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Research paper

Measuring the acceptance rate of Usage-Based Insurance (UBI) based on statistical methods (case study: Saman Insurance Company)

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Abstract:
Usage-based Insurance (UBI) is an innovative approach that distinguishes between high-risk and low-risk drivers, unlike traditional car insurance. The premium in this policy is calculated based on the distance traveled and telematics variables such as road type, time, speed, etc. This research measured the UBI acceptance rate and the factors that influence it. Global surveys and expert opinions were used to design a questionnaire, which was then distributed to 396 randomly selected respondents, meeting the requirements of Cochran's formula for indeterminate populations (at least 384). Multinomial and binary logistic regression models were used to evaluate acceptance and the willingness to purchase UBI based on distance, as well as distance and driving behaviors. These analyses were conducted across five and three scenarios, respectively, taking into account value-added services, awareness levels, and the importance of factors. Finally, a confirmatory factor analysis model was applied to validate the UBI acceptance model, with the indicators confirming its appropriateness. The findings suggest the need for plans to enhance the information and awareness levels of insurance policyholders regarding UBI. Additionally, variables such as providing warnings to policyholders to improve driving, policy price, awareness of UBI, awareness of providing UBIs by some insurance companies in Iran, and providing rewards/discounts are identified as key drivers of UBI purchases , warranting investment by insurance companies to stimulate sales.

Keywords: Usage-Based Insurance (UBI); Confirmatory Factor Analysis (CFA); Telematics; Multinomial Logistic Regression model; Binary Logistic Regression model.
Classification: G22, C10, O32.

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1 Introduction

The Internet of Things (IoT) is increasing in popularity, not only among consumers but also in various business processes. With the help of new data analysis and mining techniques, IoT can significantly improve the performance of business automation and decision support systems. One significant application of IoT is the use of telematics data in auto insurance [23]. The vehicle insurance industry is gradually adopting new trends such as digitalization, IoT, and Artificial Intelligence (AI), and has been rapidly changing due to the development of road transport which has emerged from the telematics technology [8]. The development of Usage-Based Insurance (UBI) with telematic support has introduced an innovative concept in the world of vehicle insurance [7] [12]. Traditional auto insurance policies evaluate the level of risk of a driver based on the characteristics of the vehicle and the driver's information. However, they tend to overlook the penalties imposed on drivers for dangerous driving behaviors and the significant correlation between driving behavior and accidents [10]. Calculating auto insurance rates is also based on empirical experience, leading to unreasonable premiums for consumers and facing challenges for the use of digital technologies and the Internet [16].
UBI is becoming a popular alternative to traditional auto insurance. The main idea behind this product is to directly monitor driver behavior while driving [21]. This type of insurance is based on numerous data such as mileage, speed, location, time, total trip duration, etc., extrapolated from telematics devices, and companies could gain a competitive advantage by analyzing drivers' behavior [5]. UBI can take different forms such as pay-as-you-drive (PAYD) and pay-how-you-drive (PHYD) insurance. In PAYD, the premium depends on the real distance traveled by the policyholder, monitored by a telematics device installed in the car. In PHYD insurance, the premium calculation is based on other telematics variables such as road type, time, speed, sudden brakes, etc. [17].
In Iran, various transportation challenges such as high road deaths, increased car prices and parts, severe air pollution, and traffic in large cities like Tehran have made it necessary to consider using UBI. To determine the acceptance rate of UBI, we aim to investigate the insurers of Saman Insurance Company, a leader in this field that has provided related products. Section 2 introduces UBI and its advantages and disadvantages. Section 3 outlines the design of the questionnaire based on global surveys to measure the UBI acceptance rate. The models used in the study are also discussed in this section. In Section 4, the analysis of the questionnaire and the UBI acceptance rate are discussed using multinomial and binary logistic regression models. Finally, the paper is concluded in Section 5.

2 Theoretical framework

UBI is an insurance type facilitated by connected devices, providing a chance to customize insurance based on customers' behavior, usage patterns, and lifestyle [26]. UBIs offer numerous advantages to insurers, consumers, and society, as detailed in Table 1

Table 1: Categories of the advantages of using UBI program [5]

Benefits	Description
Social benefits	Reduce accident frequency and severity; reduce accident response time; track and recover stolen vehicles; reduce driving, pollution, traffic congestion and energy consumption
Economic benefits	Reduce chance of accidents; enhance efficiency of claims processing; enable early detection and prevention of frauds; enable pricing based on risk profiles
Environmental benefits	Increase use of congestion-free routes and limit vehicle usage; reduce fuel consumption; limit the use of vehicle; improve vehicle maintenance; reduce CO2 emissions
Benefits for insurance providers	Correct risk misclassifications; enhance pricing accuracy; retain profitable accounts; fight fraudulent claims; enable lower premiums; reduce claim costs; differentiate brand
Benefits for users	Reduce premiums; demonstrate safe driving habits; value-added services (vehicle diagnostics, stolen vehicle recovery, emergency services, teen driver monitoring etc.)

However, they also have some disadvantages, including [4]:

- Driving typically involves braking and acceleration. Driver monitoring technology struggles to differentiate between prudent and risky behavior by the policyholder.

- Privacy concerns and how driver information is utilized have always been customer worries with these products. Telematic devices are always connected, and if they disconnect (even for a short trip), the premium discount may not apply.

- Downloading the application by family members or employees, or installing approved trackers in any of the policyholders cars, often doesn't justify the discount.

- Should the insured wish to change insurance companies, they may need to remove the device from their vehicle, return it, and install another approved device from the new insurer.

- For many drivers, the cost savings may not justify switching to a new company if their current insurer doesn't operate a UBI program, or take steps to acquire, install, and maintain a UBI telematics device.
- While insurance companies inform customers about the parameters considered in scoring driving behavior and provide regular feedback, the conversion of tracked parameters into driving behavior scores and subsequent premium discounts remains unclear.
- The installation costs of telematics devices are also a UBI challenge that should be factored into estimating hardware, software, and installation costs.

The concept of UBI stems from discussions in the United States in the late 1960s and early 1970s. Vickery was among the first to criticize the idea of lump-sum premium pricing and proposed tariffs based on the distance traveled by the policyholder's vehicle in a certain period [22]. UBI has been around for over two decades. In 1997, Progressive Insurance Company in the United States introduced the first UBI. Since then, other companies have followed suit and now offer UBI programs in many countries around the world [6]. Interest in UBI has grown since the 2010s with the development and expansion of big data, IoT technologies, and machine learning techniques [1].

3 Literature Review

The UBI acceptance among individuals is crucial. UBI is not only a new insurance product concept but can also be considered a form of technological innovation. Its acceptance level can be directly explained by factors such as perceived usefulness, perceived ease of use, and perceived risk [22].

Rejikumar (2013) gathered Indian consumers' perceptions of UBI pricing using structural equation modeling (SEM). The model contained critical variables to identify a statistically significant relationship between perceived individual benefits, perceived social benefits, perceived value, perceived easiness to understand, and acceptance intentions. The results showed that perceived individual benefits, perceived easiness, and perceived value influence the acceptance rate of UBI in India [19].

Zand et al. (2016) conducted a study in Iran to investigate the adoption of UBI by drivers using a nested logit model. The results revealed that people are more likely to change their insurance plans based on discounts and costs. Individuals who travel longer distances annually are less inclined to buy UBI [27].

Kumarage (2018) explored the acceptance factors of UBI among Sri Lankan consumers based on the Technology Acceptance Model (TAM). The findings indicated that individual benefits and concerns were the primary factors influencing the current premium calculation method. Additionally, younger customers and those who used their vehicles less often and had fewer accidents were more likely to accept UBI. Privacy concerns were found to be insignificant in the UBI acceptance in Sri Lanka [9].

Sahebi (2019) used the binary logistic regression model to measure the UBI acceptance by drivers. The results showed that older drivers, drivers with more speeding fines, and those more concerned about privacy were less willing to accept UBI. The study also employed a parametric risk analysis model to measure the effects of UBI economic incentives, including attitude toward the intelligent communication system, driving experience, speed behavior, economic behavior, and social behavior. The results suggested that as the incentive increases, the acceptance rate also increases, but the effect of the incentive on acceptance gradually decreases [20].

Tian et al. (2020) developed a conceptual model of UBI acceptance by millennials based on the TAM and the Theory of Planned Behavior (TPB). The research found that the perceived ease of use of millennials only indirectly affects the attitude towards the behavior through the perceived usefulness of insurance telematics. Additionally, perceived enjoyment was found to influence use rather than attitude formation. Trust was shown to be an important factor influencing both behavioral attitudes and the intention to use for millennials [25].

Milanovic et al. (2020) used the Unified Theory of Acceptance Technology and Use of Technology (UTAUT) to investigate the acceptance rate. They interviewed 502 new car buyers to investigate factors affecting the potential use of telematics devices for insurance purposes. The variables used in their model included performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intentions, and privacy concerns. The findings suggested that facilitating conditions are the main predictors of using telematics. Additionally, privacy concerns regarding the potential abuse of driving behavior data play an important role in the UBI acceptance [15].

Quintero et al. (2023) proposed a UBI acceptance model based on an adaptation of the Unified Theory of Acceptance Technology and Use of Technology 2 (UTAUT2) and tested it with 585 participants using SEM. The variables of this model include performance expectancy for improving driving style (PD), performance expectancy for saving money (PM), effort expectancy (EE), social influence (SI), hedonic motivation (HM), facilitating conditions (FC), trust in insurer (TI), trust in UBI technology (TU), perceived privacy (PP), perceived safety (PS), perceived transparency (PT) in UBI, and perceived driving style (DS). The results indicated that SI and HM are the most important predictors of intention to use UBI, and PP affects it indirectly [18].

4 Methodology

In this study, a field survey (questionnaire) was conducted to evaluate the UBI acceptance and conduct related analyses. The questionnaire was designed based on insights from five global surveys regarding customers' willingness towards UBI. The Future of Insurance Survey USA in December 2019 involved 1,200 consumers to validate the preferences of US consumers for UBI [14]. The Future of European Insurance Survey 2020 focused on the interest of European drivers in various UBI pricing, services, and rewards, interviewing 4,000 insured drivers of all ages group from France, Germany, Italy, and the UK [2]. A 2016 survey by Bain Company and SSI survey included 3,525 customer respondents in seven countries (Austria, France, Germany, Italy, Spain, UK, and USA) to provide insights into customers telematics perception, preferred telematics insurance product, and value-added service [13]. The 2016 Market segment assessment survey in the South African insurance market evaluated the demand for digital insurance services, including modern UBI, among 1,500 participants and assessed policyholders perceptions, preferences and behavior [3]. The LexisNexis Risk Solutions USA Survey used an online panel as a sample source to collect feedback from approximately 4,000 US auto insurance consumers in March 2016 [11].

Subsequently, a questionnaire was designed based on the survey results and input from specialists and experts to gauge the acceptance rate of UBI. The target population for this assessment was the car insurance policyholders of Saman Insurance Company. Sampling was conducted randomly, resulting in 396 respondents, meeting the requirements of Cochran's formula for indeterminate societies (at least 384). To evaluate acceptance using statistical methods of the data mining process, the multinomial logistic regression model was employed, which is from the family of discrete selection models. Binary logistic regression and multinomial logistic regression are a key tool in data analysis, especially supervised learning. These two regression methods operate based on qualitative values for the response variable and are able to classify the observations into two or more groups with the help of a model based on the relationship between the independent variables (with quantitative or qualitative values) and the response variable (with qualitative values). When the response variable or the dependent variable is in the form of a categorical variable or a nominal variable in a regression problem, the regression analysis method is in the form of multinomial logistic regression.

SPSS software was used to implement this model, measuring UBI acceptance under different scenarios. The UBI acceptance was measured using a multinomial logistic regression model under five scenarios. The dependent variable in the first three scenarios was the willingness to buy UBI based on the distance and in the fourth and fifth scenarios, based on the distance and driving behaviors. In all scenarios, demographic information was taken as one of the independent variables. Then, the effect of factors affecting the purchase of UBI was measured using the binary logistic regression model and under three different scenarios, including the level of awareness, value-added services, and the level of importance.

The questionnaire used in the study showed a high level of reliability, with a Cronbach's alpha index of 0.80. To ensure validity, the questionnaire was reviewed by

14 experts, resulting in acceptable content validity ratio and content validity index (calculated by Waltz and Basels equation) values of 0.92 and 0.95, respectively.

5 Discussion

5.1 Questionnaire analysis

In this section, we will analyze the questionnaire results for UBI acceptance. The number of respondents was 396. First, we will analyze the demographic information including gender, age, marital status, city of residence, education, occupation, and monthly salary in. The results are as follows:

- 80% of respondents are male and 20% are female.
- 43% of the respondents are 20 to 39 years old, 49% are 40 to 59 years old, and 8% are over 60 years old.
- 80% of the respondents are married and 20% are single.
- Respondents reside in 27 different provinces, with 35% residing in Tehran. Fars (9%), Isfahan (8%), Karaj (6%), Khuzestan, Kerman, and Razavi Khorasan (each 5%), and East Azerbaijan (4%) are in the next categories. 23% also live in other provinces.
- 14% of the respondents have a diploma or lower, 6% have an associate degree, 40% have a bachelor's degree, 31% have a master's degree, and 9% have a doctorate or higher.
- 2% of the respondents are unemployed, 2% are students, 17% are employed in the public sector, 36% are employed in the private sector, 21% are self-employed, 12% are retired, and 10% have other jobs.
- The monthly salary of 6% of respondents is less than 3 million Tomans, 6% between 3 and 5 million Tomans, 13% between 5 and 7 million Tomans, 18% between 7 and 9 million Tomans, and 57% above 9 million Tomans.

Also, one of the questions was dedicated to the type of insurance used by the respondents, the results of which are shown in Figure 1.

5.2 Measuring the UBI acceptance by the multinomial logistic regression model

In this study, the multinomial logistic regression model was used to measure the UBI acceptance. SPSS software was used to implement the relevant model. According to the questionnaire, the UBI acceptance was measured under different scenarios.

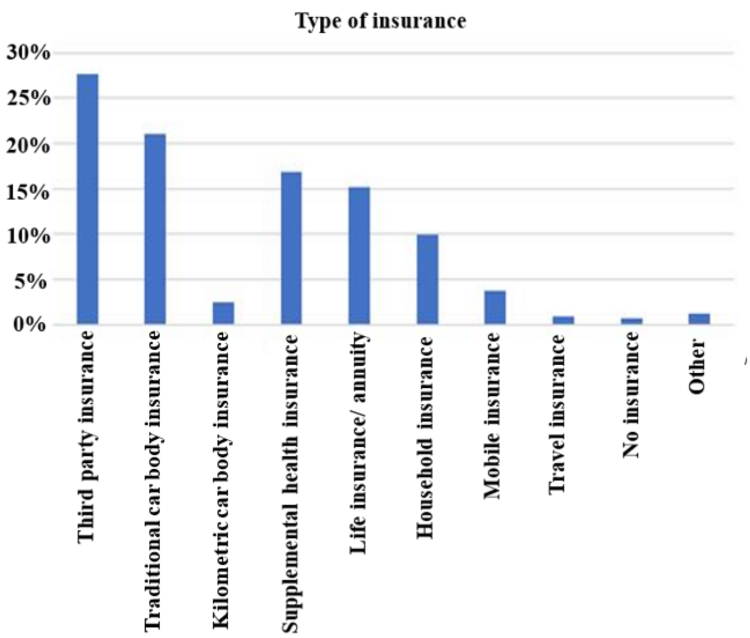

Figure 1: Type of insurance used by the respondents

In the 1st scenario, the dependent variable of willingness to buy UBI based on distance and the independent variables of demographics and value-added services were considered. The results of model implementation in SPSS software are described in the following tables.

Next, we will analyze the results presented in Table 2. The likelihood ratio test in multinomial logistic regression determines the significance of the regression model. The P-value of this test in these data is equal to zero, which is less than 0.05 and confirms the significance of the regression. What is important for us in the results of the goodness of fit test is that the P-value of this test is not significant. Thus, it is determined that the fitted regression model is optimal. The P-value is equal to 1, which is greater than 0.05. The null hypothesis in this test is the goodness and appropriateness of the fitted model. Based on the goodness of fit test and the probability value obtained, the null hypothesis is confirmed, indicating that the model obtained is appropriate. Also, in the above table, R^2 values are shown in 3 different types. This statistic demonstrates that the independent variables can explain how much of the dependent variable, based on the values provided in Table 2, the obtained values are also appropriate and show a good explanation of the dependent variable. Also, in Table 2, the results of the likelihood test are presented to examine the significance of each of the variables on the willingness to buy UBI

Table 2: The results of implementing the model based on multinomial logistic regression (1st scenario)

Variable	Test Statistic Value	P-value
Intercept	0.000	
Gender	6.448	.168
Age	17.994	.021
Marital status	7.529	.110
City of residence	141.035	.009
Education	18.676	.286
Occupation	35.877	.056
Monthly salary	20.328	.206
Automatic emergency assistance in case of severe crash	44.512	.000
Active monitoring anti-theft device	24.124	.087
Car maintenance reminders	17.635	.346
Weather information	39.424	.001
Information about how teens and family members are driving	21.997	.143
Suggestions for driving improvement	30.244	.017
Personalized insurance offers	16.540	.416
Likelihood ratio test	438.113	.000
Goodness-of-fit test (Deviance)	606.924	1.000

R^2 value: Nagelkerke= .758 , Cox and Snell:= .722, McFadden= .419

based on distance where P-values less than 0.05 mean effectiveness and higher than 0.05 mean no significant effect. According to the results, age, city of residence, automatic emergency assistance in case of a severe crash, weather information, and suggestions for driving are the variables that affect the willingness to buy.

In the 2nd scenario, the study considered the dependent variable of willingness to buy UBI based on distance, along with the independent variables of demographics and level of awareness. The P-value confirms the significance of the regression based on the model fit information. In Table 3, the results of the model implementation in the second scenario are shown, according to which, awareness of providing UBIs by some insurance companies in Iran, calculating of UBIs premiums based on how to drive, providing rewards/discounts in UBIs, and installing telematics tools or devices in the car for monitoring the driving behavior affect the willingness to buy.

In the 3rd scenario, we considered the dependent variable of the effect of the willingness to buy UBI based on distance and the independent demographic variables and the importance of the factors affecting the willingness to buy. The P-value based on the model fit information confirms the significance of the regression. Table 4 shows the results of the model implementation in the 3rd scenario, according to which, the variables of age, marital status, occupation, considering the reward in case of favorable and low-risk driving, and the policy price affect the willingness to buy.

Table 3: The results of implementing the model based on the multinomial logistic regression (2nd scenario)

Variable	Test Statistic Value	P-value
Intercept	0.000	
Gender	2.234	.693
Age	9.814	.278
Marital status	4.329	.363
City of residence	125.035	.078
Education	21.779	150
Occupation	28.861	.225
Monthly salary	25.146	.067
Awareness of UBIs	8.858	.354
Telematics devices	12.025	.150
Providing UBIs by some insurance companies in Iran	17.504	.025
Calculation of UBIs premiums based on how to drive	15.606	.048
Providing rewards/discounts in UBIs	16.779	.032
Installing telematic tools or devices in the car for monitoring the driving behavior	19.753	.011
Monitoring how to drive using mobile applications	8.940	.347
Likelihood ratio test	283.919	.011
Goodness-of-fit test (Deviance)	743.436	1.000

R^2 value: Nagelkerke= .592 , Cox and Snell:= .564, McFadden= .272

Table 4: The results of implementing the model based on the multinomial logistic regression (3rd scenario)

Variable	Test Statistic Value	P-value
Intercept	0.000	
Gender	3.014	.556
Age	15.834	.045
Marital status	17.839	.001
City of residence	125.952	.071
Education	18.641	.288
Occupation	42.246	.012
Monthly salary	22.332	.133
Considering the reward in case of favorable and low-risk driving	30.146	.017
Policy price	39.268	.001
Considering the discount in renewing policy in the case of favorable and low-risk driving	25.037	.069
Providing warnings to policyholder to improve driving	18.112	.317
Likelihood ratio test	413.986	.000
Goodness-of-fit test (Deviance)	607.823	1.000

R^2 value: Nagelkerke= .737 , Cox and Snell:= .702, McFadden= .396

In the 4th scenario, the dependent variable of the willingness to buy UBI based on the distance and driving behaviors and independent demographic variables and value-added services provided were considered. The P-value based on the model fit information confirms the significance of the regression. Table 5 shows the results of the implementation of the model in the fourth scenario, according to which, the variables of the city of residence, weather information, and personalized insurance offers affect the willingness to buy.

Table 5: The results of implementing the model based on the multinomial logistic regression (4th scenario)

Variable	Test Statistic Value	P-value
Intercept	0.000	
Gender	1.515	.824
Age	9.181	.327
Marital status	4.435	.488
City of residence	152.965	.001
Education	11.339	0.788
Occupation	32.081	.125
Monthly salary	23.835	.093
Automatic emergency assistance in case of severe crash	25.638	.059
Active monitoring anti-theft device	19.829	.228
Car maintenance reminders	20.734	.189
Weather information	42.726	.000
Information about how teens and family members are driving	21.078	.176
Suggestions for driving improvement	19.095	.264
Personalized insurance offers	29.145	.023
Likelihood ratio test	435.812	.000
Goodness-of-fit test (Deviance)	630.642	1.000

R^2 value: Nagelkerke= .753 , Cox and Snell:= .720, McFadden= .408

In the 5th scenario, the dependent variable of the willingness to buy UBI based on the distance and driving behaviors and independent demographic variables and the importance of factors affecting the willingness to buy were considered. The P-value based on the model fit information confirms the significance of the regression. In Table 6, the results of the implementation of the fifth scenario model are shown, according to which, the variables of the city of residence, considering the rewards in case of favorable and low-risk driving, considering the discount in renewing the policy in case of favorable and low-risk driving, and providing warnings to policyholders to improve driving affect the willingness to buy. Compared to the third scenario, factors related to driving behaviors in this scenario have a greater effect.

5.3 Measurement of the UBI Acceptance by the Binary Logistic Regression Model

One of the questions examines whether policyholders have purchased a UBI or not, with 'yes' or 'no' being the answers. This question is considered as a dependent variable, and different independent variables are used in a binary logistic regression

Table 6: The results of implementing the model based on the multinomial logistic regression (5th scenario)

Variable	Test Statistic Value	P-value
Intercept	0.000	
Gender	-	-
Age	2.725	.950
Marital status	0.665	.956
City of residence	142.852	.007
Education	16.303	.432
Occupation	384.117	.000
Monthly salary	7.590	.960
Considering the reward in case of favorable and low-risk driving	41.127	.001
Policy price	20.267	.208
Considering the discount in renewing policy in the case of favorable and low-risk driving	28.594	.027
Providing warnings to policyholder to improve driving	46.819	.000
Likelihood ratio test	462.090	.000
Goodness-of-fit test (Deviance)	583.909	1.000

R^2 value: Nagelkerke= .775 , Cox and Snell:= .741, McFadden= .432

model to measure the impact of various factors on the purchase of UBIs under three scenarios. In the first scenario, demographic information and the level of awareness are the independent variables. The P-value based on test results confirms the regression model's appropriate fit, and the results in Table 7 indicate that awareness of UBI, awareness of UBIs provided by some insurance companies in Iran, and providing rewards/discounts for UBIs are among the factors influencing UBI purchases.

In the 2nd scenario, demographic information and value-added services are considered independent variables. The P-value, based on test results, confirms the regression model's appropriate fit and the results in Table 8 indicate that the variable of suggestions for driving improvement is a significant factor influencing UBI purchase. In the 3rd scenario, demographic information and the level of importance are taken as independent variables. The P-value, based on test results, confirms the regression model's appropriate fit and the results in Table 9 indicate that providing warnings to policyholders to improve driving and the policy price are among the factors influencing UBI purchase.
The results of model fit is also shown in Table 10.

5.4 Model Testing Using Confirmatory Factor Analysis Method

Confirmatory factor analysis is a multivariate statistical method that assesses how accurately measured variables represent a number of constructs. This method helps researchers to identify the necessary factors in the data and the relationship between

Table 7: The results of model implementation based on the binary logistic regression (1st scenario)

Variable	B	S.E.	Wald	df	Sig.	Exp(B)
Gender	-.237	.491	.232	1	.630	.789
Age	.399	.342	1.360	1	.243	1.491
Marital status	-.033	.528	.004	1	.951	.968
City of residence	-.008	.024	.107	1	.743	.992
education	.132	.206	.406	1	.524	1.141
Occupation	.076	.124	.375	1	.540	1.079
Monthly salary	.019	.192	.010	1	.922	1.019
Awareness of UBIs	.841	.347	5.872	1	.015	2.318
Telematics devices	.633	.269	5.557	1	.018	1.884
Providing UBIs by some insurance companies in Iran	-.064	.297	.046	1	.830	.938
Calculation of UBIs premiums based on how to drive	-.426	.282	2.281	1	.131	.653
Providing rewards/discounts UBIs	.979	.292	11.270	1	.001	2.663
Installing telematic tools or devices in the car for monitoring the driving behavior	-.250	.337	.549	1	.459	.779
Monitoring how to drive using mobile applications	.036	.302	.015	1	.904	1.037
Constant	-7.304	1.448	25.448	1	.000	.001

the measured and latent variables [24]. In this study, LISREL software and second-order confirmatory factor analysis were used to examine the model's compatibility for the impact of awareness, importance, beliefs, satisfaction, and value-added services on UBI acceptance. The strength of the relationship between the factor (latent variable) and the observable variable (questionnaire questions) is indicated by the factor loading, with values between -1 and 1 considered acceptable. The final output of the factor analysis is presented in Figure 1 demonstrating a high correlation between all variables and the model. It is important to evaluate the model fit through various methods and criteria to assess its fit from different perspectives. One crucial indicator is the chi-square to degrees of freedom ratio, or relative chi-square, where values lower than 3 are indicative of a very good fit. Another important index is the root mean square error of approximation (RMSEA), where values less than 0.1 indicate an acceptable fit. Some resources recommend using the Non-Normed Fit Index (NNFI) and the Comparative Fit Index (CFI) to evaluate the model's fit, with acceptable values above 0.9. Additionally, the Normed Fit Index (NFI) and the Incremental Fit Index (IFI) are other indices that can be used to assess a model's fitness, with acceptable values also above 0.9. Table 11 presents some important indicators resulting from the factor analysis, demonstrating the model's

Table 8: The results of model implementation based on the binary logistic regression (2nd scenario)

Variable	B	S.E.	Wald	df	Sig.	Exp(B)
Gender	-.106	.461	.053	1	.817	.899
Age	.140	.310	.203	1	.652	1.150
Marital Status	.058	.481	.014	1	.904	1.060
City of residence	-.001	.024	.002	1	.963	.999
education	.204	.170	1.434	1	.231	1.226
Occupation	.074	.112	.438	1	.508	1.077
Monthly salary	.030	.164	.033	1	.856	1.030
Automatic emergency assistance in case of severe crash	-.166	.323	.264	1	.608	.847
Active monitoring anti-theft device	-.331	.366	.815	1	.367	.718
Car maintenance reminders	.436	.306	2.029	1	.154	1.547
Weather information	-.079	.274	.084	1	.772	.924
Information about how teens and family members are driving	-.248	.218	1.295	1	.255	.780
Suggestions for driving improvement	.733	.331	4.903	1	.027	2.082
Personalized insurance offers	.228	.255	.802	1	.370	1.256
Constant	-5.395	1.469	13.483	1	.000	.005

appropriateness.

6 Conclusions and recommendations

In recent years, car insurance has undergone significant changes. Traditional risk assessment models, which relied on factors such as the driver's age, gender, or vehicle characteristics to determine premium rates, have been replaced by new models that assess risk and premium rates based on data obtained from the type of vehicle, duration of usage, mileage, individual driving behavior, and location. UBI enables insurers to assess customer risk profiles of customers based on their driving behavior. UBI has gained popularity in developed and some developing countries, and it has forced insurance companies to develop these products. UBI offers social, economic, and environmental benefits, but it also presents challenges such as privacy concerns, application download hassles,strict regulations, etc.

In this research, the UBI acceptance rate was measured using a multinomial logistic regression model under five scenarios based on a questionnaire. The questionnaire included demographic information, awareness of related concepts, willingness to buy, the importance of various factors in buying, agreement, satisfaction with some features, and the customer's preference for added-value services of UBI. The depen-

Table 9: The results of model implementation based on the binary logistic regression (3rd scenario)

Variable	B	S.E.	Wald	df	Sig.	Exp(B)
Gender	-.180	.464	.151	1	.697	.835
Age	.324	.298	1.182	1	.277	1.383
Marital Status	.161	.465	.120	1	.729	1.175
City of residence	.005	.023	.051	1	.822	1.005
education	.257	.171	2.246	1	.134	1.293
Occupation	.023	.112	.042	1	.838	1.023
Monthly salary	-.091	.162	.317	1	.574	.913
Considering the reward in case of favorable and low-risk driving	-.532	.277	3.688	1	.055	.588
Policy price	.770	.336	5.240	1	.022	2.160
Considering the discount in renewing the policy in case of favorable and low-risk driving	-.168	.385	.191	1	.662	.845
Providing warnings to policyholder to improve driving	.567	.284	3.971	1	.046	1.762
Constant	-5.743	1.485	14.958	1	.000	.003

dent variable in the first three scenarios was the willingness to buy UBI based on distance and in the 4th and 5th scenarios, based on distance and driving behaviors. The demographic information was also an independent variable in all scenarios. The results revealed various factors influencing UBI purchases, including:

- Age, city of residence, and value-added services, including Automatic emergency assistance in case of a severe crash, weather information, and suggestions for driving improvement in the 1st scenario.
- Level of awareness, including the calculation of UBI premiums based on how to drive, providing rewards/discounts, and installing telematics tools to monitor driving behavior in the 2nd scenario.
- Age, marital status, and occupation, as well as considering the reward in case of favorable and low-risk driving and the policy price in the 3rd scenario.
- City of residence, as well as value-added services, including weather information and personalized insurance, offers in the 4th scenario.
- City of residence, considering the reward in case of favorable and low-risk driving and providing warnings to policyholders to improve driving in the 5th scenario.

Then, the effect of factors influencing the purchase of UBI was measured using the binary logistic regression model under three different scenarios, including the level of awareness, value-added services, and the level of importance. The results showed that in the first scenario, awareness of providing UBIs by some insurance

Table 10: The results of model fit

Results	Likelihood ratio test (Omnibus)	Goodness-of-fit test (Hosmer and Lemeshow)
1st scenario	sig=.000,Chi-square= 63.965	sig=.555,Chi-square= 6.829
2nd scenario	sig=.036 ,Chi-square= 24.896	sig=.715 ,Chi-square= 5.388
3rd scenario	sig=.043 ,Chi-square= 20.175	sig=.279,Chi-square= 9.807

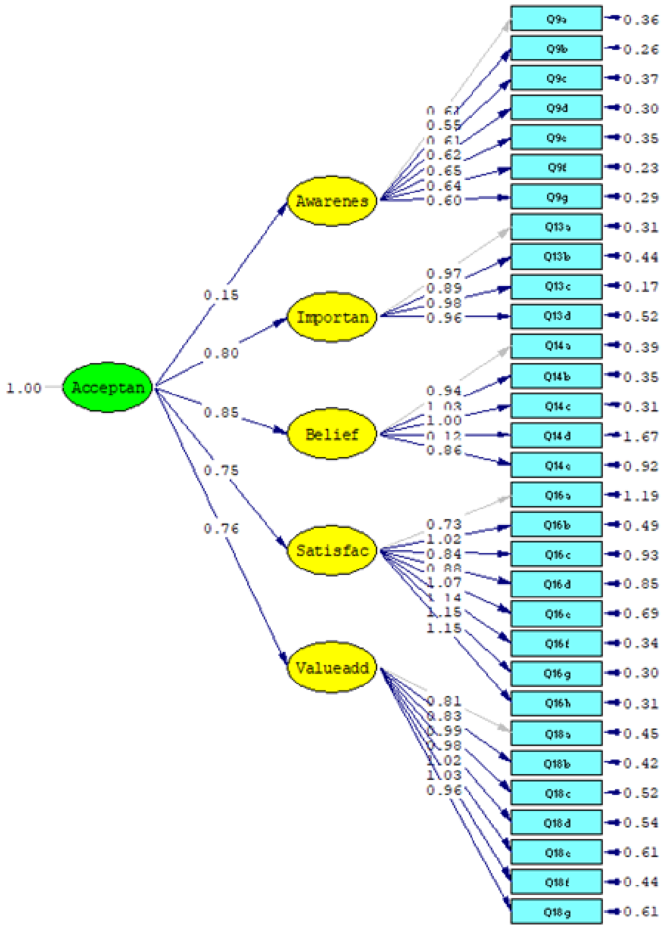

Figure 2: Implementation results of the confirmatory factor analysis model

companies in Iran and providing rewards/discounts for UBIs, in the second scenario, suggestions for driving improvement, and in the third scenario, providing warnings to policyholders to improve driving and the policy price were the influential factors to buy UBIs.
Finally, the study utilized confirmatory factor analysis to assess whether the model for the impact of awareness, importance, beliefs, satisfaction, and value-added ser-

Table 11: Fitting results of confirmatory factor analysis model

Index	Model estimation
Chi-Square	1197.52
df	429
Chi-Square/df	2.79
P-value	0
RMSEA	.097
NNFI	.94
CFI	.94
NFI	.93
IFI	.94

vices on UBI acceptance was compatible.

Based on the study's findings, insurance companies are recommended to take the following actions:

- One of the challenges of UBI is the lack of specialized staff in this field. Insurance companies should take the initiative to hire or train specialized staff who can comprehend the diverse insurance telematics service offerings and opt for products that enable genuine insurance scoring, rather than being overloaded with an excess of telematics indicators.
- Insurance companies should take maximum information security measures to protect customer's personal data, because soon, as a result of the development of digital technologies, there will be a risk of manipulation or misuse of other people's data, which is one of the most dangerous risks in any country.
- The regulatory and technical framework for the use of UBI is weak and insurance companies should strengthen it.
- There is no unified database of drivers and their driving styles that is available to all participants in the insurance market. Therefore, insurance companies should pay attention to the creation of this database.
- Developing plans to raise policyholders' financial literacy to increase interest in telematic Customers' interest in buying telematic insurance policies is low due to low financial literacy and the low margin for the cost of these insurance policies compared to non-telematic insurance policies, so insurance companies should make plans to raise the level of financial literacy of their policyholders.
- Insurance companies should consider the mindset of policyholders towards additional options and services when creating new smart insurance products.
- To expand the UBI market, insurers must adjust how they market their UBI programs and also consider who they are marketing to. Companies that explore other incentives, such as discounted deductibles or roadside assistance, may be able to

tap into untapped opportunities in the UBI market. Additionally, promoting UBI as a way to achieve other customer outcomes, such as reduced gas consumption or improved safety for young drivers, may help companies attract a wider audience.
- Creating an educational campaign can be an important step to be taken by insurers who intend to implement UBI. Such a campaign can potentially convince customers with lower product acceptance to adopt new or innovative products. Insurers should explain what benefits these products can have.

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