Research Paper

Understanding Smartwatch Adoption in a Developing Economy: An Extended Technology Acceptance Model (TAM) Perspective

Md. Al Mamun[1], Md. Chhali Uddin[1], Shayla Khanom[2], Abu Daud Mahir[1], Radoan Islam[1]
[1]Jashore University of Science and Technology, Bangladesh
[2]University of Dhaka, Bangladesh

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Abstract

This study examines the factors that influence the adoption and purchase intention of smartwatches among people in Bangladesh by adding additional factors to the Technology Acceptance Model (TAM). The research tests a sequential model using data from 406 respondents, in which technological and social factors affect intention to use, which in turn affects purchase intention, using PLS-SEM. The results suggest that social influence is the most important predictor of intention to use, followed by perceived usefulness and perceived visibility (which has effects similar to perceived usefulness), and then perceived ease of use (which is not significant). Intention to use is a significant predictor of purchase intention, and perceived affordability has a positive relationship with purchase intention. An important contribution is the explicit separation between intention to use and purchase intention, reflecting the difference between attitudes towards the technology and the actual purchase of the technology, especially in price-sensitive developing economies. The results provide concrete pointers for the communicative interaction between marketers and manufacturers in order to convey functional value, social influence, and a flexible pricing policy. The study provides empirical evidence on the adoption of wearable technology in the underexplored economies of the developing world.

Keywords: *Smartwatch Adoption, Visibility, Technology Acceptance Model, Social Influence, Purchase Intention*

INTRODUCTION

Wearable technology has become one of the fastest-growing markets in the consumer electronics industry, with smartwatches being the most popular and successful wearable technology product (Seçkin et al., 2023). The smartwatch was originally conceived as a digital watch but has since morphed into a multifunctional device that monitors health, tracks fitness, features communication and hands-free smartphone integration, and fits seamlessly into consumers' lives (Jung et al., 2016; Raptis et al., 2022).

The spread has been swift due to advancements in sensor technology, increased awareness of health and well-being, and demand for customized digital services (Gumasing et al., 2024). The Technology Acceptance Model (TAM) remains one of the most influential models for explaining the adoption of innovative technologies.

According to TAM, perceived usefulness (PU) and perceived ease of use (PEOU) are the two main factors influencing users' behavior in adopting technology (Davis, 1989; Ahmad et al., 2020). Perceived usefulness, in the context of smartwatches, refers to the belief that the smartwatch can improve productivity, health monitoring, and efficiency in daily life, while perceived ease of use indicates how easy the smartwatch is to learn and use (Almheiri et al., 2025).

While TAM has proven to be a good predictor of adoption in a range of technology settings, some researchers have suggested that the basic utilitarian beliefs of these models are not sufficient for adopting technologies that are highly visible and emotionally charged, such as smartwatches (Fricke et al., 2024). Recent research indicates that the uptake of smartwatches is not limited to

Corresponding author's email: mamun.mkt.just@gmail.com

functional aspects, and is strongly shaped by socio-cultural and symbolic meanings.

One of the most significant factors affecting consumer behavior towards wearable technologies is visibility, while social influence comes second. Visibility refers to how visible smartwatches are in the modern world, lifestyle, and social position, while social influence refers to how other people, peers, families, and reference groups affect technology choice (Borulu et al., 2025; Luo et al., 2025).

These factors are particularly important in collectivist societies, where social norms, peer acceptance, and status signaling (Akyel, 2025; Zhang & Tao, 2025) play a major role in consumption choices. As they gain increasing significance, however, their visibility and social influence are underrepresented in the study of smartwatch adoption, especially in the TAM studies in developing economies.

An important aspect of technology adoption decisions is economic, too. Cost is a major constraint for introducing innovative technologies, as consumers in developing countries often consider technologies based on cost and value-for-money, making cost an important criterion in evaluating innovative technologies (Attri et al., 2025).

Previous studies have consistently found that price sensitivity is far greater in emerging markets than in developed economies, where consumers are more likely to have higher purchasing power (Gupta et al., 2025; Yu, 2025). While smartwatch companies are creating cheaper options, perceptions of cost remain a factor in purchase decisions and in whether positive intentions for smartwatch use actually translate into purchase.

Bangladesh provides a highly relevant context for studying these relationships. The country has undergone rapid digital transformation, reached a high level of smartphone penetration, and demonstrated interest in wearable technologies (Rahman et al., 2025). However, smartwatch adoption is still in its infancy, and consumers face challenges tied to income, digital literacy, and social influences. These factors make Bangladesh different from most developed markets and suggest that the drivers of smartwatch adoption may differ in Bangladesh (Wu et al., 2025).

Although wearable technology is gaining academic interest, three important areas of research remain unexplored. First, previous studies on smartwatch adoption have not paid much attention to socio-cultural factors (such as visibility and social influence) that influence adoption and have focused mainly on technological factors such as usefulness and ease of use. Secondly, previous studies have not integrated technological, socio-cultural, and economic factors, leading to a fragmented understanding of smartwatch adoption behavior.

Third, most studies have focused on intention to use, and the natural assumption is that intention will automatically translate into purchase behavior without taking into account the potential mediating role of intention to use. This is especially true in price-sensitive emerging markets. This study proposes and examines an extended TAM that includes three additional factors, in addition to the original factors of perceived usefulness and perceived ease of use: visibility, social influence, and cost.

Specifically, this research examines the extent to which technological factors (PU and PEOU), socio-cultural factors (visibility and social influence), and economic factors (cost) affect consumers' intention to use smartwatches, and how that intention translates into purchase intention. The study, conducted in the context of Bangladesh, provides empirical evidence from a less explored developing economy, analyzing these relationships and developing a more holistic view of smartwatch adoption behavior.

The following are three major contributions that this study makes to the literature. First, its approach goes beyond TAM to incorporate socio-cultural and economic factors that are important for visible consumer technologies. Second, it sheds light on the process that moves from intention to use to purchase intention, which has been an underexplored aspect in smartwatch adoption studies. Third, it offers context-specific evidence regarding wearable technology adoption in Bangladesh, a nation where there is limited information available on the topic. The results have implications for marketers and policymakers interested in increasing smartwatch adoption through product positioning, social influence tactics, and pricing strategies.

LITERATURE REVIEW

Wearable Technologies and Smartwatches

Wearable technologies refer to electronic devices integrated into accessories, clothing, or body-worn products that enable continuous interaction between users and digital environments (Zhang & Wang, 2025). Wearable technologies can be grouped into different categories. Among them, smartwatches have become one of the more commercially successful products, as they integrate and miniaturize health monitoring, communication, fitness tracking, and smartphone connectivity in one wearable product (Almheiri et al., 2025).

In addition to their practical use, smartwatches have become increasingly symbolic consumption products that convey the users' lifestyle, technological sophistication, and social identity (Fricke et al., 2024). Current studies indicate that the adoption of smartwatches is a phenomenon distinct from that of older forms of information technology, owing to their functional and symbolic qualities.

Smartwatches are important for their use and convenience but also as physical status symbols, symbols of innovation, and symbols of group membership. The adoption of smartwatches is a complex matter that can be understood not only through technological analysis but also by taking into account social and economic factors.

Technology Acceptance Model and Smartwatch Adoption

The Technology Acceptance Model (TAM) remains one of the most widely applied frameworks for explaining technology adoption behavior. According to TAM, perceived usefulness (PU) and perceived ease of use (PEOU) influence users' behavioral intentions toward technology adoption (Davis, 1989). Numerous studies have confirmed the explanatory power of these constructs in wearable technology contexts (Kang & Hwang, 2022; Ghaith et al., 2025). However, the results of the TAM variables in the development of smartwatches have been rather inconsistent. Perceived usefulness has consistently been found to positively impact intention to adopt, while perceived ease of use has yielded mixed findings across studies.

However, as smartwatch technology becomes easier and more sophisticated, ease of use may become less crucial than other considerations like social recognition, visibility, and perceived value. The findings indicate that traditional TAM is probably not appropriate for fully understanding the broader decision-making processes involved in visible consumer technologies.

The Role of Visibility and Social Influence

Over recent years, socio-cultural aspects have been increasingly highlighted in smartwatch studies. Smartwatch visibility is the degree to which others can see an individual wearing a smartwatch and link it with modernity, innovativeness, and social status (Chuah et al., 2016). Social influence is the influence of peers, family members, and reference groups on consumers' decision to adopt.

Prior research has been synthesized to show that two factors, visibility and social influence, are key to publicly observable technologies. Smartwatches are not hidden away when used socially, unlike smartphones. This visibility strengthens social signaling and heightens the impact of peer influence. Wearable technology is influenced by social approval and conformity in collectivist cultures, as evidenced by consistent findings across studies conducted in these contexts, in contrast to studies conducted in individualistic societies.

Although various findings have been reported, previous studies have focused on either visibility or social influence, or treated them as additional factors alongside other variables examined, but have not yet systematically embedded these two factors in an extended TAM framework. This gives only a partial insight into the interaction of technology and social-cultural aspects in decisions not to use a smartwatch.

The Role of Cost in Purchase Decisions

Technology and social aspects are important for understanding consumers' willingness to buy smartwatches, but economic considerations may still play a role in the actual decision to purchase. Cost is consumers' perception of how easy it is to afford and/or how much they need to sacrifice to get the smartwatch (He et al., 2023). Previous research findings have consistently shown that positive attitudes and intentions of use are not always associated with purchase intentions when products are perceived as high cost.

The intention-purchase gap is particularly high in developing economies, where the importance of disposable income restrictions and price sensitivity strongly affect consumer behavior. Therefore, analyzing purchase intention alone without considering cost could be incomplete for understanding smartwatch adoption. Hence, cost is not simply another adoption antecedent, but an important economic factor affecting purchase intention.

Conceptual Framework

An analysis of the literature on smartwatch adoption shows three key gaps. First, most TAM-based studies still emphasize PUE and PEO and pay less attention to socio-cultural factors like visibility and social influence. Second, the existing literature tends to focus on technological, social, and economic aspects individually, and thereby provides disjointed explanations of smartwatch adoption behavior. Third, previous studies often equate intention to use with purchase intention without accounting for the process by which intention to use becomes intention to purchase.

To overcome these drawbacks, this research proposes an expanded TAM framework that combines technological (PU and PEO), socio-cultural (vis and soc), and economic (cost) factors in one framework. Specifically, perceived usefulness, perceived ease of use, visibility, and social influence are hypothesized to be cause variables for intention to use. In contrast, cost is hypothesized to hurt purchase intention. These hypothesized relationships are summarized in Figure 1, which is a conceptual framework.

The link between the technological and social evaluations and consumers' purchase decisions is mediated by intention to use. The study overcomes the limitations of previous TAM-based explanations and contributes to a comprehensive explanation of consumer behavior in the context of a developing economy.

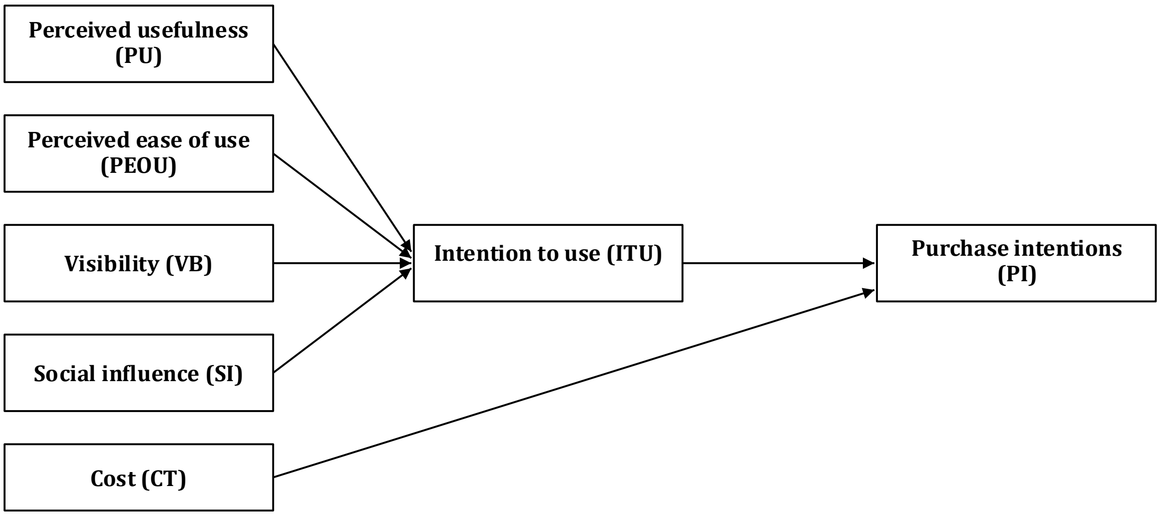

Figure 1. Conceptual framework

Hypothesis development

Perceived Usefulness (PU) and Intention to Use (ITU)

Perceived Usefulness (PU) is the construct that refers to how consumers feel that a technology will help in improving their performance, productivity, or lifestyle (Al-Emran, 2021). The empirical studies in the field of wearable technology always confirm that PU is an effective trigger of the intentions of users to wear smartwatches, as the latter are encouraged to interact with the devices that bring them tangible benefits, i.e., health monitoring, communication, and convenience (Al-Maroof et al., 2021; Saheb et al., 2022).

Under the Technology Acceptance Model (TAM) and its extensions based on the Theory of Planned Behavior (TPB), PU is a key antecedent of behavioral intention toward technology adoption (Ghaith et al., 2025; Zin et al., 2023). The ability to evaluate technology adoption carefully on the functional utility basis makes consumers in emerging economies like Bangladesh especially sensitive to PU when it comes to their adoption intentions (Arpaci et al., 2021).

H1: Perceived Usefulness positively influences Intention to Use smartwatches.

Perceived Ease of Use (PEOU) and Intention to Use (ITU)

PEOU is the degree to which consumers feel that the use of technology is easy (Davis, 1989; Dutot et al., 2019). PEOU, as it applies to the smartwatch concept, involves interface ease, a smooth connection with mobile devices, and easy-to-use functionality (Saheb et al., 2022). It has also been found that highly beneficial technology can face a low adoption rate when seen as complicated or hard to use (Ghaith et al., 2025).

The TAM literature also demonstrates that PEOU not only has a direct positive effect on intention to use but also an indirect positive strengthening effect on perceived usefulness, thus resulting in adoption (Zin et al., 2023). PEOU, a very important consumer-engaging tool, is a vital facilitator of consumer interaction in Bangladesh, particularly the younger generation (Rahman et al., 2025; Sabbir et al., 2020).

H2: Perceived Ease of Use positively influences Intention to Use smartwatches.

Visibility (VB) and Intention to Use (ITU)

Visibility (VB) entails the conspicuousness of a technology in an individual's social environment (Almuraqab, 2021). In wearable technology, the activation of visibility is a decisional factor in adoption due to the perception of desirability, perceived social acceptance, and social approval that emerge when others wear smartwatches (Chuah et al., 2016).

It is theorized that elevated product visibility provokes initial adopters to develop a positive social perception of the product and strengthens normative expectations (Fricke et al., 2024). Youth of Bangladesh are also highly responsive to social and peer cues and therefore make visibility a primary factor in influencing behavioral intent towards smartwatches (Gumasing et al., 2024).
H3: Visibility positively influences Intention to use smartwatches.

Social Influence (SI) and Intention to Use (ITU)

Social Influence (SI) summarizes the effect of family, friends, and peers on a person's technology adoption process (Almheiri et al., 2025). For example, Almuraqab (2021) shows that peers' views and social endorsement significantly influence the decision to buy a smartwatch. Similarly, Usman et al. (2025) point out that social pressure and peer influence are important factors in determining how consumers react to digital payment systems, especially in new market environments.

Research on wearable technology indicates that recommendations, peer usage, and endorsements significantly influence the intention to wear a smartwatch (Gumasing et al., 2024). This effect is especially pronounced in collectivist societies and emerging markets, where social approval is the most important aspect of technology adoption (Dwivedi et al., 2021).
H4: Social Influence positively influences Intention to Use smartwatches.

Cost (CT) and Purchase Intention (PI)

Cost (CT) refers to the financial loss that must be made to obtain a technology and is a key factor that drives a purchasing decision (Zhu et al., 2023). Price is one of the fundamental elements of perceived value, which reflects functional benefits and brand-related cues in consumers' minds (Ramkumar & Liang, 2020).

In the case of a smartwatch, a perceived high price may become an obstacle even when usefulness and social visibility are very high (Almheiri et al., 2025). This is heightened in emerging economies, where budget constraints increase value consciousness. Empirical research also shows that perceived cost negatively affects purchase intention by reducing the net value of high-tech features (Uzir et al., 2021).
H5: Cost negatively influences purchase intention for smartwatches.

Intention to Use (ITU) and Purchase Intention (PI)

Intention to Use (ITU) is the motivational state of a user to use a technology, and it is a major predictor of actual purchase behavior (Davis, 1989). ITU reflects consumers' willingness and intention to use smartwatches and counteracts the impact of antecedents (PU, PEOU, visibility, social influence) on actual purchase intention in the context of wearable devices (Almheiri et al., 2025). It was confirmed that ITU is a strong predictor of purchase intention because users who have high PI are more inclined to invest in the device (Chuah et al., 2016; Dwivedi et al., 2021).
H6: Intention to Use positively influences Purchase Intention of smartwatches.

RESEARCH METHOD

Research Design

The study employed quantitative and cross-sectional survey methodology to analyze the factors influencing the intention to purchase a smartwatch among consumers in Bangladesh. A quantitative approach was deemed suitable because the study tested theoretically derived hypotheses and investigated relationships among multiple latent constructs through statistical analysis. The cross-sectional design allowed for data collection from a wide range of respondents at one point in time, making it appropriate to test consumer perceptions and intentions to adopt smartwatch technology.

A structured questionnaire comprising two parts was used to collect data. Demographic information and the study constructs (perceived usefulness, perceived ease of use, visibility, social influence, intention to use, cost, and purchase intention) were captured in the first and second sections, respectively. The content validity and construct reliability of all the measurement items were adapted from previously validated scales.

The questionnaire was translated from English to Bengali using back-translation, in which bilingual experts translated the instrument twice. A pre-test pilot test was administered to 20 participants, who wore a smartwatch to evaluate item clarity, readability, and context. After receiving feedback from the participants, slight wording changes were made prior to survey administration.

Measurement and Scaling

All latent constructs were operationalized through existing measures relevant to consumers' purchase intention for smartwatches. Participants' responses were recorded on a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), a commonly used approach in behavioral research to assess attitudes and perceptions.

The items to be measured were modified based on the validated scales to be adjusted to the smartwatch setting: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) in Ghaith et al. (2025) which are consistent with the Technology Acceptance Model (TAM); Visibility (VB) in Chuah et al. (2016); Social Influence (SI) in Almheiri et al. (2025), Cost (CT) in Almuraqab et al. (2021); Intention to Use (ITU) in Almuraqab et al. (2021) and Purchase Intention in Chuah et al. (2016).

The use of validated measures improves construct validity and allows for comparison with previous smartwatch adoption research. Appendices 1 and 2 include details of the measurement items and sources.

Source of the Data and Target Population

Sample and Data Collection

Information was gathered through a mixed online and paper survey to be administered between October and November 2025 in Bangladesh. The final sample comprised 406 valid responses from a diverse group including university students, working professionals, and entrepreneurs.

Demographic Profile

Table 1 indicates that 57.9% of the respondents were male while 42.1% were female. The majority (86.0%) were aged 21–30 years. Of these, most were Muslims (91.9%) and had undergraduate education (60.3%). The largest number of respondents were employed (39.7%) and students (38.4%) in terms of occupation. The respondents' economic background was fairly balanced among the three income groups, suggesting a diverse distribution.

Table 1. Demographic Profile

Attributes	Characteristics	Frequency	Percentage
Gender	Male	235	57.9
	Female	171	42.1
Age	Below 20 years	12	3.0
	21-25 years	175	43.1
	26-30 years	174	42.9

	31-35 years	45	11.1
Religion	Islam	373	91.9
	Hindu	33	8.1
	Others	0	0
Educational Qualification	SSC	16	3.9
	HSC	105	25.9
	Undergraduate	245	60.3
	Masters	40	9.9
Occupation	Student	156	38.4
	Employed	161	39.7
	Self-employed	71	17.5
	Other	18	4.4
Monthly Income	Less than BDT 10,000	139	34.2
	BDT 10,001-25,000	129	31.8
	BDT 25,001-40,000	138	34.0
	Above BDT 40000	0	0

Sampling Technique

The researcher used a non-probability purposive sampling method to identify respondents in Bangladesh who were current or potential users of smartwatches. Purposive sampling was considered the most suitable because it allows selecting participants intentionally based on their knowledge, experience, and behavioral characteristics that fit the goals of the research (Malhotra, 2020).

The sample comprised university students and young professionals, who constitute a significant percentage of technology adopters and smartwatch users in Bangladesh. This also allowed efficient access to the respondents of interest and lowered the time and data collection costs. G*Power 3.1 (Figure 2) was utilized to determine the minimal sample size required to ascertain the statistical power necessary for conducting PLS-SEM analysis (Faul et al., 2007).

The software indicated that the minimum requisite number of participants was 146, with an effect size of f^2 = 0.15, alpha = 0.05, power = 0.95, and eight predictors. Not only did our investigation go beyond this standard, validating 406 responses and thus adding to the accuracy and relevance of the estimates (Hair Jr et al., 2021), but it also intelligently utilized a purposive sampling scheme to ensure that the data were obtained only among reliable and contextually appropriate subjects (Rather & Hollebeek, 2021).

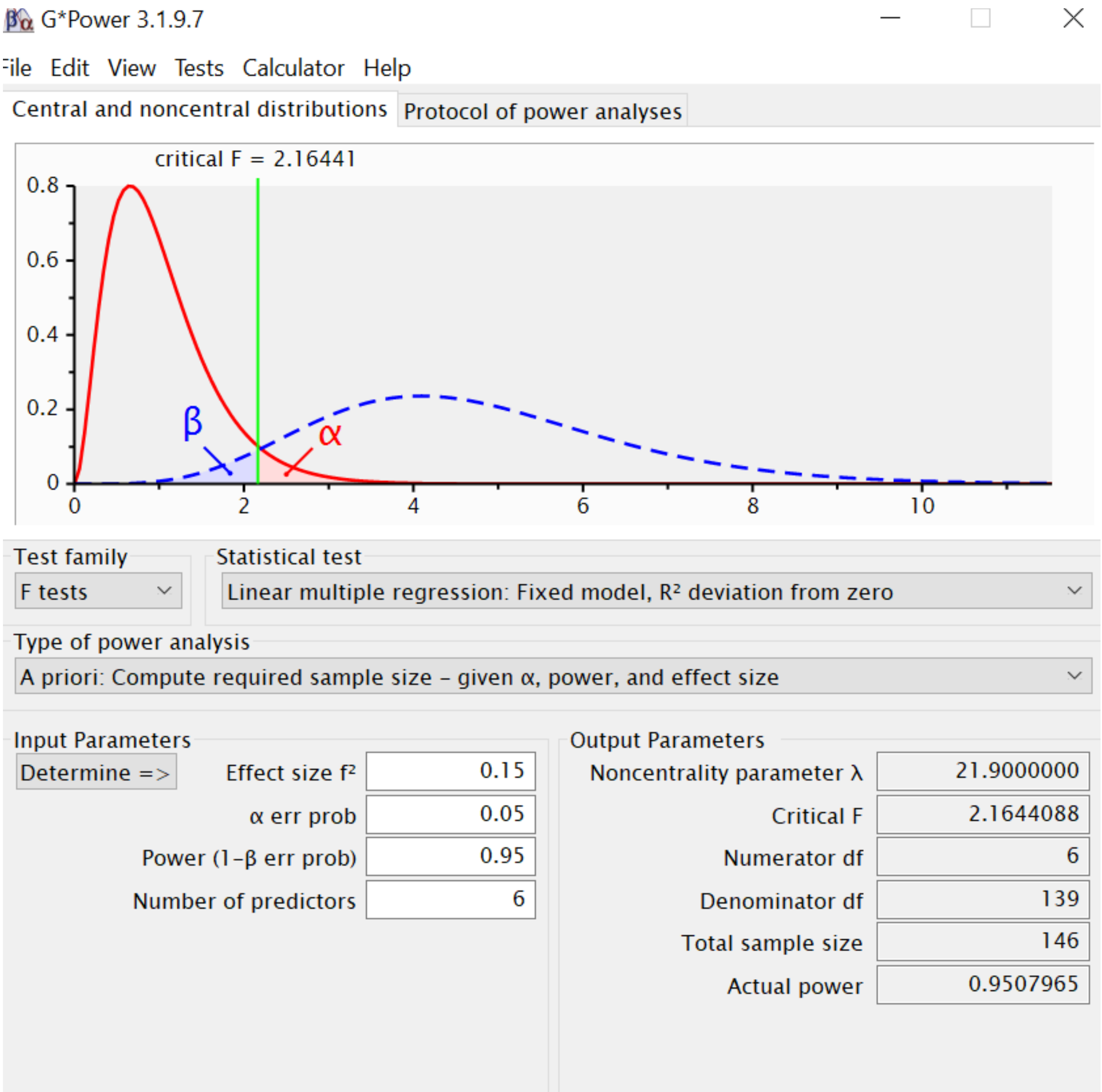

Figure 2. G*power Analysis

Ethical Considerations

The study adheres to the ethical standards of social science studies. There was no compulsion for participation, and respondents were made aware of the purpose of the study before completing the questionnaire. Collecting personally identifiable information was avoided; all responses were kept confidential and used only for academic purposes. Respondents could withdraw from the survey at any point without repercussion.

FINDINGS AND DISCUSSION

Measurement Model Assessment

Construct Reliability and Validity

The measurement model results are shown in Table X. All indicator loadings were above the recommended 0.70 threshold, ranging from 0.726 to 0.994, indicating good indicator reliability. The three items (PU1 (0.766), VIS1 (0.726), and ITU3 (0.741)) were slightly lower than the other items but still above the acceptable level and were kept. Internal consistency reliability was also tested, and the results showed Cronbach's alpha values between 0.749 and 0.921, which were above the required level of 0.70.

Likewise, the rho-A scores ranged from 0.810 to 0.930, with strong construct reliability. Convergent validity was also proven, with all Average Variance Extracted (AVE) values being more than 0.5, ranging from 0.601 to 0.865. Purchase Intention had the best AVE (0.865), indicating excellent explanatory power. Variance Inflation Factor (VIF) was used to test for multicollinearity—no collinearity concerns, as all the VIF values were less than 5.0.

The overall results indicate acceptable indicator reliability, internal consistency, convergent validity, and acceptable multicollinearity, thereby supporting the appropriateness of the constructs for further analysis of the structural model.

Table 2. Factor Loadings, Reliability, Validity, and Multicollinearity diagnostics

Latent Variable	Item Description	Outer loadings	Cronbach's Alpha	rho_a	AVE	VIF
Perceived	PU1	0.766				1.442
usefulness	PU2	0.932	0.774	0.915	0.683	2.091
	PU3	0.772				1.732
Perceived	PEOU1	0.799				1.543
Ease of Use	PEOU2	0.838	0.793	0.914	0.601	1.417
	PEOU3	0.780				1.928
Visibility	VIS1	0.726				1.726
	VIS2	0.994	0.907	.852	0.835	2.610
	VIS3	0.994				1.516
Social	SI1	0.866				2.610
influence	SI2	0.903	0.823	0.828	0.655	3.111
	SI3	0.794				1.536
Cost	CT1	0.972				3.902
	CT2	0.767	0.871	0.910	0.789	2.875
	CT3	0.914				3.746
Intention to	ITU1	0.832				2.249
use	ITU2	0.836	0.749	0.810	0.648	1.257
	ITU3	0.741				2.018
Purchase	PI1	0.963				3.078
Intention	PI2	0.936	0.921	0.930	0.865	3.869
	PI3	0.889				2.575

Discriminant Validity

The Heterotrait -Monotrait ratio (HTMT) and Fornell-Larcker criterion were used to evaluate the discriminant validity of the measurement model. The values of all HTMTs were lower than 0.85 (See Table 3), indicating sufficient discriminant validity and that the constructs capture conceptually different constructs (Sarstedt et al., 2020).

In addition to this, the Fornell–Larcker criterion showed that the square root of the AVE of each construct was greater than the correlations to any other construct (see Table 4), which was within the recommended criterion (Hair et al., 2017). As a result, the measurement model will achieve an acceptable level of discriminant validity.

Table 3. Discriminant Validity-Heterotrait-Monotrait Ratio (HTMT) Matrix

	CT	ITU	PEOU	PI	PU	SI	VIS
CT							

ITU	0.484					
PEOU	0.178	0.164				
PI	0.435	0.673	0.163			
PU	0.195	0.186	0.825	0.159		
SI	0.826	0.682	0.156	0.522	0.150	
VIS	0.259	0.246	0.440	0.111	0.520	0.165

Note(s): CT = Cost, ITU = Intention to Use, PEOU = Perceived Ease of Use, PI = Purchase Intention, PU = Perceived Usefulness, SI = Social Influence, VIS = Visibility.

Table 4. Discriminant Validity- Fornell–Larcker Criterion

	CT	ITU	PEOU	PI	PU	SI	VIS
CT	0.888						
ITU	0.435	0.805					
PEOU	0.124	0.169	0.775				
PI	0.416	0.644	0.156	0.930			
PU	0.087	0.170	0.716	0.142	0.827		
SI	0.801	0.572	0.098	0.456	0.050	0.810	
VIS	0.218	-0.087	0.345	0.097	0.412	0.141	0.914

Note(s): CT = Cost, ITU = Intention to Use, PEOU = Perceived Ease of Use, PI = Purchase Intention, PU = Perceived Usefulness, SI = Social Influence, VIS = Visibility.

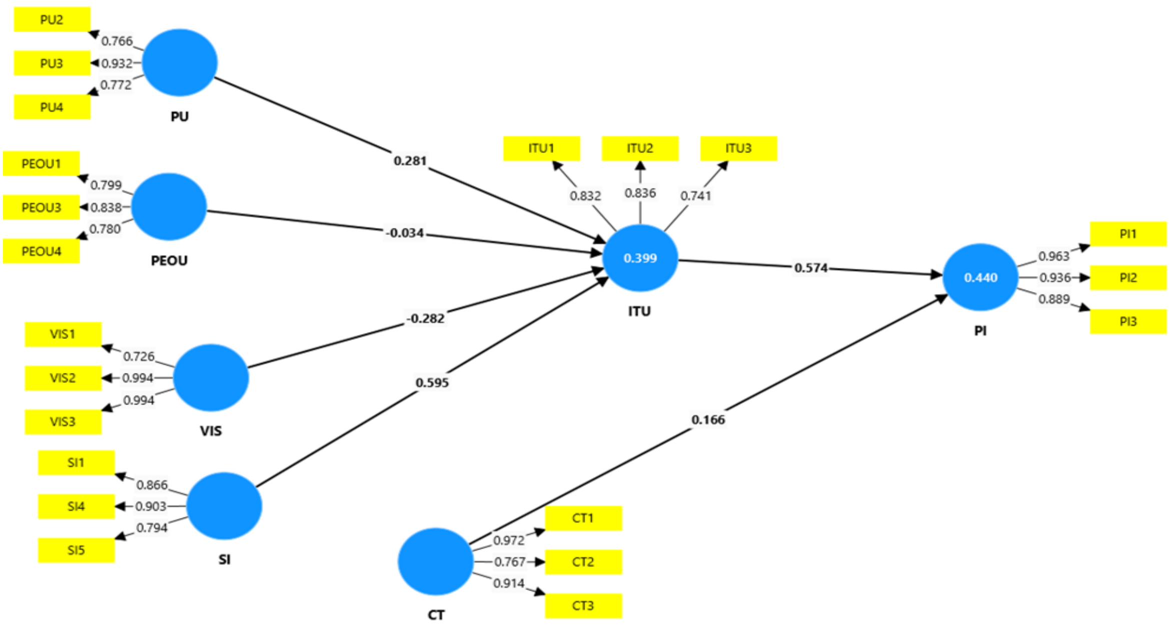

Figure 3. Output Model 1 (PLS)

Source: Author-generated figure from survey data utilizing SmartPLS4

Common Method Bias or Variance

The common method bias (CMB) was examined in a two-step process. First, the single-factor test showed that the first factor explained 26.53% of variance, which is significantly lower than the 50% mark, indicating that there is no significant CMB (Podsakoff et al., 2003). Second, a detailed collinearity test with VIF values using a dummy variable, as suggested by Kock (2015), demonstrated that all VIFs were below 3.30 (see Table 5), indicating that CMB does not threaten the integrity of the model.

Table 5. Full collinearity test (VIF) to examine common method bias

		VIF
CT	-> PI	1.233
ITU	-> PI	1.233
PEOU	-> ITU	2.078
PU	-> ITU	2.199
SI	-> ITU	1.027
VIS	-> ITU	1.231

Note(s): CT = Cost, ITU = Intention to Use, PEOU = Perceived Ease of Use, PI = Purchase Intention, PU = Perceived Usefulness, SI = Social Influence, VIS = Visibility.
Source: Author-generated table from survey data utilizing SmartPLS4

Structural Model Estimation

Coefficient of determination (R^2) & Q- square assessment

The coefficient of determination (R^2) was used to evaluate the explanatory power of the structural model. The results show that Intention to Use (ITU) has an R^2 value of 0.410 (R^2_adj = 0.404). In contrast, Purchase Intention (PI) has an R^2 value of 0.438 (R^2_adj = 0.435), indicating moderate explanatory power and that the exogenous constructs explain a good portion of the variance of the endogenous constructs (Hair Jr et al., 2021).

In addition, the model's predictability was assessed using Q^2_predict, RMSE, and MAE. The positive values of Q^2_predict for ITU (0.007) and PI (0.060) indicate that the model has good out-of-sample predictive ability and can well predict respondents' behavioral and purchase intentions.

Table 6. Coefficient of Determination R-square

	R-square	R-square Adjusted
ITU	0.410	0.404
PI	0.438	0.435

Note(s) : ITU=Intention to Use, PI=Purchase Intention.
Source: Author-generated table from survey data utilizing SmartPLS4

Table 7. Q- square Predict

	Q^2predict	RMSE	MAE
ITU	0.007	1.034	0.501
PI	0.060	0.999	0.463

Note(s) : ITU=Intention to Use, PI=Purchase Intention.
Source: Author-generated table from survey data utilizing SmartPLS4

Structural Model Estimations: Hypothesized Direct Effects

The results of the structural model are provided in Table 8. Perceived Usefulness (PU) had a sizable positive impact on Intention to Use ($\beta = 0.284$, $t = 3.087$, $p = 0.002$), thus substantiating H1. Conversely, Perceived Ease of Use (PEOU) did not produce a statistically significant effect on ITU ($\beta = 0.049$, $t = 0.548$, $p = 0.584$), and thus H2 was rejected (See Figure 4). Visibility (VIS) had a positive impact on ITU ($\beta = 0.279$, $t = 2.083$, $p = 0.037$), and Social Influence (SI) had a significant positive effect on ITU ($\beta = 0.595$, $t = 8.203$, $p < 0.001$), which proved H3 and H4, respectively.

Cost (CT) had a positive impact on Purchase Intention (PI) ($\beta = 0.167$, $t = 2.177$, $p = 0.030$), thus supporting H5, and ITU had a strong positive impact on PI ($\beta = 0.572$, $t = 8.951$, $p < 0.001$). Therefore, supporting H6. All of these findings imply that PU, visibility, and social influence have a major influence on intention, and intention and cost have a significant impact on purchase behavior.

Table 8. Results of Hypothesis Testing via Bootstrapping

Hypothesis and relationship	β	STDEV	T	Bias-corrected confidence intervals 2.5%	Bias-corrected confidence intervals 97.5%	P values	Decision
H1: PU->ITU	0.284	0.092	3.087	0.126	0.417	0.002	Supported
H2: PEOU -> ITU	0.049	0.089	0.548	-0.126	0.215	0.584	Not Supported
H3: VIS -> ITU	0.279	0.134	2.083	0.012	0.466	0.037	Supported
H4: SI -> ITU	0.595	0.073	8.203	0.420	0.715	0.000	Supported
H5: CT -> PI	0.167	0.077	2.177	0.015	0.314	0.030	Supported
H6: ITU -> PI	0.572	0.064	8.951	0.440	0.689	0.000	Supported

Note(s): CT = Cost, ITU = Intention to Use, PEOU = Perceived Ease of Use, PI = Purchase Intention, PU = Perceived Usefulness, SI = Social Influence, VIS = Visibility.

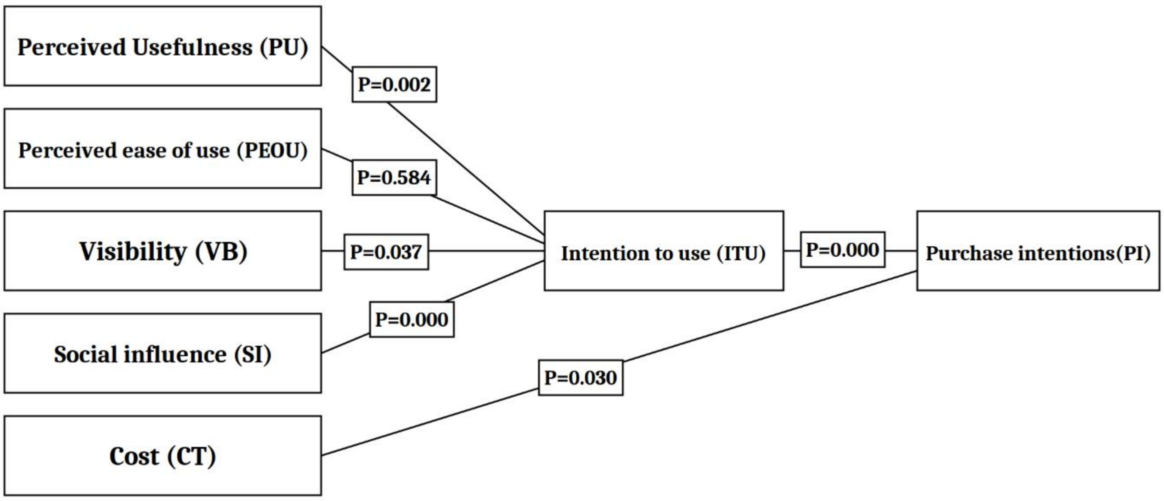

Figure 4. Author-Generated Output Model

Source: Author-generated table from survey data utilizing SmartPLS4

Discussion

The findings help explain smartwatch adoption behavior in Bangladesh, focusing on technological, social, and economic influences. In line with the basic TAM model, Perceived Usefulness (PU) positively and significantly influenced Intention to Use (ITU) as predicted in Hypothesis 1. This is consistent with Davis (1989), who found perceived usefulness to be the most important factor affecting technology acceptance, and with Chuah et al. (2016) and Al-Maroof et al. (2021), who found that perceived usefulness was important in the context of smartwatches.

This has been confirmed more recently by Almheiri et al. (2025) and Ghaith et al. (2025) across various cultural settings. As a developing country, smartwatches are expensive for consumers in Bangladesh relative to their average income, and consumers tend to emphasize the technology's functional and practical value to justify the investment (also seen by Sabbir et al., 2020, in their study on Bangladesh). This highlights the timeless nature of TAM and the importance of valuing technology in the developing world.

Based on the original premise of TAM (Davis, 1989), that PEOU would significantly affect ITU, Hypothesis 2 was rejected because it was not found to be true. This is not new, however. PEOU tends to diminish as technology becomes familiar (Marangunić & Granić, 2015), and ease of use was found to be less influential than usefulness in the context of smartwatch adoption (Al-Emran, 2021).

In Bangladesh, with the high penetration of smartphones (Sabbir et al., 2020), ease of use may not be a differentiator, as users might already have a certain level of digital literacy to use smartwatch user interfaces. A study spanning several countries came to a similar conclusion (Dutot et al., 2019). This indicates that, for today's digitally capable consumers, the functions provided by the technology and the social relevance are more important than its ease of use, adding to the growing evidence that the explanatory value of PEOU decreases as wearable technologies evolve.

The variable of visibility (VIS) was found to be a significant predictor of ITU in support of Hypothesis 3. This aligns with the first systematic identification of visibility as a driver of smartwatch adoption by Chuah et al. (2016), and with Sekardhani and Song (2022), who established its relevance for smartwatch adoption in both South Korea and Indonesia. Smartwatches are worn on the body, embodying and symbolizing modernity and social status, a symbolic consumption sheen also found by Ramkumar and Liang (2020) and Borulu et al. (2025). This study adds to the current literature by establishing that image-related and symbolic considerations are important factors in the adoption process, in the context of an emerging market like Bangladesh.

Social Influence (SI) had the most significant influence on ITU and thus supported Hypothesis 4. It is consistent with the Theory of Planned Behavior (Ajzen, 1991), which recognized subjective norms as an important factor in behavior prediction, and with Chuah et al. (2016) and Dutot et al. (2019), who found that social influence is significant cross-culturally in the adoption of smartwatches. Peer recommendations and exposure to social media also seem to have a strong influence on consumer perceptions in Bangladesh, where society is collectivist.

The findings in the Philippines were similar, as reported by Gumasing et al. (2024), and herding and social validation were identified as important technology adoption mechanisms by Luo et al. (2025). This validates that technology adoption is not only an individual cognitive process, but also a social one, and that peer influence in developing market settings is thus particularly important.

The direction of the coefficient for the Cost (CT) is reversed, hence the positive sign. The finding, therefore, is in line with what is anticipated theoretically: lower perceived costs are associated with higher purchase intention. The finding is also consistent with Ramkumar and Liang (2020) and Almuraqab (2021), who identified cost as one of the major obstacles to the adoption of smartwatches, especially among budget-conscious consumers in developing markets. ITU showed a significant prediction for Purchase Intention (PI), as predicted in Hypothesis 6.

Remarkably, the vast majority of purchase intention. Unlike the prior studies which considered usage intention as the final result (Dutot et al., 2019; Chuah et al., 2016), the present study added a step between the intention and the actual result, namely financial constraints, especially in the context of developing economies, where the intention does not necessarily lead to immediate transactions (Rahman et al., 2025; Sabbir et al., 2020).

Theoretical Implications

The contributions of this study to the technology adoption literature are in a few ways. First, it shows that the explanatory power of the TAM is greatly enhanced when it is extended with socio-cultural and economic factors in the context of wearable technologies. The current results show that social and symbolic factors are also important for smartwatch uptake, while previously, TAM only accounted for cognitive assessments.

Second, the lack of significance of PEOU may indicate that the dimensions of TAM are not equally important across different levels of technology maturity and user experience. The discovery adds to the controversy over the diminishing importance of ease of use in current technology adoption studies. Third, the salience and impact of visibility and social influence suggest that wearable technologies ought to be considered not simply as information technologies but also as socially visible consumption products.

This view combines technology adoption theory and consumer behavior theory with social identity theory. Finally, the study distinguishes between intention to use and purchase intention, arguing that consumers may be willing to use a technology without a definitive intention to buy it, especially in developing economies where economic factors influence purchase decisions.

Managerial Implications

The results provide several helpful takeaways for smartwatch manufacturers and marketers in developing economies. First, companies, when promoting the adoption of smartwatches, should focus on the functional benefits of the smartwatch, particularly health monitoring, fitness tracking, and productivity enhancement, which are most likely to influence intention to adopt the product. Marketing messages should focus on the product's practical, achievable advantages, not just its technical features.

Second, the presence of social influence as the strongest predictor of intention to use signals a call to action for marketing strategies to use peer-driven marketing channels to foster community endorsement and social proof through influencer marketing, user-generated content, and referral programs. Third, smartwatches need to be marketed as a sign of modern living and innovation, as it is crucial to their visibility. Consumers' social value of ownership can be reinforced by lifestyle branding which emphasizes visible, status-increasing attributes of the product.

Last, pricing strategies should take into consideration the affordability constraints of consumers in developing markets. Easy payment options and installment plans, combined with low-cost product variations, can reduce financial pressure and help turn positive usage intentions into purchases.

CONCLUSIONS

The current research extends the original Technology Acceptance Model (TAM) by introducing social and economic factors to explore smartwatch adoption in Bangladesh. The results show that perceived usefulness continues to play a significant role in the intention to use. However, the effect of social influence and visibility is more pronounced on the consumers' adoption decisions.

This implies that not only the functional but also the social meaning of smart watches as status and modernity indicators is important. The study also emphasizes the need to differentiate intention to use and intention to purchase and proves that customers' final purchase decision remains influenced by economic factors. Theoretically, the results show that the traditional TAM can be reinforced by integrating socio-cultural and economic factors.

In practice, marketers should focus on making the product more useful, using digital marketing and influencers to build social influence, and offering reasonable prices to promote adoption. In summary, this research can help to enhance the understanding of the adoption of wearable technology in developing economies and offer insights for researchers and practitioners.

LIMITATION & FURTHER RESEARCH

The study has some limitations that should be taken into account when interpreting the results. The results of the study may not be representative of the general population of Bangladesh, due to purposive sampling and the fact that the sample respondents were young, educated, and technology-oriented. While this group is an important user segment, future studies could use probability sampling and be wider in scope to better cover older adults, rural users, and those who are not digitally involved, to generalize findings to the broader population of smartwatch users.

Second, the cross-sectional design is measurement-based, and it is not possible to make causal inferences or to track consumer adoption behavior over time. Longitudinal studies might be considered in the future to explore the progression from intention to use, to purchase, and to subsequent use. Third, the extended TAM successfully merges the technological, social, and economic aspects. However, factors such as privacy concerns, data security perceptions, health consciousness, brand trust, hedonic motivation, and lifestyle compatibility were not investigated.

Considering these factors might give a better understanding of smartwatch adoption behavior. Lastly, the impact of visibility and social influence seen in this study could be attributed to Bangladesh's collectivist society. Comparative studies in collectivist and individualist cultures in the future would help clarify whether these relationships are context-dependent or universal. This research could make a significant contribution towards understanding the adoption of wearable technologies in various socio-cultural settings.

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