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Article

Decoding consumer perspective for tech-based health insurance products

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Decoding consumer perspective for tech-based health insurance products

Innovation &
Management
Review

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Abstract

Purpose – Technology-driven health insurance products have significant applications for business firms and customers. With their growing popularity, these products can disrupt legacy insurance systems. Based on this notion, this study seeks to identify and validate the factors that affect customers' attitudes toward their buying intentions and readiness to pay for these products.

Design/methodology/approach – This study extended the technology acceptance model with privacy, trust, purchase intention and willingness to pay to improve its predictive capability. The data were analyzed using the partial least square technique on a sample comprising 150 respondents.

Findings – The results indicated that all model variables except for privacy concerns were significant and influenced consumers' attitudes toward these technology-driven products. The authors also found a significant difference in the influence of trust on attitude when comparing the genders. A significant mediation between perceived ease of use and attitude was also established.

Research limitations/implications – The empirical investigation in this study offers valuable insights for insurance companies to plan effective marketing strategies that help them disseminate information about the utility and user-friendly aspects of their products, thereby increasing positive attitudes and the plausibility of adoption. It is also advised that the companies tie up with reliable technology platforms. Pricing policies can be designed keeping in mind that the consumers are willing to pay even more to avail the benefits of the products.

Originality/value – The current study intends to fill the gaps in the existing literature by demystifying the purchase intention–willingness to pay relation regarding technology-based health insurance products in India.

Keywords Technology-based health insurance, Wearable technology, Willingness to pay, Purchase intention, Extended TAM

Paper type Research article

Introduction

The convergence of technology in the healthcare sector has brought about transformative changes across various healthcare products and services. This paradigm has led to many growth opportunities in the health insurance context, as more customer-oriented products can be delivered with the integration of technology. In an increasingly interconnected and digital world, technological interventions in the insurance domain can redefine how individuals engage, manage and enhance their overall health and well-being (Caciatori & Cherobim, 2020).

To modernize legacy insurance systems, insurers can leverage technologies like wearable devices, mHealth, data analytics and others to broaden their customer base and forge ahead of their competitors (Nunes & Filho, 2018). Technology-driven health insurance offerings can

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help facilitate a more robust insurance ecosystem that can move beyond the traditional risk assessment and claim management processes to a more active and empowered health decision-making approach. After the COVID-19 pandemic, countries across the globe are focusing more on building a resilient healthcare system that can cater to the health and well-being needs of the population. The United Nations also emphasizes this compelling necessity in Sustainable Development Goal 3 (SDG 3) to ensure universal health and welfare.

There is a growing inclination in the insurance industry to integrate the Internet of Things (IoT) with wearable technology and mobile devices to develop novel health insurance products. Consequently, insurance companies are actively changing their business strategies. It is believed that chronic diseases and stress are the major killers in modern life and can be tackled by increasing the amount of physical activity (Lee, 2023). Therefore, health prevention and management behavior are paramount in modern life. With technology integration, customers can be offered more personalized health insurance coverage, benefits, wellness programs and data-driven insights. These technology-based health insurance offerings help in the collaborative working of insurers and healthcare providers and, thus, enable a more proactive health journey for the policyholders. In this product, if the health of a policyholder improves over time, their premium rates can be lowered. The insurers are actively using this incentive to lure people toward a more active lifestyle (Lee, 2023). Insurance companies track policyholders' daily movements via mHealth applications or wearable technologies to record physical activities like daily steps, gym sessions and others. The company also offers free routine health checkups to examine whether a person is entitled to a policy premium reduction. These products also benefit insurance firms by providing information about consumers' lifestyle choices and health. This information is crucial for R&D and health insurance marketing.

Integrating technology with health insurance products also benefits consumers, as they can access their health and insurance-related information anytime using online portals and mobile applications. These offerings allow consumers to personalize their health management through wellness programs and health checkup reminders. Through the centralized portal, customers can leverage the benefits offered by insurance companies, like free routine health checkups, discounts and reduced premium options.

Due to intense competition in the health insurance sector, firms must closely assess customers' needs. With the adoption of technology-based health insurance products, insurers improve their customers' lifestyles, lower the likelihood of disease and lower medical costs. Customers who are offered monetary incentives are believed to be more likely to adopt healthy habits and thus benefit society as a whole. This research delves into this emerging landscape of technology-based health insurance products to explore the opportunities and challenges ahead of this evolving innovation. Health insurance products involve complex features, including different plans, customization and technology-integration options, which can significantly impact consumers' intentions. These new technology products offer new personalization and well-being offerings, and understanding consumers' perspectives can help examine the growth prospects. The study aimed to explore consumers' purchase intention (PI) and willingness-to-pay (WTP) behavior toward this technology-based health insurance product. It is imperative to comprehend the PI and WTP behavior, as these parameters can help understand the market demand and feasibility of these tech-based health insurance products. Through WTP, insurance companies can better understand whether consumers are willing to pay for this technological innovation. By understanding consumer PI, insurers can develop more customized products to meet consumer needs and preferences.

This study contributes in the following ways. Firstly, it integrates privacy concerns, trust, PI and WTP with "TAM" factors. TAM is extensively used by researchers to study technology adoption in the healthcare context (Bandyopadhyay, Meso, & Negash, 2017; Hoque, Bao, & Sorwa, 2016; Huang, 2010; Mensah, 2022; Rajak & Shaw, 2021; Sun, Wang, Guo, & Peng, 2013) because of its robustness and high predictive power. Secondly, it analyzes the differences between genders using multigroup analysis (MGA) to examine the group-specific effect on PI and WTP. Thirdly, to the best of our knowledge, it is one of the pioneer studies in

the Indian context. The findings will also benefit insurers in building their marketing and sales strategies more effectively.

Section 2 of the manuscript reviews the relevant literature, identifies important gaps and presents the hypotheses formulated. Section 3 outlines the empirical methodology employed in this study. The study findings are provided in section 4, followed by a discussion in section 5. Section 6 concludes the results and discusses the important managerial and policy implications. Finally, the limitations of the study, along with the scope for future research, are addressed in Section 7.

Literature review and hypotheses

Wearable technology and health insurance

Recent times have seen the transformation of wearable devices from mere gadgets to quintessential healthcare tools that help users to keep a check on their daily health activities and bring about positive changes in their routine (Montgomery, Chester, & Kopp, 2018). The fast development of such devices has led to active health monitoring and management, thereby resulting in reduced healthcare costs (Serrano, Fortunati, & Lacerda, 2021).

The advancement of wearable technology has gained substantial attention from the insurance sector. According to Forum (2015), the ubiquity of wearable devices and the IoT can enable insurers to provide personalized insurance. It also helps the insured by focusing on disease prevention rather than treatment through constant health tracking (Miraldo, Monken, Motta, & Ribeiro, 2019; Soliño-Fernandez, Ding, Bayro-Kaiser, & Ding, 2019). The concomitance of wearable technology and health insurance and a rising focus on the health and financial well-being of all citizens has led to the development of technology-based health insurance products. Various health insurance companies like Prudential Life Insurance in the UK, John and Hancock Life Insurance in the US and Aditya Birla Life Insurance in India (refer to Table 1 of the supplementary file) have focused their attention on the use of wearable technology in healthcare (Lee, 2023). These companies offer premium concessions to the insured if they follow a healthy routine, like attending gym sessions or walking a certain number of steps. The development of such products testifies that health insurers are embracing a change from reactive to taking data-driven, proactive measures of providing health insurance (Nayak, Bhattacharyya, & Krishnamoorthy, 2019). The anonymized data generated from such products can provide a plethora of opportunities in the insurance and healthcare sectors. The programs for disease prevention, public health initiatives and the development of personalized health insurance products are some of them (Montgomery *et al.*, 2018).

Lee (2023) in his recent research reported that perceived usefulness (PU), perceived ease of use (PEOU), subjective norms and trust have a positive and significant effect on the attitudes toward the use of wearable device-based health insurance products. Additionally, Soliño-Fernandez *et al.* (2019) concluded that two out of three Americans would be willing to adopt wearable device-based health insurance products given the conducive financial, data secrecy and technical settings. Additionally, the literature highlights certain obstacles to using wearable devices for adjusting the health insurance premium. The first is regulatory problems as the users feel that because of lax data privacy regulations, their health data would be shared and could lead to discrimination based on their potential ailments (Montgomery *et al.*, 2018; Neumann, Tiberius, & Biendarra, 2022; Wathieu & Friedman, 2007). The second is the technological barrier, which includes reliability concerns of the wearable devices because if the data is captured incorrectly, it will have a direct impact on the calculation of the insurance premium (Groß & Schmidt, 2018; Neumann *et al.*, 2022). Figure 1 displays the conceptual model of this study.

Technology acceptance model

The technology acceptance model (TAM) is a well-established information systems theory that explains how users adopt a new technology (Davis, Bagozzi, & Warshaw, 1989). Derived

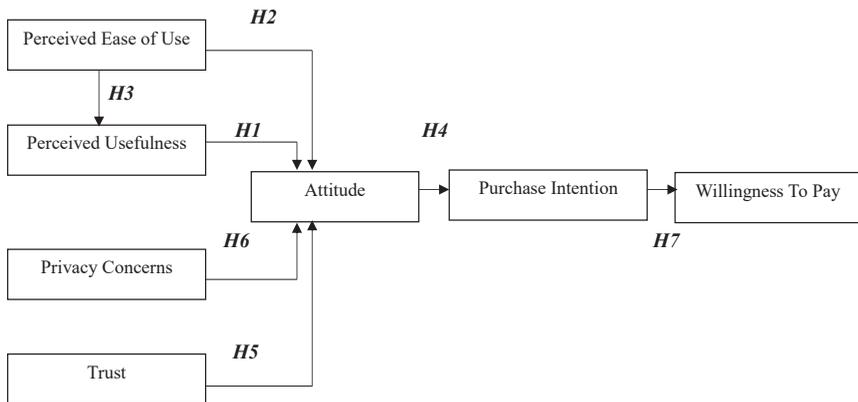


Figure 1. Conceptual model. Source: Authors' work

from the “Theory of Reasoned Action” (TRA) and the “Theory of Planned Behavior” (TPB), TAM examines the behavioral aspects associated with the technology adoption process (Lee, 2023; Rajak & Shaw, 2021). TAM assumes that behavioral intention directly influences individuals’ usage of a system, which is further influenced by their attitude (Davis *et al.*, 1989; Lee, 2023; Rajak & Shaw, 2021). TAM emphasizes the cognitive and affective responses to gauge the behavioral response of the user. PEOU and PU are the cognitive variables of TAM that influence users’ attitudes, which is considered an effective response. These two responses together predict the behavioral response of users, which is the intention to adopt a technology (Davis, 1985). TAM is used in this research as it is a relatively more robust model and has been validated several times in the healthcare context (Hossain, Yokota, Sultana, & Ahmed, 2019; Rajak & Shaw, 2021; Sun *et al.*, 2013; Zhang, Guo, Guo, & Lai, 2014). TAM primarily focuses on two main constructs: PEOU and PU; these constructs help in understanding individual-level acceptance of new technological innovation. TAM is well-suited to understand the initial acceptance of technology, whereas other models like UTAUT2 are more focused on understanding the different aspects of technology that can lead to adoption. As tech-based health insurance products are yet to diversify in the consumer market, it’s relevant to understand whether individuals find these useful. Hence, TAM has been used. We extended TAM with privacy, trust and WTP as different technologies have unique challenges, and in health-related data, trust and privacy play a key role in shaping consumer behavior (Gu *et al.*, 2021; Khan, Xitong, Ahmad, & Shahzad, 2019).

PEOU refers to the magnitude to which a user perceives that technology would be effort-free. At the same time, PU assesses how users believe the new technology would improve their performance. Attitude refers to the degree of evaluative effect that a user associates with the technology and is the major determinant of intention to use a technology (Davis, 1985). TAM postulates that PEOU considerably influences PU. Also, the impact of PEOU is more on users’ acceptance when compared to PU.

In its original and extended forms, TAM is one of the most widely used models in healthcare to explain users’ acceptance of technology. Kamal, Shafiq, and Kakria (2020) extended TAM to study the factors influencing telemedicine adoption in Pakistan. Their findings suggested the positive influence of perceived ease of use and perceived usefulness on the intention to adopt. Liu and Tao (2022) studied an extended TAM model to explore the determinants affecting the adoption of smart healthcare services. They found a significant impact of perceived usefulness on intention, whereas perceived ease of use did not affect users’ intention. Deng, Hong, Ren, Zhang and Xiang (2018) extended TAM to explore the determinants of mHealth adoption in China. Hoque (2016) also used extended TAM to study

the adoption of mHealth in Bangladesh. Thus, this model is actively being used to study the adoption behavior in the healthcare context. Based on these premises, the following propositions are made:

- H1. Perceived usefulness influences consumers' attitudes toward using technology-based health insurance products.
- H2. Perceived ease of use influences consumers' attitudes toward using technology-based health insurance products.
- H3. Perceived ease of use influences perceived usefulness.
- H4. Users' attitude positively influences intentions to purchase health technology-based health insurance products.

Trust

Over the years, trust has been one of the most studied variables in theoretical models for explaining technology adoption in the healthcare context (Kamal *et al.*, 2020; Luo, Li, & Ye, 2023; Sawand, Djahel, Zhang, & Nait-Abdesselam, 2015). Trust has been widely studied as a moderator variable to explore health insurance products (Lee, 2023). For our study, it can be defined as the degree to which an individual perceives that technology-based healthcare products are reliable, trustworthy and dependable. Available literature emphasizes the importance of trust while studying users' adoption behavior (Klaver, Van De Klundert, Van Den Broek, & Askari, 2021; Lee, 2023; Rajak & Shaw, 2021; Chib, van Velthoven, & Car, 2015). Thus, the following hypothesis was postulated.

- H5. Trust influences consumers' attitudes toward adopting technology-based health insurance products.

Privacy concerns

Privacy is another important variable that is studied in the context of healthcare technology adoption. Privacy can be defined as the degree to which a user is comfortable enough to provide personal health information. There is no denying the significance of privacy when sharing medical information within the healthcare system. In our study, the term privacy concern refers to people's concern about how others might utilize their personal information. Several studies have focused on the importance of privacy concerns while investigating technology adoption behavior (Deng *et al.*, 2018; Kamal *et al.*, 2020; Liu & Tao, 2022; Zhang *et al.*, 2014). Thus, the following hypothesis was postulated.

- H6. Privacy concerns influence consumers' attitudes toward adopting technology-based health insurance products.

Relationship between purchase intention and willingness to pay

PI represents consumers' preference toward a product, service or brand combined with their inclination to make a purchase (Mamun, Rahman, Munikrishnan, & Permarupan, 2021). WTP is consumers' readiness to pay a higher price for a product or service based on its perceived value (Bushara *et al.*, 2023). This decision-making process guides consumers in their purchases, driven by their desires. If a consumer strongly desires a product, then he/she may be willing to pay a higher price, which increases their purchase intention.

Previous studies have studied the PI and WTP in varied disciplines to understand consumer behavior toward new technology adoption (Barta, Gurrea, & Flavián, 2023; Chang, Lee, Lee, & Wang, 2023; Jayaraman, Alesa, & Azeema, 2017; Ooi, Leh, Lim, Lye, & Ong, 2019; Nguyen & Hoang, 2017; Nguyen, Truong, & Le-Anh, 2023; Pihlström & Brush, 2008). As a

result, the consumer will be willing to spend more for a product if they are more inclined to purchase it. Thus,

- H7. Purchase intention influences WTP for adopting technology-based health insurance products.
- H8. Perceived usefulness mediates the association between perceived ease of use and consumers' attitudes toward technology-based health insurance products.

Methodology

Measures

The data collection and evaluation for the current study adopted a quantitative methodology. Scales from the prevalent literature have been adapted in the context of technology-based health insurance products. The items for constructs of the TAM model and purchase intention were adapted from Davis *et al.* (1989), Huang (2010), Taylor, and Todd (1995). The scale for privacy concerns was adapted from Zhang *et al.* (2014) and for trust from Khan *et al.* (2019). The scale for willingness to pay was adapted from Mamun, Naznen, Yang, Ali and Hashim (2023), Bushara *et al.* (2023), Yildirim, Saygili and Yalcintekin (2021).

This study employs a 5-point Likert agreement scale where one signifies strong disagreement and five signifies strong agreement, with intermediate values. The questionnaire was developed in English, and a pre-survey was conducted with 25 respondents to test whether the questionnaire was well-developed. All the suggestions were incorporated into the final questionnaire.

Data collection

The questionnaire for this study was divided into two parts; the first part focused on basic demographic information like age, gender and prior health insurance experience. The second part contained measurement questions related to our eight variables, each consisting of three to five items. For this study, we targeted individuals who had prior awareness of or experience with health insurance. The data were collected through both online and offline modes. For offline mode, we visited nearby hospitals and diagnostic labs and requested individuals to participate in our survey. Additionally, individuals were targeted through LinkedIn with online forms. We also approached university students and staff members for data collection purposes. A total of 170 forms were received, of which 150 were further included in the analysis. The demographic profile is shared in [Table 2 of the supplementary file](#). Over 70% of our respondents were under the age of 34 and are considered more tech-savvy than the other age groups.

Data analysis

This study used "variance-based structural equation modeling," or PLS-SEM, to evaluate the suggested framework. This technique is more appropriate for our research since it can work with non-normal data and produce robust results even with smaller sample sizes. The application of a two-step analytical technique begins with the assessment of the measurement model to ensure the validity and reliability of our model and continues with the evaluation of the structural model to verify the provided hypotheses. Furthermore, partial least squares multi-group analysis (PLS-MGA) can examine differences in the inciting factors among different groups.

Measurement model

To verify that the measurement model is robust, it is evaluated against the following standards. The factor loading, Cronbach's alpha and average variance extracted (AVE) are all shown in

Table 3 of the supplementary file. According to Hair, Rische, Sarstedt and Ringle (2019), each construct’s Cronbach’s alpha value should fall between 0.70 and 0.90 to be considered satisfactory when measuring internal consistency reliability. According to Hair et al. (2019), the construct must account for over 50% of the variation in the indicator for the factor loadings to be deemed acceptable. They must be above 0.70. The convergent validity of each measured concept is evaluated using the third robustness metric, the AVE, and it must be 0.50 or above to be considered (Hair et al., 2019). To determine how much a construct in the structural model differs from others experimentally, the discriminant validity of the construct is evaluated as the fourth measurement. The heterotrait-monotrait (HTMT) ratio of correlations can be used to measure this; for anything to be conceptually distinct, the HTMT value must be smaller than 0.90 (Hair et al., 2019). In our investigation, every factor loading is higher than the threshold point (refer to Table 4 of the supplementary table file). The measurement model is regarded as robust because the Cronbach alpha, AVE values and HTMT ratio are all within the acceptable range.

Common method bias

To avoid the influence of common method bias, this study uses Harman’s one-factor test method using SPSS 24 (Wang, Esperança, Yang, & Zhang, 2023). The results showed that one single factor explained 30%, which was less than the critical value of 50% (Kock, Berbekova, & Assaf, 2021). Hence, this research is devoid of any common method bias.

Structural model

We further analyzed our results by bootstrapping them using 5,000 samples, as tabulated in Table 1. The *t*-statistics and *p*-value were further determined to test the hypotheses (Hair, Ringle, & Sarstedt, 2011).

The hypotheses represented in this study were verified and tested, and the path coefficients empirically supported all except H6. Among all the variables impacting attitude, PU ($\beta = 0.367, P = 0.00^{**}$) is the most important factor, followed by PEOU ($\beta = 0.144, P = 0.02^{**}$). For PI, attitude is the most important factor. WTP was significantly impacted by PI. Figure 2 shows the structural model created for this study.

The explanatory power of the model was assessed on thresholds of 0.25 for weak, 0.5 for moderate and 0.7 for strong relationships. The empirical observations of the present study revealed a moderate relationship among the variables. The values of Q^2 higher than 0, 0.15 and 0.50 indicate small, medium and large predictive relevance (Hair et al., 2019). Our results indicate medium and large predictive relevance. Effect size (f^2) values of 0.02, 0.15 and 0.35 denote small, medium and large effects, with this study pointing at a large effect size for attitude. The value of the standardized root mean square (SRMR) indicates the goodness of fit of the model, for which the observed value is 0.068 against the threshold value of 0.08, indicating a good fit (Hair et al., 2018). Table 2 displays the structural model results of this study.

Table 1. Hypotheses testing results

Hypothesis	Relationship	<i>t</i> statistics	<i>p</i> -value	Remarks
H1	Perceived Usefulness → Attitude	5.258	0.000	Supported
H2	Perceived Ease of Use → Attitude	2.228	0.026	Supported
H3	Perceived Ease of Use → Perceived Usefulness	9.406	0.000	Supported
H4	Attitude → Purchase Intention	8.436	0.000	Supported
H5	Trust → Attitude	5.956	0.000	Supported
H6	Privacy Concerns → Attitude	0.215	0.830	Not Supported
H7	Purchase Intention → Willingness to Pay	4.643	0.000	Supported

Source(s): Authors’ work

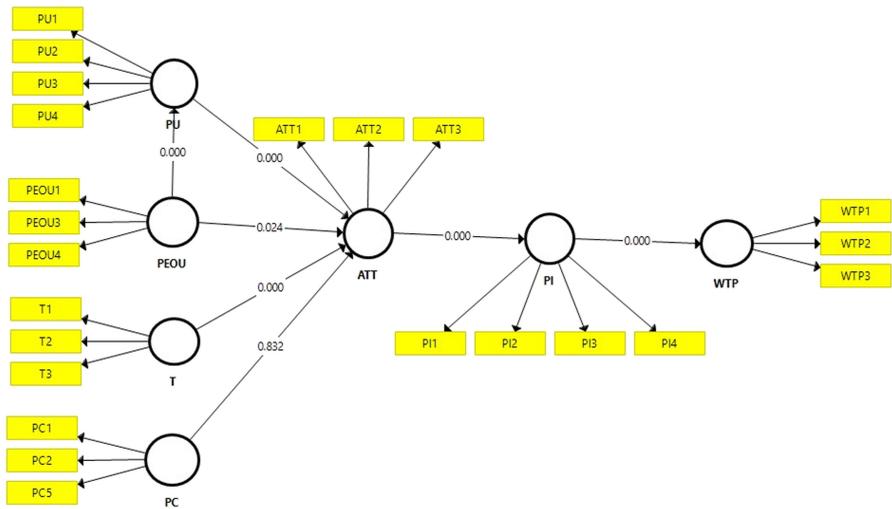


Figure 2. Structural model. Source: Authors' work

Table 2. Structural model results

	R-square	R-square adjusted	SSO	SSE	Q2	F2
ATT	0.645	0.635	450.000	214.639	0.523	0.696
PI	0.639	0.634	600.000	294.391	0.509	
PU	0.378	0.374	600.000	426.631	0.289	0.160
WTP	0.564	0.558	450.000	241.692	0.463	
PC			450.000	450.000		0.001
PEOU			450.000	450.000		0.608
T			450.000	450.000		0.223

Source(s): Authors' work

Mediation

To test the H8 for mediation, we used bootstrapping using 5,000 samples. An analysis of the results (Table 5 of the supplementary file) shows that PU mediates the connection involving PEOU and attitude ($\beta = 0.226, P = 0.00^{**}$). Therefore, H8 has been supported due to the significant indirect effect. It was also observed that a significant direct impact of PEOU on attitude was also established in H2 and thus, partial mediation is observed. The mediation is complementary as both the direct and indirect effects establish a positive relationship between PEOU and attitude (Zhao, Lynch, & Chen, 2010).

Multi-group analysis

The authors performed the MGA to study whether there is any difference between males and females in terms of adoption behavior for technology-based health insurance products. Firstly, we performed the Measurement Invariance of Composite Models (MICOM) procedure, where we established full measurement variance and, thus, performed MGA (Cheah, Thurasamy, Memon, Chuah, & Ting, 2020). As shown in Table 3, MGA showed a significant difference between the two genders regarding trust in technology-based health insurance products.

Table 3. MGA results

Path	Male	Female	Path coefficient difference	p-value	Remarks
ATT → PI	0.818	0.778	0.040	0.671	No Difference
PC → ATT	0.030	-0.158	0.187	0.206	No Difference
PEOU → ATT	0.028	0.160	-0.132	0.281	No Difference
PEOU → PU	0.615	0.633	-0.018	0.900	No Difference
PI → WTP	0.765	0.652	0.113	0.197	No Difference
PU → ATT	0.323	0.488	-0.165	0.229	No Difference
T → ATT	0.552	0.243	0.309	0.020	Different

Source(s): Authors' work

Discussion

The hypotheses represented in this study were verified and tested, and the path coefficients empirically supported all except **H6**. The empirical findings of this study find a significant and positive impact of PEOU, PU and trust on attitude toward technology-based health insurance, thus supporting **H1**, **H2** and **H5**. A positive attitude toward these innovations, in turn, positively affects PI and WTP. Given that the younger population is more familiar with technology, this skewness can be the factor leading to the significant impact of PU and PEOU, as they are more inclined toward new technology. The significant impact of PU and PEOU on consumer attitudes can be attributed to the fact that people place a high priority on maintaining a healthy lifestyle, not only for themselves but also for their families. If this benefit is realized using a technology that involves the least amount of effort, it results in an increased probability of adoption of such products. Similar were the findings of [Lee \(2023\)](#) in the context of Taiwan. Findings also suggest significant impact of PEOU on PU, supporting **H3**. A mediating role of PU on the relationship between PEOU and attitude was also reported, which is consistent with previous literature ([Raut, Goel and Taneja, 2024](#)). Both direct and indirect effects were observed, demonstrating a positive and complementary mediation; therefore, **H8** was supported. Therefore, it can be interpreted that if users perceive a technology as easy to use, they are more likely to find it useful, thus leading to a more positive attitude toward the technology.

Trust is also seen as a significant predictor of attitude toward technology-based health insurance products, which is consistent with the previous literature ([Klaver et al., 2021](#); [Lee, 2023](#); [Rajak & Shaw, 2021](#); [Chib et al., 2015](#)). This means that people weigh in on the credibility of the devices used to capture the health data for such insurance offerings. This is an important finding for insurance companies, as they can collaborate with reputable wearable device brands whose products are considered secure and trusted. It would facilitate a positive attitude among customers, which would enhance their PI and acceptance of technology-driven health insurance solutions. The relationship between privacy concerns and attitude was not significant, and thus, **H6** was not supported. The reason for this non-significant impact can be rooted in how consumers perceive tech-based health insurance from its utilitarian benefits, which outweigh the associated privacy concerns. Additionally, as consumers today are accustomed to sharing our information on social media apps, ordering apps and other platforms, they do not worry too much about associated data-sharing risks while using a new technology. As trust was found to be a significant factor, we can also interpret that because consumers believe in the credibility of the platforms providing insurance, they let go of their risk concerns.

The results of MGA were significant to this discourse, providing evidence that trust was the only construct that exhibited gender-based differences. This means that males and females held distinct opinions about the impact of trust on attitude toward adopting health insurance products. For males, trust in technology-based insurance products was significant for

developing a positive attitude toward these products. It could be deciphered that males generally make important financial decisions for their families, including the purchase of health insurance for themselves or their family members (Wang, Wang, & Gao, 2021). Therefore, they place considerable emphasis on the trustworthiness and reliability of these products. Conversely, females generally have less involvement in such buying decisions, the reason for which could be that females undermine the opportunity cost of their non-monetary efforts and toil that they put in, and they do not emphasize much on their health in comparison to the “earning” member of the family (generally male). This makes them less inclined toward buying an insurance product (Luciano, Outreville, & Rossi, 2016). Additionally, the gender differences in terms of investment and insurance are backed by differences in financial knowledge and risk appetite (Prast, Rossi, Torricelli, & Druta, 2014; Wang *et al.*, 2021). Therefore, trust is perceived as less important in formulating their attitude toward health insurance products.

These insights highlight the nuanced gender dynamics at play in consumer attitudes toward technology-driven health insurance solutions, accentuating the importance of tailoring marketing and communication strategies to resonate with diverse consumer perceptions and preferences.

A significant relationship between attitude and PI has also been identified, supporting H4, indicating that a positive attitude can increase consumers’ intention to buy technology-based health insurance products. Further, PI has been found to positively influence WTP for these health insurance products and thus, H7 was supported (Barta *et al.*, 2023; Chang *et al.*, 2023). Thus, it can be inferred that if a consumer has a positive outlook toward these products and intends to purchase them, then they are willing to pay a premium price to avail of these features. This finding holds implications for insurance companies considering dynamic pricing strategies. This understanding of the linkage between attitude, PI and WTP helps insurance companies to strategically price their products as per consumers’ perceptions and PI, optimizing their profits while meeting the expectations of their customers.

Conclusion

Technology-based health insurance products can revolutionize the healthcare and insurance sector by reducing the out-of-pocket expenditure of the insured in return for maintaining a healthy lifestyle. This study is an attempt to decode the consumer perspective on such products. To this discourse, the authors extended TAM to include PI and WTP for amalgamating the behavioral and economic considerations for such products and providing empirical evidence. The study used PLS-SEM for the purpose and showed that the easy usage of technology, the benefits of the product and the trust therein would bring about a positive attitude, which results in an intention to purchase and thereby leads to WTP for the product. The findings offer certain essential implications for enhancing the theoretical base of the extant literature.

Implications

Theoretical implications

This paper enriches the theoretical base of the literature and provides an understanding of technology-based health insurance in various ways. The present research extends TAM to include PI and WTP to study the consumer’s perspective of technology-based health insurance products and to provide empirical evidence. Extending the model to include these two variables paves the way for demystifying the adoption of such products from psychological and financial perspectives. This broadens the scope of understanding the adoption of the product from behavioral and economic outlooks.

Managerial implications

Implications for consumers. The adoption of technology-based health insurance products is in the best interest of consumers since health management and maintaining a healthy lifestyle are

important characteristics that lie in the very genesis of such products. The adoption of such products reduces the plausibility of adverse health outcomes and insurance premium charges. This ultimately lessens the out-of-pocket health expenditure and increases the monetary benefits to the users.

Implications for insurance companies. The empirical investigation found a positive association between PU, PEOU and attitude toward adopting technology-based health insurance products; hence, insurance companies need to disseminate information through marketing campaigns and messages about the benefits and ease of use of such products. This could increase the positive attitude of the consumers, thereby enhancing the plausibility of adoption.

Another important finding of this paper is that trust develops a positive attitude. Therefore, companies are advised to build trust in their products by partnering with trusted and secure health apps and wearable device companies. Emphasizing reliability and dependability would ultimately lead to a positive attitude and, consequently, higher PI. The advertising campaigns should also aim to build trust specifically among male customers, as the MGA signaled that trust is a significant factor affecting males' attitudes compared to their female counterparts.

The findings of this study confirm that consumers are willing to pay higher prices to enjoy the advantages of technically enhanced insurance products; thus, insurance companies can follow premium pricing policies without any apprehension of losing their customers.

Implications for policymakers. The technology-based health insurance products would provide a large database of users' health conditions. This would enable the government to keep a check on public health, thereby reducing the plausibility of the onset of outbreaks like COVID-19. These products can also allow the government to achieve the SDG 3 target of ensuring health and overall well-being. The government can also join hands with the companies to provide these products at a lower cost to lower-middle and middle-income families as part of the Ayushman Bharat scheme, thereby increasing the ambit of the scheme and combining the Pradhan Mantri Jan Arogya Yojana and the Digital India Program.

Limitations and future research directions

This research has certain limitations. The study had a small sample size, as this is a pilot study and would be developed further. Also, other relevant variables like awareness, social influence, the existence of a government-sponsored healthcare system, etc., can be studied in the future to explore users' adoption behavior. In this study, we extended TAM, but future studies can integrate behavioral theories to better understand the different aspects that shape consumer attitudes toward technology. Additionally, similar studies can be conducted in different geographical areas, viz., other emerging nations, or a comparative analysis between rural and urban customers to understand the behavioral variances in adopting such products. As our data are more inclined toward the younger population, future studies can confirm these findings with the older generation or a more balanced target audience.

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Supplementary material

The supplementary material for this article can be found online.

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