

The Role of Trust and Data Sharing Willingness in Users' Acceptance of Insurance Telematics

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Understanding customers' attitudes toward insurance telematics can significantly affect knowledge management practices within the insurance industry. This study explores the factors affecting users' acceptance of insurance telematics. A theoretical adoption model was proposed by extending the technology acceptance model and theory of planned behavior with a priorly proved construct trust and a new construct data sharing willingness (DSW). Trust is built upon perceived usefulness, ease of use, and DSW in this research. The findings display that trust is crucial in increasing a positive feeling toward insurance telematics, which affects users' acceptance of insurance telematics, along with subjective norms. DSW was found to impact users' level of trust significantly. Theoretically, these findings imply that trust offers a significant passage for factors influencing consumers' adoption of technology. Practically, the findings shed light on assisting the auto insurance industry in its digital transformation and designing interventions to improve consumers' adoption of insurance telematics. The authors also suggest regulators take actions to oversee the technology to ensure customer privacy protection and fair market competition.

Keywords: knowledge management, digital transformation, insurance telematics, technology adoption, trust, privacy

INTRODUCTION

Insurance companies are adopting digital strategies using disruptive technologies to increase operational efficiency, business value, and social welfare. Their investment in new technologies continues to grow (Mustafina et al., 2020). As a novel Internet of Things technology, insurance telematics has reshaped the relationship between auto insurers and drivers by collecting and communicating data concerning drivers' mileage and driving behaviors. It offers customized driving diagnoses, safe-driving incentives, and potential cost reductions on drivers' auto coverage policies for reliable driving (Coleman, 2022). This technology allows policyholders to get discounts if they demonstrate safe driving habits. It also allows insurance carriers to gather enormous amounts of data about individuals' driving patterns through different hardware, such as mobile apps, onboard diagnostics devices, and GPS tracking. Insurance telematics enables insurers to use various factors to predict policyholders' driving performance more accurately rather than solely relying on conventional risk factors, such as years of driving, address, and driving history (Tian et al., 2020). They also positively affect insurance claims, risk management, and fraud

detection (Baecke & Bocca, 2017). Telematics can help reduce insurance claims by identifying high-risk drivers and providing targeted and personalized feedback and coaching to educate their policyholders on managing their own risk. They can be used to detect and prevent insurance fraud by providing real-time data on driving behavior. Insurance companies can use telematics data to understand better the risks associated with different types of drivers and vehicles, which can help reduce accidents and improve road safety. Therefore, insurance telematics plays a vital role in shaping the information society. Effective utilization of data and insights from telematics devices can leverage decision-making, risk assessment, product development, and continuous improvement within the insurance industry.

Many insurance companies are working on different types of telematics because they can help grow businesses and improve customer experience. For example, several insurance providers, such as Allstate, Nationwide, Geico, and Progressive, offer telematics programs to extend potential discounts to policyholders (Coleman, 2022). These insurance telematics programs enable insurance companies to capture the driving behavior of the policyholder. When a policyholder drives, the location, and transporting habits are tracked nearly every second and aggregated on the device level. Next, all of the information is transmitted to the insurance carriers. Several additional capabilities can simultaneously be embedded with the device, including automatic emergency notifications, tracking of stolen vehicles, and diagnostic feedback (Coleman, 2022).

Moreover, telematics programs deployed by auto insurers and car manufacturers like Ford are updating their connected vehicle technology to capitalize on the trend. Since 2020, Ford owners who have deployed telematics technology in their vehicles can participate in insurers' telematics programs for more customized rates (Bekemeyer, 2021). According to the Orion Market Report (2021), the compound annual growth rate of the insurance telematics industry is expected to attain 21.01% between 2021 and 2027.

Studies have revealed that telematics-based models can significantly improve risk assessment in the auto insurance industry (Verbelen et al., 2018). The Drive Ability Score and Octo's risk score have been proven to increase the accuracy of driving risk prediction by 10 to 12 times. Insurance telematics also provides insights into driver behavior and habits, allowing insurance companies to detect risky behaviors and provide feedback and education to mitigate driving risks. Through telematics data, insurers, such as Zurich, Ageas, and Co-operative, reduced claims costs by 20% to 60% (Gartner, 2019).

While insurance telematics offers a variety of benefits in terms of safety, cost savings, and management enhancement, these benefits cannot be obtained unless the technology is massively adopted in the market. While less expensive rates may be an attractive incentive for policyholders to enroll in the telematics programs, some drivers may have concerns about losing their behavioral controls. Not all drivers are willing to share their data with insurance carriers monitoring their location and transporting habits (Coleman, 2022). A recent survey has shown that only a small percentage (6%) of Americans have enrolled in an insurance telematics program. It is a meager number compared to 50% of those willing to share driving information with insurance companies (Scrimgeour-Brown, 2021).

To increase the individual's adoption of insurance telematics, it is essential to identify and interpret its acceptance drivers. Some preliminary attempts have been made to study the reasons behind the acceptance of insurance telematics (Chen & Chen, 2009; Tian et al., 2020). These theoretical research studies explain user attitudes and adoption intention based on cognitive mechanisms. They are helpful to insurers and information systems designers when developing products and services to invoke user adoption intention of the technology. However, gaps still exist in this field of research. Although some researchers have included trust constructs in their adoption model (Tian et al., 2020), their acceptable pathways and antecedents have not been well studied. Furthermore, there is a current trend and prevalence of individual IoT applications taking the lead in the commercial IoT sector. Consequently, scholars are urged to focus their attention on the utilization of IoT in connection with individual users (Rock et al., 2022).

The study is motivated to address the research gap by positing and validating a theoretical model for insurance telematics. The model was built by integrating trust and data sharing willingness (DSW) with two well-established theories, the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), with trust.

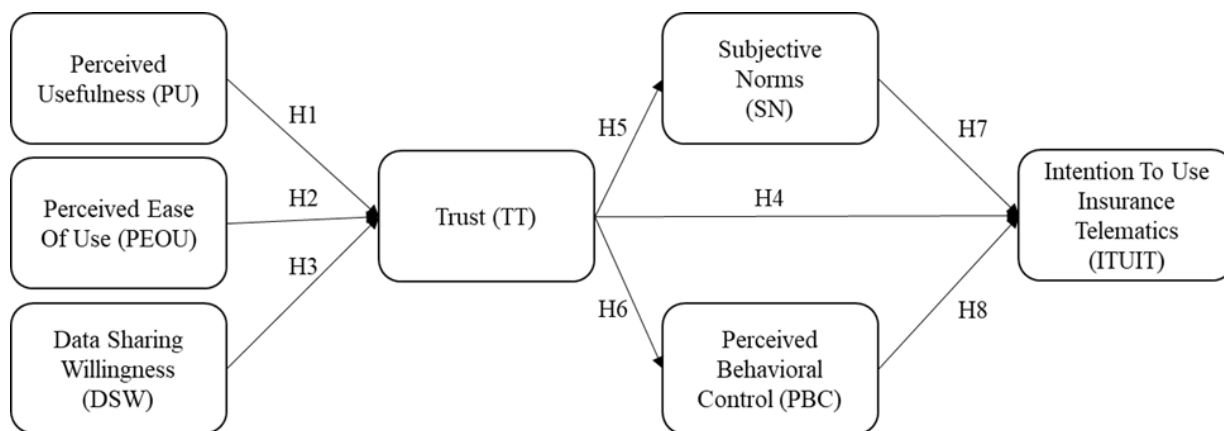
This study is among the first attempts to evaluate the adoption of insurance telematics by combining TAM and TPB with trust and its antecedents, especially the DSW. In addition, it proposes that trust can be regarded as the prime path in affecting the adoption of insurance telematics. The study’s results delved deeper into how psychological factors like trust interact with other factors to change insurance telematics adoption. This study will help insurers and system developers design better products and services, provide proper strategies to increase insurance acceptance, and gain market advantages from a practical perspective.

RESEARCH MODEL AND HYPOTHESES

The study proposes an adoption model for insurance telematics to explain users’ acceptance of insurance telematics better. The research model integrated trust and DSW into the TAM and TPB. TAM and TPB were chosen because of their effectiveness in explaining the adoption of various technologies (Koul & Eydgahi, 2018; Rahman et al., 2017; Rodrigues et al., 2016; Wang et al., 2016) and adaptability in the context of telematics (Kongmuang & Thawesaengskulthai, 2019; Tian et al., 2020).

The research model is presented in Figure 1.

**FIGURE 1
RESEARCH MODEL**



Many theoretical models explain users’ behavior and their adoption of emerging technologies. The most prevalent ones are TAM (Davis, 1989), TAM2 (Venkatesh & Davis, 2000), TPB (Ajzen, 1991), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), and UTAUT2 (Venkatesh et al., 2012). These models are based on the theoretical framework that users’ perceptions and attitudes toward technology can influence its adoption. This study is based on TAM and TPB because both theories are well-developed to explain individuals’ adoption and use of technology (Choi & Ji, 2015; Parasuraman et al., 2008; Tian et al., 2020).

The TAM proposes that the perceived ease of use (PEOU), perceived usefulness (PU), and attitude toward the use of technology are antecedents of technology acceptance. According to the TAM, individuals’ behavioral intention (BI) is determined by their attitude toward technology usage. As two primary predictors of attitude, PEOU influences PU, and PU is expected to affect BI directly. TPB focuses on explaining general human behavior and proposes that intentions drive a person’s behavior. TPB maintains three core elements: attitude, subjective norms (SN), and perceived behavioral control (PBC).

Both TAM and TPB can provide robust predictions and explanations of the determinants of intention to adopt insurance telematics. Previous research has found that PEOU, attitude, and PBC significantly affect an individual’s will to utilize telematics (Chen & Chen, 2009). Tian et al. (2020) extended the theoretical framework of TAM-TPB to explain the adoption and use of insurance telematics. Their findings ascertained that several factors were crucial in shaping an individual’s attitude and intention to use insurance telematics.

Trust

PEOU, PU, and Trust

According to Lee and See (2004), trust is “the attitude that an agent will help achieve an individual’s goals in a situation characterized by uncertainty and vulnerability.” Trust is also “a tool for the reduction of cognitive complexity” (Earle & Cvetkovich, 1995), and it helps to simplify and facilitate people’s decision-making in situations of uncertainty (Kim et al., 2008). Previous research reveals a wide variety of factors that impact trust in technology. Some of the research integrated trust in technology adoption models and investigated the impact of trust and its role as a moderator on TAM (Gefen et al., 2003; Chaouali, et al., 2016). Some others focused on risk-related factors, such as privacy and security, and their impacts on trust and adoption (Angst & Agarwal, 2009; Carlos Roca et al., 2009; Gupta & Xu, 2010; Shin, 2010).

The interplay between trust, PU, and PEOU has been widely discussed in the literature. Their relationships are hypothesized to adopt many technologies (Gefen & Straub, 2004; Wu & Chen, 2005). In particular, PEOU and PU are hypothesized to positively affect trust because these factors can improve the users’ impressions of technologies. Trust in insurance telematics is mainly based on users’ first impressions, and PEOU and PU can be considered as the initial feeling or expectation for acceptance of the technology. Therefore, the study hypothesizes that:

H1: *PU has a positive effect on users’ trust in insurance telematics.*

H2: *PEOU has a positive effect on users’ trust in insurance telematics.*

DSW and Trust

With insurance telematics installed in their automobiles, users’ travel and behavioral data can be transmitted to insurance companies, technology developers, automobile manufacturers, and other parties. The transmission of the telematics users’ current location, past travel habits, and future travel agenda could make them a target of marketing and surveillance. The possibility of a privacy breach affects a user’s feelings and adoption of driving-related technologies. Menon (2015) reported that about one-third of the surveyed US drivers were apprehensive about the unauthorized use of driving data leading to privacy violations.

Ohkubo et al. (2005) stated that people’s views on privacy are not uniform as the tolerance level for privacy concerns varies from person to person. Individuals who are more tolerant of privacy violations are less concerned about protecting their privacy and more likely to use technology compared to those with a lower tolerance for privacy issues (Hossain & Prybutok, 2008). In this study, DSW, a user’s willingness to share personal data, was identified as a factor that impacts trust in insurance telematics. In other words, a specific desire to share personal data is necessary for trust to be operative.

Therefore, the study hypothesizes that:

H3: *DSW has a positive effect on users’ trust in insurance telematics.*

Relationship Between Trust and Adoption Intention

Insurance telematics allows technology to collect a user’s data, including driving behavior and vehicle condition, transmit that data through networks, and share it with other agencies, who may use such data. Such a loss of control could undermine a user’s willingness to accept the technology. People are more willing to share information and adopt new technology when they trust the organization or individual collecting it. When users believe that the potential benefits of insurance telematics outweigh its disadvantages, they will start developing trust in this technology, which can favorably impact their intention to use it. Trust’s impact on technology adoption has been investigated and proved by several information systems research (AlHogail, 2018; Kaur & Rampersad, 2018; Tian et al., 2020).

Therefore, the study hypothesizes that:

H4: *Trust has a positive effect on BI to use of insurance telematics.*

Relationship Between PBC, SN, Trust, and Adoption Intention

The relationships between trust, PBC, and SN have been examined in various studies. Trust is generally hypothesized to be a common antecedent of the other two constructs.

Trust can increase PBC over technology use as interactions between users and technology providers become more regular (Pavlou, 2002; Wu & Chen, 2005). Trust can be viewed as a confident expectation that creates a positive belief toward the perceived behavior control, leading to adoption intentions (Hansen et al., 2018). Furthermore, as a perceptual source that helps users gain information control over technology, trust between users and technology vendors should increase their confidence and PBC.

Prior research mainly focused on the effects of SN on trust (Chaouali et al., 2016; Gong et al., 2019; Wu et al., 2008). Only a few studies have discussed trust's effect on SN. Research has found that trust in technology providers about their brand, reputation, and service positively influences SN (Wu & Chen, 2005). The influencers' opinion is positive for insurance telematics in the market. Trust in influencers can make users believe in technology and insurers and, in turn, leverage positive SN toward insurance telematics.

Therefore, the study hypothesizes that:

H5: *Trust has a positive effect on the SN of using insurance telematics.*

H6: *Trust has a positive effect on PBC when using insurance telematics.*

Both PBC and SN are significant factors that affect BI. The extant literature showed that the users' intentions become more robust as they perceive that they have the power to control technology (Chen & Chen, 2009; Tian et al., 2020). People may be more willing to share their data and use new technology if they have control over how it is used and can see how it is being used. Social norms can play a powerful role in shaping adoption intentions by influencing people's perceptions of what is normal or acceptable and their beliefs about what others are doing. People often look to others, such as friends, family, and peers, to guide their behavior. If they perceive that others are using new technology, they may be more likely to believe it is good and adopt it themselves. The study posits that a higher level of resources and control for users is associated with a greater likelihood of adopting and using insurance telematics. Additionally, the study suggests that individuals are more likely to use new technology when someone they trust recommends it. In summary, the study hypothesizes that:

H7: *SN positively affects the BI to use insurance telematics.*

H8: *PBC positively affects the BI to use insurance telematics.*

METHOD

Survey and Measurements

For this study, empirical data was gathered using a web-based questionnaire. The questionnaire was structured into three parts and was designed to collect information from participants. The first section briefly introduced the functionality of insurance telematics systems, helping the participants understand the concept correctly. The second section collected the participants' demographic characteristics and driving-related information, including age, driving experience, the amount of driving in the past year, and their experience with insurance telematics.

The third section presents an adoption questionnaire that includes the scales measuring the constructs in the proposed model (Figure 1). The survey used in the study was constructed by referencing prior research and was scrutinized by experts to guarantee its validity and reliability. Modifications were made based on the experts' comments and feedback. Questions/items like "Using insurance telematics would make my claim experience faster and easier" were used to measure PU, "I am willing to share my personal information with my insurance company" was utilized to measure DSW, and "The company, which uses

insurance technology, would keep its customers' best interests" was applied to measure trust. All items were measured using a 5-point Likert-type scale ranging from "strongly disagree (1)" to "strongly agree (5)."

Participants

The study considered a sample of higher education students enrolled at one of the largest public universities in the Southwest United States. The study utilized an online survey tool, Qualtrics, to gather data from 138 young consumers. It is noted that younger people are the early adopters of innovative technologies (Liu & Prybutok, 2021; Ogbanufe et al., 2019). The significant advantage of focusing on the younger group is that this group is exceptionally knowledgeable about innovative technologies (Gerpott, 2009) and exerts tremendous effort in identifying potential discounts, savings, and benefits from adopting innovative technologies. Nearly all participants had previous driving experiences and enrolled in an auto insurance plan. The majority of the participants, over 90%, had at least two years of driving experience. Moreover, 89% of the respondents reported driving over 1000 miles in the previous year, showing that they are a group that is experienced with driving, and 13% of them reported using insurance telematics.

RESULTS AND DISCUSSION

This study examined convergent validity. When evaluating the convergent validity of a construct, a factor loading of an item on its underlying construct should have a significant correlation (above 0.6). Adequate validity is indicated by an average variance extracted (AVE) value greater than 0.5. Discriminant validity is demonstrated when the square root of the AVE for a construct is higher than any of its correlations with other constructs in the model (Fornell & Larcker, 1981).

The study evaluated the measurement model's reliability by examining the constructs' internal consistency using Cronbach's alpha and composite reliability scores. Finally, the Common Methods Variance (CMV) was investigated using Harman's one-factor test, which involved conducting a principal component factor analysis of all items without rotation.

We tested our research model using partial least squares (PLS) structural equation modeling and used Smart PLS 4.0 (Hair et al., 2014; Wong, 2013) to examine the proposed research model. Therefore, we determined the significance of path coefficients by utilizing the bootstrapping resampling approach with 5,000 subsamples (Chin, 1998a, 1998b). We used IBM SPSS Statistics for all other analyses. The standardized root mean square residual (SRMR) criterion was applied to evaluate the goodness-of-fit of the proposed model. SRMR is a more appropriate measure for PLS-SEM to avoid model misspecification (Hair et al., 2014). The confirmatory factor and SEM analyses were performed using Smart PLS 4.0. An SRMR value of less than 0.08 is considered a good fit (Hu & Bentler, 1998).

CMV Analysis. Before validating reliability and validity, this research ran Harman's Single-Factor Test to detect CMV. CMV refers to the phenomenon where a shared measurement method distorts the relationship between variables. This test conducted an exploratory factor analysis to identify whether one general factor explains the majority of the variance of all items (Podsakoff et al., 2012). The results showed that the first factor did not extract large enough variance, leading to overestimating the relationships between measured constructs. Next, this study further tested the CMV by using the modified marker variable, and the result demonstrated that the marker variable had no statistically significant impacts on trust, PBC, and intention, and common methods bias had little effect on the research model (Rönkkö & Ylitalo, 2011).

Non-response Bias Analysis. Non-response bias refers to the bias that can occur when certain groups of people do not respond to a survey. It occurs when the characteristics of those who respond to a survey differ from those who do not respond, resulting in a sample that is not representative of the population. This can lead to inaccurate or misleading conclusions if not taken into account. The most common way to examine non-response bias is to compare the characteristics of the first respondents (viewed as respondents) and the late respondents (viewed as non-respondents): By comparing the characteristics of those who first responded to the survey with those who responded late, it is possible to identify any patterns or differences

that may indicate bias (Dalecki et al., 1993). We compared the first 90% of the respondents with the 10% of late respondents. The result showed no notable distinctions between the two groups of survey participants, which suggests the non-response bias had little impact on the study's results.

Constructs and Measurements Assessment

The results of Cronbach's alpha and composite reliability scores, as displayed in Table 1, indicate that the reliability of the constructs is sufficient. The scores are higher than the acceptable threshold of 0.7, which suggests that all the constructs have adequate reliability.

**TABLE 1
OUTER LOADING, CRONBACH'S ALPHA, AND
COMPOSITE RELIABILITY OF THE ITEMS AND CONSTRUCTS**

Items	Outer Loadings	Cronbach's Alpha	Composite Reliability
PU01	0.731	0.804	0.864
PU05	0.734		
PU06	0.767		
PU07	0.803		
PU08	0.705		
PEOU01	0.791	0.887	0.915
PEOU02	0.852		
PEOU03	0.838		
PEOU04	0.823		
PEOU05	0.830		
DSW01	0.876	0.797	0.879
DSW02	0.769		
DSW03	0.876		
TT01	0.868	0.912	0.932
TT02	0.849		
TT03	0.803		
TT04	0.807		
TT05	0.814		
TT06	0.860		
SN01	0.924	0.93	0.948
SN02	0.911		
SN03	0.940		
SN04	0.764		
SN05	0.880		
PBC02	0.868	0.911	0.937
PBC03	0.870		
PBC04	0.925		
PBC05	0.889		
ITUIT01	0.839	0.939	0.952
ITUIT02	0.915		
ITUIT03	0.905		
ITUIT04	0.879		
ITUIT05	0.871		
ITUIT06	0.841		

The significance and strength of the correlation between each item and its corresponding underlying concept are demonstrated by the significant factor loadings (above 0.6) seen in Table 1. The results of the AVE statistic in Table 2 also support this convergence of validity. Further evidence of discriminant validity was obtained by analyzing the square root of AVE values and cross-loading criteria of items, as shown in Table 2. These results show that the square root of AVE values is greater than 0.5 for each construct and higher than the inter-construct correlations, thus indicating a clear distinction between the different constructs.

TABLE 2
AVE, SQUARE ROOT OF AVE, AND CORRELATIONS OF CONSTRUCTS

	AVE	PEOU	ITUIT	PBC	SN	TT	PU	DSW
PEOU	0.684	0.827*						
ITUIT	0.766	0.324	0.875*					
PBC	0.789	0.516	0.425	0.888*				
SN	0.785	0.370	0.637	0.370	0.886*			
TT	0.695	0.449	0.713	0.544	0.510	0.834*		
PU	0.561	0.477	0.634	0.443	0.528	0.615	0.749*	
DSW	0.708	0.099	0.417	0.217	0.274	0.423	0.332	0.842*

AVE: Average Variance Extracted

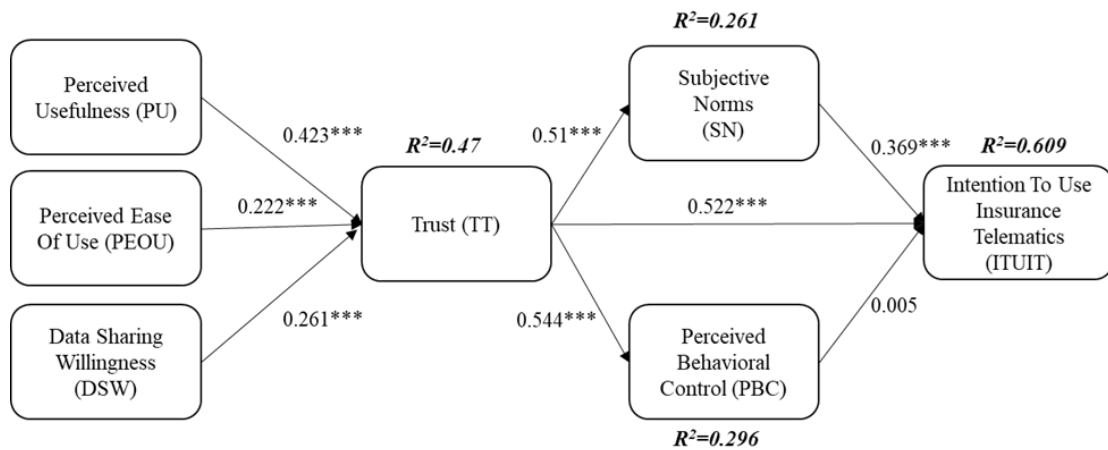
* Square root of AVE

Structural Model Assessment

The goodness-of-fit index (SRMR) is 0.072, indicating that the model meets the suggested criteria (SRMR <0.08) and the proposed model is a good representation of the hypothesized relationships.

The structural model was validated by examining path coefficients and R², which indicate the model’s goodness-of-fit. Followed by Hair et al. (2014), the significance of path coefficients was determined using the SmartPLS 4.0 bootstrapping method with a sample size of 5000. Figure 2 shows the PLS-SEM analysis results.

FIGURE 2
PLS-SEM ANALYSIS RESULTS



*** indicates statistical significance at the 1% level

A summary of the path coefficients and the results of hypothesis testing are presented in Table 3. Seven of the eight hypotheses (H1 to H8) are supported.

TABLE 3
RESEARCH HYPOTHESES AND STATISTICAL RESULTS

Hypotheses	Path Coefficient	Statistical Significance (p-value)	Results
H1: PU has a positive effect on users' trust in insurance telematics	0.423	<0.001	Supported
H2: PEOU has a positive effect on users' trust in insurance telematics	0.222	0.001	Supported
H3: DSW has a positive effect on users' trust in insurance telematics	0.261	<0.001	Supported
H4: Trust has a positive effect on the BI to use insurance telematics	0.522	<0.001	Supported
H5: Trust has a positive effect on the SN to use the insurance telematics	0.51	<0.001	Supported
H6: Trust has a positive effect on the PBC to use the insurance telematics	0.544	<0.001	Supported
H7: SN has a positive effect on the BI to use insurance telematics	0.369	<0.001	Supported
H8: PBC has a positive effect on the BI to use insurance telematics	0.005	0.952	Not Supported

Specifically, trust positively affects the intention to use insurance telematics ($\beta=0.522$, $p < 0.001$), which supports H6. PU, PEOU, and DSW are significant positive predictors of trust ($\beta=0.423, 0.222, 0.261$, respectively, $p < 0.001$). Therefore, H1, H2, and H3 are supported. Additionally, trust has a significant positive effect on SN ($\beta=0.51$, $p < 0.001$), and SN has a positive impact on the intention to use insurance telematics ($\beta=0.369$, $p < 0.001$). Thus, H4 and H7 are supported.

Although trust is a significant predictor of PBC ($\beta=0.544$, $p < 0.001$), PBC is not a significant predictor of intention to use insurance telematics ($\beta=0.005$, $p=0.952$); therefore, H5 is supported, and H8 is rejected.

In addition, the proposed model explains 47% of the variance in trust and 61% of the variance in ITUIT.

CONCLUSION

Understanding customers' attitudes toward insurance telematics can significantly affect knowledge management practices within the insurance industry. This study proposed and empirically tested an extended TAM to understand users' BI when using insurance telematics, including trust and DSW. The model argued that the level of trust largely determines a user's intention to use insurance telematics. Furthermore, trust is a function of PEOU, PU, and DSW. Trust also affects SN, which is positively associated with ITUIT. The results strongly support the research model, with trust identified as the most significant predictor of insurance telematics acceptance. This research contributes to research and practice from multiple perspectives. The trust construct offers another explanation for the factors affecting users' adoption of insurance telematics. DSW was found to impact users' level of trust significantly. From a business and marketing perspective, this finding suggests that the insurance sector should improve the trustworthiness of insurance telematics by enhancing privacy protection features.

Meanwhile, trust can also be increased if users find insurance telematics useful and easy to use. Therefore, insurers can emphasize the benefits of using insurance telematics, such as reducing insurance costs, promoting safe driving, and being good for the environment. A well-designed interface would reduce users' efforts to understand and facilitate their acceptance of insurance telematics.

Theoretical Implications

This research found that the role of trust was much more robust in predicting consumers' intention to use insurance telematics directly and indirectly, which is its first and most important contribution. In the context of telematics, this research is the initial effort to recognize trust as the most critical antecedent in determining insurance telematics usage. Trust exhibited a substantial direct effect on BI in the work of other researchers as well. The results align with existing technology adoption studies (Choi & Ji, 2015; Tian et al., 2020).

In terms of its second contribution, this study demonstrated that trust could be built upon a combination of cognitive beliefs of capabilities and functionalities of a technology. The study results showed that PU and PEOU are appropriate for investigating trust in insurance telematics. In addition, these findings demonstrated that it is vital to improve the consumers' perception of the usefulness and ease of use to help them gain confidence in the operation of insurance telematics. This is consistent with the trust models that Zhang et al. (2019) proposed. According to their findings, trust relies on the performance of a system; the usefulness and ease of a system should be fundamental determinants of trust. This implies that enhancing insurance telematics' effectiveness and ease of use would be essential and valuable for users to develop trust in the technology.

The third theoretical contribution was that our results helped clarify the relationship between DSW and trust in the technology adoption literature. While privacy risk has been frequently cited as a major concern in technology adoption (Gao et al., 2015; Lemay et al., 2017; Zhou, 2011), our results revealed that DSW determines users' intention to use technology by impacting their level of trust.

Trust has a significant influence on SN and, in turn, on adoption. The analysis showed that trust could explain 26% of the total variance in SN, providing an alternative to conceptualizing and predicting SN. Although trust was found to affect PBC significantly, the PBC was not a factor affecting the intention to adopt insurance telematics. This finding provided evidence against previous research (Dikmen & Burns, 2017; Wu & Chen, 2005). A possible explanation is that most of the survey participants in our study were not direct users of insurance telematics. Less experience may have undermined this relationship. Another reason is that these participants felt it was easy to use insurance telematics, and the PBC did not enhance their trust levels.

Practical Implications

Telematics leverages digital technology to provide customers with a superior auto insurance product. It enables insurers to build a closer relationship with customers and helps mitigate losses and fraud. It also helps reduce the claim settlement time for a better customer experience. However, data collection through telematics comes with privacy concerns and skeptical attitudes on the part of users. The insurance company should enhance engagement, transparency, privacy protection, and customer experience to facilitate telematics adoption.

The findings of this study can help auto insurers, car manufacturers, and telematics designers to create feasible practices for developing and deploying insurance telematics. Trust showed the most substantial effect on users' adoption intentions. Facilitating user trust should be the primary focus in marketing insurance telematics. The results suggested that marketers should explain how the technology helps and protects drivers to promote universal access to insurance telematics. They can also consider offering users a free trial to improve PU and explain its benefits. As a significant factor, PEOU can boost trust. This finding implies that insurance telematics designers should reduce the complexity of interaction between users and the telematics system and make insurance telematics easy to use by designing user-friendly and easy-to-use apps and devices. Clarifying how the technology application and algorithm work for the benefit of users would enhance their understanding and trust. Insurance companies should educate their customers by making sure consumers understand the benefits of telematics, such as lower rates for safe driving and how it works. They should offer incentives by including discounts or rewards for signing up for and using the telematics program. The insurers should ensure that customer service is responsive and helpful, as this will help to establish trust and encourage customers to adopt the telematics program. They should continuously evaluate the program's performance and adjust to improve its value and customer experience.

Data privacy is a negative issue when discussing the adoption of insurance telematics. However, several approaches can be applied to reduce barriers to trusting the technology and improve adoption. According to our model, decreasing users' perceived threats to their privacy and increasing their willingness to share personal data would enhance trust. Therefore, it is suggested that insurers provide privacy and security plans and communicate how drivers' data are collected, stored, used, analyzed, and archived, as well as how security and privacy rules are implemented to protect their personal information. Insurers should improve the data quality by ensuring the data collected is accurate, reliable, and valuable for the insurance company and the customer. These clarifications would go a long way in increasing users' trust and improving the adoption of telematics. Insurers can increase data sharing willingness by building trust, being transparent about data use, providing clear customer benefits, and addressing privacy concerns. Overall, the key to improving the adoption of insurance telematics is to create a user-friendly program that creates value for customers and is perceived as trustworthy.

In addition, insurance companies can maintain excellent customer service to build long-term trust with customers. They can offer concise and timely tips and feedback on driving behaviors to help customers enhance their driving skills and feel more in control of their premium rate. Their efficient responses to customers' inquiries and complaints and quick resolution of claim issues also build solid trust with customers.

Regulations are critical in overseeing new technology use in the insurance industry. Regulators should regulate the new technology's application and deployment, ensure insurance companies comply with laws and regulations, and protect customers. Regulators need to monitor the use of telematics data, enforce data protection laws, and ensure insurance customers are provided with explicit, accurate, and legitimate information about data policies. The regulators must also review insurance companies' policies and practices to avoid discrimination or anti-competitive. For those who violate the compliant requirements, regulators should conduct on-site examinations and take enforcement actions to ensure fair market competition and the fair use of telematics technology.

Limitations and Future Scope of the Study

The form and functionality of insurance telematics technology may change in the future. Our study and recommendations are based on how this technology currently works. Therefore, the first limitation of our study is that if the technology changes significantly in the future, it may affect our results' applicability. Second, the respondents were relatively young, indicating that the collected data were biased toward young people's opinions. Another limitation is that most respondents did not have experience with insurance telematics. Therefore, the trust discussed in this study reflected the respondents' knowledge acquired from sources such as the Internet and media. Future studies should investigate the trust of those users who have experienced insurance telematics. Moreover, future research can explore the impacts of other factors, such as perceived risk and value to adoption.

REFERENCES

- Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211. DOI: 10.1016/0749-5978(91)90020-T
- AlHogail, A. (2018). Improving IoT technology adoption through improving consumer trust. *Technologies*, 6(3), 64. DOI: 10.3390/technologies6030064
- Angst, C.M., & Agarwal, R. (2009). Adoption of electronic health records in the presence of privacy concerns: The elaboration likelihood model and individual persuasion. *MIS Quarterly*, pp. 339–370.
- Baecke, P., & Bocca, L. (2017). The value of vehicle telematics data in insurance risk selection processes. *Decision Support Systems*, 98, 69–79. DOI: 10.1016/j.dss.2017.04.009
- Bekemeyer, J. (2021). Ford announces agreement with Italian telematics firm to personalize insurance rates. *Detroit's Premier Business Journal*. Retrieved July 15, 2021 from <https://www.dbusiness.com/daily-news/ford-announces-agreement-with-italian-telematics-firm-to-personalize-insurance-rates/>
- Carlos Roca, J., José García, J., & José de la Vega, J. (2009). The importance of perceived trust, security and privacy in online trading systems. *Information Management & Computer Security*, 17(2), 96–113.
- Chaouali, W., Ben Yahia, I.B., & Souiden, N. (2016). The interplay of counter-conformity motivation, social influence, and trust in customers' intention to adopt Internet banking services: The case of an emerging country. *Journal of Retailing and Consumer Services*, 28, 209–218. DOI:10.1016/j.jretconser.2015.10.007
- Chen, H.H., & Chen, S.C. (2009). The empirical study of automotive telematics acceptance in Taiwan: Comparing three technology acceptance models. *International Journal of Mobile Communications*, 7(1), 50–65. DOI: 10.1504/IJMC.2009.021672
- Chin, W.W. (1998a). Issues and opinion on structural equation modeling. *MIS Quarterly*, 22(1). Retrieved from <http://www.jstor.org/stable/249674>
- Chin, W.W. (1998b, January). The Partial Least Squares Approach to Structural Equation Modeling. *Quantitative Methodology Series*, pp. 295–336. <https://doi.org/10.1016/j.aap.2008.12.010>
- Coleman, S. (2022, November 22). Car insurance with telematics programs. *Bankrate*.
- Choi, J.K., & Ji, Y.G. (2015). Investigating the importance of trust on adopting an autonomous vehicle. *International Journal of Human-Computer Interaction*, 31(10), 692–702.
- Dalecki, M., Whitehead, J., & Blomquist, G. (1993). Sample non-response bias and aggregate benefits in contingent valuation: An examination of early, late, and non-respondents. *Journal of Environmental Management*, 38, 133–143.
- Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of Information Technology. *MIS Quarterly*, 13(3), 319–340. <https://doi.org/10.2307/249008>
- Dikmen, M., & Burns, C. (2017, October). Trust in autonomous vehicles: The case of tesla auto pilot and Summon. In *IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, (pp.1093–1098). IEEE Publications.
- Earle, T.C., & Cvetkovich, G.T. (1995). *Social trust: Toward a cosmopolitan society*. Westport, CT: Praeger Publishers.
- Fornell, C., & Larcker, D.F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, 18(3), 382–388. DOI:10.1177/002224378101800313
- Gao, Y., Li, H., & Luo, Y. (2015). An empirical study of wearable technology acceptance in healthcare. *Industrial Management and Data Systems*, 115(9), 1704–1723. DOI: 10.1108/IMDS-03-2015-0087
- Gartner (2019). *Digital Transformation Through Connected Insurance*. Retrieved from <https://www.gartner.com/teamsiteanalytics/servePDF?g=/imagesrv/media-products/pdf/Octo-Telematics/octo-telematics-1-1OE6YIM6.pdf>

- Gefen, D., Karahanna, E., & Straub, D.W. (2003). Trust and TAM in online shopping: An integrated model. *MIS quarterly*, pp. 51–90.
- Gefen, D., & Straub, D.W. (2004). Consumer trust in B2C e-Commerce and the importance of social presence: Experiments in e-Products and e-Services. *Omega*, 32(6), 407–424.
- Gerpott, T.J. (2009). Biased choice of a mobile telephony tariff type: Exploring usage boundary perceptions as a cognitive cause in choosing between a use-based or a flat rate plan. *Telematics and Informatics*, 26(2), 167–179. <https://doi.org/10.1016/j.tele.2008.02.003>
- Gong, Z., Han, Z., Li, X., Yu, C., & Reinhardt, J.D. (2019). Factors influencing the adoption of online health consultation services: The role of subjective norm, trust, perceived benefit, and offline habit. *Frontiers in Public Health*, 7, 286. DOI: 10.3389/fpubh.2019.00286
- Gupta, S., & Xu, H. (2010). Examining the relative influence of risk and control on intention to adopt risky technologies. *Journal of Technology Management & Innovation*, 5(4), 22–37.
- Hansen, J.M., Saridakis, G., & Benson, V. (2018). Risk, trust, and the interaction of perceived ease of use and behavioral control in predicting consumers' use of social media for transactions. *Computers in Human Behavior*, 80, 197–206. <https://doi.org/10.1016/j.chb.2017.11.010>
- Hair, J.F., Henseler, J., Dijkstra, T.K., & Sarstedt, M. (2014). Common beliefs and reality about partial least squares: Comments on Rönkkö and Evermann. *Faculty Publications*, 3666. Retrieved from <https://digitalcommons.kennesaw.edu/facpubs/3666>
- Hossain, M.M., & Prybutok, V.R. (2008). Consumer acceptance of RFID technology: An exploratory study. *IEEE Transactions on Engineering Management*, 55(2), 316–328. DOI:10.1109/TEM.2008.919728
- Hu, L.T., & Bentler, P.M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods*, 3(4), 424–453. DOI:10.1037/1082-989X.3.4.424
- Kaur, K., & Rampersad, G. (2018). Trust in driverless cars: Investigating key factors influencing the adoption of driverless cars. *Journal of Engineering and Technology Management*, 48, 87–96. DOI: 10.1016/j.jengtecman.2018.04.006
- Kim, D.J., Ferrin, D.L., & Rao, H.R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems*, 44(2), 544–564.
- Kongmuang, P., & Thawesaengskulthai, N. (2019). Improvement of telematics solution for motor insurance in Thailand by 5-D innovation development process. In *6th International Conference on Industrial Engineering and Applications (ICIEA)* (pp. 6–11). IEEE Publications.
- Koul, S., & Eydgahi, A. (2018). Utilizing technology acceptance model (TAM) for driverless car technology adoption. *Journal of Technology Management and Innovation*, 13(4), 37–46. DOI:10.4067/S0718-27242018000400037
- Lee, J.D., & See, K.A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors*, 46(1), 50–80. DOI: 10.1518/hfes.46.1.50_30392
- Lemay, D.J., Doleck, T., & Bazalais, P. (2017). 'Passion and concern for privacy' as factors affecting snapchat use: A situated perspective on technology acceptance. *Computers in Human Behavior*, 75, 264–271. DOI: 10.1016/j.chb.2017.05.022
- Liu, X., & Prybutok, V.R. (2021). An empirical investigation of factors that drive a user decision to continue using cloud storage services. *Journal of Decision Systems*, 30(1), 4–26. <https://doi.org/10.1080/12460125.2020.1798590>
- Menon, N. (2015). *Consumer perception and anticipated adoption of autonomous vehicle technology: Results from multi-population surveys*. University of South Florida.
- Mustafina, A.A., Kaigorodova, G.N., Alyakina, P.D., Velichko, N.Y., & Zainullina, M.R. (2020). Digital technology in insurance. In *Advances in Intelligent Systems and Computing*. Cham: Springer, (678–685). DOI: 10.1007/978-3-030-11367-4_65

- Ogbanufe, O., Dinulescu, C., Liu, X., & Kucuk, C. (2019). It's in the cloud : Theorizing context- specific factors influencing the perception of mobile cloud storage. *The Data Base for Advances in Information Systems*, 50(3), 116–137. <https://doi.org/10.1145/3353401.3353408>
- Ohkubo, M., Suzuki, K., & Kinoshita, S. (2005). RFID privacy issues and technical challenges. *Communications of the ACM*, 48(9), 66–71. DOI: 10.1145/1081992.1082022
- Orion Market Reports. (n.d.). *Global Insurance Telematics Market to 2027, Global Trends, Opportunity, Future Outlook, COVID-19 Impact Analysis, Forecast 2021–2027*. Retrieved July 23, 2021 from <https://www.orionmarketreports.com/insurance-telematics-market/44248/>
- Parasuraman, R., Sheridan, T.B., & Wickens, C.D. (2008). Situation awareness, mental workload, and trust in automation: Viable, empirically supported cognitive engineering constructs. *Journal of Cognitive Engineering and Decision Making*, 2(2), 140–160. DOI: 10.1518/155534308X284417
- Pavlou, P.A. (2002). Institution-based trust in interorganizational exchange relationships: The role of online B2B marketplaces on trust formation. *The Journal of Strategic Information Systems*, 11(3–4), 215–243.
- Podsakoff, P.M., Mackenzie, S.B., & Podsakoff, N.P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, 63, 539–569. <https://doi.org/10.1146/annurev-psych-120710-100452>
- Rahman, M.M., Lesch, M.F., Horrey, W.J., & Strawderman, L. (2017). Assessing the utility of TAM, TPB, and UTAUT for advanced driver assistance systems. *Accident Analysis & Prevention*, 108, 361–373. DOI: 10.1016/j.aap.2017.09.011
- Rock, L.Y., Tajudeen, F.P., & Chung, Y.W. (2022). Usage and impact of the internet-of-things-based smart home technology: A quality-of-life perspective. *Universal Access in the Information Society*, pp. 1–20.
- Rodrigues, L.F., Oliveira, A., & Costa, C.J. (2016). Does ease-of-use contributes to the perception of enjoyment? A case of gamification in e-banking. *Computers in Human Behavior*, 61, 114–126. DOI: 10.1016/j.chb.2016.03.015
- Rönkkö, M., & Ylitalo, J. (2011). PLS marker variable approach to diagnosing and controlling for method variance. *CIS 2011 Proceedings*, 8.
- Scrimgeour-Brown, M. (2021). Telematics “a total Game Changer” for auto insurers. *Insurance Business*. Retrieved August 1, 2021, from <https://www.insurancebusinessmag.com/us/news/commercial-auto/telematics-a-total-game-changer-for-auto-insurers-259488.aspx>
- Shin, D.H. (2010). The effects of trust, security and privacy in social networking: A security-based approach to understand the pattern of adoption. *Interacting with Computers*, 22(5), 428–438.
- Tian, X., Prybutok, V.R., Mirzaei, F.H., & Dinulescu, C.C. (2020). Millennials acceptance of insurance telematics: An integrative empirical study. *American Business Review*, 23(1), 156–181. DOI:10.37625/abr.23.1.156-181
- Venkatesh, V., & Davis, F.D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186–204. DOI:10.1287/mnsc.46.2.186.11926
- Venkatesh, V., Morris, M.G., Davis, G.B., & Davis, F.D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. DOI: 10.2307/30036540
- Venkatesh, V., Thong, J.Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157–178. DOI: 10.2307/41410412
- Verbelen, R., Antonio, K., & Claeskens, G. (2018). Unravelling the predictive power of telematics data in car insurance pricing. *Journal of the Royal Statistical Society: Series C*, 67(5), 1275–1304. <https://doi.org/10.1111/rssc.12283>

- Wang, Q., Sun, X., Cobb, S., Lawson, G., & Sharples, S. (2016). 3D printing system: An innovation for small-scale manufacturing in home settings? –Early adopters of 3D printing systems in China. *International Journal of Production Research*, 54(20), 6017–6032. DOI:10.1080/00207543.2016.1154211
- Wong, K.K.K. (2013). Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. *Marketing Bulletin*, 24(1), 1–32.
- Wu, I., & Chen, J.L. (2005). An extension of trust and TAM model with TPB in the initial adoption of online tax: An empirical study. *International Journal of Human-Computer Studies*, 62(6), 784–808. DOI: 10.1016/j.ijhcs.2005.03.003
- Wu, J.H., Shen, W.S., Lin, L.M., Greenes, R.A., & Bates, D.W. (2008). Testing the technology acceptance model for evaluating healthcare professionals' intention to use an adverse event reporting system. *International Journal for Quality in Health Care*, 20(2), 123–129. DOI:10.1093/intqhc/mzm074
- Zhang, T., Tao, D., Qu, X., Zhang, X., Lin, R., & Zhang, W. (2019). The roles of initial trust and perceived risk in public's acceptance of automated vehicles. *Transportation Research Part C*, 98, 207–220. DOI: 10.1016/j.trc.2018.11.018
- Zhou, T. (2011). The impact of privacy concern on user adoption of location-based services. *Industrial Management and Data Systems*, 111(2), 212–226.