Hyper-Personalization in Motor Insurance : Understanding Telematics Insurance Adoption Using the Extended Technology Acceptance Model

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Abstract

Purpose : The analysis of driving behavior and vehicle dynamics using telematics technology paved the way for current insurance underwriting and disruptions in automobile insurance. This study aimed to understand the behavioral intentions of users toward adopting telematics-based insurance products.

Design/Methodology/Approach : Relevant constructs from extant literature were used to extend the technology acceptance model (TAM) to improve its explanatory power and identify meaningful linkages among the variables. A cross-sectional design with a quantitative survey examined how individuals perceived insurance telematics technology.

Findings : Perceived enjoyment had the greatest impact, while perceived trust had the least impact on behavioral intentions. Perceived privacy risk lowered intentions to use telematics insurance. The extended TAM model proved valid, explaining 59% of the variance in behavioral intentions. Additionally, two-thirds of the respondents were open to adjusting their driving habits for safer driving if it meant lowering insurance premiums.

Practical Implications : Telematics insurers and marketers were advised to prioritize ensuring a smooth transition for users to attain scalability and profitability. Marketers should emphasize the enjoyable aspects of telematics insurance while also addressing privacy concerns. Additionally, aligning users' discount expectations with actual offerings was suggested to be crucial to bridge gaps.

Originality/Value : This research provided valuable insights into a recent advancement in motor insurance in India, i.e., telematics-based insurance. As far as we know, it is among the pioneering studies conducted on this subject within the Indian subcontinent.

Keywords : telematics, motor insurance, behavioral intention, technology adoption, usage-based insurance

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Until recently, motor insurers relied primarily on traditional risk assessment and claims processing methods. However, technological advancements like telematics allowed insurers to consider vehicle dynamics and real-time driving behavior. Telematics, encompassing telecommunication and informatics, emerged as a new technology within the Internet of Things (IoT), with diverse applications across industries, such as logistics, insurance, road safety, and assistance. Telematics insurance, specifically applying telematics technology in motor insurance, not only aided firms in profitability but also in exploring new customer segments. Its benefits included reduced accidents and thefts, availability of quantitative data for insurers, competitive pricing, hyper-personalization, positive environmental impact, vehicle tracking, and emergency signal activation (Insurance Regulatory and Development Authority of India (IRDAI), 2020). Emerging economies, notably BRICS nations—Brazil, Russia, India, China, and South Africa—were identified as promising markets for telematics insurance. Global Market Insights (2022) forecasted that the global telematics insurance market is expected to grow by 20% annually by 2027. A variant, usage-based insurance (UBI), reached USD 40 billion as of FY 2019–20, with the Asia Pacific region accounting for 15% of global usage-based insurance, primarily led by China, while India held less than 5%.

In India, according to the Motor Vehicles Act 1988, vehicle owners were mandated to insure against third-party risk. Despite owning just over 1% of global vehicles, India accounted for 11% of global deaths in road accidents in 2020 (The World Bank, 2021), with 52% of global road accidents occurring in India despite only having 5% of the global road network (Mishra & Mishra, 2017). Accidents and vehicle thefts burden insurers with increased claims, leading to higher consumer premium rates. The Insurance Regulatory and Development Authority of India (IRDAI) recommended telematics use in motor insurance, aiming to align Indian motor insurance industry practices with global standards through initiatives like the "Sandbox" program (IRDAI, 2020). However, data ownership, sharing, portability, and privacy challenges were highlighted (Sardana et al., 2023). Telematics insurance in India is nascent, requiring a thorough understanding of factors affecting user behavioral intentions for successful mass implementation.

As Indian insurers conducted pilot studies, with only a few launching telematics insurance products in the Indian market, a clear gap was identified where only a few attempts were made to understand the factors supporting or hindering telematics insurance adoption among Indian motor insurance customers. This study is among the first to focus on understanding adoption intentions among users in the Indian subcontinent. The proposed conceptual framework extended the final version of the technology acceptance model (TAM) proposed by Venkatesh and Davis (1996) and aimed to integrate relevant factors to enhance explanatory power.

To this end, the present study aims to address the following research questions:

- ***RQ1 :*** How do motor insurance users perceive telematics hyper-personalization features, and what are their expectations from the product regarding utility and discounts?

- ***RQ2 :*** How do users develop behavioral intentions toward using telematics technology?

- ***RQ3 :*** Is using telematics motor insurance associated with reduced risk-taking behavior in its users?

Literature Review and Hypotheses Development

Telematics

Insurance telematics is a recent worldwide development in the motor insurance industry, aligning users' insurance premiums with their usage and driving behavior. Conventional underwriting variables, such as engine capacity, vehicle types, and drivers' age, were primarily used to decide premium rates. However, these variables presented a static and partial picture of vehicle usage, resulting in improper premium charges for low-risk and high-risk users. This discussion gave rise to the concept of usage-based insurance (UBI), a type of telematics insurance.

Vickrey (1968) was among the first to endorse the idea of dynamic premiums. Doecke et al. (2020) argued that a vehicle's speed, an important parameter, affects crash risk and seriousness. Ben-Shahar (2023) proposed periodic readings from vehicle odometers and incorporated 12 additional factors to improve underwriters' accuracy. Henckaerts and Antonio (2022) suggested collecting GPS and driving data to calculate premiums. Stevenson et al. (2021) argued that telematics insurance premium differentiation would improve consumers' driving behavior and road safety. Cheng et al. (2023) highlighted the inefficiency of fixed-amount premiums in motor insurance, which puts users who drive less in an unfavorable position. This recent technological development in motor insurance can be understood using technology acceptance models.

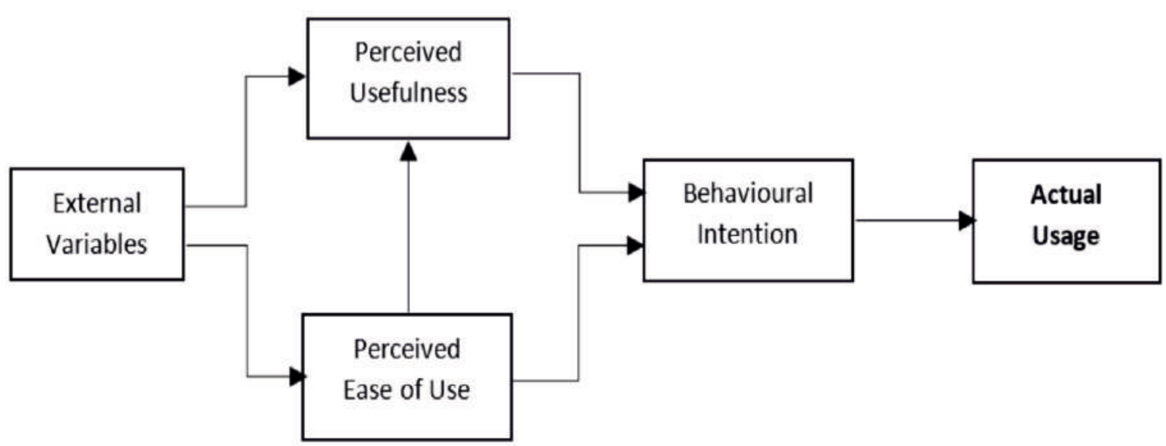
Technology Acceptance Model

The technology acceptance model by Venkatesh and Davis (1996) (refer to Figure 1) proposed constructs of perceived ease of use (PEOU) and perceived usefulness (PU). Depending upon the interaction between PU and PEOU, behavioral intentions (BI) and motivation leading to the use of new technology can be studied. TAM found its roots in the theory of reasoned action (TRA) (Ajzen & Fishbein, 1975), which explains human behavior and intentions. TRA was developed to understand human behavior in a general sense. In contrast, TAM specifically helped understand the acceptance of computer systems by the users and has been applied in various technological domains.

A literature review on technology adoption suggested TAM as one of the most widely used and influential models (Alturas, 2021). TAM, a simple and verifiable model, was applied in various technological fields to enhance its explanatory power and factors, such as perceived trust (PT), social influence (SI), facilitating conditions (FC), perceived enjoyment (PE), and perceived risk. Perceived financial risk (PFR) and perceived privacy risk (PPRIVR) were incorporated. The subsequent section of the literature review illustrates the diverse application of TAM.

Tian et al. (2020) explained millennials' acceptance of telematics insurance in the USA based on TAM and the theory of planned behavior (TPB) models. They found significant relationships within PU, PEOU, SN, and BI. BI was positively influenced by subjective norms (SN) and perceived enjoyment (PE). Kongmuang and Thawesaengskulthai (2019) studied telematics in Thailand by integrating TAM and the diffusion of innovation

Figure 1. ***Technology Acceptance Model (TAM) (Venkatesh & Davis, 1996)***



(DOI) theory and found low adoption rates of telematics technology in Thailand. Tabeck and Singh (2022) examined the adoption of mobile applications among low-income customers in the Indian context and found it suitable for explaining BI. Chauhan et al. (2016) used TAM on e-banking services in India. All primary factors of TAM, i.e., PU, PEOU, and BI, showed significant relationships. However, the driver's age and experience were negatively associated with using driverless cars. Rahman et al. (2017) integrated TAM, TPB, and the unified theory of acceptance and use of technology (UTAUT) models to study the advanced driver assistance systems (ADAS) in the USA. They found that TAM was the most capable of explaining the driver's acceptance of technology out of the three models. In other technological domains, implemented TAM was used to explain the adoption of a smartwatch (Wu et al., 2016), global positioning system (Chen & Chen, 2011), and fleet management systems (Tseng et al., 2013).

Perceived Usefulness (PU)

PU was defined as "the degree to which a user believed that the system would help increase his or her performance at work or in real-life situations" (Chen & Chen, 2011). These benefits were identified as key drivers and could be physiological, psychological, sociological, or material (Tian et al., 2020). Some direct benefits to customers included premium discounts for exhibiting good driving behavior, enhanced safety, and improved claim settlement experience (Tian et al., 2020). High-risk customers did not have direct monetary gains; however, they still had the added benefits of tracking their vehicle and driving habits and could even avail of off and on-road vehicle assistance (Henckaerts & Antonio, 2022). Telematics studies about usage intentions in different countries shared exciting insights. Rejikumar (2013), in a pre-launch survey in India, stated that consumers were likely to adopt UBI in the future because of the significant impact of perceived individual and social benefits, value, and ease of understanding. Litman (2011) argued how UBI would bring fairness, reduce traffic issues and affordability, and assist in achieving public policy objectives, i.e., benefits for all stakeholders. The following hypothesis is proposed for perceived usefulness:

- **Ha_1 :** BI's use of insurance telematics services is positively impacted by PU.

Perceived Ease of Use (PEOU)

PEOU was defined as "the degree to which a person believes that using a particular system would be free of effort" (Chen & Chen, 2011). PEOU construct is related to the concept of minimal effort, which states that "an individual will adopt a course of action that involves least average work from that person" (Joshi, 2024). If a technology is seen as easy to use and interact with, the chances of its adoption increase (Tian et al., 2020). Regarding telematics insurance, this corresponds to saying that chances of adoption correlate with how easily prospective users understand and get hold of the overall telematics systems, i.e., required information, mobile application, black box, accessories, and motor insurance policy. Studies on TAM further suggested that PEOU affects behavioral intentions directly and indirectly through PU (Venkatesh & Davis, 1996). However, Tian et al. (2020) pointed out that PEOU for telematics adoption in the millennial age group only indirectly affected the attitude toward behavior through PU, the reason being more millennials' familiarity with the latest technology. To further develop the course of the discussion, we propose the following hypotheses:

- **Ha_2 :** PU is positively impacted by PEOU.
- **Ha_3 :** BI's use of insurance telematics services is positively impacted by PEOU.
- **Ha_4 :** BI's use of insurance telematics services is indirectly and positively impacted by PEOU through PU.

Perceived Trust (PT)

Perceived trust was "a state of emotion encouraging one's trust in the other party based on the acceptable behavior of the latter" (Gupta & Barkathunissa, 2022). It was extensively noticed in various telematics insurance contexts (Chauhan et al., 2023; Gupta & Pande, 2017). Studies also suggested that Indian consumers exhibit a moderate level of trust in technology-based insurance solutions (Mukhopadhyay & Chakraborty, 2018), along with considerable emphasis on the reputation and credibility of insurers when considering telematics programs (Gupta & Pande, 2017). However, concerns about data accuracy, potential manipulation, and privacy violations can undermine this trust. In telematics insurance, data integrators collect user data and share it with the insurers. A lack of user awareness of information regarding the collection, storage, and usage of this information may give rise to trust issues (Chauhan et al., 2023). The following hypothesis is proposed for perceived trust:

➯ **Ha_5 :** BI's use of insurance telematics services is positively impacted by PT.

Social Influence (SI)

Apart from direct interaction with technology, individuals' adoption intentions were also affected by their psychological attributes and social interactions. The literature stated that an individual's surroundings and behavior influenced his/her behavior and defined social influence as "the extent to which supposedly important people in one's circle affect his/her behavior" (Chauhan et al., 2023). Zhang et al. (2020) argued that SI is necessary for adopting automated vehicles in China. Research by Singh and Kumar (2019) suggested that individualism, collectivism, and socioeconomic status influenced attitudes toward telematics-based insurance. Jain and Singla (2019) found that peer recommendations and experiences significantly encouraged adoption among Indian consumers. Thus, an individual's family, friends, workplace colleagues, and social influencers can affect his/her adoption intention. The following hypothesis is proposed for social influence:

➯ **Ha_6 :** BI's use of insurance telematics services is positively impacted by SI.

Facilitating Conditions (FC)

In the telematics insurance context, facilitating conditions are defined as the facilitating factors, such as system knowledge, resources to use the technology, service personnel, and compatibility to be the most important predictors of telematics usage intentions in the users (Milanović et al., 2020). Technology users seek timely assistance and support, complete information, and available resources. It can help individuals accept technologies (Shokeen et al., 2023). Mukhopadhyay and Chakraborty (2018) highlighted the significance of organizational policies and infrastructure that support technology use. Insurers need to ensure that users perceive the necessary support and resources to facilitate the adoption and use of telematics-based insurance. Thus, we propose that:

➯ **Ha_7 :** BI to adopt insurance telematics services is positively impacted by FC.

Perceived Enjoyment (PE)

Perceived enjoyment was associated with the usage process and users' pleasure and enjoyment while using technology (Tian et al., 2020). While limited, some studies have explored the role of perceived enjoyment in insurance telematics adoption. In the Indian context, Chauhan et al. (2023) posited that hedonic motivations play the most significant role in affecting intentions to use telematics insurance in Indian users, which may stem from features such as gamification elements, personalized feedback, and rewards for safe driving. Enjoyment propels an individual intrinsically to adopt a technology without extrinsic compulsions. Technology users of different age groups tend to derive enjoyment differently. As per Tian et al. (2020), new technological developments, such as telematics insurance, especially attract younger individuals who are generally more familiar with the technology. Their comfort with new developments gives them more positive experiences than other age groups (Gupta et al., 2020; Tian et al., 2020). Thus, we hypothesize that:

- **Ha_8 :** BI's use of insurance telematics services is positively impacted by PE.

Perceived Financial Risk (PFR)

Financial concerns derive from the users' feelings about a product or technology not worth their monetary investment, i.e., the users' adverse financial outcomes, if any, while adopting or after adopting the product (Senyo & Osabutey, 2020). It corresponds to the risk associated with the utilitarian value of the investment made by the user and limits a user's motivation to search for further information (Shetty & Basri, 2021). Thus, it becomes less necessary for people to search for product-related information if they have already perceived an investment as financially risky, as the users would exhibit risk-reducing behavior (Holzapfel et al., 2023). However, Eling and Kraft (2020) argued that telematics insurance may not directly affect users' risk-reducing behaviors. Users may initially perceive telematics insurance as a financially risky venture, as there are specific concerns related to its monetary costs, risks associated with the installation and working of telematics apparatus, and the accuracy of the mathematical models. The following hypothesis is thus proposed for perceived financial risk:

- **Ha_9 :** BI's use of insurance telematics services is negatively impacted by PFR.

Perceived Privacy Risk (PPRIVR)

Privacy risk, associated with customers' perceptions of responsible data usage by businesses (Gupta et al., 2020), became a significant concern as insurers intensified the collection of driving data following the implementation of telematics insurance (Ben-Shahar, 2023). Users remained cautious about data privacy and potential misuse by firms (Ben-Shahar, 2023), leading to heightened concerns about privacy risks. Regulatory frameworks governing data privacy and security were essential for fostering trust and facilitating adoption (Bhatia & Breaux, 2018). As India drafted data protection legislation (Murthy & Kumar, 2015), targeted educational campaigns were suggested to alleviate concerns about data privacy, security, and the benefits of telematics insurance (Gupta et al., 2020).

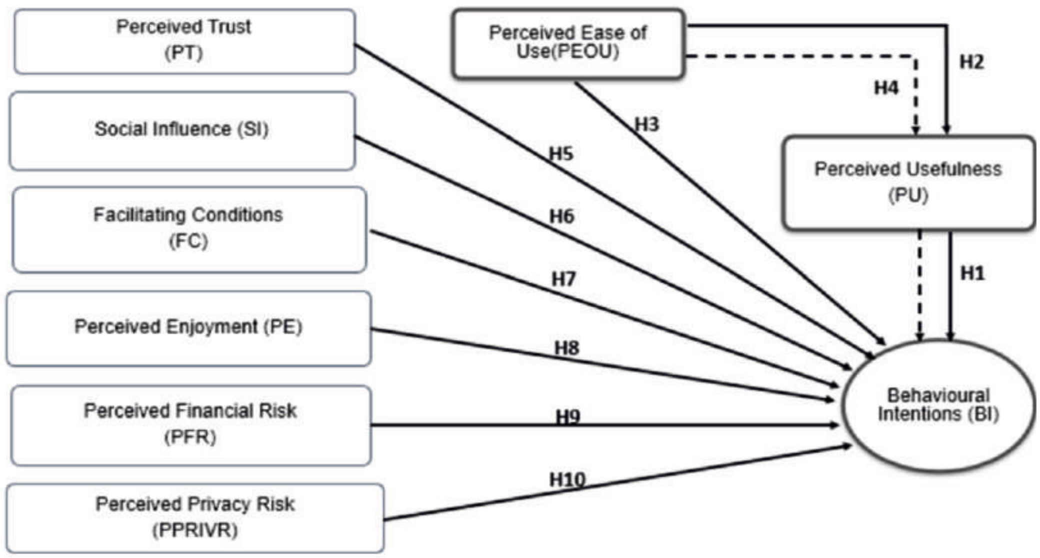
Bhatia and Breaux (2018) observed that as individuals recognized the benefits of new technology, they tended to share more information and perceived less privacy risk in general. Studies indicated that consumers reduced their privacy concerns after considering the financial benefits of the technology (Derikx et al., 2016), leading to increased perceived effectiveness. However, Rejikumar (2013), in a study of telematics in India, found that perceived privacy risks did not influence users' acceptance intentions. Given the consistent significance of perceived privacy risk in prior research, it was hypothesized that:

- **Ha_{10} :** BI's use of insurance telematics services is negatively impacted by PPRIVR.

Behavioural Intentions (BI)

Behavioral intention is an individual's intention to perform a specific behavior. The construct is said to include motivational factors. According to Ajzen and Fishbein (1975), it is considered the best predictor of actual behavior

Figure 2. ***Conceptual Model for Measuring Behavioural Intentions of Users Toward Telematics Motor Insurance***



when the actions are performed voluntarily (Rekha et al., 2020). Considering the hypotheses mentioned, we formulate the conceptual model for this study, as depicted in Figure 2. Six additional constructs were incorporated; the solid and dotted lines represent direct and indirect relationships between the independent and dependent variables.

Research Methodology

A cross-sectional study utilized a quantitative survey to investigate the usage of insurance telematics technology. The methodology involved analyzing factors relevant to the hypothesized interactions, constructing a conceptual model to experimentally assess selected variables experimentally, collecting and analyzing data, and systematically reporting the findings.

Telematics insurance, a nascent product category in India, had a limited customer base. While most insurers conducted pilot studies, only a few had launched final telematics insurance products. Most actual telematics insurance customers were concentrated in major Indian metropolitan areas like Mumbai, Pune, and Bangalore, where insurers' headquarters and pilot study vendors were located. A two-stage non-random sampling method was employed to engage with actual telematics users. Initially, seven automobile vendor outlets in Mumbai, where insurers conducted pilot studies, were identified. In the subsequent stage, pilot study participants and actual users were intercepted at these vendor locations, selected via convenience sampling, and briefed about the study objectives beforehand.

The resulting sample included a diverse mix of actual users and pilot study participants with varying experiences with telematics insurance products, ranging from a few weeks to several months. Tian et al. (2020) emphasized the importance of research design, sampling techniques, and meticulous execution in their study on telematics insurance in the USA, targeting millennials with limited experience in such services. Data coding and analysis were conducted using IBM SPSS 26.0, employing basic descriptive statistics, factor analysis, and structural equation modeling (SEM) through IBM SPSS AMOS 26.0 to explore causal relationships between constructs.

Data Collection and Respondents' Profile

A structured questionnaire was crafted drawing from the literature for data collection, with questionnaire items derived from well-established studies in telematics and related technological fields. A pilot study conducted by a panel of experts assessed the instrument for face and content validity. This review involved seven senior professors and five PhD scholars actively engaged in research and teaching in technology and consumer behavior. Additionally, the questionnaire was shared with several full-time insurance agents at a reputable motor insurance company, and their feedback was integrated, resulting in modifications to certain aspects of the initial instrument.

The final questionnaire comprised of 44 scale items for different constructs, tailored to the study's needs in two sections. Utilizing a 5-point Likert scale ranging from *"strongly disagree"* to *"strongly agree."* The first section gathered information on respondents' demographic profiles, motor insurance, and value-added telematics services, while the second recorded responses to the shared scale items. Background information was provided to respondents before the commencement of the study. The survey started by sharing the study's objectives and explaining the overall purpose and process of telematics insurance inquiry. Convenience sampling was used to approach a total of 400 respondents, and the survey was administered online over 38 days, from April 12, 2022, to May 19, 2022, using "Google Forms" due to its user-friendly interface and widespread familiarity. A total of 354 completed responses were received, and Table 1 provides a summary of scale items, sources, factor loadings, and Cronbach's alpha values.

Table 1. ***Summary of Scale Items, Source, Factors Loadings, and Cronbach's Alpha Value***

Scale Items	Factor Loading	Cronbach's Alpha Value
Perceived Usefulness (Chen & Chen, 2011)		
(1) 'Using insurance telematics would enhance my driving skills.'	0.849	0.896
(2) 'Using insurance telematics would make my claim experience better.'	0.902	
(3) 'Insurance telematics would make an insurer customize insurance coverage for me.'	0.663	
(4) 'The advantages of using insurance telematics will exceed the disadvantages.'	0.857	
Perceived Ease of Use (Chen & Chen, 2011)		
(1) 'My interaction with insurance telematics while driving is clear and understandable.'	0.913	0.935
(2) 'Interaction with telematics does not require lots of mental and physical effort.'	0.459	
(3) 'It will be easy to learn how to use insurance telematics.'	0.947	
(4) 'It will be simple to operate/ manage insurance telematics while driving.'	0.931	
(5) 'I will feel less mental challenge while learning to use insurance telematics.'	0.829	
Social Influence (Chauhan et al., 2023)		
(1) 'People who influence my behavior think I should use the system.'	0.691	0.881
(2) 'People who are important to me think I should use the system.'	0.741	
(3) 'The senior management of this business has been helpful in the use of the system.'	0.778	
(4) 'In general, the organization has supported the use of the system.'	0.723	
(5) 'Well-known individuals on social platforms might suggest the adoption of insurance telematics.'	0.708	
(6) 'My intimate circle might recommend utilizing insurance telematics.'	0.769	
Facilitating Conditions (Chauhan et al., 2023)		
(1) 'I have the resources necessary to use telematics.'	0.49	0.469
(2) 'I know the necessity to use telematics.'	0.431	

(3) 'Telematics is not compatible with other systems I use.'	0.409	
(4) 'A specific person (or group) is available for assistance with system difficulties.'	0.389	
Behavioral Intention to Use the Technology (Tian et al., 2020)		
(1) 'I intend to use telematics in the next months.'	0.799	0.882
(2) 'I predict I will use telematics in the next months.'	0.657	
(3) 'I plan to use telematics in the next month.'	0.645	
(4) 'I foresee myself utilizing insurance telematics down the road.'	0.808	
(5) 'I will advocate for others to consider using insurance telematics.'	0.439	
(6) 'I will remain committed to utilizing insurance telematics myself.'	0.685	
Perceived Enjoyment (Wu et al., 2016)		
(1) 'Interacting with insurance telematics would make me feel happy.'		0.796
(2) 'Using insurance telematics would make me feel enjoyment.'	0.748	
(3) 'Using insurance telematics would be entertaining.'	0.718	
(4) 'Using insurance telematics would be an ideal recreation.'		
(5) 'Using insurance telematics would make me feel pleasure.'	0.693	
(6) 'The real-time communication via insurance telematics would make me feel excited.'		
Perceived Trust (Zhang et al., 2020)		
(1) 'I would believe that insurance telematics is trustworthy.'	0.881	0.931
(2) 'I would trust in the benefits of the insurance telematics.'	0.879	
(3) 'This insurance telematics company would keep its promises and commitments.'	0.849	
Perceived Financial Risk (Eling & Kraft, 2020)		
(1) 'I think purchasing telematics insurance is risky given the potential investment.'	0.468	0.517
(2) 'I think that the purchase of the product would lead to financial risk for me.'	0.497	
(3) 'Given the potential expenses associated with purchasing the product, I would use it.'	0.43	
Perceived Privacy Risk (Gupta et al., 2020)		
(1) 'I am confident that I know all the parties who collect the information I provide during a transaction with this store.'	0.485	0.84
(2) 'I am aware of the exact nature of the information that will be collected during a transaction with this store.'	0.776	
(3) 'I know what information I need to provide during a transaction with this store.'	0.766	
(4) 'I believe I have control over how the information I provide will be used by this store.'	0.798	
(5) 'I believe I can subsequently verify the information I provide during a transaction with this store.'	0.786	
(6) 'I believe that this store will disclose my information without my consent.'	0.479	
(7) 'I believe there is an effective mechanism to address any violation of the information I provide to this store.'	0.751	

Data Analysis and Results

Descriptive Statistics

Table 2 describes the summary of demographic and motor insurance-related details asked of the respondents. Of 354 respondents, 63% were male, and 37% were female, i.e., gender representation is acceptable. Regarding age, 55% of the respondents were under 25, and 87% were younger than 45. Only 53.4% of the respondents were

Table 2. *Descriptive Statistics*

Item	Total (n = 354)	Frequency (%)
Gender		
'Male'	222	62.71%
'Female'	132	37.29%
Age		
'18 – 25 years'	193	54.52%
'26 – 35 years'	65	18.36%
'36 – 45 years'	50	14.12%
'46 – 55 years'	28	7.91%
'Above 55 years'	18	5.08%
Education		
'Graduate'	116	32.76%
'Post-Graduate'	204	57.63%
'Professional'	16	4.52%
'Doctorate'	18	5.08%
Motor Insurance Type		
'Own Damage'	43	12.15%
'Third-Party'	102	28.81%
'Comprehensive'	209	59.04%
How Long Respondent has had Motor Insurance		
'1 year'	61	17.23%
'2 years'	37	10.45%
'3 years'	52	14.69%
'4 years'	11	3.11%
'5 years or more'	193	54.52%
Number of Claims Filed		
'0 claims'	219	61.86%
'1 claim'	75	21.19%
'2 claims'	37	10.45%
'3 claims'	15	4.24%
'4 or more claims'	8	2.26%
Yearly Distance Travelled		
'up to 5,000 km'	94	26.55%
'5,001 – 10,000 km'	107	30.22%
'10,001 – 15,000 km'	76	21.47%
'15,001 – 20,000 km'	45	12.71%
'Over 20,000 km'	32	9.04%

willing to share their driving data with insurers in exchange for just the telematics value-added services, such as information related to driving habits and vehicle location tracking, as an anti-theft provision. However, monetary

Table 3. ***Respondents' Discount Expectations***

Discount Expectations	Total (n = 354)	Frequency (%)
The number of respondents who thought a 15% additional discount on yearly car insurance premiums in exchange for driving style/ behavior information was enough.	182	51.41%
The number of respondents who thought a 30% additional discount on yearly car insurance premiums in exchange for driving style/ behavior information was enough.	121	34.18%
The number of respondents who thought a 45% additional discount on yearly car insurance premiums in exchange for driving style/ behavior information was enough.	35	9.89%
The number of respondents who did not want to share their driving data with insurers for any offered discount.	16	4.52%

discounts on yearly premiums and the above-mentioned value-added services provoked the interest of 66.7% of the respondents.

Table 3 describes the respondents' inclination toward annual premium discounts they expected from insurers under telematics insurance. Most respondents, i.e., 85.59%, thought that a 30% or less yearly discount on their motor insurance premium was sufficient for them to share their driving data with insurers.

Measurement Model Assessment

Factor analysis reveals that the loadings for the constructs fell in the range of 0.645 to 0.947. These values exceeded the prescribed minimum of 0.6 (Awang, 2012). Internal consistency of all constructs is ensured using Cronbach's alpha (CA) coefficients (refer to Table 1). CA values ranged from 0.796 for PE to 0.935 for PEOU, indicating high internal consistency (Hair Jr. et al., 2016). To analyze the reliability, composite reliability (CR) and average variance extracted (AVE) values are used. Hair Jr. et al. (2016) suggested that the AVE and CR values should be greater than 0.5 and 0.7 to establish sufficient reliability for all constructs (refer to Table 4).

Additionally, it is noted that all constructs have CR values surpassing their AVE values, with each construct's AVE values exceeding 0.5, ensuring acceptable convergent validity (Hair Jr. et al., 2016). To achieve satisfactory discriminant validity (DV), Hair Jr. et al. (2016) recommended that the square root of a construct's AVE should exceed its correlations with other constructs. Furthermore, Hu and Bentler (1999) proposed that the diagonal values in the respective columns and rows should surpass the off-diagonal values. Two factors, i.e., facilitating

Table 4. ***Cronbach's Alpha, Factor Loadings, Composite Reliability, AVEs, and Square Root of the AVEs***

Construct	No. of Items	α	Item Loading	CR	AVE	MSV	*PU*	*PEOU*	*PT*	*SI*	*PE*	*PPRIVR*	*BI*
PU	4	0.896	**0.663 – 0.902**	0.902	0.702	0.060	0.838						
PEOU	4	0.935	0.829 – 0.947	**0.938**	0.792	0.060	0.246***	0.89					
PT	3	0.931	0.840 – 0.881	0.935	**0.829**	0.252	0.159**	0.048	0.911				
SI	6	0.881	0.691 – 0.778	0.859	0.523	**0.317**	0.341***	0.030	0.471***	**0.723**			
PE	3	0.796	0.693 – 0.748	0.801	0.574	0.450	**0.434*** **	0.126*	0.502***	0.563***	**0.758**		
PPRIVR	5	0.840	0.751 – 0.786	0.847	0.526	0.195	–0.187**	**–0.006**	–0.294***	–0.224***	–0.271***	**0.725**	
BI	5	0.882	0.645 – 0.808	0.855	0.542	0.450	0.542***	0.240***	**0.468*** **	0.524***	0.671***	–0.442***	**0.736**

Note. *p < 0.050, **p < 0.010, ***p < 0.001.

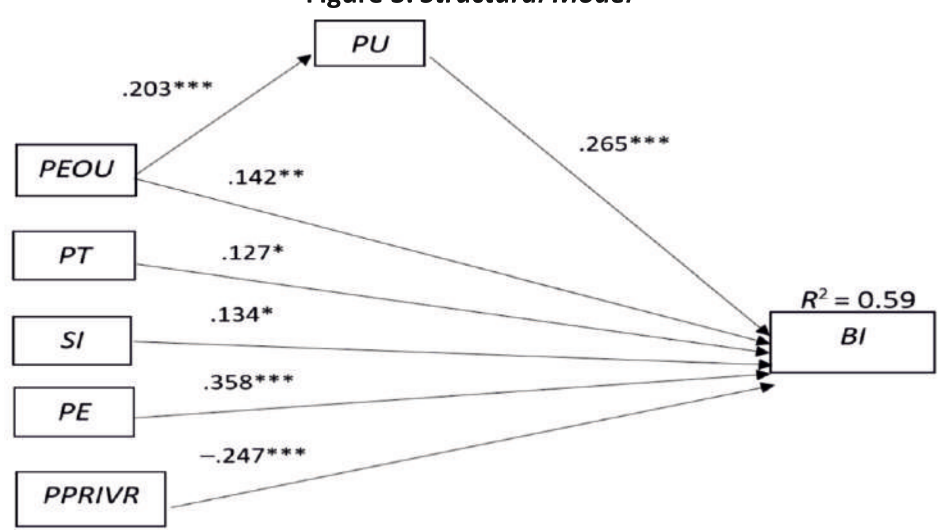
conditions (FC) and perceived financial risk (PFR), are subsequently dropped from the study as their factor loadings and validity values are not in the desired range. In the diagonal cells, bold figures represent the square root of AVE values, where CR stands for composite reliability, and AVE denotes average variance extracted.

Further, structural equation modeling uses three categories of fitness indices to evaluate the models: absolute, incremental, and parsimonious fit indices. The model fit values for the measurement model are found to be in range as per Hu and Bentler (1999), with "CMIN/*DF*" value (chi-square/degrees of freedom)—1.484, "SRMR" (Standardized Root Mean Square Residual)—0.056, "GFI" (Goodness of Fit Index)—0.909, "RMSEA" (Root Mean Square Error of Approximation)—0.037, "TLI" (Tucker-Lewis Index)—0.974, and "CFI" (Comparative Fit Index)—0.978.

Structural Model Assessment

A structural model examines the strength of proposed direct and indirect relationships (refer to Figure 3). We used the bootstrap method to address nonnormality concerns and get more accurate results with 2,000 resamples at a 95% confidence level. Evaluating overall model fit requires the analysis of several indices, and the values of "CMIN/*DF*"—1.484, "SRMR"—0.056, "GFI"—0.909, "RMSEA"—0.037, "TLI"—0.974, and "CFI"—0.978, fell in the suggested range, which indicates that the data fits the model well (Hu & Bentler, 1999).

Figure 3. ***Structural Model***



Note. (***) significant at 0.001 level, (**) at 0.01 level, and (*) at 0.1 level, respectively.

Hypotheses Testing

Positive test results for measurement and structural model further lead to hypothesis testing. While the goodness-of-fit measures how well the model fits the data, the explanatory power measures how strongly an endogenous variable correlates with the explanatory variables. The conceptual model's evaluation for good acceptability is made comprehensively depending on the values of path coefficients, statistical significance, and coefficient of determination (R^2).

Eight hypothesized paths in the structural model are found to be statistically significant. Table 5 shows the summary of the hypotheses tested for the study. Five constructs, PE (β = 0.358, p < 0.001), PU (β = 0.265, p < 0.001), PEOU (β = 0.142, p = 0.002), SI (β = 0.134, p = 0.026), PT (β = 0.127, p = 0.023), affect BI directly but positively. However, PPRIVR (β = –0.247, p < 0.001) affects BI significantly and negatively. It was also observed

Table 5. ***Hypotheses Estimates, Standard Error, Critical Ratio, p-Values, and Status***

S. No.	Hypotheses Tested	Expected Sign	Estimate	SE	CR	*p*-value	Result
Ha_1	$BI \leftarrow PU$	+	0.265	0.047	4.792	***	Accepted
Ha_2	$PU \leftarrow PEOU$	+	0.203	0.056	3.987	***	Accepted
Ha_3	$BI \leftarrow PEOU$	+	0.142	0.044	3.123	0.002	Accepted
Ha_5	$BI \leftarrow PT$	+	0.127	0.033	2.280	0.023	Accepted
Ha_6	$BI \leftarrow SI$	+	0.134	0.072	2.230	0.026	Accepted
Ha_7	$BI \leftarrow FC$	+	--	--	--	--	Dropped
Ha_8	$BI \leftarrow PE$	+	0.358	0.054	4.806	***	Accepted
Ha_9	$BI \leftarrow PFR$	–	--	--	--	--	Dropped
Ha_{10}	$BI \leftarrow PPRIVR$	–	–0.247	0.053	–4.890	***	Accepted

Table 6. ***Mediating Effect of PU on PEOU and BI Relationship***

S. No.	Hypothesis Tested	Total Effect	Indirect Effect	Direct Effect	Result
H_4	$BI \leftarrow PU \leftarrow PEOU$	0.196 (significant)	0.054 (significant)	0.142 (significant)	Supported (Partial Mediation)

that PEOU affects PU significantly and positively ($\beta = 0.203, p < 0.001$), and approximately 4% variation in PU is explained by the PEOU (Adj. $R^2 = 0.04$).

To test the mediating effect of PU on PEOU and BI, we used the bootstrapping method to derive confidence intervals for significance testing. The standardized indirect effect of PEOU on BI is 0.054. This is in addition to the direct effect that PEOU has on BI. By observing coefficient values from Table 6, we can infer that PU partially mediates the effect of PEOU on BI in a positive and statistically significant way; this confirms the findings of the original TAM (Venkatesh & Davis, 1996). Overall, 59% of the variability observed in the behavioral intentions is explained collectively by six observed variables (Adj. $R^2 = 0.59$).

Discussion and Implications

Key Findings

This study provides evidence of the modified TAM's applicability, fitness, and predictive power in telematics insurance. Concerning the first research question (RQ1), our study reveals that most respondents perceived telematics insurance as intriguing and expected monetary discounts in the range of 15–30% of their annual vehicle insurance premiums if they were to share driving data with insurers. Regarding the second proposed research question (RQ2), our findings reveal that PEOU affects BI directly and indirectly through PU, implying that the focus must be on developing easy-to-use and hassle-free telematics insurance products, highlighting the product's usefulness. Perceived enjoyment is found to be a significant factor. Apart from the core benefits of telematics insurance, insurers also need to provide additional value-added services, such as information related to driving habits, driving scores, and vehicle location tracking as an anti-theft provision. Respondents look forward to this innovative insurance product category to derive enjoyment, happiness, and pleasure from it. This corroborates the previous findings of Tian et al. (2020) on telematics adoption.

Perceived trust plays a critical role in this product category. Insurance, by nature, is an unsought category product, and novel technologies like telematics are further bringing an element of uncertainty. Insurers need to address this with the utmost care. Perceived privacy risk negatively affects behavioral intention, meaning users are quite cautious about their shared information. Insurers should develop more robust applications for their users and address users' concerns about data collection, storage, and sharing. Working on users' data privacy concerns will help insurers gain a competitive advantage in the long run by building trust. Social influence also affects the behavioral intention of respondents, which implies that insurers must focus on creating positive word of mouth by leveraging online and offline media influencers. Telematics motor insurance is a radical shift in the way motor insurance will work in the future, and apparently, the existing motor insurance customers would experience dissonance initially. Thus, insurers must make this experience seamless for them.

Regarding the third proposed research question (RQ3), the results suggest that 68% of the respondents changed their driving style towards a safer, balanced driving behavior and reduced their car insurance premium, which corresponds to saying that telematics insurance is associated with reduced risk-taking behavior in its users and confirmed the findings of Stevenson et al. (2021).

Managerial/Theoretical Implications/Policy Implications

The research findings provide significant managerial insights for the Indian telematics insurance sector. Firstly, as perceived enjoyment emerged as a key determinant of usage intentions, insurers should prioritize enhancing the interface, incorporating gamification elements, or introducing rewards for safe driving behavior to boost enjoyment and promote usage (Chauhan et al., 2023; Tian et al., 2020). Secondly, the substantial influence of perceived usefulness on intentions to adopt insurance telematics suggests that emphasizing the practical advantages, such as reduced premiums, enhanced safety, and convenience, could effectively drive adoption rates among customers (Gupta et al., 2020), especially by showcasing its superior performance compared to traditional motor insurance (Cheng et al., 2023). Thirdly, given the positive impact of perceived ease of use, perceived trust, and social influence on telematics insurance adoption intentions, insurers should focus on ensuring user-friendly technology, fostering trust through transparent communication and robust data security measures, and leveraging social networks to promote the benefits of telematics insurance (Chauhan et al., 2023). Fourthly, the detrimental effect of perceived privacy risk on telematics insurance adoption underscores the necessity of addressing customer privacy concerns. Implementing robust privacy policies, providing clear information on data practices, and offering opt-in/opt-out mechanisms can empower customers to manage their data, alleviating privacy anxieties and fostering acceptance of telematics insurance solutions (Chauhan et al., 2023). Insurers must transparently communicate data collection, usage, and protection measures to build trust. Lastly, insurers may need to reevaluate their discounting strategies to better align with customer expectations, potentially exploring hyper-personalized pricing and promotional approaches in India. Introducing personalized discounts or loyalty programs could address the preferences of the customer base.

Limitations of the Study and the Way Forward

Like other research works, this study, too, has a few limitations. First, users with limited experience could be interviewed using convenience sampling due to the limited telematics-insurance product customer base. This may affect and limit the generalizability of this study's findings. We suggest conducting further studies on users with prolonged telematics insurance experience to get more affirmative results. Second, this study integrated TAM with other factors identified through the literature review. We suggest conducting additional in-depth interview rounds to understand the effect of more contextual factors.

Authors' Contribution

Rohit Joshi conceived the idea and developed the quantitative design to undertake the empirical study and perform the literature review. Dr. Sunil Mishra executed the data collection process and performed numerical computations using SPSS 25.0 and AMOS 23.0. Dr. Anupama Pardeshi and Dr. Manpreet Kaur Bhatia wrote the manuscript, verified the analytical methods, and supervised the study. All authors carried out the revision as a mixed effort after an in-depth analysis of the editorial comments.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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References

Ajzen, I., & Fishbein, M. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*. Addison-Wesley.

Alturas, B. (2021). Models of acceptance and use of technology research trends: Literature review and exploratory bibliometric study. In M. Al-Emran & K. Shaalan (eds.), *Recent advances in technology acceptance models and theories*. *Studies in systems, decision and control* (Vol. 335, pp. 13–28). Springer. https://doi.org/10.1007/978-3-030-64987-6_2

Awang, Z. (2012). *Research methodology and data analysis* (2nd ed.). UiTM Press.

Ben-Shahar, O. (2023). Privacy protection, at what cost? Exploring the regulatory resistance to data technology in auto insurance. *Journal of Legal Analysis, 15*(1), 129–157. https://doi.org/10.1093/jla/laad008

Bhatia, J., & Breaux, T. D. (2018). Empirical measurement of perceived privacy risk. *ACM Transactions on Computer-Human Interaction, 25*(6), 1–47. https://doi.org/10.1145/3267808

Chauhan, V., Choudhary, V., & Mathur, S. (2016). Demographic influences on technology adoption behavior: A study of e-banking services in India. *Prabandhan: Indian Journal of Management*, *9*(5), 45–59. https://doi.org/10.17010/pijom/2016/v9i5/92571

Chauhan, V., Joshi, R., & Choudhary, V. (2023). Understanding intention to adopt telematics-based automobile insurance in an emerging economy: A mixed-method approach. *Journal of Financial Services Marketing*. https://doi.org/10.1057/s41264-023-00253-5

Chen, C.-F., & Chen, P.-C. (2011). Applying the TAM to travelers' usage intentions of GPS devices. *Expert Systems with Applications, 38*(5), 6217–6221. https://doi.org/10.1016/j.eswa.2010.11.047

Cheng, J., Feng, F. Y., & Zeng, X. (2023). Pay-as-you-drive insurance: Modeling and implications. *North American Actuarial Journal*, *27*(2), 303–321. https://doi.org/10.1080/10920277.2022.2077220

Derikx, S., de Reuver, M., & Kroesen, M. (2016). Can privacy concerns for insurance of connected cars be compensated? *Electronic Markets, 26*(1), 73–81. https://doi.org/10.1007/s12525-015-0211-0

Doecke, S. D., Baldock, M. R., Kloeden, C. N., & Dutschke, J. K. (2020). Impact speed and the risk of serious injury in vehicle crashes. *Accident Analysis & Prevention*, *144*, 105629. https://doi.org/10.1016/j.aap.2020.105629

Eling, M., & Kraft, M. (2020). The impact of telematics on the insurability of risks. *Journal of Risk Finance*, *21*(2), 77–109. https://doi.org/10.1108/JRF-07-2019-0129

Global Market Insights. (2022). *Usage-based insurance market*. Gminsights. https://www.gminsights.com/industry-analysis/usage-based-insurance-ubi-market

Gupta, P., & Barkathunissa. (2022). Exploring the plausibility of pre-purchase decision process in user acceptance of smart wearable technology devices. *Indian Journal of Marketing*, *52*(4), 44–62. https://doi.org/10.17010/ijom/2022/v52/i4/169109

Gupta, S., & Pande, S. (2017). Emerging trends in insurance sector in India: The case study of telematics. *International Journal of Trend in Research and Development, 4*(6), 42–45.

Gupta, S., Yadav, A., & Singla, D. (2020). Factors affecting adoption of telematics in the Indian insurance sector. *International Journal of Advanced Science and Technology, 29*(6s), 1005–1012.

Hair Jr., J. F., Hult, G. T., Ringle, C. M., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage Publications.

Henckaerts, R., & Antonio, K. (2022). The added value of dynamically updating motor insurance prices with telematics collected driving behavior data. *Insurance: Mathematics and Economics*, *105*, 79–95. https://doi.org/10.1016/j.insmatheco.2022.03.011

Holzapfel, J., Peter, R., & Richter, A. (2023). Mitigating moral hazard with usage-based insurance. *Journal of Risk and Insurance*. https://doi.org/10.1111/jori.12433

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Insurance Regulatory and Development Authority of India. (2020, January 14). *Granting approval to proposals from health, motor, and intermediaries department under the Regulatory Sandbox* [Press release]. https://www.irdai.gov.in/ADMINCMS/cms/frmGeneral_Layout.aspx?page=PageNo4010&flag=1

Jain, S., & Singla, D. (2019). Influence of social networks on the adoption of telematics insurance: A study on Indian consumers. *International Journal of Business Analytics and Intelligence, 7*(2), 132–144.

Joshi, R. (2024). A mixed methods UTAUT2-based approach to understanding unified payments interface adoption among low-income users. *Banks and Bank Systems, 19*(1), 58–73. https://doi.org/10.21511/bbs.19(1).2024.06

Kongmuang, P., & Thawesaengskulthai, N. (2019). Improvement of telematics solution for motor insurance in Thailand by 5D innovation development process. In, *2019 IEEE 6th International Conference on Industrial Engineering and Applications (ICIEA)* (pp. 6–11). https://doi.org/10.1109/IEA.2019.8715152

Litman, T. (2011). *Distance-based vehicle insurance feasibility, costs and benefits* (Comprehensive Technical Report). Victoria Transport Policy Institute. https://www.vtpi.org/dbvi_com.pdf

Milanović, N., Milosavljević, M., Benković, S., Starčević, D., & Spasenić, Ž. (2020). An acceptance approach for novel technologies in car insurance. *Sustainability*, *12*(24), 10331. https://doi.org/10.3390/su122410331

Mishra, P., & Mishra, P. (2017). *Vital stats: Overview of road accidents in India*. PRS Legislative Research. https://prsindia.org/files/policy/policy_vital_state/Overview%20of%20Road%20Accidents.pdf

Mukhopadhyay, I., & Chakraborty, A. (2018). An empirical study on the trustworthiness of telematics technology: Evidence from India. *Journal of Insurance and Risk Management, 4*(2), 78–88.

Murthy, D. N., & Kumar, B. V. (2015). Internet of Things (IoT): Is IoT a disruptive technology or a disruptive business model? *Indian Journal of Marketing, 45*(8), 18–27. https://doi.org/10.17010/ijom/2015/v45/i8/79915

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. https://doi.org/10.1016/j.aap.2017.09.011

Rejikumar, G. (2013). A pre-launch exploration of customer acceptance of usage based vehicle insurance policy. *IIMB Management Review*, *25*(1), 19–27. https://doi.org/10.1016/j.iimb.2012.11.002

Rekha, I. S., Basri, S., & Kavitha, T. C. (2020). Acceptance of internet banking: Comparing six theoretical models. *Indian Journal of Finance*, *14*(3), 7–21. https://doi.org/10.17010/ijf/2020/v14i3/151073

Sardana, V., Mohapatra, A. K., Singh, A. K., & Singhania, S. (2023). Unveiling insurance and risk management insights through bibliometric and cluster analysis. *Prabandhan: Indian Journal of Management*, *16*(11), 8–26. https://doi.org/10.17010/pijom/2023/v16i11/173213

Senyo, P. K., & Osabutey, E. L. (2020). Unearthing antecedents to financial inclusion through FinTech innovations. *Technovation*, *98*, 102155. https://doi.org/10.1016/j.technovation.2020.102155

Shetty, A., & Basri, S. (2021). Mediating effect of attitude on the determinants of financial misselling of life insurance products in India. *Prabandhan: Indian Journal of Management, 14*(11), 41–57. https://doi.org/10.17010/pijom/2021/v14i11/166980

Shokeen, A., Kumar, A., & Khanna, S. (2023). Understanding students' behavioral intention to adopt blended learning: Modified UTAUT model. *Prabandhan: Indian Journal of Management*, *16*(11), 43–64. https://doi.org/10.17010/pijom/2023/v16i11/170915

Singh, A., & Kumar, A. (2019). An empirical investigation of the impact of cultural dimensions on consumer acceptance of telematics-based insurance in India. *Journal of Insurance and Financial Planning, 3*(2), 112–124.

Stevenson, M., Harris, A., Wijnands, J. S., & Mortimer, D. (2021). The effect of telematic based feedback and financial incentives on driving behaviour: A randomised trial. *Accident Analysis & Prevention, 159*, 106278. https://doi.org/10.1016/j.aap.2021.106278

Tabeck, P. S., & Singh, A. B. (2022). Acceptance of mobile apps among bottom of pyramid customers of urban areas. *Indian Journal of Marketing, 52*(9), 43–58. https://doi.org/10.17010/ijom/2022/v52/i9/171984

The World Bank. (2021). *Traffic crash injuries and disabilities: The burden on Indian society* (Report No. 156336). https://documents.worldbank.org/en/publication/documents-reports/documentdetail/761181612392067411/main-report

Tian, X., Prybutok, V., Mirzaei, F., & Dinulescu, C. C. (2020). Millennials acceptance of insurance telematics: An integrative empirical study. *American Business Review, 23*(1), 156–181. https://doi.org/10.37625/abr.23.1.156-181

Tseng, H. C., Tu, P. P., Lee, Y. C., & Wang, T. S. (2013). A study of satellite navigation fleet management system usage in Taiwan with application of C-TAM-TPB model. *Information Technology Journal, 12*(1), 15–27. https://doi.org/10.3923/itj.2013.15.27

Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision Sciences*, *27*(3), 451–481. https://doi.org/10.1111/j.1540-5915.1996.tb00860.x

Vickrey, W. (1968). Automobile accidents, tort law, externalities, and insurance: An economist's critique. *Law and Contemporary Problems*, *33*(3), 464–487. https://doi.org/10.2307/1190938

Wu, L.-H., Wu, L.-C., & Chang, S.-C. (2016). Exploring consumers' intention to accept smartwatch. *Computers in Human Behavior, 64*, 383–392. https://doi.org/10.1016/j.chb.2016.07.005

Zhang, T., Tao, D., Qu, X., Zhang, X., Zeng, J., Zhu, H., & Zhu, H. (2020). Automated vehicle acceptance in China: Social influence and initial trust are key determinants. *Transportation Research Part C: Emerging Technologies, 112*, 220–233. https://doi.org/10.1016/j.trc.2020.01.027

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