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Black box technology, usage-based insurance, and prediction of purchase behavior: Evidence from the auto insurance sector

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ABSTRACT

Disruptive technologies are changing the car insurance sector, with behavioral and adaptive impacts for individuals as well as organizations. An innovative factor in this industry is connected to telematics and concerns the installation of a small device called a 'black box', which is becoming more and more widespread, with consequent financial impacts on the insurance policy market. However, the psychological drivers that underpin consumers' intentions to purchase black box auto insurance are scarcely researched. To fill this gap, we used a mixed-methods sequential exploratory design to analyze a sample of 757 consumers. Our results, obtained through PLS-SEM, highlight that attitude, awareness, subjective norms, risk perception, and trust have a significant positive influence on consumers' intentions to purchase black box technology auto insurance, while the effect of perceived behavioral control is not supported. Furthermore, the blindfolding analysis underscores the predictive relevance of the model. Our results have important implications for auto insurance companies interested to better understand consumers' needs and motives in relation to the purchase of black box insurance.

1. Introduction

The development of new technologies (e.g., the Internet of Things, artificial intelligence, machine learning, cryptocurrencies, blockchains, cloud computing, mobile devices, and cognitive systems) is changing the competitive landscape in many ways and at various levels (e.g., Christofi et al., 2019; Santoro et al., 2018; Lu et al., 2018). Organizations, particularly, increasingly use new strategies, data, and business models developed from, or driven by, these new technologies, to comprehend consumer choices and behavior and to obtain a competitive advantage (Manika et al., 2015).

In this regard, new disruptive digital technologies are also transforming the automotive industry, both in terms of actual products and their production, and the business models employed in the sector (Giacosa et al., 2022; Llopis-Albert et al., 2021). Traditional cars are infused with innovative technologies, which enhance their functionality and complexity (Llopis-Albert et al., 2021), such as assisted driving and autonomous driving technologies, driver connectivity, location-based services, and telematics (Wells et al., 2020; Llopis-Albert et al., 2021). The present paper focuses on advances in vehicle telematics, which are changing the auto insurance sector. Vehicle telematics include a combination of computers and wireless telecommunications technologies that enable the efficient transmission of information across large networks (Eling and Kraft, 2020). In 1988, the European Economic Community (ECC) proposed a program to test vehicle telematics, while ten years later, Progressive Insurance (PI) in the United States issued the first telematics policies. Subsequently, telematics has been applied increasingly in the insurance sector, and it has achieved important market penetration in recent years (Deloitte, 2016). While the insurance sector as a whole is often considered traditional and rigid (Eling and Lehmann, 2018), the auto insurance sector has capitalized on telematics' cutting-edge technologies and features as the most illustrative use case of telematics to date. Telematics involves the installation of a small device called a 'black box', which is an In-Vehicle Data Recorder (IVDR) that uses GPS technology and sensors to accurately record data such as speed patterns, idling times, number of vehicles on the road, weather conditions, road type, driving time, driving behavior, and driving habits of the vehicle being insured (Baecke and Bocca, 2017; Deloitte, 2016). Telematics technology allows auto insurers to collect real-time data on driver behavior, which can be used to offer usage-based policies based on actual behavior, such as Pay-As-You-Drive (PAYD) (Baecke and Bocca, 2017).

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The number of car insurance customers opting to switch from traditional car insurance to black box technology insurance is steadily increasing worldwide (Deloitte, 2016). Customers realize that telematics offers many valuable benefits, such as lower premiums, increased peace of mind, better claims experience, and a variety of value-added services, including roadside assistance, emergency assistance, stolen vehicle recovery, parental controls, and reliability. With 4.8 million cars equipped with black boxes, Italy is the market with the highest coverage of black boxes in the world, ahead of the United States and the United Kingdom (respectively with 3.3 million and 0.6 million). In particular, Italy has been promoting the installation of black boxes since 2012 through a 'mandatory rebate'.

Past research on black box insurance has primarily investigated the outcomes associated with the installation of these technologies into cars. Substantial work has looked into the way black box technology can help gather rich data to be used in motor insurance ratemaking (e.g., Ayuso et al., 2019; Gerpott and Berg, 2012; Cosconati, 2018; Porrini et al., 2020). In this context, studies have raised the relevance of black boxes in monitoring, recording, and analyzing data on both driving habits (e.g., average distance travelled per day, frequency of driving, and driving routes) (Ayuso et al., 2019; Verbelen et al., 2018) and driving styles (e.g., driving speed, accelerations, braking, cornering) (Verbelen et al., 2018; Cevolini and Esposito, 2020; Milanović et al., 2020). Other outcome-based work has examined the impact of black box installation on the prevention of incidences of risky driver behavior and the prediction of car accidents (Farmer et al., 2010; Yuksel and Atmaca, 2021). However, literature on the antecedents of black box auto insurance adoption has been very limited. What evidence exists reveals that certain demographic groups, such as younger people, are more reluctant and uncommitted about installing black boxes in their cars (McNally and Bradley, 2018). Yet, the factors underpinning the perceptions, attitudes, and adoption intentions of black box technology insurance are yet to be examined. Literature on life insurance has looked into the individual drivers' purchasing intentions influences (e.g., Masud et al., 2020; Rizwan and Al-Malkawi, 2021; Valentina-Daniela and Gheorghe, 2015; Omar, 2007; Sundjaja and Komala, 2019). However, this area of work does not reflect adoption intentions linked to the high technological component that is the black box. Given the above discussion, our study is the first to look into the individual-specific factors connected to the adoption of black box auto insurance. We adopt a psychological perspective, aiming to investigate drivers' thoughts, perceptions, and attitudes, and the way these influence their intention to purchase black box auto insurance.

To fulfill this research aim, we adopt a mixed-methods sequential exploratory design (e.g., Creswell, 1999; Tashakkori et al., 1998). Since the phenomenon we focus on is largely under-investigated, we first conducted two exploratory focus groups with fourteen people (consumers and insurance company employees), with the intention to understand our phenomenon more thoroughly and to guide the subsequent survey design (Saunders et al., 2012). Building on the literature and the information collected from the two focus groups, we gathered data through a survey questionnaire involving 757 consumers. Finally, in order to test our research hypotheses, we used a partial least square-structural equation modeling (PLS-SEM) approach.

Our results highlight that attitude, awareness, subjective norms, risk perception, and trust have a significant positive influence on the intention to purchase black box technology insurance, while the effect of perceived behavioral control is not supported. Moreover, the study reveals a significant mediating role of intention to purchase between psychological variables and purchase behavior, excepting perceived behavioral control. Finally, the blindfolding analysis underscores the predictive relevance of the model.

These results lead to important theoretical and practical implications. First, the present study integrates three psychological theories (i.e., the Theory of Planned Behavior, the Theory of Protection Motivation, and the Technology Acceptance Model, which is based on the Theory of Reasoned Action) on the study of consumer adoption and use intentions of high-tech solutions. In doing so, it contributes with a comprehensive theoretical base to the study of high-tech adoption under a psychological perspective, which has not been sufficiently employed to date. Second, this research provides new knowledge on the psychological drivers of consumers' intentions to adopt telematics and black box technologies in auto insurance. In doing so, it fills a literature gap on the lack of knowledge on the antecedents of black box technology insurance adoption. Finally, this study provides practical insights for insurance companies, helping them to understand the psychological factors that drive customers to purchase telematics insurance. We propose that the increase in trust (particularly in the protection of shared data) and the development of knowledge through insurance literacy can enhance the penetration of black box technology into the auto insurance market.

The structure of this paper is organized as follows. The next part presents the background literature; this is followed by hypotheses development. After a sufficient description and justification of our chosen methods, we report and discuss our results, providing implications (for theory and practice), limitations, and future lines of research.

2. Telematics, IVDRs, and a usage-based insurance model: the financial consequences for drivers and insurance companies

Automotive telematics (Duri et al., 2002) enables vehicles to share information with the outside world. Some of the telematics services offered directly by car manufacturers include real-time navigation, roadside assistance, and vehicle tracking. In the case of telematics, the insurance refers to black box technology, which collects information on the distance travelled, on the geographical position (thanks to GPS), on the speed, on the type of road travelled, etc. (Verma et al., 2021; Ma et al., 2018; Nicoletti, 2020).

Black box technology is officially known as In-Vehicle Data Recorder (IVDR) systems. IVDRs collect data on driving behavior and provide continuous feedback to the driver and the insurance company by recording information on movement, speed, and driving patterns (e.g., Toledo et al., 2008; Prato et al., 2010; Correia et al., 2001). The black box represents a major opportunity for the insurance industry and its customers. The proliferation of telematics tools not only helps insurers to measure and manage risks more accurately, including to combat fraud, but also offers policyholders better protection in the event of an accident, not just if the vehicle is stolen (Baecke and Bocca, 2017). Black boxes, precisely because they perform a variety of functions, are the most important way to achieve a reduction in car insurance prices. Reduction in levels of fraud leads to lower compensation costs (Derrig, 2002). The rate adjustment made possible by the devices offers advantages superior to traditional rating systems, such as the Bonus Malus system (Denuit et al., 2007).

The personalization of risk within the limits of underwriting (which requires the creation of homogeneous risk categories based on the principle of mutuality) is beneficial to both the consumer and the insurer. Contrary to popular belief, so-called information asymmetry is a condition from which the insurer suffers when dealing with a contracting party about whom they know little at the outset (Cohen, 2005). Black boxes allow knowledge of the characteristics of the insured in order to better assess their risk propensity. The benefit to the consumer must be measured against their actual risk. In the most sophisticated models of black boxes already on the market, the cost of the policy is determined on the basis of actual use of the vehicle, kilometers driven, driving style, and compliance (Cappiello, 2018).

The main beneficiaries (in terms of rates) of more accurate risk measurement will be the honest and prudent drivers in the most critical areas of the country, who currently suffer some of the consequences of the widespread phenomena of fraudulent and unfair practices.

Thanks to telematics devices, it has been possible to formulate tailor-made policies: the black box policies that belong to the usage-based insurance model (UBI) (Husnjak et al., 2015; Tselentis et al., 2017).

UBI telematics policies can be divided into two different insurance models: the pay-as-you-drive (PAYD) and the pay-how-you-drive (PHYD) models. In PAYD insurance, insurance premiums are directly based on the driving behavior of the policyholder (Litman, 2004). In general, PAYD links the amount of the insurance premium to the risk associated with the policyholder's driving behavior (e.g., higher mileage and speed is associated with a higher risk of accidents and therefore leads to a higher insurance premium) (Bolderdijk et al., 2011; Desyllas and Sako, 2013). This variable premium system is an alternative to the current fixed insurance system, where premiums are set solely on the basis of risk delegations such as age and gender, and not on the actual driving behavior of policyholders. Besides increasing actuarial accuracy (risks are better reflected in the premium) (Litman, 2011), PAYD could lead to a change in policyholders' driving behavior. This is because the willingness to take risks is reflected in individual insurance premiums, so that careless and risky driving leads to negative financial consequences. Instead, policyholders can save money on their insurance by changing their driving behavior. PAYD measures can help counteract increased road risks such as speeding and night driving (Ayuso et al., 2014), and can bring additional benefits to society by reducing certain driving behaviors, such as by decreasing vehicle emissions and road traffic volumes. The PHYD model is an extension of PAYD and rewards people who behave responsibly and safely on the road. They even receive a higher rebate if they improve their driving, as they take a lower risk. The devices installed in the car measure the driving performance, which is defined in terms of speed, acceleration, braking, cornering, etc. (Roth et al., 2020).

3. Hypotheses development

New technologies have the ability to influence consumer purchasing behaviors (Kamolsook et al., 2019), and the theories and research that draw on psychology can help identify the mechanisms that allow companies to create the conditions to maximize business, determine which additional services (Araujo, 2018) are most important for achieving customer satisfaction, and assess the effectiveness of technological innovations. There are several traditional psychological theories that allow us to understand insurance policy buying behavior: the Theory of Planned Behavior (TPB), the Protection Motivation Theory (PMT), the Technology Acceptance Model (TAM), and the General Deterrence Theory (GDT). Previous studies investigating the purchase of non-demand products such as life insurance (Masud et al., 2021; Nasir et al., 2017; Brahmana et al., 2018) or cyber insurance (Branley-Bell et al., 2021) have used these theoretical models, but we do not have a clear view of their applicability in interpreting black box technology car insurance purchase intention. Nevertheless, the present paper draws on these theoretical models to provide a comprehensive understanding of consumer attitudes, awareness, and purchasing propensity towards telematics.

The TPB is the most commonly used of the four models (Lebek et al., 2014). It is explained by Nasir et al. (2018) as "the most dominant theory" with "the most important main constructs for predicting and explaining consumer behavior". Even though the TPB is the most widely used model in the field, this does not mean that its predictive ability cannot be improved. Models are often combined to further increase the variance, explaining and producing better understanding of the factors (Ifinedo, 2012; Sommestad et al., 2014). McNally and Bradley (2018) drew on the TPB to assess the intention of young novice drivers to install IVDR technology to improve road safety. Toledo and Shiftan (2016) analyzed how in-vehicle data recorders improve driver behavior and reduce fuel consumption.

The TPB is used as a frame of reference for drivers' intention to commit certain traffic offences: drink-driving, speeding, tailgating, and overtaking in risky circumstances (e.g., Parker et al., 1992; Warner and Åberg, 2006; Elliott et al., 2003; Leandro, 2012; Conner et al., 2007). The TPB explains that the performance of a particular behavior is determined by both attitude and subjective norms, which influence intention, and that the action leads to a particular behavior (Ajzen and Fishbein, 1980). Furthermore, this theory clearly describes that an individual's intention to behave in a certain way will lead to greater consequences if the person carries out their intention. This model, which is well established in social psychological research, is able to explain almost all human behaviors.

In this theory, attitude is the most important determinant of beliefs. Attitude is a psychological tendency to evaluate an individual's favorable or unfavorable appraisal towards an object (Ajzen, 1991), and this action enables prediction of human behaviors (Ajzen and Fishbein, 1980). If an individual has a positive attitude towards certain products or services, they are likely to embrace them accordingly. On the other hand, if a person has a negative attitude towards these products or services, they are less likely to approve and/or accept these products or services (Ajzen, 2002; Ajzen and Madden, 1986). An individual's attitude may be modeled by cultural traditions, media, parents, and friends (e.g., Hargreaves and Tiggemann, 2003; Sinclair et al., 2005; van de Gaer et al., 2007; Dunham et al., 2006). A significant relationship between behavioral intention and attitude is underlined by Jung et al. (2016). Awareness of value-added services offered by black box car insurance, lower premiums, and customized products are factors that affect consumer attitude. It is undeniable that people choose the option that offers them different alternatives (Arvola et al., 1999). The TPB suggests that reinforcing positive attitudes towards insurance (e.g., reinforcing the belief that black box car insurance is beneficial) may increase take-up. Therefore, the following hypothesis is proposed:

Hypothesis 1. Consumers' attitudes (ATT) towards black box insurance policy are positively linked to their purchase intention.

Another element of the TPB that influences intention is subjective norms. The subjective norm is a social pressure exerted by individuals or groups to influence their decision on whether or not to perform a certain behavior. Subjective norms arise from normative and behavioral beliefs (Lada et al., 2009), or feelings of pressure to make decisions from parents, friends, or neighbors (Ajzen, 1987; Khalil, 2005; Shimp and Kavas, 1984). Several studies have found that the subjective norm is a significant construct that is able to predict an individual's intention to behave in a certain way during the course of an action (Echchabi and Abd. Aziz, 2012; Suddin et al., 2009), such as buying life insurance (Husin et al., 2016) or financial products (Omar and Frimpong, 2007; Hasbullah et al., 2016; Dzuljastri and Muhamad, 2012; Hanudin, 2013). Strong subjective norms predict intentions to install IVDR technology (McNally and Bradley, 2018). The TPB suggests that reinforcing subjective norms may help increase uptake (e.g., reinforcing perceptions that others encourage consumers to purchase black box car insurance).

Therefore, the following hypothesis is proposed:

Hypothesis 2. Subjective norms (SNs) towards black box insurance policy are positively linked to consumers' purchase intentions.

Perceived behavior control is described as a person's perception of whether it is easy or difficult to perform certain behaviors (Ajzen and Madden, 1986), and this may influence a person's willingness to execute a specific plan of action (Ajzen and Driver, 1992). Therefore, perceived behavior control represents a person's thought process in performing or not performing a specific behavior without the influence of an external factor (Shih and Fang, 2004; Francis et al., 2004). In the TPB, perceived behavior control is also considered as self-efficacy, which retraces an individual's decisions to perform a behavior based on their competencies, skills, and abilities (Shih and Fang, 2004; Taylor and Todd, 1995; Aziz et al., 2016).

Perceived behavioral control measures the same construct as perceived self-efficacy, which is defined in the PMT. Therefore, in addition to subjective norms and attitude, perceived behavioral control is considered to be another antecedent of behavioral intention that ultimately leads to action. High levels of perceived behavioral control lead to willingness towards IVDR installation and to purchase usage-based insurance (McNally and Bradley, 2018).

Therefore, the following hypothesis is proposed:

Hypothesis 3. Perceived behavior control (PBC) towards black box insurance policy is positively linked to consumers' purchase intentions.

The PMT was originally developed to explain protective engagement in health-related behaviors (Nasir et al., 2018). Gradually, the theory has been applied to other protective behaviors, including insurance utilization (Rogers, 1975; Grahn and Jaldell, 2019). The PMT assumes that people protect themselves by making both a threat appraisal (risk perception) and a coping appraisal. Threat appraisals depend on both the perceived severity of a threatening event (e.g., car theft) and the perceived vulnerability to the event (i.e., the perceived likelihood that the event will occur). Coping ratings reflect the perceived effectiveness of the recommended protective behavior and the individual's perceived self-efficacy (e.g., their ability to successfully access the information needed to select black box auto insurance). The importance of risk perception has been confirmed by Omar (2007), who defines it as the most important element motivating people to purchase life insurance. Similarly, Md Husin and Ab Rahman (2016) emphasize that people are more willing to purchase life insurance if they are aware of the risks involved.

Therefore, the following hypothesis is proposed:

Hypothesis 4. Risk perception (RP) towards black box insurance policy is positively linked to consumers' purchase intentions.

The Technology Acceptance Model (TAM) (Davis, 1989) is widely used to analyze the purchase intention factor from the perspective of customer technology acceptance (Wang et al., 2018; Venkatesh and Davis, 2000; Chen and Chen, 2009, 2011). Telematics enables the collection of a large amount of information, and the analysis of Big Data provides significant opportunities for insurance companies in terms of better knowledge of customers, which contributes to a more effective identification of the risk profile of each customer (Porrini, 2015).

Finally, data sharing is a sensitive issue in terms of privacy and monitoring. In this context, trust in an insurance company is important to persuade consumers to buy black box car insurance. The customer needs to feel safe and trust the company. Indeed, the challenge for insurers is to introduce telematics policies and have them accepted by policyholders. Indeed, some customers would be concerned about the protection of their personal data, and some would be skeptical about the use of the information collected (Friedman and Canaan, 2014). Insurers should therefore convince consumers of the benefits that the UBI model brings, and show that the data collected through the Internet of Things (IoT) will be used for their benefit and not to exempt them from insurers' liability for damages. If there is no trust in the insurance company, few people would agree to monitoring, because they would suspect retaliation from the insurance company if they denied use of personal data and did not comply with the contract set by the insurer (Derikx et al., 2016). Therefore, the following hypothesis is proposed:

Hypothesis 5. Trust (TRUST) towards black box insurance policies is positively linked to consumers' purchase intentions.

Rogers (1995) defines awareness as a customer's perception and knowledge of a particular product, service, or situation. Awareness helps the customer to select a product or service and make a purchase decision (Percy and Rossiter, 1992). Customers will not be pushed to buy a product or service if they are unaware and/or unfamiliar with it (Rogers, 1995). Customers prefer products and services with which they are familiar. According to previous studies, awareness has a significant and positive influence on insurance purchase intention (Nekmahmud et al., 2017; Andrew et al., 2014; Arun et al., 2012). Being aware of the benefits, in terms of paid and additional services, and knowing how the technology works, (Tselentis et al., 2017) leads motorists to take out usage-based insurance, such as a black box policy. Therefore, the following hypothesis is proposed:

Hypothesis 6. Awareness (AW) towards black box insurance policies is positively linked to consumers' purchase intentions.

Several studies have shown that there is a direct relationship between the intention to perform a behavior and the resulting action (Ordun, 2015; Madahi and Sukati, 2012; Muda et al., 2016).

According to Ajzen (1991), consumer intentions are an indicator of the extent to which people are willing to perform a particular behavior, which in this study would be translated as buying behavior for the black box car insurance policy. Therefore, the following hypothesis is proposed:

Hypothesis 7. Consumers' intention to purchase (ITP) towards a black box insurance policy is positively linked to their purchase behavior (PB).

The PMT covers similar factors to the GDT model. The GDT states that people make rational decisions by weighing the perceived severity of sanctions and the perceived certainty of sanctions. For example, risk assessment (risk perception) may include the threat of sanctions (according to the GDT). For this reason, TPB, PMT and TAM were selected as the three models to be applied. In particular, the conceptual framework of this study is based on the TPB and includes the variables of awareness, trust, and risk perception derived from the models PMT and TAM. The theories are used to develop the conceptual model that is ultimately used to understand the customer's intention to purchase black box auto insurance. The structural model combines awareness (AW), attitudes (ATT), subjective norms (SN), perceived behavior control (PBC), trust (TRUST), and risk perception (RP), as shown in Fig. 1.

4. Methodology

4.1. Design

In order to better explore the phenomenon, a mixed-methods sequential exploratory design is used (e.g., Creswell, 1999; Edmondson and McManus, 2007; Miglietta et al., 2018; Battisti et al., 2022b). Specifically, with the purpose to improve the definition of the items for the constructs underlined in the literature and in order to enhance the structure of the survey questionnaire, two focus groups were initially carried out (Battisti et al., 2022a). Focus groups are frequently used in different disciplines in the preliminary phase of research to define items of any questionnaires used, and to formulate contextually appropriate questions (e.g., Battisti et al., 2022a; Morgan, 1997; Guest et al., 2017; Dumka et al., 1998). The focus group activity was developed in two groups (Guest et al., 2017) with a total of fourteen participants. The two focus groups were organized separately and the authors facilitated the session. A first group was based on a dialogue with nine consumers – four women and five men (aged between 19 and 55 years), five of whom had already purchased a black box car insurance policy. A second focus group was based on a dialogue with five insurance company employees – three women and two men (aged between 28 and 60). The two focus groups lasted approximately three hours. In both focus groups, the researchers asked the participants some questions about car insurance involving black box technology. The discussion led the participants to identify and describe the psychological aspects associated with purchase intention and behavior, highlighting that the awareness, the risk perception, and technological readiness factors are important elements. At the same time, the participants pointed out the sensitive issue of data sharing, privacy protection, and monitoring. Trust in an insurance company is important to attract consumers to buy black box car insurance.

4.2. Data collection

To gain insight into the psychological attitudes and factors that promote the purchase of black box insurance, data were collected using

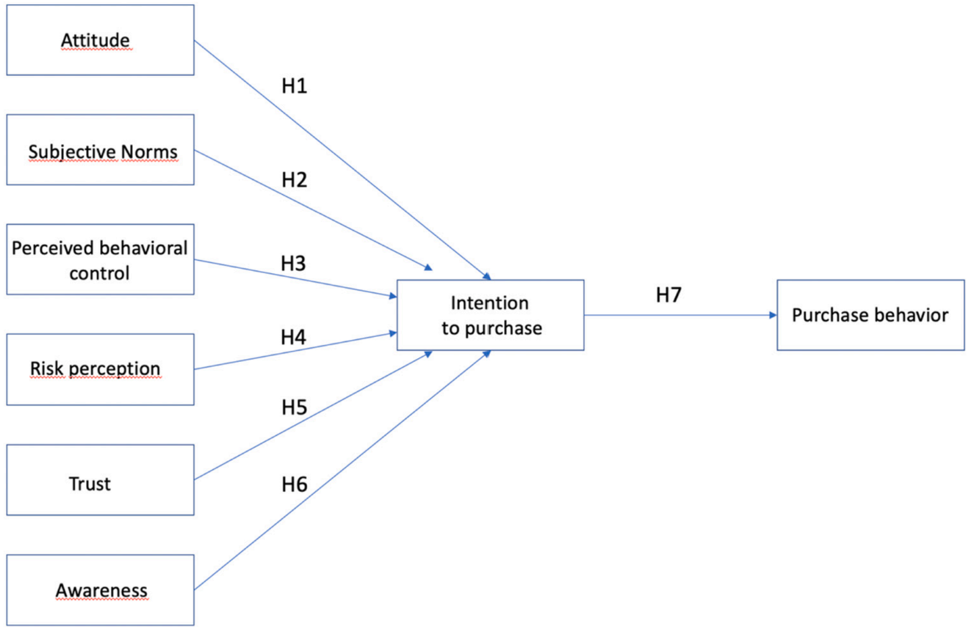

Fig. 1. Proposed research model.

a structured survey questionnaire (Das et al., 2019). To reach a good representation of consumers or potential consumers, our sample was contacted via email or social media. After the initial preparation, the survey was conducted over a period of about one month, from the end of September to the end of October 2021, and the questionnaire was generated using Google Forms (Rey et al., 2021). After a brief overview of the study topic, the first part of the questionnaire informed the participants about the general aim of the research, and guaranteed their anonymity and confidentiality in terms of data analysis (Sarra et al., 2015).

The structured questionnaire was divided into three subsections with closed-ended questions. The first section asked some initial information about the respondent, i.e., gender, age, type of employment, education, place of residence, level of income. The second section dealt with the topic of black box insurance and focused on the knowledge aspects of how the black box works, and the additional benefits offered by the insurance companies. Finally, the last section focused on psychological aspects related to the purchase intention and purchase behavior involved in choosing black box insurance.

4.3. Psychological measures

In order to carry out the survey research, specific measures were developed, drawing on existing literature in psychology. Our intention through these measures was to elicit data on the importance of psychological factors in the purchase of black box auto insurance. Each variable was measured using a five-point Likert scale, with 1 representing 'strongly disagree' and 5 representing 'strongly agree'. Table 1 shows the items and the constructs.

4.4. Sample description

A total of 788 questionnaires were received through the survey. The responses were collected through Google forms and downloaded to Excel files. Two authors scanned all the readable values on the database and logical checks were made on the values that the detected variables had assumed. To verify the consistency of the answers provided, descriptive analyses (mean, frequency distribution, and interquartile range) were carried out using Stata software (Stata/SE 17.0). This verification resulted in the omission of 31 questionnaires due to invalid answers or incomplete information. Thus, we obtained 757 valid responses (51.65 % male; 48.35 % female). The majority of the respondents (60.36 %) were 31–60 years old (20.87 % were 31–40 years old, 22.32 % were 41–50 years old and 17.17 % were 51–60 years old). In terms of occupational status, 51.39 % worked in the private sector, 25.23 % in the public sector, 12.42 % were self-employed, 7.40 % were students and the remaining 3.57 % were unemployed. Most participants lived in Northern Italy (42.54 %) and 71.6 % had a monthly salary of up to 2000 euros (people earning up to 1500 euros comprised 38.97 %, while 28.67 % had a salary between 1500 euros and 2000 euros). 47.5 % of respondents had taken out a black box policy, while 56.3 % knew someone who had taken out a black box policy. 6.3 % of the respondents were novice drivers and 87.5 % owned one or more cars. Table 2 shows the descriptive statistics of the characteristics of the sample.

4.5. Structural equation model

To analyze the psychological factors affecting black box car insurance buying behavior, this study applies a partial least square (PLS) approach to structural equation modeling (SEM). PLS-SEM is used in a variety of disciplines (Hair et al., 2011, 2012) and is an alternate approach to CB-SEM. This technique applies statistical analysis to the proposed relationships by exploring and predicting the dependent variables and allowing the effects of some variables on others to be calculated and quantified (Hallak et al., 2018). PLS-SEM allows us to conduct an exploratory analysis (Edmondson and McManus, 2007), and secondly a predictive analysis (Hair et al., 2014) of the constructs on purchase behavior (Ciocirlan et al., 2020). Our analysis of black box car insurance is relatively new, so using PLS-SEM is an excellent choice (Hair et al., 2014). Lastly, estimating PLS-SEM is more resistant to deviations from normality than CB-SEM (Hair et al., 2011).

4.6. Measurement model

The PLS-SEM method imposes, first of all, the evaluation of the measurement model used to analyze the reliability and validity of each construct. Composite reliability, convergent validity, and discriminant validity of the model are tested. The internal consistency is tested by Cronbach's alpha (Hair et al., 2011) and composite reliability (CR). Convergent validity is the assessment of the extent to which

Table 1
Constructs and items.

Awareness of black box technology auto insurance (AW)	
AW1	I am aware of the benefits of black box technology auto insurance.
AW2	I am aware of the importance of black box technology auto insurance.
AW3	I am aware of the terms and services of black box technology auto insurance
Attitudes towards black box technology auto insurance (ATT)	
AT1	I enjoy trying out new innovative technologies.
AT2	I have a positive attitude towards innovative technologies such as the black box technology auto insurance.
AT3	I would recommend other people to buy black box technology auto insurance.
AT4	I agree with the personal data sharing associated with the use of black box technology auto insurance.
Subjective norms (SN)	
SN1	Most people who are important to me would agree with me to buy black box technology auto insurance.
SN2	Most people who are important to me (would) encourage me to buy black box technology auto insurance.
Perceived behavioral control (PBC)	
PBC1	I have access to the information necessary to make the decision to buy black box technology auto insurance.
PBC2	I will be able to pay the insurance premium on time.
Trust	
T1	I would buy black box technology auto insurance only with an insurance company which I completely trust.
T2	The reputation of the insurance company is important to me in order to buy black box technology auto insurance
T3	Purchasing experience of others (would) motivate me to buy black box technology auto insurance.
Risk perception (RP)	
RP1	Investing in black box technology auto insurance have less risk compared to traditional auto insurance.
RP2	I think investing in black box technology auto insurance will help reduce the risk of having a car accident.
RP3	I would want protection from the risks associated with the use of my personal data from third parties.
Intention to purchase black box technology auto insurance (ITP)	
ITP1	I am willing to buy black box technology auto insurance for myself.
ITP2	I am willing to buy black box technology auto insurance for my loved ones.
Purchase behavior (PB)	
PB1	I have purchased black box technology auto insurance for myself.
PB2	I am encouraging others to purchase black box technology auto insurance.
PB3	I have purchased black box technology auto insurance to protect my loved ones.

Source: adapted from Masud et al., 2021.

measurements of the same construct are positively correlated with each other, while discriminant validity refers to the assessment of the extent to which constructs can be distinguished from each other.

Table 3 shows that all the constructs have high internal reliability, with a CR that ranges from 0.70 to 0.95. The convergent validity examines whether all measures correlate positively with other measures of the same construct, and is tested by the reliability indicator of all items and the average variance extracted (AVE). Table 4 summarizes both the results of the convergent validity tests based on the AVE and the factor loadings of each item. The value of factor loadings for all 22 items is above the threshold value of 0.7, which indicates that all items share many commonalities with other items of the same construct.

The values of the AVE reach levels above 0.5 for all constructs, suggesting that the proportion of variance shared by the constructs and their associated indicators is greater than the proportion of variance attributable to measurement error. Table 5 shows the descriptive statistics of each item and their correlations.

Table 2
Sample description.

Variables	Num.	Percent.
Gender		
Male	391	51.65
Female	366	48.35
Age		
18–25	73	9.64
26–30	102	13.47
31–40	158	20.87
41–50	169	22.32
51–60	130	17.17
61–70	113	14.93
>70	12	1.59
Education		
Certificate	31	4.1
Diploma	336	44.39
Bachelor's degree	263	34.74
Postgraduate degree	109	14.40
Higher degree	18	2.38
Occupation		
Private sector	389	51.39
Public sector	191	25.23
Self-employed	94	12.42
Student	56	7.40
Out of work	27	3.57
Geographic Area		
Northern Italy	322	42.54
Central Italy	231	30.52
South and islands	204	26.95
Salary classes		
≤1000 (0)	78	10.30
≤1500 (1)	217	28.67
≤2000 (2)	247	32.63
≤2500 (3)	114	15.06
≥2500 (4)	101	13.34

Table 3
Reliability analysis.

Constructs	Items	Cronbach's Alpha	Composite Reliability
ATT	4	0.833	0.888
AW	3	0.714	0.837
ITP	2	0.809	0.912
PB	3	0.802	0.883
PBC	2	0.837	0.925
RP	3	0.765	0.865
SN	2	0.731	0.879
TRUST	3	0.850	0.909

Next, discriminant validity was tested by the item cross-loadings and the Fornell-Larcker criterion. It was found that all item loadings are highest for each construct that the items are designed to measure. Thus, the requirement of convergent validity is met when examining the cross-charges. As far as the Fornell-Larcker criterion is concerned, Table 6 shows that the square root values of the AVE for all constructs are higher than the corresponding cross loading values. The discriminant validity requirements are reached at both item and construct levels. These results suggest that the indicators represent the assigned construct and that all the constructs studied are indeed different from each other. Also, the heterotrait-monotrait ratio (HTMT) results in acceptable values for all constructs, and all values are below the 0.85 threshold, meaning that discriminant validity is established (Henseler et al., 2015).

4.7. Structural model assessment

To evaluate the structural model of the study, the collinearity and the level of R^2 are checked.

Collinearity is assessed using the variance inflation factor (VIF) test. VIF values of all the independent variables are <2.3 (see Table 7), which

Table 4
Convergent analysis and measurement.

Constructs	Items	Loadings	AVE
ATT	AT1	0.817	0.666
	AT2	0.813	
	AT3	0.830	
	AT4	0.804	
AW	AW1	0.853	0.632
	AW2	0.819	
	AW3	0.705	
ITP	ITP1	0.935	0.838
	ITP2	0.895	
PB	PB1	0.857	0.716
	PB2	0.844	
	PB3	0.837	
PBC	PBC1	0.923	0.860
	PBC2	0.932	
RP	RP1	0.790	0.681
	RP2	0.838	
	RP3	0.846	
SN	SN1	0.920	0.785
	SN2	0.850	
TRUST	T1	0.868	0.769
	T2	0.886	
	T3	0.877	

indicates the absence of a serious multicollinearity problem (Joseph et al., 2010). The R^2 values, which indicate the proportion of variance in the dependent variables, explained by all the independent variables (Hair et al., 2014), reach a good level for the two independent variables. The R^2 value for purchase intention is 0.380 and increases to 0.593 for purchase behavior.

5. Results

5.1. Path coefficients

The parameter estimates of the paths between the constructs in the proposed research model are presented in Table 8. Bootstrapping is used to assess the significance of each path coefficient and to test the hypotheses. The sample of 757 respondents was subjected to a non-parametric bootstrapping procedure with a two-tailed subsample of 5000 (recommended by Hair et al., 2011) for a 95 % confidence level.

The results show that ATT, AW, SN, and RP have an impact on ITP and PB. Therefore, H1, H2, H4, and H6 are supported. PBC has an effect only on PB. Consequently, it follows that H3 is not supported. In addition, TRUST has an impact only on ITP. Therefore, H5 is also supported.

Fig. 2 shows the research model with the path coefficients between each variable, and *p*-values (in parentheses) that indicate the significance of the relationships between the latent variables.

5.2. Indirect effects

From the indirect effects analysis (Table 9), the ITP variable plays the role of a mediator for all variables except PBC. Mediation occurs when a third variable is interposed between two other related constructs. According to Zhao et al. (2018) and Hair et al. (2012), a complete mediation exists when the direct effect of the independent variable on the mediator, the effect of the mediator on the dependent variable, and the effect of the independent variable on the dependent variable are all significant. This is the case for all variables except PBC. In this context, the analysis confirms that the psychological perspectives that consumers have regarding the intention to purchase affect consumers' black box insurance purchase behavior.

5.3. Predictive relevance

In this study, the blindfolding method is used to determine the value

Table 5
Descriptive statistics and correlation.

	Mean	SD	AT1	AT2	AT3	AT4	AW1	AW2	AW3	ITP1	ITP2	PB1	PB2	PB3	PBC1	PBC2	RP1	RP2	RP3	SN1	SN2	T1	T2	T3
AT1	4.140	0.917	1.000																					
AT2	4.118	0.895	0.649	1.000																				
AT3	3.964	0.997	0.524	0.560	1.000																			
AT4	3.919	0.997	0.525	0.504	0.572	1.000																		
AW1	4.025	0.938	0.485	0.495	0.548	0.480	1.000																	
AW2	4.248	0.878	0.388	0.388	0.366	0.328	0.515	1.000																
AW3	4.020	0.921	0.291	0.295	0.281	0.272	0.384	0.464	1.000															
ITP1	3.782	0.991	0.406	0.360	0.459	0.457	0.485	0.337	0.265	1.000														
ITP2	3.551	1.176	0.319	0.281	0.364	0.358	0.348	0.265	0.239	0.679	1.000													
PB1	3.926	1.037	0.439	0.408	0.537	0.474	0.519	0.464	0.360	0.479	0.405	1.000												
PB2	3.754	1.078	0.425	0.383	0.534	0.441	0.522	0.338	0.289	0.574	0.463	0.571	1.000											
PB3	4.094	0.976	0.445	0.411	0.463	0.432	0.489	0.414	0.277	0.459	0.337	0.600	0.554	1.000										
PBC1	3.966	0.953	0.282	0.206	0.241	0.231	0.233	0.216	0.222	0.250	0.176	0.294	0.303	0.260	1.000									
PBC2	4.050	0.925	0.319	0.262	0.286	0.242	0.288	0.238	0.245	0.277	0.202	0.321	0.301	0.265	0.720	1.000								
RP1	4.086	1.025	0.382	0.353	0.375	0.427	0.362	0.376	0.216	0.387	0.339	0.325	0.379	0.371	0.169	0.172	1.000							
RP2	4.012	0.914	0.382	0.365	0.424	0.365	0.418	0.350	0.216	0.448	0.335	0.366	0.480	0.378	0.181	0.187	0.481	1.000						
RP3	4.055	0.961	0.345	0.367	0.453	0.411	0.397	0.294	0.227	0.427	0.339	0.378	0.417	0.422	0.233	0.269	0.510	0.572	1.000					
SN1	3.736	1.107	0.401	0.379	0.456	0.435	0.394	0.244	0.221	0.437	0.352	0.422	0.468	0.320	0.156	0.166	0.249	0.498	0.350	1.000				
SN2	3.522	1.105	0.298	0.311	0.294	0.330	0.313	0.203	0.175	0.339	0.241	0.296	0.338	0.269	0.166	0.162	0.187	0.314	0.218	0.576	1.000			
T1	3.976	1.067	0.391	0.390	0.477	0.463	0.394	0.349	0.279	0.395	0.341	0.350	0.416	0.344	0.236	0.276	0.429	0.301	0.403	0.317	0.231	1.000		
T2	4.177	1.024	0.409	0.410	0.455	0.378	0.412	0.401	0.265	0.396	0.317	0.342	0.436	0.373	0.267	0.292	0.451	0.339	0.368	0.331	0.236	0.660	1.000	
T3	4.153	1.099	0.406	0.391	0.432	0.397	0.378	0.438	0.268	0.390	0.353	0.358	0.419	0.394	0.240	0.244	0.539	0.383	0.323	0.363	0.290	0.628	0.672	1.000

Table 6
Discriminant validity analysis.

Constructs	ATT	AW	ITP	PB	PBC	RP	SN	TRUST
ATT	0.816							
AW	0.614	0.795						
ITP	0.512	0.464	0.915					
PB	0.656	0.624	0.593	0.846				
PBC	0.343	0.326	0.271	0.372	0.927			
RP	0.578	0.499	0.507	0.561	0.265	0.825		
SN	0.512	0.386	0,435	0.480	0.197	0.429	0.886	
TRUST	0.584	0.515	0,458	0.515	0.319	0.539	0.386	0.877

Table 7
Inner VIF values.

Constructs	ITP	PB
ATT	2.274	2.304
AW	1.784	1.812
ITP		1.612
PBC	1.180	1.185
RP	1.739	1.814
SN	1.418	1.463
TRUST	1.765	1.785

Table 8
Hypothesis path coefficients.

Path	Original Sample (O)	Sample Mean (M)	SD (STDEV)	T Statistics	*P* Values	Remarks
ATT -> ITP	0.137**	0.138	0.047	2.910	0.004	Supported
ATT -> PB	0.231**	0.232	0.041	5.660	0.000	Supported
AW -> ITP	0.132**	0.131	0.042	3.173	0.002	Supported
AW -> PB	0.240**	0.241	0.033	7.340	0.000	Supported
ITP -> PB	0.229**	0.227	0.031	7.388	0.000	Supported
PBC -> ITP	0.056	0.055	0.034	1.642	0.101	Not significant
PBC -> PB	0.096**	0.095	0.027	3.498	0.000	Supported
RP -> ITP	0.216**	0.216	0.043	4.994	0.000	Supported
RP -> PB	0.113**	0.114	0.037	3.089	0.002	Supported
SN -> ITP	0.167**	0.167	0.035	4.751	0.000	Supported
SN -> PB	0.093**	0.093	0.031	2.975	0.003	Supported
TRUST -> ITP	0.111**	0.112	0.034	3.243	0.001	Supported
TRUST -> PB	0.023	0.023	0.043	0.536	0.592	Not significant

** $p < 0.05$ (5 % level of confidence).

of predictive relevance (Stone-Geisser's Q^2) (Geisser, 1974). The measured Q^2 value must be greater than zero for a specific endogenous latent construct (Hair et al., 2014; Shmueli et al., 2019). Therefore, the result of the blindfolding analysis (Table 10) shows that $Q^2 = 0.302$ for ITP and $Q^2 = 0.407$ for PB; these values satisfy the Q^2 criteria of $Q^2 > 0$ (Henseler et al., 2015). These values prove that the model created has predictive relevance.

6. Discussion and conclusions

The main purpose of this research was to investigate consumers' intentions to adopt usage-based auto insurance based on black box technology. A psychological perspective has been used, which helps us understand these intentions by drawing on consumers' perceptions, thoughts, responses, and attitudes. Specifically, we identified the factors that induce car insurance customers to switch from a traditional car insurance policy to a black box technology insurance policy. Through structural equation modeling, we tested a model of telematics-based insurance policy adoption, filling a significant gap in existing literature.

The present study provides interesting insights into how consumers perceive telematics and black box technology insurance solutions, and how the psychological stance they adopt towards these high-tech solutions influences their related purchase intentions. Specifically, it reveals that consumer awareness, attitudes, subjective norms, trust, and risk perception are key determinants of customers' intentions to purchase black box technology insurance. These findings enhance our understanding of the factors that contribute to consumers' intentions to purchase life insurance (e.g., Nekmahmud et al., 2017; Andrew et al., 2014) and their attitudes towards installing data-recording technologies, such as INVRs, in cars (e.g., McNally and Bradley, 2018; Farmer et al., 2010). Further, our findings reveal that awareness of benefits can elevate insurance consumers' intentions (Dalkilic and Kirkbesoglu, 2015) to purchase black box technology solutions.

In line with previous studies (e.g., Suddin et al., 2009; Husin et al., 2016; Echchabi and Abd. Aziz, 2012), our research highlights that 'subjective norms' influence consumers' purchase intentions. Consumers will be more inclined to use a new technology when a peer or someone in their close circle conceives such technology as being value added (e.g., Wu and Chen, 2005; Chong et al., 2015). Yet, our study is the first to identify the relevance of subjective norms on the intention to adopt high-tech solutions, such as telematics-based black boxes. Further, our study extends understanding on the influence of subjective norms (e.g., parental monitoring and the family climate) on drivers' decisions (Taubman-Ben-Ari and Katz-Ben-Ami, 2012, 2013), by providing insights on the role of this construct in intentions to buy black box technology auto insurance.

Moreover, our study points to the crucial role that trust plays in consumer behavioral outcomes. Helen et al. (2012) suggested that trust occurs when one party relies on another party's decision. This implies integrity, and it can be perceived in the other party's honesty, goodwill, and reliability. Nevertheless, when dealing with technology, trust arises from the experience connected to repeated transactional processes and interactions with technology (Kim et al., 2008), and it is an important factor influencing the perceived risk and uncertainty associated with the adoption of new technologies (Li et al., 2008). In traditional insurance telematics, the device and the insurance company collect and own all drivers' driving data. Therefore, consumers cannot directly perceive how much data the insurance company stores, if the insurance company sufficiently protects sensitive personal information, and how it uses the data. The reputation and goodwill of insurance companies are the most important factors that encourage consumers to purchase black box technology car insurance. Our findings are in line with previous work on the intention to install IVDRs, where concerns about data protection and privacy have been raised as a major obstacle (McNally and Bradley, 2018; Bolderdijk et al., 2011). Yet, we extend this knowledge by

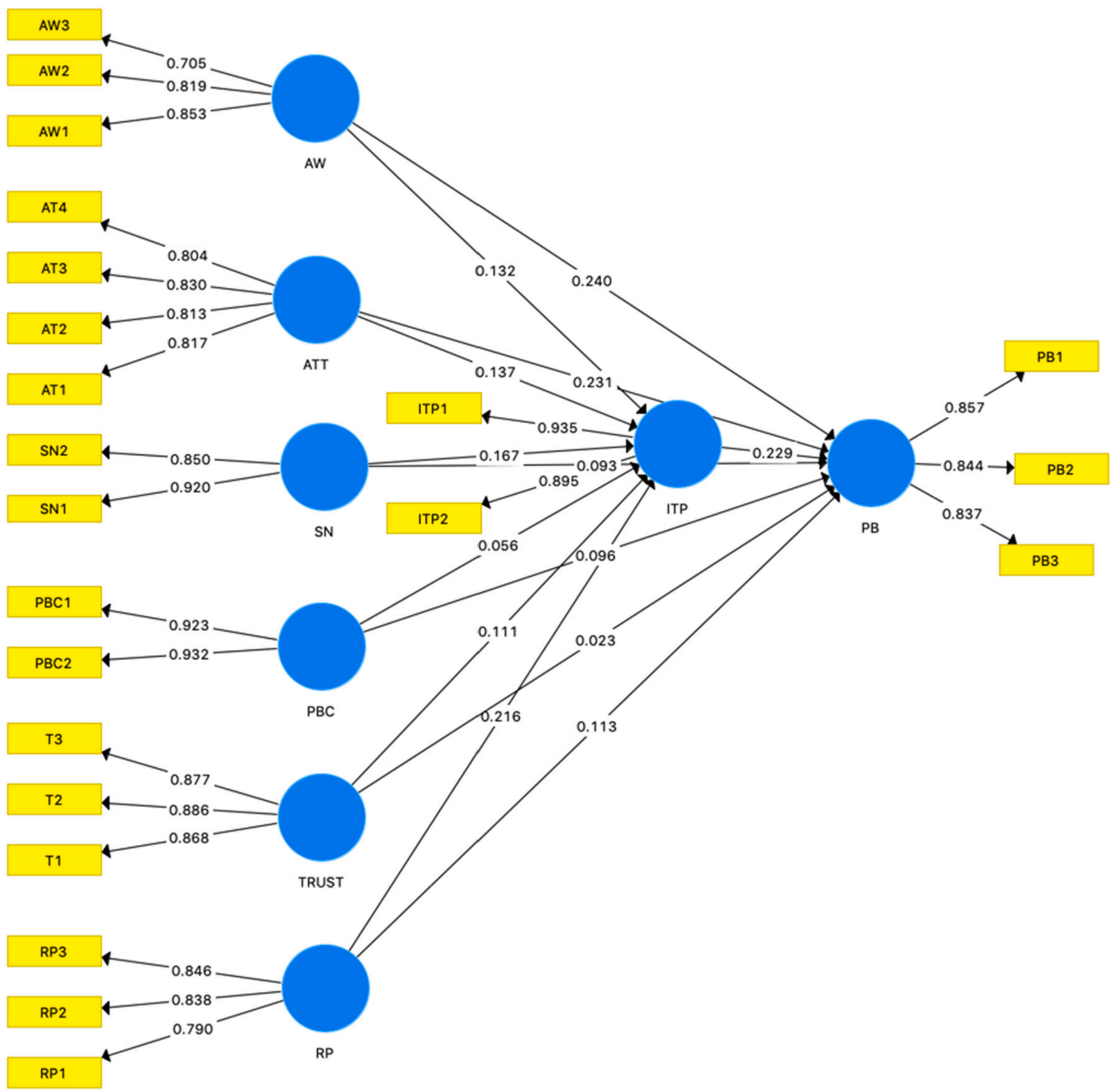

Fig. 2. PLS-SEM results.

Table 9
Indirect effects.

Path mediated by ITP	Original Sample (O)	Sample Mean (M)	SD (STDEV)	T Statistics	P Values
ATT - > PB	0.031**	0.031	0.011	2.720	0.007
AW - > PB	0.030**	0.030	0.011	2.829	0.005
PBC - > PB	0.013	0.013	0.008	1.593	0.111
RP - > PB	0.049**	0.049	0.012	3.985	0.000
SN - > PB	0.038**	0.038	0.009	4.055	0.000
TRUST - > PB	0.025**	0.025	0.008	3.091	0.002

** $p < 0.05$ (5 % level of confidence).

Table 10
Blindfolding results.

	SSO	SSE	Q^2 (=1-SSE/SSO)
ITP	1514.000	1056.510	0.302
PB	2271.000	1346.165	0.407

highlighting the role of consumers' trust towards an insurance company in adopting black box technology solutions. Trust, in our study, is not restricted to data protection concerns, but rather to the generic way that a customer may perceive a company, based on reputation and the purchasing experience of others (Michaelis et al., 2008; Walsh and Beatty, 2007).

Perceived behavioral control has an insignificant effect on the intention to buy insurance telematics; this result is consistent with the studies of Alam et al. (2012) and Tian et al. (2020). This could be due to the fact that the customers that have frequent exposure to technology are more willing to try new technologies, have access to the necessary information to opt for black box car insurance, and are less concerned about the difficulties of using such plug-in devices or paying the insurance premium.

Further, our findings identify a positive effect of risk perception on the respondents' intentions to purchase black box technology auto insurance. These findings confirm the role of risk perception as a critical factor motivating people to purchase insurance (Md Husin and Ab Rahman, 2016; Omar, 2007). Yet, our study is the first to identify this evidence in relation to consumers' intentions to purchase high-tech solutions in insurance. Telematics-based insurance policies have the potential to reduce claims risks, make roads safer, and influence driving behavior. Especially for young drivers, tracking fast acceleration, excessive speed, and sharp turns can have an educational effect (Carbone, 2016). It is, therefore, critical that insurance consumers understand the threatening events that can be mitigated (Rogers, 1975; Grahn and Jaldell, 2019) with the adoption of black box technologies before making decisions to purchase.

A positive attitude towards innovation and technology suggests an opportunity for consumers to shift their intentions to purchase from traditional insurance products to car insurance policies incorporating black box technology. Unlike the novice drivers that hold weak, negative attitudes towards IVDRs (McNally and Bradley, 2018), a heterogeneous sample similar to that of our study reveals a positive attitude towards the adoption of black box technologies. This may be due to a greater knowledge of the technological products and telematics-based insurance policies that implicate financial advantages linked to the additional services offered, and to the cost of the policies being more affordable.

Lastly, our findings find a significant relationship between 'awareness' and black box purchase intention. These findings confirm the role of awareness in helping customers make a purchase decision (Percy and Rossiter, 1992; Rogers, 1995), including insurance purchase intention (Nekmahmud et al., 2017; Andrew et al., 2014; Arun et al., 2012). Further, in line with previous work, we also identify that consumers require familiarity with innovative schemes in auto insurance before adopting them (Tselentis et al., 2017). Yet, we offer new knowledge linked to the role of awareness on the adoption of black box technology insurance solutions. Our findings highlight that once auto insurance customers are increasingly aware of the benefits of black box solutions and how their personal data are treated, they will be more induced to engage in relevant purchases. Yet, telematics insurance may be more attractive to individuals with a higher propensity for – and understanding of – technology (McLeay et al., 2022), such as younger consumers, who are more receptive to INVRs (McNally and Bradley, 2018; Farmer et al., 2010).

6.1. Contributions for theory and practice

Our study offers two important theoretical contributions. First, this study identifies the integrative and predictive power of the combined theoretical frameworks of TPB-PMT-TAM to the study of consumer intention to adopt high-tech technologies (i.e., insurance telematics). In doing so, it contributes with a comprehensive theoretical base to the study of high-tech adoption under a psychological perspective. Our findings answer the calls to establish a more adequate theoretical base to examine the adoption of high-tech solutions under a psychological lens (e.g., Curtale et al., 2021; Del Giudice et al., 2021).

Second, our study provides new knowledge on the psychological drivers of consumers' intentions to adopt telematics and black box technologies in auto insurance. Previous literature has largely focused on the outcomes from the adoption of telematics, primarily the use of telematics as a tool or extension for improving driver performance, and even leading to driverless cars (e.g., Koul and Eydgahi, 2018; Rahman et al., 2017; Toledo et al., 2008; McNally and Bradley, 2018; Conner et al., 2007; Correia et al., 2001; Farmer et al., 2010), or as a secondary tool in new product introduction (Kongmuang and Thawesaengskulthai, 2019). Outcome-based studies in the field of auto insurance have largely researched black box technology in terms of the provision of accurate data for insurance ratemaking (e.g., Ayuso et al., 2019; Gerpott and Berg, 2012; Cosconati, 2018; Porrini et al., 2020). Our study is the first to look into the individual-specific factors underpinning the adoption of black box auto insurance, including the psychological conditions of attitude, awareness, subjective norms, risk perception, and trust.

Our study provides practical insights for insurance companies to understand, from a psychological perspective, the factors that drive customers to purchase telematics insurance. It also helps them understand how the increase in trust, particularly in the protection of shared data, and the development of knowledge through insurance literacy can increase the penetration of technology in a traditional business such as insurance. Insurance companies have the opportunity through telematics to get much closer to their customers, understand their characteristics, needs, and motivations, and improve their customers' ecosystem. When it comes to trust, the results clearly suggest that insurance companies should pay attention to the issue of data sharing and the ability to share it with their customers. Insurance companies should invest in technical data protection for Big Data applications, ensuring compliance with data protection principles such as anonymization, security, notice of use, and consent to data use.

In an ever-changing market, insurance companies should build a different kind of relationship with their customers in order to adapt their offerings to consumers' needs and benefit from this growing market. In particular, insurance companies need to improve their ability to analyze the information generated by the use of Big Data in order to gain a competitive advantage, avoid the standardization of insurance products and the process of commoditization, and differentiate themselves by offering a service that goes beyond a simple policy with a lower price. This represents a departure from most of the telematics proposals currently on the market, which focus almost exclusively on potential premium discounts. Telematics can help insurance companies combat commoditization and transform a product-centric business model into customer-centricity (Manning and Bodine, 2012), reshaping the customer experience and transforming the customer relationship into an enduring and tangible service. Indeed, telematics enables a significant expansion of touch points (Park and Lee, 2017). To take advantage of this opportunity, it is necessary to consistently review the CRM by integrating the information associated with the customer/vehicle and expanding the communication channels in a real-time perspective.

6.2. Limitations and future research

Our empirical study has some limitations, which paves the way for future lines of research. First, our sample consists only of Italian participants. Although telematics insurance has reached its maximum diffusion in Italy, black box technology is being developed worldwide. The diversity of cultural backgrounds (Hofstede et al., 2005; McCrae and Costa, 2008), as well as the different penetration rates of telematics insurance, varies enormously across countries and is linked to the characteristics of individual customers (Deloitte, 2016). Future studies could draw on a larger and more diverse sample from different countries, as well as developed and emerging markets (e.g., MENA, Next Eleven) (Battisti et al., 2021), to facilitate understanding of consumer characteristics and to highlight, from a benchmarking perspective, the influence of national culture on technology adoption (e.g., Lee et al., 2013; Orlando et al., 2020). Finally, although combined PLS-SEM is used in many studies on management (Hair et al., 2014), in future research it could be useful as a different approach with which to estimate structural equation models, such as Covariance Based Structural Equation Modeling (CB-SEM) or the Multiple Indicators and Multiple Causes Model (MIMIC) (e.g., Sarstedt et al., 2016; Dash and Paul, 2021).

CRediT authorship contribution statement

Simona Alfiero: Conceptualization, Data curation, Formal analysis, Software, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Enrico Battisti:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Elias Hadjielias:** Conceptualization, Investigation, Writing – review & editing, Validation, Supervision.

Data availability

Data will be made available on request.

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