Journal of Applied Finance & Banking, vol. 6, no. 6, 2016, 71-89
ISSN: 1792-6580 (print version), 1792-6599 (online)
Scienpress Ltd, 2016

A Market Analysis of Telematics-Based UBI in Taiwan

Chiang Ku Fan[1], Xiangyou Wu[2], Dachuan Zheng[3] and Wen Lin[4]

Abstract

Telematics enabled UBI (usage-based insurance) is rapidly becoming a global phenomenon. The property and casualty insurance companies in Taiwan have suffered a deficit in their balance of payments with respect to auto insurance. Moreover, Taiwanese market only offers traditional, non-UBI automobile insurance products, and there have been no studies related to telematics-based UBI. To fill this research gap, this study tries to identify consumers' willingness to provide driving data to UBI insurers, to evaluate the importance of each type of driving data that contributes to telematics-based UBI underwriting and to measure the gap between consumers' willingness to provide driving data and the importance of driving data in telematics-based UBI underwriting. The research findings can be the references for the insurance companies to develop their marketing strategy of Telematics enabled UBI.

JEL classification numbers: O32
Keywords: Auto insurance, Usage Based Insurance, Telematics

1 Introduction

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[1] College of Management, Shih Chien University. Taiwan
[2] New Huadu Business School of Minjiang University.
[3] Straits Institute of Minjiang University / Internet Innovation Research Center of Humanities and Social Sciences Base of Colleges and Universities in Fujian.
[4] Straits Institute of Minjiang University.

Article Info: *Received* : July 30, 2016. *Revised* : August 20, 2016.
Published online : November 1, 2016.

In recent years, as data capture and transmission technology have become more advanced and as user interfaces have become more sophisticated, insurers have begun offering programs, such as "usage-based insurance" (UBI), that use telematics devices to monitor the driving habits of their insureds. According to the New York State Department of Financial Services, the term “telematics” is a combination of the words “telecommunications” and “informatics” and refers to the technology of sending, receiving, and storing information relating to remote objects, such as vehicles, via telecommunication devices. The term is often used to refer specifically to the use of such technology in the provision of auto insurance. When installed in an insured's vehicle, a telematics device can gather various forms of data pertaining to driving habits, such as the number of miles a vehicle has driven, the time of day during which a driver drives, and a driver's acceleration and braking patterns (New York State Department of Financial Services, 2014). Because of telematics, real driving information can be collected and provided to UBI underwriters. It therefore promises more efficient pricing of risks, with widespread benefits expected to accrue to insurers, consumers and society. Telematics-based UBI will increase rapidly in the next ten years as consumer awareness is boosted by the rapidly forming synergies and partnerships among telematics service providers, insurers and automotive original equipment manufacturers (OEMs) (Insurance Tekinsights, 2014; Visiongain, 2015).

As the population becomes more accepting of technology and as the generation that has grown up surrounded by technology in its everyday life ages, it is likely that the percentage of policyholders prepared to adopt telematics-based UBI will increase dramatically (Karapiperis et al., 2015; Sia Partners, 2015). UBI, otherwise known as telematics-supported or -based UBI, is rapidly becoming a global phenomenon. Already commonplace in the United States, Canada, and Europe (e.g., in Italy and Britain), the U.S. auto insurance industry is experiencing a fundamental change with the introduction of vehicle telematics technology. Many U.S. insurers currently offer telematics-based UBI policies, providing significant discounts to consumers who, according to recent market surveys, seem to overwhelmingly favor both the technology and the value that it can offer. According to research by Strategy Meets Action (SMA), telematics-based UBI is poised for rapid growth in the U.S., where approximately 36 percent of all auto insurance carriers are expected to use telematics-based UBI by 2020. Meanwhile, approximately 89 percent of the respondents to a May 2015 survey conducted by the Center for Insurance Policy and Research indicated that telematics-based UBI auto insurance is available in their states; respondents in eight jurisdictions noted the existence of 12 or more companies offering telematics-based UBI programs to consumers. Canada has also introduced telematics-based UBI programs. Thousands of Canadians have already made the switch to UBI. Moreover, telematics-based UBI has been available in the U.K. market since 2008. Now telematics-based UBI is experiencing rapid acceptance throughout the U.K., which represents one of the world’s most competitive auto-insurance marketplaces (Karapiperis et al., 2015; McKay, S., 2013; Clifford, M. et al., 2014). In addition to the U.S., Canada and Europe, many new markets have recently experienced a growth in the adoption of telematics-based UBI. These include the likes of Japan, South Africa, and Brazil. In many countries around the world, telematics-based UBI is going to be used as an effective method of competing against established players within the global auto insurance market. It will be a substantial recruitment tool with the potential to win profitable customers, as market forecasts indicate that by 2020, more than $60 billion of automotive premiums will be generated by the UBI sector (Visiongain, 2015).

Table 1. Automobile Insurance Premium and Claim Statistics

	Automobile insurance /property and casualty insurance	
Year	Premium income	Claim payment
2011	49.39%	59.50%
2012	49.51%	62.96%
2013	51.60%	64.10%
2014	53.09%	64.99%
2015	53.89%	64.39%

Source: Statistics for Automobile Insurance 2016, Taiwan Insurance Institute, ROC.

The auto insurance market is Taiwan's largest insurance market segment and is fiercely competitive as insurers strive to attract more profitable, low-risk drivers. All auto insurance companies are essentially competing for the same premium base, which is not significantly growing. As vehicles and roads are becoming safer, premiums are falling. In such an environment, opportunity for growth appears to be limited. The premium income of automobile insurance from 2011 to 2015 accounted for approximately 50% of total property and casualty premiums. Automobile insurance claims were usually more than 60% of total property and casualty claims (Marsh & McLennan Companies, 2014) (view Table 1). It is said that property and casualty insurance companies have suffered a deficit in their balance of payments with respect to auto insurance. Most property and casualty insurance companies pool their ideas to determine how to remedy future auto-insurance deficits. In other words, stagnant growth in a competitive market makes the attraction, retention and accurate rating of policyholders increasingly important: any tools that can help achieve these goals are immensely valuable.

The telematics-based UBI market is a rapidly growing developing market, with insurers in the U.S. and Europe competing for a larger slice of the auto insurance market.

Although the use of telematics has accelerated globally in recent years, one important barrier for insurers attempting to adopt or expand a telematics-based UBI program is the need to build predictive loss cost models that can identify behaviors indicative of unsafe vehicle operation (Harbage, 2015). In Taiwan, the market only offers traditional, non-UBI automobile insurance products, and there have been no studies related to telematics-based UBI.

Because there has been little objective scientific research focused on telematics-based UBI in Taiwan, insurers have limited information to aid them not only in identifying trends in consumer attitudes related to providing driving data collected from telematics but also in evaluating the weight of each type of driving data that contributes to telematics-based UBI underwriting. Is going has adopted the following objectives:

1. To identify consumers' willingness to provide driving data to UBI insurers;
2. To evaluate the importance of each type of driving data that contributes to telematics-based UBI underwriting; and
3. To measure the gap between consumers' willingness to provide driving data and the importance of driving data in telematics-based UBI underwriting.

2 Literature Review

The first automobile liability insurance was sold in the U.S. 116 years ago, and the same underwriting model has been used for decades: assessing risk based on broad demographic characteristics such as a driver's age, gender, or credit score (SIERRA WIRELESS, 2015; Karapiperis et al., 2015). Automobile premiums were generally determined at the point of sale in the absence of true causal data by using a variety of group-behavior-based demographic proxy factors that affect loss costs (Reifel, et al., 2010). For this reason, insurers used detailed and long-standing actuarial statistics both to identify and to quantify potential risks. However, in most practical cases, younger and older people, who have traditionally been considered riskier drivers, have fewer accidents than other age groups. Furthermore, a 2015 survey of 500 consumers conducted by the Group of Insurance Companies (the industry leader in UBI with Snapshot®) reveals that the majority of participants believe UBI is a fairer way to price insurance than traditional insurance rating variables such as age, geographic location and driving history. According to this survey, nearly 64 percent of drivers pay higher premiums to subsidize the highest mileage-driving minority. Therefore, views of traditional automobile underwriting are increasingly being questioned and real driving behaviors are gradually considered as the major underwriting factors in automobile insurance (Miller, 2009). UBI is not a new concept. The value of real driving behavior data for calculating a more precise premium that reflects true risk exposure was recognized in the 1930s, early in the history of automobile insurance (Dorweiler, 1929). This was the earliest concept of UBI, which identified driver habits, speed, weather conditions, seasonal and daily automobile use, and mileage as critical factors directly contributing to accident frequency and severity (Insurance Tekinsights, 2014; INSLY, 2015). Thus, UBI is a dynamic system in which premiums change based on changes in the evaluated criteria (Insurance Tekinsights, 2014).

Fast-forward approximately seven decades, and Dorweiler's solution has fortunately moved from the realm of science fiction to the realm of scientific fact and practical use for the everyday consumer. In the era of the Internet of Things

(IoT), UBI is now not only a concept but also something that can be easily implemented easily in reality. Moreover, the explosion of digital and social platforms directly influences the expectations of insureds, who expect the type of easy, transparent experience they encounter in other aspects of their daily lives that involve insurance. In the future, insurers will have to focus on delivering flexibility and personalization in all aspects of their proposition, from product offerings to service delivery and communication. This focus requires simplified, transparent and flexible products with dynamic pricing and payment capabilities. UBI is the recommended solution (Ernst & Young, 2015). There are essentially three types of UBI (INSLY, 2015):

1. Coverage based on the vehicle's odometer reading;
2. Coverage based on either mileage aggregated from GPS data or the number of minutes the vehicle is used, as recorded by a vehicle-independent module that transmits data either via cell phone or using radio frequency technology; and
3. Coverage based on other data collected from the vehicle, including speed and time-of-day information, the road's historic riskiness, and driving actions, in addition to distance or time traveled.

The latter two types of UBI are telematics-based UBI, in which vehicle information is automatically transmitted to the system, providing the driver with a much more immediate feedback loop to the driver by changing the cost of insurance dynamically with a change of risk. With technology advancing in leaps and bounds and related costs coming down in the 2000s, the doors have opened wide for viable and successful telematics-based UBI programs (Karapiperis et al., 2015).

The Differences between UBI and Traditional Insurance

Telematics-based UBI, which is a type of automobile insurance that puts power into drivers' hands by using telematics technology to track their driving habits and determine how much they can save on their premiums **(**Allstate, 2015**)**, differs from traditional insurance, which attempts to differentiate and reward "safe" drivers, giving them lower premiums and/or a no-claims bonus. However, conventional differentiation is a reflection of history, not current behavioral patterns (INSLY, 2015). By summarizing a driver's strengths, weaknesses, opportunities and threats (SWOT), the differences between telematics-based UBI and traditional insurance can be easily understood (see Table 2).

Table 2

Strengths		Weaknesses	
Traditional	Telematics UBI	Traditional	Telematics UBI
√Well understood by underwriters , agents and brokers √Well understood and accepted by customers √Vast amount of statistics available to correlate risk factors and claim statistics √Already built and well integrated into existing insurance system √Low cost as does not require a device/an installation √Impact on privacy is limited to initial declaration by customer	√ Individual pricing, based on actual driving behavior √Indirect positive effects on the environment √Indirect positive effects on fuel consumption √Ability to recover the vehicle in case of theft √Ability to provide eCall services and thus reduce the number of fatalities √Ability to strongly reduce fraud Ability to provide actual driving data to actuarial models √Strong incentive to improve driving skills and style √Ability to adjust pricing on a dynamic basis √Ability to retain good customer and weed out high risk ones	√ Based on statistical data, not individual behavioral data √Not dynamic-based on risk factors at the time of first set up √Significant delay between actual claims data and pricing decisions √Incentive to improve driving is indirect and delayed √Facilitates fraud as it is largely based on customers' own declarations √In case of an incorrect declaration, the risk exists of having an accident without indemnification √Limited opportunities to develop direct link with the customer √No ability to recover vehicle in case of theft	√ Unclear effect of telematics on the motor insurance market as whole √Cost of purchasing and installing the device when a black box is used √Difficult business model, notably in low motor premium markets √Complex business case for low premium drivers √Perception of possible infringements on privacy √Necessity for all departments in the organization to take interest and work together √Requires experience of actuaries and the recruitment of data scientists
Opportunities		**Threats**	
Traditional	**Telematics UBI**	**Traditional**	**Telematics UBI**
√ More and more statistical data sets are available, making the rating more accurate every day	√ Decreasing cost and new types of telematics devices √Better customer acceptance of the use of private data √Ability to discriminate based on real risks instead of age-based pricing that may become unlawful √eCall and other driver services available from a dashboard-mounted solution √Ability to sell more value added services √Use of more accurate CAN bus-related data √eCall becoming compulsory for new car models in the EU from March 2018 √Growing market of connected vehicles √Smartphones as sensors	√ Rising costs of insurance for young & senior drivers makes it unaffordable to drive in certain countries, pushing these segments towards telematics √Best customer segments generally pay more than they should, which could push them towards telematics-based solutions √Acceptance of traditional risk factors is decreasing as they are increasingly seen as sheer discrimination √Gender ruling and other similar anti-discrimination rulings or European directives could prevent the use of the most useful risk factors √In Europe and Russia will push automotive OEMs to sell insurance themselves and even become insurers	√ Risk of backlash against "customer tracking" √Laws preventing insurers to charge for the rental of the device √OEMs ability to act as an insurer or broker using their own data √Google becoming able to score based on smartphone data already collected in the background

Source: PTOLEMUS- Global UBI Study, 2016. www.ptolemus.com

Telematics-based UBI Modeling and Analytics

UBI has been in development since the 1990s. Initially, driving-behavior data were collected from telematics devices professionally installed in automobiles either by a technician (for aftermarket devices) or in the factory. After a certain period of monitoring the vehicle's operation, the insured is provided with a justified price that considers his or her driving behaviors as a part of the rating algorithm. In other words, UBI represents a fundamental change in how automobile insurance is underwritten: it moves away from proxy-based ratings models and historical patterns to real-time driver behavior analysis (INSLY, 2015; NAIC, 2015).

The most important issues that confront insurers attempting to adopt or expand telematics-based UBI programs relate to the ability to build a predictive loss cost model that identifies behaviors indicative of unsafe vehicle operation. Currently, there are two primary types of loss cost models for telematics-based UBI. One type relies on total mileage, time of day and a set of predefined events. Event-counter scores are limited in their capability because they are based on the assumption that a few harsh braking, acceleration or cornering events constitute the universe of variables that can predict loss costs based on patterns of vehicle operation. A second approach is based on collecting much more granular data about vehicle use on a second-by-second basis (or even slightly more granular, as needed for accelerometers) and then using the more granular detail to research the predictive power of a host of vehicle operation characteristics in a highly contextualized manner(INSLY, 2015).

The formula can be a simple function of the number of miles driven or can vary according to the type of driving and the driver's identity. Once the basic scheme is in place, it is possible to add further details, such as an extra risk premium if someone drives too long without a break, uses their mobile phone while driving, or travels at an excessive speed (INSLY, 2015).

A Fundamental Change

Driving-behavior data gathered through telematics programs introduces more detailed information than conventional methodologies of assessing policyholder and portfolio risk, and it has the potential to dramatically change the insurance business. Insurers are often slow to modify legacy ways of doing business, as was the case with credit-based insurance scoring, which was the last significant disruption in underwriting.

Increasingly, observers of the auto insurance market are noting that telematics will not be a passing fad. Instead, it will fundamentally and materially change how auto insurance is underwritten. As insurers gather more data and begin to act on insights from it, they will be able to move from a method of using corollary data to slot drivers into various risk tiers to eventually being able to price insurance based on actual driving-behavior data. Early adopters capable of innovating stand to gain more than late entrants that risk losing customers as the use of telematics data becomes an increasingly common means for insurers to evaluate policyholder risk.

Rating Factors Collected From Telematics

The first UBI program began to surface in the U.S. approximately ten years ago, when Progressive Insurance Company and General Motors Assurance Company (GMSC) began to offer mileage-linked discounts enabled by GPS technology. Recent accelerations in technology have improved the effectiveness of telematics, enabling insurers to capture not only how many miles people drive but also how and when they drive (NAIC, 2015).

Telematics has shown the potential to turn the traditional model on its head. By installing or embedding telematics into cars to transmit real-time driving data such as driving habits and driving environments, insurers can measure and price premiums more accurately (Reifel, *et al*, 2010).

In general, telematics devices measure numerous factors that are of interest to underwriters (NAIC, 2015): miles driven; time of day; where the vehicle is driven; rapid acceleration; hard braking; hard cornering; and air bag deployment. However, according to the websites reviewed, America's four largest auto insurers—State Farm, Progressive, Geico and Farmers—use mileage as the second-most-important factor (after driving record) in setting premiums (Cohen, 2015). This prompted the Consumer Federation of America to assert that insurance companies were discriminating against the poor and senior citizens by not using mileage as the most important factor (Cohen, 2015).

Similar to the study results of NAUC, Cohen (2015) claims that some insurance companies use in-vehicle technology to track drivers and provide discounts only based on actual behavior, including mileage, when people drive, speeding and hard braking. A study by Boston-based insurance consultant Strategy Meets Action (SMA) is in agreement, claiming that telematics devices can measure miles driven; time of day; where the vehicle is driven (GPS); rapid acceleration; hard braking; hard cornering; air bag deployment and other behaviors of interest to underwriters. In other words, premiums set by UBI more closely reflect actual driving behavior than premiums set by traditional pricing methods. Moreover, Deloitte Consulting and AgnikAnalytics provide insurers with UBI scoring models. This scoring model captures risk events—i.e., acceleration, braking, cornering, and fast lane changes—and enrich them with contextual data—the weather, traffic information at any given moment, and so on, to see whether conditions matched those reported by the driver or instead whether driver behavior increased or decreased the risk of external conditions (Voelker, 2014).

This study refers to the experience of markets that have implemented telematics-based UBI and frames the driving data collected from telematics devices in the following structure (Figure 1).

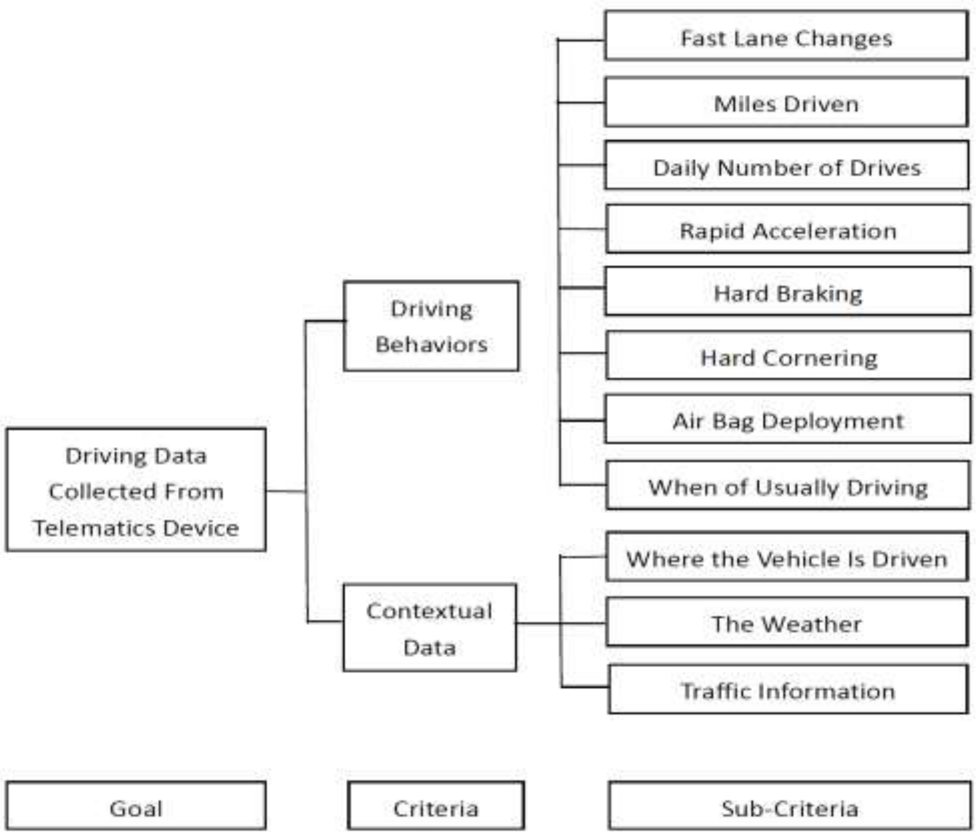

Figure 1. The Hierarchy Structure

3 Methodology

This study's purposes are to identify consumers' willingness to provide driving data to UBI insurers, to evaluate the importance of each type of driving data that contributes to telematics-based UBI underwriting and to measure the gap between the willingness to provide driving data and the importance of each type of driving data. To satisfy the purposes of this research, this study first reviews prior studies to identify the driving data considered in telematics-based UBI and then employs the analytic hierarchy process (AHP) to identify both the consumer's willingness to provide each type of driving data considered in prior related telematics UBI studies and the importance level of each type of driving data that underwriters collected from telematics devices. To compare the weight of each type of driving data, this study identifies the gap between willingness level and importance level (Figure 2).

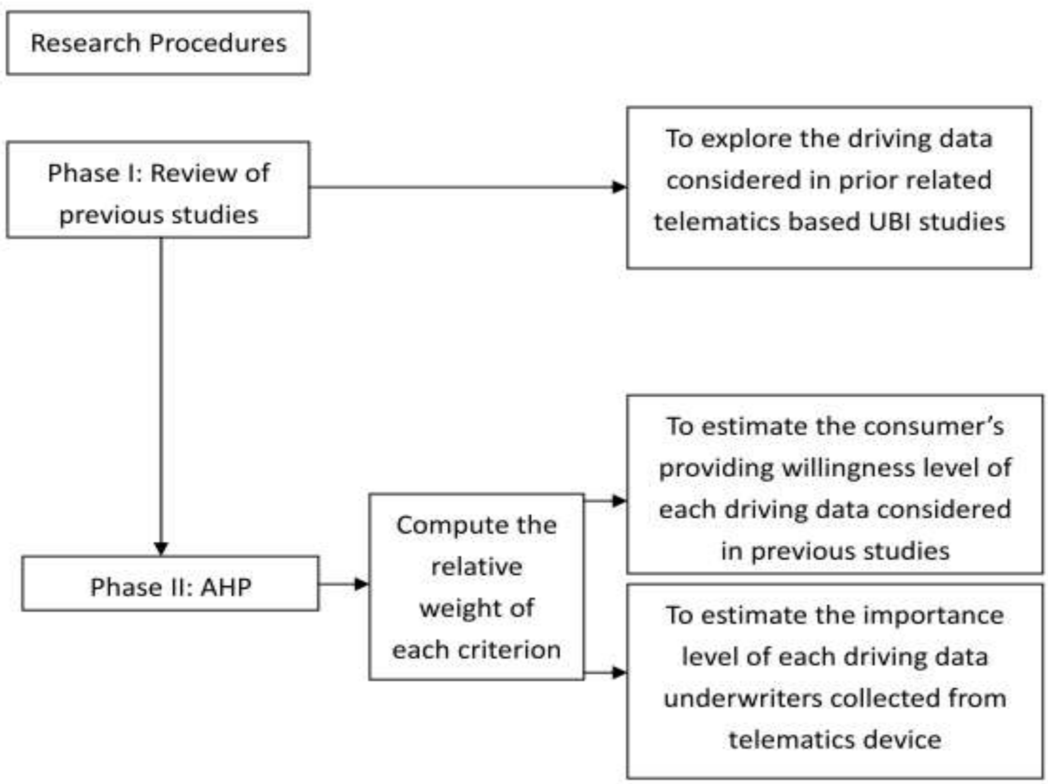

Figure 2. Research Procedure

As a decision-making method that decomposes a complex multicriteria decision problem into a hierarchy (Saaty, 1980), AHP is a measurement theory that prioritizes the hierarchy and consistency of judgmental data provided by a group of decision makers. Using pairwise comparisons of alternatives, AHP incorporates the evaluations of all decision makers into a final decision without having to elicit their utility functions on subjective and objective criteria (Saaty, 1990). The steps of AHP are set forth below.

Step 1. Establish a hierarchical structure.

Given the human inability to compare more than seven categories at a time, complex issues can be addressed effectively by using a hierarchical structure. A hierarchy should not contain more than seven elements. Under this limited condition, a rational comparison can be made and consistency can be ensured (Saaty, 1980). The first hierarchy of a structure is the goal. The final hierarchy involves selecting projects or identifying alternatives, and the middle hierarchy levels appraise certain factors or conditions. In this study, there are no selecting projects and identifying alternatives.

The hierarchy structure of this study is shown in Figure 1.

The structure shows the driving data that can be collected from telematics devices.

Step 2. Establish a pairwise comparison matrix.

Based on an element of the upper hierarchy, the evaluation standard, a pairwise comparison is conducted for each element. Although n elements are assumed, n(n-1)/2 elements of the pairwise comparison must be derived. Let $C_1, C_2, \ldots, C_n$ denote the set of elements, where a_{ij} represents a quantified judgment of a pair of elements C_i, C_j. The relative importance of two elements is rated using a scale with the values 1, 3, 5, 7, and 9, where 1 denotes "equally important", 3 denotes "slightly more important", 5 denotes "strongly more important", 7 represents "demonstrably more important", and 9 denotes "absolutely more important". This yields an *n-by-n* matrix *A* as follows:

$$A = \left[a_{ij} \right] = \begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_n \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & & C_n \end{array} \\ \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix} \end{array} \quad (1)$$

The results of the comparison of the n elements are inserted into the upper triangle of the pairwise comparison matrix *A*. The lower triangle values are relative positions for the reciprocal values of the upper triangle. Where a_{ij} = 1 and a_{ij}= $1/a_{ij}$, i, j = 1, 2, …, n, two elements (C_i, C_j) become one quantization value for an important relative judgment. In matrix *A*, aij can be expressed as a set of numerical weights, $W_1, W_2, \ldots, W_n$, in which the recorded judgments must be assigned to the n elements $C_1, C_2, \ldots, C_n$. If *A* is a consistency matrix, relations between weights W_i and judgments a_{ij} are simply given by W_i, and judgments a_{ij} are simply given by $W_i/W_j = a_{ij}$ (for i, j= 1, 2, …, n) and matrix A as follows:

$$A = \begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_n \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & & C_n \end{array} \\ \begin{bmatrix} w_1/w_1 & w_1/w_2 & \cdots & w_1/w_n \\ w_2/w_1 & 1 & \cdots & w_2/w_n \\ \vdots & \vdots & \ddots & \vdots \\ w_n/w_1 & w_n/w_2 & \cdots & 1 \end{bmatrix} \end{array} \tag{2}$$

Step 3. Compute the eigenvalue and eigenvector.
Matrix A multiplies the elements' weight vector (x) equal to nx, i.e., (A- nI)x = 0, where x is the eigenvalue (n) of the eigenvector. Given that aij denotes the subjective judgment of decision makers, the actual value (W_i/W_j) has a certain degree of difference. Therefore, $Ax = n.x$ cannot be established. Saaty (1990) suggests that the largest eigenvalueλ_{max} would be

.

$$\lambda_{\max} = \sum_{j=1}^{n} a_{ij} \frac{W_j}{Wi} \tag{3}$$

If A is a consistency matrix, eigenvector X can be calculated by

$$(A - \lambda_{\max} I)X = 0 \ . \tag{4}$$

Step 4. Perform the consistency test.
Saaty (1990) proposes utilizing a consistency Index (CI) and consistency ratio (CR) to verify the consistency of the comparison matrix. CI and RI are defined as follows:

$$CI = (\lambda_{\max} - n)/(n-1) = 0 \tag{5}$$

$$CR = CI / RI \tag{6}$$

where RI represents the average *CI* over numerous random entries of same-order reciprocal matrices. If $CR \leqq 0.1$, the estimate is accepted; otherwise, a comparison matrix is solicited until $CR \leqq 0.1$.

Step 5. Compute the entire hierarchical weight

After various hierarchies and element weights are estimated, the entire hierarchy weight is computed, ultimately enabling decision makers to select the most appropriate strategy.

4 Estimation Model and Results

The research procedures in this study consist of two phases. In the first phase, the driving data considered in prior related telematics-based UBI studies is identified through a literature review. The second phase, in which both the weights of the consumer’s level of willingness to provide each type of driving data and the underwriting importance level of each type of driving data collected from telematics devices are evaluated by employing the AHP theory. The second phase is described in detail as follows.

Step 1: Designate the AHP Participants.

There are 352 insurance brokerages and 21 non-life insurance companies. Twenty brokers were selected to represent the group of drivers under the condition of at least 10 years of professional experience in selling auto insurance. Moreover, twenty auto-insurance underwriting managers were chosen to comprise the group of experts under the condition that each expert: (a) has at least 10 years of professional experience in the auto insurance sector, and (b) has participated in decision-making process of underwriting in non-life insurance companies. However, only 11 qualified brokers and 10 underwriting managers agreed to share their opinion and answered the AHP questionnaires.

Step 2: Establish a Hierarchy Structure.

The driving data from prior related telematics-based UBI studies are considered in the 1st phase, which is composed of several levels including the goal hierarchy, criteria hierarchy, and sub-criteria hierarchy (see Figure 2).

Step 3: Establish a Pairwise Comparison Matrix.

To provide an example of this step, the primary criteria for consumers’ level of willingness to provide each type of driving data are shown in Table 3. Formulas (1) and (2) are used to calculated the aggregate pairwise comparison matrix.

Table 3. Aggregation of the Pairwise Comparison Matrix for Criteria of Main Criteria

Criteria	Driving Behaviors	Contextual Data
Driving Behaviors	1	4.6
Contextual Data	1/4.6	1

CI = 0.00; CR = 0.00 < 0.1

Step 4: Compute the Eigenvalue and Eigenvector

The pairwise comparison matrix of the criteria and sub-criteria is used to obtain each hierarchy factor weight, in which the eigenvector is calculated by Formulas (3) and (4). Tables 4 and 5, Figures 3 and 4 summarize the results.

Table 4. Weights of the Criteria Aggregation of the Pairwise Comparison Matrix for Criteria of Main Criteria

Criteria	Weight of Criteria	
	Consumers' Level of Willingness to Provide Driving Data	Underwriting Importance Level of Driving Data
Driving Behaviors	0.821	0.833
Contextual Data	0.179	0.167

Table 5. Weights of the Sub-Criteria

Driving Data	Consumers' Level of Willingness to Provide Driving Data		Underwriting Importance Level of Driving Data	
	Weights	Rank	Weights	Rank
Fast Lane Changes	0.083	6	0.084	6
Miles Driven	0.054	8	0.055	8
Daily Number of Drives	0.170	2	0.172	2
Rapid Acceleration	0.184	1	0.187	1
Hard Braking	0.100	4	0.102	4
Hard Cornering	0.079	7	0.080	7
Air Bag Deployment	0.041	10	0.042	9
Usual Time of Driving	0.109	3	0.111	3
Where the Vehicle Is Driven	0.037	11	0.040	10
Weather	0.098	5	0.092	5
Traffic Information	0.043	9	0.035	11

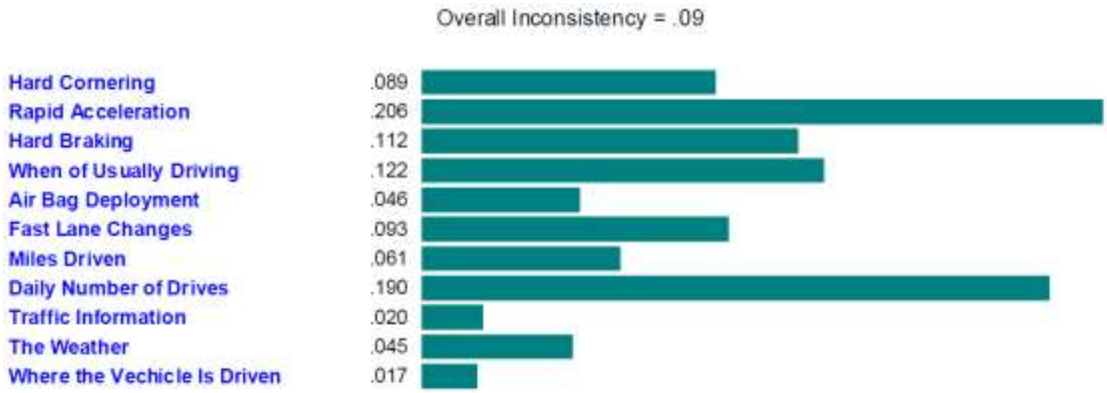

Figure 3. Consumers' Level of Willingness to Provide Driving Data

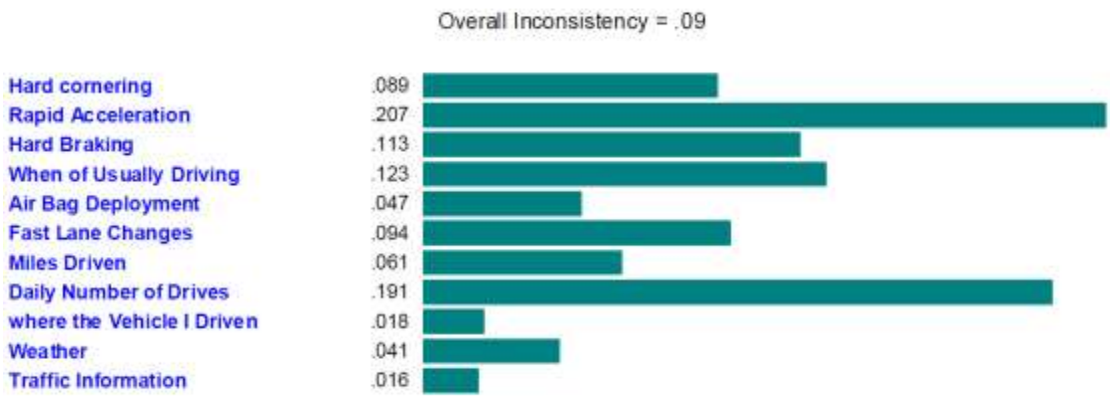

Figure 4. Underwriting Importance Level of Driving Data

Step 5: Perform the consistency Test

Based on Formulas (5) and (6), the pairwise comparison matrix of consistency is determined for each hierarchy, as shown in Table 3. If the results of the respondents in terms of the consistency ratio and consensus of CR are smaller than 0.1, they conform to principles of consistency.

Step 6: Compute the Relative Weight of Each Hierarchy

Tables 4 and 5 summarize the results for the relative weight of the elements at each level. According to Table 4, consumers select an appropriate type of driving data collected from telematics devices based on the following rank: driving behaviors (0.821) and contextual data (0.179). In addition, underwriting managers choose driving data based on the rank of driving Behaviors (0.833) and contextual data (0.167).

Table 5 shows that three types of driving data that consumers are the most willing to provide are Rapid Acceleration (0.184), Daily Number of Drives (0.170), and Usual Time of Driving (0.109). In contrast, where the Vehicle is Driven (0.037) is

the type of driving that that consumers are the least willing to provide.
The three most important types of driving data in terms of underwriting value level are Rapid Acceleration (0.187), Daily Number of Drives (0.172), and Usual Times of Driving (0.111). Traffic Information (0.035) is the type of driving data with the least underwriting importance.
Table 5 gives the relevant data and the two rankings. The statistical question is whether there is agreement between the ranking of consumers' level of willingness to provide driving data and the ranking based on the underwriting importance level of driving data. This study computes the Spearman rank-correlation coefficient for the data in Table 5. The computations are summarized in Table 7.

Table 7. Nonparametric Correlations

			Consumers' Level of Willingness to Provide Driving Data	Underwriting Importance of Driving Data
Spearman's rho	Consumers' Level of Willingness to Provide Driving Data	Correlation Coefficient Sig. (2-tailed) N	1.000 11	0.973(**) 0.000 11
	Underwriting Importance of Driving Data	Correlation Coefficient Sig. (2-tailed) N	0.973(**) 0.000 11	1.000 11

** Significant at the 0.01 level (2-tailed)

Table 7 shows that p-value = 0.000. With a 0.05 level of significance, p-value ≦ 0.05 leads to rejection of the hypothesis that the rank correlation is zero. Thus, one can conclude that there is a significant rank correlation between “Consumers’ Level of Willingness to Provide Driving Data” and “Underwriting Importance of Driving Data” (also see Figure 5).

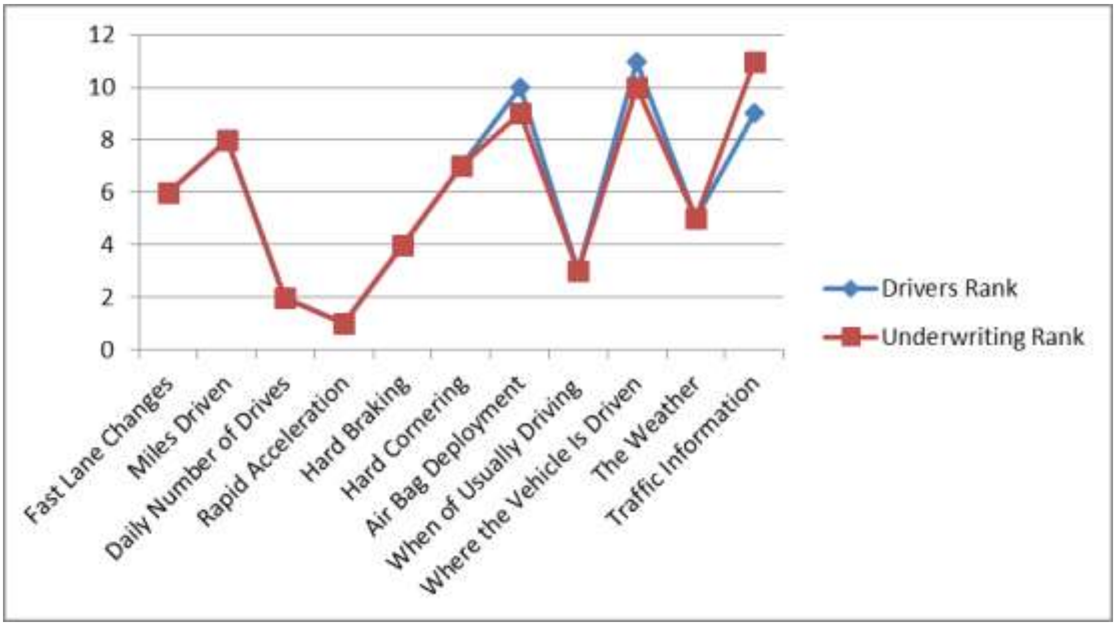

Figure 5. Rank Correlation between “Consumers’ Level of Willingness to Provide Driving Data” and “Underwriting Importance of Driving Data”

5 Conclusion

Based on the research results, this study arrives at the following conclusions and makes the following suggestions:

1. The ranking of drivers’ level of willingness to provide driving behavior data is almost same as the ranking of the underwriting importance of driving data. This means there is no obstacle to collecting driving behavior data if auto insurers conduct telematics-based UBI. For example, drivers have a higher level of willingness to provide data on driving behavior such as Rapid Acceleration, Daily Number of Drives, and Usual Time of Driving. Coincidentally, the underwriters in the auto insurance sector prefer to consider these three types of driving behavior data to make underwriting decisions.

2. Due to the privacy concerns, Where the Vehicle Is Driven is the driving behavior data that drivers are most unwilling to provide to auto insurers. In other words, the drivers are somewhat conflicted: Will their insurance companies share personal driving behavior information in return for a fair insurance product, service or other benefit? Thus, to increase the reach of the telematics-based UBI business, a method for collecting data on Where the Vehicle Is Driven while avoiding privacy concerns is a serious issue for auto insurers to overcome.

3. To attract new business, UBI programs may be oriented either toward policyholders who match certain risk characteristics or demographics or toward agents who serve those driver segments. For example, some segments of drivers could be both price sensitive and very low risk. Such drivers might be attracted to the prospect of a UBI program that offers material discounts based on their driving habits. Policyholders who believe they are better drivers than their behavior would indicate might also choose to enter a UBI program. Some policyholders might be less motivated by price than by the prospect of receiving driving safety tips for themselves and/or for their families; this is a feature made possible through the analytics of a telematics program.

When targeting existing policyholders, an insurer's goals might be to retain the best risks to price more accurately, to reduce the losses incurred through safer driving behavior, to engage more with policyholders, or to develop products and services that are tailored to policyholder driving patterns. Any discount that is offered might initially cut into profits; however, this can be offset by the lifetime economics of the policyholder relationship if the telematics program generates fewer losses and lower retention costs.

4. There are several ways to engage customers through telematics:

a. Provide a way for parents to know when their teenager driver has crossed a geographical boundary;

b. Provide contests among users to motivate drivers to improve their driving habits; and

c. Create partnerships or loyalty programs with local businesses that will advertise flash discounts to drivers in their vicinity.

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