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Navigating the Trade-Off: An Extended UTAUT2 Model for Smart Wearable Adoption Among Millennials in the Age of Personalization and Privacy Concerns

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ABSTRACT: Smart wearable technologies are becoming an integral part of daily life, yet the key factors influencing adoption decisions among consumers remain underexamined. Based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), the paper analyses smart wearable adaptation by considering the inclusion of Perceived Personalization as a fundamental advantage and Privacy Risk as a fundamental cost, with the test of Trust as the psychological process behind the personalization-privacy trade-off. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to analyze survey data obtained on 385 millennial smart wearable users. The results are partially in favor of UTAUT2. Behavioral intention is greatly increased by Effort Expectancy, Hedonic Motivation, Price Value and Social Influence but not by Performance Expectancy and Habit, which implies the possibility of functional utility being considered as a base expectation. Perceived Personalization has a positive and significant impact on behavioral intention and a positive, but not significant impact on Trust, whereas Privacy Risk has a negative impact on Trust. The model accounts 44 percent of the variation in behavioral intention. The research contributes to the literature on technology adoption by rebranding trust as an antecedent instead of a proximal factor influencing adoption in the smart wearable scenario and provides practical implications on balancing personalization and privacySmart wearable technologies are becoming an integral part of daily life, yet the key factors influencing adoption decisions among consumers remain underexamined. Based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), the paper analyses smart wearable adaptation by considering the inclusion of Perceived Personalization as a fundamental advantage and Privacy Risk as a fundamental cost, with the test of Trust as the psychological process behind the personalization-privacy trade-off. Partial Least Squares Structural Equation Modelling (PLS-SEM) was used to analyze survey data obtained on 385 millennial smart wearable users. The results are partially in favor of UTAUT2. Behavioral intention is greatly increased by Effort Expectancy, Hedonic Motivation, Price Value and Social Influence but not by Performance Expectancy and Habit, which implies the possibility of functional utility being considered as a base expectation. Perceived Personalization has a positive and significant impact on behavioral intention and a positive, but not significant impact on Trust, whereas Privacy Risk has a negative impact on Trust. The model accounts 44 percent of the variation in behavioral intention. The research contributes to the literature on technology adoption by

rebranding trust as an antecedent instead of a proximal factor influencing adoption in the smart wearable scenario and provides practical implications on balancing personalization and privacy

1. INTRODUCTION

The spread of smart wearable technologies, including smartwatches, fitness trackers, and emerging types of form factors, including smart rings and glasses, has fundamentally changed the way people are engaging with digital ecosystems (Ferreira et al., 2021). These gadgets are able to collect, process, and personalize health, activity, communication, and lifestyle data in real time, making them the confluence of the Internet of Things (IoT), artificial intelligence, and mobile computing (Liverani et al., 2021). The use of smart wearables has increased at a very fast pace globally due to the improved effect of sensor accuracy, data analytics, and integration of the platform. Nevertheless, the uneven user adoption is still prevalent even at the stage of the widespread diffusion and depends on the complicated relationship of technological benefits, experience value, and perceived risks (Su et al., 2024). Awareness of the factors that determine the use of smart wearables is hence theoretically important and practically important (Pancar & Ozkan Yildirim, 2023).

Millennials are one of the most vital user groups in terms of smart wearable adoption (Shamsi, 2023). Being digital natives, millennials are very accustomed to mobile and connected technologies, have an open attitude to innovation, and interact with personalized digital services (Adebesin & Mwalugha, 2020). Meanwhile, they are growing conscious of the dangers of privacy invasion and information insecurity related to constant surveillance technologies (Kokolakis, 2017). This dualism orientation that puts the personalization benefits and privacy issues on a distinct plane makes millennial adoption decisions particularly difficult (Awad and Krishnan, 2006). Although current literature has done a lot in studying technology acceptance in the light of the prevailing theoretical frameworks, there has been little focus on the cognitive and psychological process of millennials to deal with the personalization-privacy trade-off that is inherent in smart wearable devices.

One of the strongest theories that explain the adoption of technology among consumers has become the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2012). As an expansion of the original UTAUT framework, UTAUT2 includes both consumer-specific constructs like Hedonic Motivation, Price Value, and Habit, as well as the traditional predictors like Performance Expectancy, Effort Expectancy and Social Influence (Venkatesh et al., 2012). The model has been extensively used in mobile payments, e-commerce, health technologies, and wearable devices (Tamilmani et al., 2021). However, the critics state that UTAUT2 is a powerful one, but it does not specify the most important psychological and contextual mechanisms, which are becoming more and more relevant in technologies based on data-intensive technologies, especially the problems of personalization and privacy (Lunney et al., 2016).

There are two fundamental differences between smart wearables and many of the previous consumer technologies (Wang et al., 2023). First, they are highly personalized, i.e. their value proposition rests upon the idea of personalizing feedback, recommendations, and insights based on ongoing, personal data streams. Second, this customization cannot be discussed outside of increased privacy risks because wearables regularly gather sensitive physiological, behavioral, and, in some cases, location-related information (Banerjee, 2019). These properties imply that adoption choices cannot be fully described using utilitarian and hedonic assessments, but a wider adoption calculus where users balance perceived benefits with perceived risks. The recent literature tends to think of technology adoption as a benefit-cost analysis procedure, especially when it comes to the use of personal data (Plester et al., 2024). In this sense, Perceived Personalization is one of the advantages that help to increase relevance, enjoyment, and perceived usefulness of smart wearables (Tuch et al., 2010). Personalization has been found to enhance user satisfaction, engagement and continuance intention on digital platforms (Sundar and Marathe, 2010). Personalized health insights, adaptive interfaces, and personalized notifications will go a long way toward increasing perceived value in the case of wearables (Ferreira et al., 2021). Nevertheless, personalization is a process that is necessarily tied to the large volume of data gathering, which also contributes to the increasing fear of surveillance, abuse, and loss of control among users (Acquisti et al., 2015).

Privacy Risk, on the other hand, reflects the perceptions of users of the risks that might be caused by data collection, storage, and sharing (Jakobi et al., 2022). Previous studies show that privacy issues may hinder the adoption of technology especially when the information is sensitive, or the information is being recorded continuously (Dinev and Hart, 2006). The risk of privacy is compounded in the case of smart wearables because the data is intimate and longitudinal (Sivakumar et al., 2024). Nonetheless, the existing empirical evidence on the importance of privacy in wearing wearable has been inconclusive, with some studies showing significant deterrent effects and some showing that users can accept privacy risks in exchange of functionality or experiences.

To address this seeming contradiction, researchers are focusing on Trust as one of the key psychological processes of technology adoption more and more (Choung et al., 2023). Trust indicates the opinions of users that technology providers will behave in a competent, ethical, and responsible way when dealing with personal data (Mayer et al., 1995). Theoretically, trust has the potential to decrease perceived uncertainty and risk and thus lead to adoption even when dealing with privacy sensitive situations (Gefen et al., 2003). Previous research on e-commerce, mobile services, and health technologies indicates that trust usually acts as an intermediary between perceived risk and behavioural intention (Kim et al., 2008; Wang et al., 2023). However, the impact of trust on smart wearable adoption, especially among millennials, is both under-examined and empirically inconclusive.

Notably, millennials might have a different relationship to other generations with regard to the role of trust in the adoption process (Shamsi, 2023). Millennials have been raised in data-saturated online worlds, and they might develop a sort of data pragmatism, in which trust is not a direct basis of adoption decisions. Rather, experiential value, ease of use, social endorsement, and perceived personalization can have a more direct impact on behavioral intention (Misra et al., 2023). This leads to a major theoretical inquiry: Is trust a proximal determinant of adoption or is it an antecedent influenced by the benefit-risk perceptions but does not directly convert to usage intention?

It is against this background that the current study aims at expanding UTAUT2 by formally incorporating Perceived Personalization, Privacy Risk, and Trust into a single model of smart wearable adoption by millennials. In this way, the study will fill a number of gaps in the literature. First, it answers calls of the contextual enrichment of UTAUT2 by adding theoretically salient constructs to data-driven and personalized technologies. Second, it contributes to the knowledge of the personalization-privacy trade-off by not only modeling its benefit dimension but also its cost dimension at the same time. Third, it conducts an empirical test of mediating effects of trust, which explains whether trust is a significant transmission channel among personalization, privacy risk, and behavioral intention.

This study provides a complete evaluation of measurement and structural relationships by utilizing survey data gathered on 385 users of smart wearables who are millennials and analyzed with the help of the Partial Least Squares Structural Equation Modeling (PLS-SEM). The Millennial emphasis will make it relevant to a superior user base, whereas the PLS-SEM model can handle complex models and forecasting goals. Through the analysis of supported and unsupported paths, the study offers subtle information regarding which dimension of UTAUT2 is still relevant and which can be losing explanatory power in more mature and experience-based technology situations.

Overall, this paper contributes to a more context-sensitive view of the smart wearable adoption by combining UTAUT2 with personalization-privacy relations and trust. It provides a sophisticated theoretical perspective and practical support to the emerging wearable technology landscape by focusing on how a digitally savvy user makes the complex trade-off between benefits and risk.

2. REVIEW OF LITERATURE

2.1 Smart Wearable Technologies and Millennial Adoption

Smart wearable technologies can be described as sensor-enabled, body-worn devices that can constantly gather, process, and send information about physiological states, activities, and behaviors of users (Motti, 2020). Examples of common ones are smartwatches, fitness trackers, and newer form factors, including smart rings and smart glasses (Patnaik et al., 2024). Wearables, unlike other types of mobile devices, work in close physical proximity to the user and serve as always-on companions, delivering real-time feedback, customised insights, and integrating with digital platforms seamlessly (Ferreira et al., 2021). These attributes make smart wearables a unique type of consumer technology that has a functional utility, an experiential, and lifestyle value (Su et al., 2024).

The millennials form one of the biggest and most dominant user bases in the wearable technology market (Nawaz, 2020). Being digital natives, they demonstrate high technological self-efficacy and receptiveness to innovation and are aware of data-driven services. According to previous research, millennials are not just driven by practical perks, but by fun, social indicators, and customization attributes built in smart technologies. At the same time, they are already much more sensitive to the privacy of the data and online surveillance, particularly in those technologies that imply constant surveillance. The two orientation traits render millennial adoption decisions especially appropriate to study the benefit-driven and risk-driven processes in technology acceptance models.

2.2 UTAUT2 and Consumer Technology Adoption

Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) is one of the most popular frameworks of describing consumer adoption of new technological development. The extended model, based on the original UTAUT, includes additional elements of Hedonic Motivation, Price Value and Habit in order to reflect consumer-related situations (Venkatesh et al., 2012). UTAUT2 assumes that the Behavioral Intention is mostly influenced by Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Price Value, and Habit.

The use of UTAUT2 in practice has demonstrated its strength in the context of mobile services, e-commerce platforms, health technologies, and wearables, but with some contextual differences (Tamilmani et al., 2021). Some of the studies indicate that the constructs of experience and value, like Hedonic Motivation and Price Value, are especially acute in consumer technologies, but in mature or highly diffused settings, the performance-related factors might diminish. These results indicate that although UTAUT2 is a solid framework of baseline, its explanatory capacity can be advanced by incorporating constructs that reflect the emerging user issues and benefits.

2.3 Performance Expectancy and Effort Expectancy

Performance Expectancy is the level to which individuals think that the utilization of a technology will increase the task performance or productivity (Oh et al., 2009). Performance gains can be a key motivator in the initial stages of technology diffusion. The performance expectancy in the case of smart wearable usually applies to the enhanced health-monitoring, fitness-tracking, and effectiveness in coping with everyday life. Previous studies have given contradictory results on its impact, and some studies have indicated that it becomes less important as such functionalities become the norm.

Effort Expectancy, which can be described as the perceived ease of use of a technology, is a key factor that is instrumental in the context of consumer adoption (Rahi et al., 2019). Wearables need to be frequently communicated with, data analyzed, integrated and connected with other devices (Walle et al., 2023). Ease of use can greatly influence adoption intentions in the case of millennials who are more concerned with convenience and an intuitive design. Effort expectancy has always been a good predictor of behavioral intention in the context of wearable and mobile technologies studies.

Accordingly, the following hypotheses are proposed:

H1: Performance Expectancy positively influences Behavioral Intention to use smart wearables.
H2: Effort Expectancy positively influences Behavioral Intention to use smart wearables.

2.4 Social Influence and Hedonic Motivation

Social Influence is the level of perception that individuals have on how those significant people in their lives, like peers, family members, or social networks, feel they should utilize a specific technology (Joa et al., 2023). The social influence is essential in consumer and lifestyle-oriented technologies, as it defines the norms, indicates status, and makes adoption stronger because of the visibility (Adapa et al., 2018). Smart wearables tend to be socially salient, and placed in social contexts of fitness communities, so peer approval is especially relevant to millennials.

Hedonic Motivation means the enjoyment, fun, or pleasure of using a technology (Al-Azawei and Alowayr, 2020). Gamification and aesthetic design, as well as interactive interfaces are gradually integrated into wearables, turning the functional tracking into the immersive experience (Windasari and Lin, 2021). Previous studies have always emphasized hedonic motivation as a powerful predictor of behavioral intention in consumer technologies particularly in younger groups who believe in experience consumption.

On the basis of these arguments, the following hypotheses are proposed:

H3: Social Influence positively influences Behavioral Intention to use smart wearables.
H4: Hedonic Motivation positively influences Behavioral Intention to use smart wearables.

2.5 Price Value and Habit

Price Value is a cognitive trade-off that is established by consumers between the perceived advantages of a technology and its financial expense (Kowalczuk and Hof, 2025). Price value in wearable adoption shows whether or not the functional, experiential and personalization values are worth the cost of the device and the related subscription costs. There is empirical evidence indicating that price value plays a significant role in adoption, specifically when the technology is discretionary (Yang et al., 2016).

Habit is a term used to refer to the degree of habitual behavior among people who learn and repeat their actions (Gardner, 2015). When technologies are so integrated into everyday life, habit may become a strong indicator of further use (Tricas-Vidal et al., 2022). Nevertheless, even in comparatively developing markets like smart wearables, routine use habits can still be developing and thus the empirical results on the matter can be inconclusive on its influence on the intention to adopt.

Therefore, the hypotheses put forward are as follows:

H5: Price Value positively influences Behavioral Intention to use smart wearables.

H6: Habit positively influences Behavioral Intention to use smart wearables.

2.6 Perceived Personalization as a Benefit Driver

Perceived Personalization means the attitudes of users that a technology can provide content, feedback, and services to its individual preferences, behavior, and needs (Krishnaraju et al., 2016). Personalization in smart wearables can be observed in the form of customized health insights, customized recommendations, and customized notifications. Previous studies have shown that personalization improves the sense of relevance, satisfaction, and involvement, which leads to the reinforcement of behavioral intention (Aggrawal, & Pandey, 2025).

In addition to having a direct effect on adoption, personalization may establish Trust, as it indicates competence, responsiveness, and user-centric design. Users can conclude that the technology provider has benevolent intentions when they believe that the system knows who they are and adapts to them (Wu et al., 2014).

Based on this, the hypotheses are developed as follows:

H7: Perceived Personalization positively influences Behavioral Intention to use smart wearables.

H9: Perceived Personalization positively influences Trust.

2.7 Privacy Risk as a Cost Factor

Privacy Risk is an indicator that shows how people understand the possible adverse effects of collecting, storing, and using personal data (Cheng et al., 2022). Privacy risk is increased in smart wearables because sensitive physiological and behavioral data is constantly being collected (Sivakumar et al., 2024). Previous research indicates that privacy threat always reduces user trust in digital technologies and negatively affects trust in service providers (Mone and Shakhlo, 2023).

Privacy risk is also theorized to have an indirect effect on deterring adoption, rather than directly, by undermining trust, which causes a perceived uncertainty and vulnerability (Kenesei et al., 2022). This process is especially applicable to the technologies that are heavy on personalization, which cannot avoid data disclosure.

Thus, the following hypothesis is proposed:

H8: Privacy Risk negatively influences Trust.

2.8 Trust and Its Mediating Role

The trust is described as the confidence that a technology provider will behave in a competent, reliable, and ethical manner, especially when it comes to processing personal data (Asgarinia et al., 2023). Trust has been established as a key process in technology adoption (Alrawad et al., 2023), particularly when the situation is perceived to be uncertain and risky. According to the prior studies, trust has the potential to mediate the impacts of the perceived benefits and the perceived risks on the behavioral intention.

The concept of trust can be used as a psychological prism in the framework of smart wearables where users can balance the advantages of personalization with the privacy issues. When the user trusts the provider, they will accept the data collection in exchange of personal value, and vice versa, low trust will only increase the perceived risks (Chan-Olmsted et al., 2024).

In that regard, the following hypotheses are put forward:

H10: Trust positively influences Behavioral Intention to use smart wearables.

H11: Trust mediates the relationship between Privacy Risk and Behavioral Intention.

H12: Trust mediates the relationship between Perceived Personalization and Behavioral Intention.

2.9 Summary of the Conceptual Framework

This paper is based on UTAUT2 and the personalization-privacy calculus, therefore, the present study presents an integrated model, whereby behavioral intention to use smart wearables is determined by the core technology acceptance variables, perceived personalization advantages, and trust-based assessments, which depend on privacy risk. The direct and mediated relationships are tested empirically, which allows the model to contribute to a subtle comprehension of the millennial adoption of smart wearables.

2. MATERIALS AND METHODS

3.1 Research Design

The research design followed in this study is descriptive research design that employs cross-sectional survey methodology to investigate the factors that determine the adoption of smart wearables by millennials. The cross-sectional design is suitable because it allows the collection of data on a large sample at one time, which would allow analysing the relationships between latent constructs based on a well-established theory.

The proposed research framework is premised on Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and supplemented with Perceived Personalization (PP) as the benefit and Privacy Risk (PR) as the cost of the smart wearable technologies. Moreover, Trust (TR) is also placed at the center of psychological processes by which users assess the value of personalization and privacy issues. The main endogenous construct is Behavioral Intention (BI). The model looks at the direct impacts of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Hedonic Motivation (HM), Price Value (PV), Habit (HA) and Perceived Personalization (PP) on Behavioral Intention, and the impacts of Perceived Personalization and Privacy risk on Trust. Further, the mediating role of Trust in the personalization-privacy risk-behavioral intention relationships is empirically validated.

Since the model is of great complexity, predictive orientation, and mediation effects are considered, Partial Least Squares Structural Equation Modeling (PLS-SEM) was considered appropriate to analyze the data. Figure 1 shows the conceptual framework.

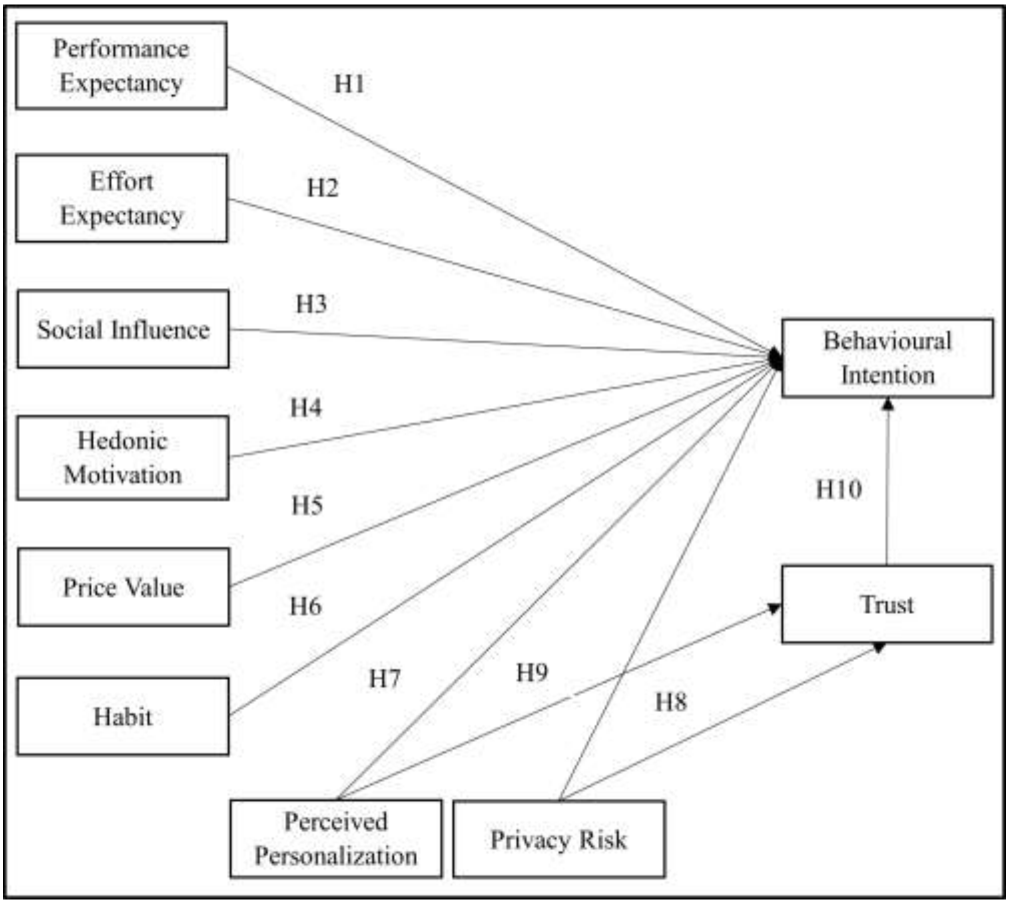

Figure 1: Proposed theoretical model; Source(s): Author's own work.

3.2 Sampling Design and Sample Characteristics

The population to be used in this study is the millennial users of smart wearable technologies living in Punjab, India. The age range of millennials was 28 to 43 years, based on the generational definitions that are usually applied when analyzing the adoption of technology. Punjab was chosen as the location of the study because it is highly urbanized, digital infrastructure is increasing, and wearable technologies are becoming more popular.

The respondents were chosen to live in four large cities of Punjab that is Amritsar, Ludhiana, Chandigarh and Jalandhar, as they are significant commercial, educational, and technological centers of the state with different and technologically advanced populations. The non-probability purposive sampling method was used to make sure that only those respondents who got previous experience using smart wearables (e.g. smartwatches or fitness trackers) were considered in the study. The 450 questionnaires were sent out through an online survey system, and 385 valid responses were retained after filtering on completeness and eligibility, which gave a satisfactory response rate. The sample size is bigger than the minimum limits that are required in the PLS-SEM analysis. The researcher recommend that the sample size must be 5-10 responses to an item. As Behavioral Intention is being fed with several predictors, the acquired sample size of 385 offers enough statistical power and strength.

The demographic profile shows a well-balanced gender distribution and well-educated respondent pool which are typical of urban millennial wearable users. The most widely used wearable device was smartwatches, and then fitness trackers, which confirms the topicality of the chosen population to the study.

3.3 Data Collection Instrument

A structured self-reported questionnaire based on already validated measurement scales in the literature on technology adoption, personalization, privacy and trust was used to collect data. Reflective measurement models were applied to operationalize all the constructs, which aligns with the UTAUT2 assumptions and previous empirical research. The questionnaire was split into two parts. The initial part was a demographic section, where gender, age, education level, and the kind of smart wearable were collected.

The second part comprised of several items that measured ten latent constructs, which included: Performance Expectancy, Effort Expectancy, Social Influence, Hedonic Motivation, Price Value, Habit, Perceived Personalization, Privacy Risk, Trust, and Behavioral Intention. All questions were answered using a five-point Likert scale, where 1 = strongly disagree and 5 = strongly agree. The objects were a little reformulated where it was required to fit in the smart wearable scenario without losing their meaning.

4. RESULTS

4.1 Demographic Characteristics

The demographic characteristics of the respondents are presented in Table 1. The final sample comprised of 385 millennial users of smart wearable technologies who live in large urban centres of Punjab, i.e. Amritsar, Ludhiana, Chandigarh, and Jalandhar. The sex distribution was quite even with 201 respondents (52.2) being females, 179 respondents (46.5) being male and 5 respondents (1.3) not specifying their gender.

The respondents were all millennials and were aged between 28 and 43 years. The participants were divided into approximately 48.8 percent between the age group of 28-35 years and 51.2 percent between the age group of 36-43 years. The urban wearable users are technologically literate, and therefore the sample was mainly highly educated, with 68.3% having a bachelor degree or above.

Regarding the use of devices, smartwatches were the most used wearable (65.7%), followed by fitness trackers (31.2%), with a low number (3.1) reporting usage of other wearables like smart rings or smart glasses. On the whole, the demographic population is quite consistent with the target audience of the study, which is an educated and tech-savvy generation of millennials.

Table 1: Respondent Demographic Profile (N=385)

Characteristic	Category	Frequency	Percentage (%)
Gender	**Female**	**201**	**52.2**
	Male	**179**	**46.5**
	Other/Prefer not to say	**5**	**1.3**
Age	**28-35 years**	**188**	**48.8**
	36-43 years	**197**	**51.2**
Education	**High School or less**	**21**	**5.5**
	Some College / Associate Degree	**102**	**26.5**
	Bachelor's Degree	**158**	**41.0**
	Master's Degree or higher	**104**	**27.0**
Primary Wearable	**Smartwatch (e.g., Apple Watch, Galaxy Watch)**	**253**	**65.7**
	Fitness Tracker (e.g., Fitbit, Garmin)	**120**	**31.2**
	Other (e.g., Smart Ring, Smart Glasses)	**12**	**3.1**

Source(s): Author's own work

4.2 Assessment of Normality and Multicollinearity

The assumptions of normality and multicollinearity were checked before the measurement and structural models were assessed. Table 2 demonstrates that values of skewness and excess kurtosis of all indicators are mostly within acceptable limits (between −0.8 and +1.4) and, therefore, there are no drastic deviations of normality. Although PLS-SEM does not impose rigid conditions on normality, these findings are also indicative of the soundness of the data.

The Multicollinearity was evaluated by the Variance Inflation Factor (VIF) values at the indicator level. The values of all VIFs were between 1.933 and 4.552, which is lower than the conservative value of 5.0, signifying the lack of problematic multicollinearity between the indicators. The findings affirm that the indicators are not overlapping and can be incorporated in the reflective measurement model.

Table 2: Examining the skewness and Kurtosis

Item indicator	Mean	Excess kurtosis	Skewness	VIF
BI1	3.821	0.153	0.128	2.433
BI2	3.821	-0.043	0.281	2.621
BI3	3.709	-0.044	0.257	2.949
EE1	3.610	0.441	0.076	3.522
EE2	3.875	-0.182	-0.025	3.825
EE3	4.008	0.079	0.181	3.070
EE4	3.984	-0.079	-0.037	3.013
HA1	4.345	-0.267	-0.288	2.707
HA2	4.034	-0.202	0.084	4.552
HA3	4.223	-0.297	0.024	4.245
HA4	4.044	0.031	0.109	3.371
HM1	4.070	0.882	-0.557	1.933
HM2	3.805	-0.113	0.226	2.296
HM3	3.683	-0.097	0.287	2.302
PE1	4.049	-0.187	-0.115	3.244
PE2	3.873	-0.088	0.277	3.127
PE3	3.777	0.033	0.302	2.756
PE4	4.125	1.418	0.085	2.790
PP1	3.917	-0.132	0.030	3.741
PP2	3.969	-0.311	0.118	3.387

PP3	3.919	-0.217	-0.014	3.914
PP4	4.013	0.048	0.201	3.824
PR1	3.717	-0.629	-0.021	3.941
PR2	4.114	-0.620	-0.047	3.749
PR3	4.026	-0.643	0.036	3.642
PR4	3.938	-0.780	0.095	3.584
PV1	4.099	-0.379	-0.193	2.950
PV2	4.208	-0.435	-0.026	4.248
PV3	4.109	-0.311	0.150	3.541
SI1	4.065	-0.291	-0.079	2.885
SI2	4.229	-0.118	0.016	3.041
SI3	4.086	0.777	-0.347	3.008
TR1	3.878	-0.024	0.154	3.016
TR2	3.977	-0.313	0.142	4.299
TR3	3.901	-0.037	0.250	4.048
TR4	4.047	-0.146	0.154	3.541

Source(s): Author's own work

4.3 Measurement Model Assessment

The measurement model reliability and validity were determined using outer loading, internal consistency reliability, convergent validity, and discriminant validity.

According to Table 3, all reflective indicators were found to have high outer loadings of 0.873 to 0.946 which is greater than the recommended 0.7. This shows that the indicators are very reliable and no items were dropped to the model. All the indicators show a high level of correlation with the latent constructs.

Table 3: Outer loading indicator score

Indicator	Outer loadings	Indicator	Outer loadings	Indicator	Outer loadings
BI1 ⟵ BI	0.892	HM1 ⟵ HM	0.882	PV1 ⟵ PV	0.916
BI2 ⟵ BI	0.909	HM2 ⟵ HM	0.874	PV2 ⟵ PV	0.946
BI3 ⟵ BI	0.917	HM3 ⟵ HM	0.886	PV3 ⟵ PV	0.925
EE1 ⟵ EE	0.913	PE1 ⟵ PE	0.905	SI1 ⟵ SI	0.907
EE2 ⟵ EE	0.916	PE2 ⟵ PE	0.894	SI2 ⟵ SI	0.921
EE3 ⟵ EE	0.902	PE3 ⟵ PE	0.873	SI3 ⟵ SI	0.926

EE4 ⟵ EE	0.902	PE4 ⟵ PE	0.901	TR1 ⟵ TR	0.890
HA1 ⟵ HA	0.875	PP1 ⟵ PP	0.913	TR2 ⟵ TR	0.933
HA2 ⟵ HA	0.937	PP2 ⟵ PP	0.911	TR3 ⟵ TR	0.930
HA3 ⟵ HA	0.929	PP3 ⟵ PP	0.919	TR4 ⟵ TR	0.909
HA4 ⟵ HA	0.905	PP4 ⟵ PP	0.925	PR1 ⟵ PR	0.924
		PR2 ⟵ PR	0.918	PR3 ⟵ PR	0.913
		PR4 ⟵ PR	0.923		

Source(s): Author's own work

Cronbachs alpha (Cα) and Composite Reliability (CR) were used to assess internal consistency reliability. Table 4 indicates that the range of Cronbach alpha values was between 0.857 and 0.939 whereas CR was between 0.867 and 0.944 which is higher than the minimum value recommended of 0.70. These findings verify high consistency of internal consistency of all the constructs.

Table 4: Construct reliability and validity analysis

Construct	**Cronbach's alpha**	**Composite reliability**	**Average variance extracted (AVE)**
BI	0.891	0.893	0.821
EE	0.929	0.933	0.825
HA	0.932	0.936	0.832
HM	0.857	0.867	0.776
PE	0.916	0.929	0.798
PP	0.937	0.939	0.841
PR	0.939	0.944	0.845
PV	0.921	0.922	0.863
SI	0.907	0.914	0.843
TR	0.936	0.938	0.838

Source(s): Author's own work

Average Variance Extracted (AVE) was used to measure convergent validity. The values of all AVE were between 0.776 and 0.863, which is significantly higher than the value of 0.50, meaning that each construct contributes a significant percentage of variance to its indicators.

The Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio were used to test the discriminant validity. Table 5 indicates that the square root of AVE of individual construct surpassed its correlations with other constructs, which met the Fornell-Larcker criteria. Also, all the HTMT values in Table 6 were less than the conservative 0.85 and the maximum of 0.703. Combined, these findings support sufficient discriminant validity and prove that the constructs are empirically different.

Table 5: Fornell- Larcker Criterion

	BI	EE	HA	HM	PE	PP	PR	PV	SI	TR
BI	0.906									
EE	0.443	0.908								
HA	0.480	0.366	0.912							
HM	0.531	0.453	0.524	0.881						
PE	0.480	0.479	0.462	0.516	0.893					
PP	0.452	0.310	0.481	0.450	0.417	0.917				
PR	-0.149	-0.023	-0.109	-0.149	0.022	-0.077	0.919			
PV	0.499	0.386	0.508	0.509	0.518	0.439	-0.111	0.929		
SI	0.536	0.468	0.479	0.624	0.581	0.485	-0.107	0.588	0.918	
TR	0.482	0.417	0.477	0.505	0.491	0.435	-0.175	0.496	0.510	0.916

Source(s): Author's own work

Table 6: Heterotrait–Monotrait (HTMT) ratio

	BI	EE	HA	HM	PE	PP	PR	PV	SI	TR
BI										
EE	0.483									
HA	0.525	0.392								
HM	0.600	0.503	0.579							
PE	0.522	0.511	0.496	0.574						
PP	0.493	0.331	0.513	0.501	0.446					
PR	0.162	0.034	0.117	0.167	0.029	0.083				
PV	0.549	0.414	0.548	0.563	0.560	0.472	0.119			
SI	0.593	0.505	0.522	0.703	0.629	0.523	0.114	0.640		
TR	0.526	0.447	0.511	0.562	0.527	0.463	0.186	0.534	0.552	

Source(s): Author's own work

4.4 Structural Model and Hypotheses Testing

To test the hypothesized construct relationships, the structural model was evaluated to test the relationship between the constructs. The significance of path coefficients was estimated using a bootstrapping process that used 5,000 resamples. Table 7 shows the results of hypotheses testing.

The results show that there is a significant positive impact of Effort Expectancy on Behavioral Intention ($\beta = 0.127$, $t = 2.331$, $p = 0.020$), which validates H1. Behavioral Intention is also positively impacted by Hedonic Motivation ($\beta = 0.146$, $t = 2.242$, $p = 0.025$), which is in favor of H3. Likewise, Price Value ($\beta = 0.115$, $t = 1.999$, $p = 0.046$) and Social Influence ($\beta = 0.120$, $t = 2.107$, $p = 0.035$) have significant positive impacts on Behavioral Intention, which supports H8 and H9, respectively.

Conversely, Behavioral Intention is not significantly affected by Performance Expectancy (β = 0.067, t = 1.190, p = 0.234) or Habit (β = 0.105, t = 1.873, p = 0.061), which rejects H4 and H2. These findings indicate that performance improvements and usage patterns might not be determining factors in smart wearable use amongst millennials yet.

Speaking of the personalization-privacy mechanism, Perceived Personalization has a strong direct impact on Behavioral Intention (β = 0.115, t = 2.216, p = 0.027) which proves the H7 hypothesis. Also, the Perceived Personalization has a significant positive impact on Trust (β = 0.424, t = 8.608, p < 0.001), which supports H6 well. Privacy Risk on the other hand has a negative correlation with Trust (β = -0.142, t = 3.187, p = 0.001) in favor of H8.

Table 7: Assessment of hypotheses

Hypothesis	Proposed relationship	Path coefficient (β)	t-statistics	P values	Comments
H1	EE → BI	0.127	2.331	0.020	Supported
H2	HA → BI	0.105	1.873	0.061	Not supported
H3	HM → BI	0.146	2.242	0.025	Supported
H4	PE → BI	0.067	1.190	0.234	Not supported
H5	PP → BI	0.115	2.216	0.027	Supported
H6	PP → TR	0.424	8.608	0.000	Supported
H7	PR → TR	-0.142	3.187	0.001	Supported
H8	PV → BI	0.115	1.999	0.046	Supported
H9	SI → BI	0.120	2.107	0.035	Supported
H10	TR → BI	0.104	1.763	0.078	Not supported

Source(s): Author's own work

Nevertheless, the relationship between Trust and Behavioral Intention is not significant (β = 0.104, t = 1.763, p = 0.078), which leads to the rejection of H10. This shows that trust is affected by personalization advantage and privacy issues but it does not directly correlate with the adoption intention in this case.

4.5 Mediation Analysis

The mediating effect of Trust was tested in the relationships between Perceived Personalization and Behavioral Intention and between Privacy Risk and Behavioral Intention. Table 8 indicates that, even though Perceived Personalization is a significant predictor of Trust, and Privacy Risk is a significant deterrent to Trust, the non-significant association between Trust and Behavioral Intention makes it impossible to establish a mediation.

Table 8: Assessment of mediation effect

Hypothesis	Mediation Path	Indirect Effect Support	Direct Effect Significance	Mediation Type	Comments
H11	PP → TR → BI	Not supported (PP → TR: β = 0.424, p < 0.001; TR → BI: β = 0.104, p = 0.078)	Significant (PP → BI: β = 0.115, p = 0.027)	No Mediation	Trust does not mediate the relationship between price perception and behavioral intention
H12	PR → TR → BI	Not supported (PR → TR: β = −0.142, p = 0.001; TR → BI: β = 0.104, p = 0.078)	Not significant (PR → BI: path not supported)	No Mediation	Trust does not mediate the relationship between perceived risk and behavioral intention

Source(s): Author's own work

In line with this, the relationship between Perceived Personalization and Behavioral Intention does not go through Trust and thus rejects H12. In the same way, Trust does not go between the relationship of Privacy Risk and Behavioral Intention thus the rejection of H11. These results suggest that the impact of personalization and privacy risk are independent but not transmitted by a trust-based mechanism.

4.6 Model Explanatory Power and Fit

The coefficient of determination (R^2) was used to test the explanatory power of the model. According to Table 9, the model has a moderate explanatory power of 44.0% (R 2 = 0.440; adjusted R^2 = 0.428) in explaining Behavioral Intention. The explanation of trust is less comprehensive as the R^2 = 0.209 (R^2 adjusted = 0.205) is mainly caused by Perceived Personalization and Privacy Risk.

Table 9: R-Square overview

	R-square	**R-square adjusted**
BI	0.440	0.428
TR	0.209	0.205

Source(s): Author's own work

Standardized root mean square Residual (SRMR) and other associated indices were used to evaluate model fit. Table 10 indicates a SRMR value of the saturated model is 0.038, which implies a good fit, and the estimated model SRMR is 0.096, which is slightly above the generally accepted 0.08 threshold. Nevertheless, this value is acceptable in PLS-SEM, especially in complicated models. The values of the Normed Fit Index (0.871-0.876) also suggest a good fit to the model.

Table 10: Model Fit

	Saturated model	**Estimated model**
SRMR	0.038	0.096
d_ULS	0.977	6.124
d_G	0.659	0.714
Chi-square	1593.438	1662.721
NFI	0.876	0.871

Source(s): Author's own work

In general, the findings indicate that the suggested model has good measurement characteristics, reasonable explanatory power, and reasonable fit, which gives it a dependable foundation on which the further discussion and interpretation can be based.

5. DISCUSSION

The current research sought to contribute to the existing knowledge on millennial adoption of smart wearable technologies through the simultaneous analysis of UTAUT2 constructs: performance expectancy, effort expectancy, social influence, hedonic motivation, price value, and habit, as well as personalization-privacy mechanisms, namely, perceived personalization, privacy risk, and trust. Although earlier studies have greatly investigated the acceptance of wearables employing conventional technology acceptance models, there has been very little focus on the duality of the personalization advantages and privacy issues in influencing acceptance intentions, especially in the Indian millennial setting.

The proposed research model proves to have a moderate explanatory power, as it explains 44.0% of the variance in the behavioral intention and 20.9% of the variance in the trust, meaning that both utilitarian and psychological aspects are significant in the formation of wearable adoption decisions (Misra et al., 2023). The results confirm effort expectancy, social influence, hedonic motivation and price value have a significant effect on the behavioral intention of millennials to adopt smart wearables (Shamsi et al., 2023).

Effort expectancy turned out to be a key predictor of behavioural intention (Niknejad et al., 2020), which explains the fact that millennials will be more willing to wear smart devices when they feel that the equipment is user-friendly and simple to use. The result is consistent with previous literature on wearable and mobile technologies, where usability and cognitive simplicity turned out to be essential factors of adoption (Lee, 2021). Since smart wearables can be used in many ways, user-friendly interfaces and compatibility with smartphones seem to make them seem less complex and promote the use of the devices.

Social influence was also reported to have a positive impact on behavioral intention (Adapa et al., 2018), which means that peers, social networks, and social trends have a strong influence on the choices made by millennials to wear wearable technologies. This finding is indicative of the socially conspicuousness of wearables, which can be used not only as health or productivity devices but also as a lifestyle and status symbol (Lee et al., 2016; Ogbanufe and Gerhart, 2022). The result aligns with the previous studies that have found the significance of normative pressure and social validation in the adoption of technology, especially in younger consumer groups (Basha et al., 2022).

Hedonic motivation proved to have the stronger positive effect on behavioral intention indicating the significance of fun, thrill, and experience in wearable adoption (Misra et al., 2023). As opposed to strictly utilitarian technologies, smart wearables have interactive capabilities, gamification, and real-time feedback that make users feel more entertained. This finding indicates that emotional involvement and pleasure can be a significant factor in addition to functional advantages in encouraging adoption (Nawi et al., 2024).

Another aspect that had a great impact on behavioral intention was price value, which suggests that millennials are very conscious of the cost-benefit trade-off with smart wearables adoption. Adoption intentions are enhanced when the perceived benefits are better than the financial cost, which includes better health monitoring, convenience, and personalization (Mathavan et al., 2024). This result supports the previous evidence that price sensitivity is one of the key factors, especially in the emerging markets.

Against all odds, the performance expectancy had no significant effect on behavioral intention. This implies that smart wearables can be viewed by millennials as an addition to their lifestyle, as opposed to being a performance-enhancing device. Considering the wearable technology maturity, functional benefits like fitness tracking or notifications can be considered as a standard feature and not a strong adoption reason.

On the same note, habit did not have a strong impact on behavioral intention meaning that wearable adoption among the millennials is not yet guided by routine or automatic patterns of usage. This observation reflects that wearables are yet to be treated as a daily necessity instead of a discretionary technology (Sandham et al., 2023).

In terms of personalization-privacy relationships, the perceived personalization had a positive direct impact on the behavioral intention, meaning that the customized insights and recommendations, as well as adaptive features, increase the willingness of users to use smart wearables. In addition, perceived personalization was a strong predictor of trust, which demonstrates the role of personalization as a trust-building process (An & Ngo, 2025).

On the other hand, the threat of privacy adversely affected trust, which proves that the fear of data abuse, monitoring, and unauthorized access are the factors that make users less confident in wearable technologies (Sivakumar et al., 2024). Nevertheless, trust was not found to have a strong effect on behavioral intention, which implies that trust although moulded by the benefits of personalization and privacy issues, does not directly affect the adoption decisions. The implication of this finding is that younger generations have a pragmatic mentality, so that decisions concerning adoption are more determined by immediate value and experience than solely by trust considerations (Yu, 2025).

6. THEORETICAL CONTRIBUTIONS

The paper makes a contribution to the literature on technology adoption and smart wearables by broadening the UTAUT2 model to capture the reality of data-intensive consumer-oriented technology. Through the addition of perceived personalization, privacy risk, and trust, the model includes value creation and risk perception mechanisms that are becoming a key focus on smart wearable adoption. These constructs further expand the scope of explanatory power of UTAUT2 beyond conventional utility-based determinants, and addresses the demand to use more context-sensitive adoption frameworks. The results also challenge the suppressed core UTAUT2 relationships. The insignificant impact of performance expectancy and habit on behavioral intention are indicative of the fact that in the example of smart wearables, operational performance and routines use can be viewed as supporting properties as opposed to a driving factor. This implies that the explanatory power of the UTAUT2 constructs is not universal in technologies, especially those that are positioned as lifestyle-enhancing and experience-oriented as opposed to productivity-oriented ones.

Moreover, the research contributes to the personalization-privacy theory through showing that perceived personalization has a twofold effect: it positively results in behavioural intention and, at the same time, increases trust. Meanwhile, privacy risk compromises trust, which shows the delicate quality of trust building in technologies that rely on constant data gathering. But, there is no significant relationship between trust and behavioural intention which indicates a gap in theory between the formation and adoption behaviour of trust. This indicates that trust can be a hygiene variable - needed but not sufficient to stimulate adoption - with voluntary consumer technologies like smart wearables. Lastly, the research contributes to the growing body of literature on the emerging markets by availing empirical data on the Indian context, which has not been well represented in the wearable technology research. The findings highlight the need to contextualize technology acceptance models instead of regarding them as applicable to all cultural and market settings.

7. PRACTICAL IMPLICATIONS

The results provide a number of relevant lessons to wearable manufacturers, technology developers, and policymakers who want to encourage its use by millennial consumers. The importance of the expectancy of effort defines the role of an intuitive design, smooth onboarding, and user-friendly navigation. The process of simplifying the setup of the devices and reducing cognitive load of the processes can significantly reduce the barriers to adoption especially of multifunctional wearable devices. The usefulness of social influence in marketing wearable technologies can be highlighted by the positive impact of social influence. Peer-driven communication, influencer partnership and community-based engagement can increase credibility and visibility in digitally reachable consumer segments. Wearables that are socially acceptable and aligned with lifestyle have a higher chance to spread. The concept of hedonic motivation also becomes significant, which shows that enjoyment and experience value are significant aspects in the process of adoption. The gamification, interactive dashboard, and on-the-fly personalized feedback are some of the features that can contribute to user engagement and their long-term interest.

These experiential aspects are the supplement to functional benefits and reinforce the overall value proposition. Value of price is also still a vital factor especially in developing markets. Perceived affordability can be enhanced by flexible pricing arrangements, subscription plans, bundling, or student-friendly discounts to motivate price-sensitive customers to adopt them. Regarding the data governance, the results indicate that personalization must be used as a value-creating approach and privacy issues must be proactively handled. By enhancing perceived privacy risk through transparent data practices, privacy control settings that the user can manage, and explicit communication about the use of data, the perceived privacy risk can be reduced and trust strengthened. Simultaneously, the insignificance of trust in influencing the behavioral intention implies that ethical promises and assurances are not likely to result in adoption. The functional value, usability, and user experience are kept as the key, which implies that companies should take a moderate approach to reconcile the ethical responsibility with innovation and design superiority.

8. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Although the study provides valuable theoretical and practical resources, some limitations are to be made. The cross-sectional research design does not allow causal interpretation and fails to provide any transformations in user perceptions over time. Longitudinal studies would be more insightful in understanding the changing trust, privacy issues, and usage patterns by users over a long time of experience with smart wearables. The sample was limited to urban millennials living in large cities in Punjab and this might limit the extrapolation of the results. Future studies might expand the model to other demographic clients such as older customers, rural areas, or cross-cultural environments to determine whether there is a variation in the adoption drivers across contexts. The use of self-reported information could also bring about common method bias or social desirability. The use of mixed-method strategies, including survey data and behavioral usage data, or qualitative interviews might be used to strengthen future research. More studies can also be done to look into other psychological and contextual factors that were not within the perspective of the current study. Perceived health outcomes, data literacy, regulatory awareness, AI transparency, or algorithmic explainability are only some of the variables that can provide more detailed information about wearable adoption and refine technology acceptance models in the context of emerging digital ecosystems.

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AUTHOR CONTRIBUTIONS

Gunreet Kaur: Conceptualization, Methodology, Investigation, Data Curation, Writing, Original Draft.
Aditya Kumar Divyam: Formal Analysis, Software, Validation, Writing, Review & Editing.
Mohd Farhan: Supervision, Validation, Writing, Review & Editing.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

Ethical approval was not required for this study.

DATA AVAILABILITY STATEMENT

Data supporting the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] Acquisti A, Brandimarte L, Loewenstein G. Privacy and human behavior in the age of information. Science. 2015 Jan 30;347(6221):509-14.
[2] Adapa A, Nah FF, Hall RH, Siau K, Smith SN. Factors influencing the adoption of smart wearable devices. International Journal of Human–Computer Interaction. 2018 May 4;34(5):399-409.
[3] Adebesin F, Mwalugha R. The mediating role of organizational reputation and trust in the intention to use wearable health devices: Cross-country study. JMIR mHealth and uHealth. 2020 Jun 9;8(6):e16721.
[4] Aggrawal, N., & Pandey, A. (2025). The Impact of the Internet of Behavior on Wearable Technology: Enhancing User Engagement and Health Outcomes. In *Mapping Human Data and Behavior With the Internet of Behavior (IoB)* (pp. 337-410). IGI Global Scientific Publishing.
[5] Al-Azawei A, Alowayr A. Predicting the intention to use and hedonic motivation for mobile learning: A comparative study in two Middle Eastern countries. Technology in Society. 2020 Aug 1;62:101325.
[6] Alrawad M, Lutfi A, Almaiah MA, Elshaer IA. Examining the influence of trust and perceived risk on customers intention to use NFC mobile payment system. Journal of Open Innovation: Technology, Market, and Complexity. 2023 Jun 1;9(2):100070.
[7] An GK, Ngo TT. AI-powered personalized advertising and purchase intention in Vietnam's digital landscape: The role of trust, relevance, and usefulness. Journal of Open Innovation: Technology, Market, and Complexity. 2025 Sep 1;11(3):100580.
[8] Asgarinia H, Chomczyk Penedo A, Esteves B, Lewis D. "Who should I trust with my data?" ethical and legal challenges for innovation in new decentralized data management technologies. Information. 2023 Jun 21;14(7):351.
[9] Awad NF, Krishnan MS. The Personalization Privacy Paradox: An Empirical Evaluation of Information Transparency and the Willingness to be Profiled Online for Personalization1. MIS quarterly. 2006 Mar 1;30(1):13-28.
[10] Banerjee S. Geosurveillance, location privacy, and personalization. Journal of Public Policy & Marketing. 2019 Oct;38(4):484-99.

[11] Basha NK, Aw EC, Chuah SH. Are we so over smartwatches? Or can technology, fashion, and psychographic attributes sustain smartwatch usage?. Technology in Society. 2022 May 1;69:101952.
[12] Chan-Olmsted S, Chen H, Kim HJ. In smartness we trust: consumer experience, smart device personalization and privacy balance. Journal of Consumer Marketing. 2024 Sep 3;41(6):597-609.
[13] Cheng X, Su L, Luo X, Benitez J, Cai S. The good, the bad, and the ugly: Impact of analytics and artificial intelligence-enabled personal information collection on privacy and participation in ridesharing. European Journal of Information Systems. 2022 May 4;31(3):339-63.
[14] Choung H, David P, Ross A. Trust in AI and its role in the acceptance of AI technologies. International Journal of Human–Computer Interaction. 2023 May 28;39(9):1727-39.
[15] Dinev T, Hart P. An extended privacy calculus model for e-commerce transactions. Information systems research. 2006 Mar;17(1):61-80.
[16] Ferreira JJ, Fernandes CI, Rammal HG, Veiga PM. Wearable technology and consumer interaction: A systematic review and research agenda. Computers in human behavior. 2021 May 1;118:106710.
[17] Gardner B. A review and analysis of the use of 'habit'in understanding, predicting and influencing health-related behaviour. Health psychology review. 2015 Aug 7;9(3):277-95.
[18] Gefen D, Karahanna E, Straub DW. Trust and tam in online shopping: An integrated model1. MIS quarterly. 2003 Mar 1;27(1):51-90.
[19] Jakobi T, Von Grafenstein M, Smieskol P, Stevens G. A Taxonomy of user-perceived privacy risks to foster accountability of data-based services. Journal of Responsible Technology. 2022 Jul 1;10:100029.
[20] Joa CY, Magsamen-Conrad K. Social influence and UTAUT in predicting digital immigrants' technology use. Behaviour & Information Technology. 2022 Jun 11;41(8):1620-38.
[21] Kenesei Z, Ásványi K, Kökény L, Jászberényi M, Miskolczi M, Gyulavári T, Syahrivar J. Trust and perceived risk: How different manifestations affect the adoption of autonomous vehicles. Transportation research part A: policy and practice. 2022 Oct 1;164:379-93.
[22] Kim DJ, Ferrin DL, Rao HR. A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. Decision support systems. 2008 Jan 1;44(2):544-64.
[23] Kokolakis S. Privacy attitudes and privacy behaviour: A review of current research on the privacy paradox phenomenon. Computers & security. 2017 Jan 1;64:122-34.
[24] Kowalczuk P, Hof N. The customer's perceived value-in-use of voice-assisted smart products and its impact on continuance intention: a trade-off between benefits and costs. Journal of Product & Brand Management. 2025 Jun 10;34(5):690-706.
[25] Krishnaraju V, Mathew SK, Sugumaran V. Web personalization for user acceptance of technology: An empirical investigation of E-government services. Information Systems Frontiers. 2016 Jun;18(3):579-95.
[26] Lee EJ. Impact of visual typicality on the adoption of wearables. Journal of Consumer Behaviour. 2021 May;20(3):762-75.
[27] Lee J, Kim D, Ryoo HY, Shin BS. Sustainable wearables: Wearable technology for enhancing the quality of human life. Sustainability. 2016 May 11;8(5):466.
[28] Liverani M, Ir P, Wiseman V, Perel P. User experiences and perceptions of health wearables: an exploratory study in Cambodia. Global health research and policy. 2021 Sep 23;6(1):33.
[29] Lunney A, Cunningham NR, Eastin MS. Wearable fitness technology: A structural investigation into acceptance and perceived fitness outcomes. Computers in Human Behavior. 2016 Dec 1;65:114-20.
[30] Mathavan B, Vafaei-Zadeh A, Hanifah H, Ramayah T, Kurnia S. Understanding the purchase intention of fitness wearables: using value-based adoption model. Asia-Pacific Journal of Business Administration. 2024 Jan 2;16(1):101-26.
[31] Mayer RC, Davis JH, Schoorman FD. An integrative model of organizational trust. Academy of management review. 1995 Jul 1;20(3):709-34.
[32] Misra S, Adtani R, Singh Y, Singh S, Thakkar D. Exploring the factors affecting behavioral intention to adopt wearable devices. Clinical Epidemiology and Global Health. 2023 Nov 1;24:101428.
[33] Mone V, Shakhlo F. Health data on the go: navigating privacy concerns with wearable technologies. Legal Information Management. 2023 Sep;23(3):179-88.
[34] Motti VG. Introduction to wearable computers. InWearable interaction 2020 Jan 2 (pp. 1-39). Cham: Springer International Publishing.

[35] Nawaz IY. Characteristics of millennials and technology adoption in the digital age. InHandbook of research on innovations in technology and marketing for the connected consumer 2020 (pp. 241-262). IGI Global Scientific Publishing.
[36] Nawi NB, Mamun AA, Hayat N, Yang Q. Attitude of Fashion consumers toward the IoT: estimating consumer hedonic and utilitarian shopping motivations. Journal of Ambient Intelligence and Humanized Computing. 2024 Jan;15(1):751-63.
[37] Niknejad N, Hussin AR, Ghani I, Ganjouei FA. A confirmatory factor analysis of the behavioral intention to use smart wellness wearables in Malaysia. Universal Access in the Information Society. 2020 Aug;19(3):633-53.
[38] Ogbanufe O, Gerhart N. Exploring smart wearables through the lens of reactance theory: Linking values, social influence, and status quo. Computers in Human Behavior. 2022 Feb 1;127:107044.
[39] Oh S, Lehto XY, Park J. Travelers' intent to use mobile technologies as a function of effort and performance expectancy. Journal of Hospitality Marketing & Management. 2009 Oct 15;18(8):765-81.
[40] Pancar, T., & Ozkan Yildirim, S. (2023). Exploring factors affecting consumers' adoption of wearable devices to track health data. *Universal Access in the Information Society*, *22*(2), 331-349.
[41] Patnaik SK, Medimi N, Ariwa E. Smart rings: Redefining wearable technology. InHandbook of Artificial Intelligence and Wearables 2024 Apr 4 (pp. 217-235). CRC Press.
[42] Plester B, Sayers J, Keen C. Health and wellness but at what cost? Technology media justifications for wearable technology use in organizations. Organization. 2024 Mar;31(2):358-80.
[43] Rahi S, Othman Mansour MM, Alghizzawi M, Alnaser FM. Integration of UTAUT model in internet banking adoption context: The mediating role of performance expectancy and effort expectancy. Journal of Research in Interactive Marketing. 2019 Sep 26;13(3):411-35.
[44] Sandham M, Reed K, Cowperthwait L, Dawson A, Jarden R. Expensive ornaments or essential technology? a qualitative metasynthesis to identify lessons from user experiences of wearable devices and smart technology in health care. Mayo Clinic Proceedings: Digital Health. 2023 Sep 1;1(3):311-33.
[45] Shamsi MS, Verma A, Verma M. Unveiling Millennialsâ€™ Motivations to Purchase Smartwatches. Indian Journal of Marketing. 2023 Dec 1:63-81.
[46] Sivakumar CL, Mone V, Abdumukhtor R. Addressing privacy concerns with wearable health monitoring technology. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery. 2024 May;14(3):e1535.
[47] Su J, Sun X, Wang J. Expanding the psychological domain of technological acceptance: The use of smart wearable devices in leisure. Applied Sciences. 2024 Jun 19;14(12):5316.
[48] Sundar SS, Marathe SS. Personalization versus customization: The importance of agency, privacy, and power usage. Human communication research. 2010 Jul 1;36(3):298-322.
[49] Tamilmani K, Rana NP, Wamba SF, Dwivedi R. The extended Unified Theory of Acceptance and Use of Technology (UTAUT2): A systematic literature review and theory evaluation. International journal of information management. 2021 Apr 1;57:102269.
[50] Tricás-Vidal HJ, Lucha-López MO, Hidalgo-García C, Vidal-Peracho MC, Monti-Ballano S, Tricás-Moreno JM. Health habits and wearable activity tracker devices: analytical cross-sectional study. Sensors. 2022 Apr 12;22(8):2960.
[51] Tuch AN, Trusell R, Hornbæk K. Analyzing users' narratives to understand experience with interactive products. InProceedings of the SIGCHI conference on human factors in computing systems 2013 Apr 27 (pp. 2079-2088).
[52] Venkatesh V, Thong JY, Xu X. Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology1. MIS quarterly. 2012 Mar 1;36(1):157-78.
[53] Walle AD, Jemere AT, Tilahun B, Endehabtu BF, Wubante SM, Melaku MS, Tegegne MD, Gashu KD. Intention to use wearable health devices and its predictors among diabetes mellitus patients in Amhara region referral hospitals, Ethiopia: using modified UTAUT-2 model. Informatics in Medicine Unlocked. 2023 Jan 1;36:101157.
[54] Wang Z, Rucker M, Toner ER, Larrazabal MA, Boukhechba M, Teachman BA, Barnes LE. Understanding privacy risks versus predictive benefits in wearable sensor-based digital phenotyping: A quantitative cost-benefit analysis. In2023 IEEE 19th International Conference on Body Sensor Networks (BSN) 2023 Oct 9 (pp. 1-4). IEEE.
[55] Windasari NA, Lin FR. Why do people continue using fitness wearables? The effect of interactivity and gamification. Sage Open. 2021 Nov;11(4):21582440211056606.
[56] Wu CC, Huang Y, Hsu CL. Benevolence trust: a key determinant of user continuance use of online social networks. Information Systems and e-Business Management. 2014 May;12(2):189-211.

[57] Yang H, Yu J, Zo H, Choi M. User acceptance of wearable devices: An extended perspective of perceived value. Telematics and informatics. 2016 May 1;33(2):256-69.
[58] Yu UJ. Investigating antecedents of adopting wearable technology products among Gen Z. International Journal of Fashion Design, Technology and Education. 2025 Jan 31:1-4.