied the effect of privacy concerns on creepiness in the context of chatbots, which is relatively similar to the context of smartwatches since, in both cases, personal data is being used to provide personalized services. Creepiness seems to be negatively impacting behavioural intentions, which is also validated through the data. The reason may be that the intimidating nature of the construct creepiness will naturally have a negative effect on behavioural intentions. Performance expectancy and effort expectancy are positively associated with behavioural intentions in the context of customer adoption of smartwatches, which is consistent with the existing literature (Beh *et al.*, 2021; Kamal Basha *et al.*, 2022).

6.1 Theoretical implications

We have tried to explain the customer adoption process in the context of smartwatches using the theoretical bases of privacy calculus theory, SOR theory and UTAUT. Through the help of privacy calculus theory, we have taken both the perceived benefits and perceived costs associated with the customer adoption of smartwatches. We have conceptualized performance expectancy and effort expectancy as perceived benefits and privacy concerns and creepiness as perceived psychological cost while determining the factors affecting customer adoption of smartwatches. Although privacy concerns have been studied in the context of smartwatches, we have included the concept of creepiness in the inhibiting factors of the adoption of smartwatches, which is a critical contribution of this research. As mentioned earlier in the previous sections, creepiness has emerged as an essential factor in the use of personal data for personalized services.

6.2 Managerial implications

Marketers can infer from this research by focusing on the factors that enable and inhibit the customer adoption of smartwatches. As a high-technology consumer durable product manufacturer and seller, marketers need to focus on performance expectancy and effort expectancy from developing to selling smartwatches. They need to ensure that individuals' expectations are met with the product and that they do not need to make a lot of effort to deal with the smartwatches. Marketing managers need to communicate about the functional benefits of smartwatches. At the same time, marketers must ensure that a system is in place to protect the data collected through smartwatches. Proper communication about the need for personal data should be communicated so that users will be assured that providing personal information is necessary for personalized benefits and that the collected data will be secured through a robust system. Proper communication will reduce the fear of the unknown and ultimately reduce the perceived creepiness.

6.3 Limitations and future research opportunities

We would like to point out some limitations of the study so that future researchers can correct those mistakes with their research. Although we tried to take both the costs and benefits aspects of the customer adoption of smartwatches, we missed some important factors like social influence and anthropomorphism that could also impact the adoption. Since the smartwatches are AI-based, anthropomorphism could play a significant role in explaining customer adoption of smartwatches. Regarding research design and sampling procedures, future researchers can use probability sampling and some robust designs, such as experimental designs, to establish causal relationships.

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Appendix

Table A1. Questionnaire items

Items	Questions
BINT1	I expect to use smartwatches in the near future
BINT2	I intend to use smartwatches frequently
BINT3	I intend to recommend that other people use smartwatches
CR1*	I have a queasy feeling while using the smartwatch's functions
CR2	I have a fear of using smartwatches
CR3	I somehow feel threatened by smartwatches while using it
CR4*	I do not know precisely how to behave while using a smartwatch
CR5	I do not know exactly what to expect during the use of smartwatches
CR6	I do not know precisely what is happening to me while using the smartwatches
EE11	We can save time on essential work with the help of smartwatches
EE12	My interaction with the smartwatches would be clear and understandable
EE13	It would be easy for me to become skilful by using smartwatches
EE14	Smartwatches are easy to use
EE15	Learning to operate smartwatches is easy for me
PC1	It bothers me that the smartwatch is able to track information about me
PC2	I am concerned that the smartwatch has too much information about me
PC3*	It bothers me that the smartwatch can access information about me
PC4	I am concerned that my information could be used in many ways I could not foresee
PE11	Smartwatches are more accurate, with fewer errors
PE12	Smartwatches provide more consistent services than humans
PE13	Information provided by smartwatches is more consistent than humans

Note(s): *Items dropped due to its low loadings
Source(s): Authors' own work

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