Advances in Management & Applied Economics, vol. 7, no. 1, 2017, 17-30
ISSN: 1792-7544 (print version), 1792-7552(online)
Scienpress Ltd, 2017

A Comparison of Underwriting Decision Making Between Telematics-Enabled UBI and Traditional Auto Insurance

Chiang Ku Fan[1] and Wei-Yuan Wang[2]

Abstract

Because of telematics-enabled UBI (usage-based insurance), real driving information can be collected and provided to underwriters. It promises more efficient pricing of risks, with widespread benefits expected to accrue to insurers, consumers and society. From the perspective of auto insurance underwriters, compare to the driving data collected by a traditional auto insurance application form , the underwriting data collected from a telematics devices more effective or not is a question and to answer. By employing prior literature reviewing and grey relational analysis, this study found most of driving behavior data collected from telematics devices is very helpful for auto insurance underwriting, some traditional data collected by an application form is still necessary for underwriters to make a well underwriting decision. The implication is, in order to improve the effective of an underwriting decision making, insurance companies need to take advantage of IoT(Internet of Things) tech to collect more helpful underwriting data as well as adjust their underwriting policy accordingly.

JEL classification numbers: O32
Keywords: usage-based insurance, auto insurance, telematics, Underwriting

1 Introduction

Because of telematics-enabled UBI (usage-based insurance), real driving

[1] Dept. of Risk Management and Insurance, Shih Chien University,Taiwan.
[2] Dept. of Business Administration, Shih Chien University, Taiwan.

Article Info: *Received*: October 14, 2016. *Revised:* November 7, 2016.
Published online: January 5, 2017

information can be collected and provided to underwriters. It therefore promises more efficient pricing of risks, with widespread benefits expected to accrue to insurers, consumers and society. 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-enabled UBI will increase dramatically (Karapiperis et al., 2015).Telematics-enabled UBI, otherwise known as telematics-supported or -based UBI, is rapidly becoming a global phenomenon.

The auto insurance market is Taiwan's largest insurance market segment. 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). It is said that property and casualty insurance companies have suffered a deficit in their balance of payments with respect to auto insurance. Thus, the auto insurance market in Taiwan is fiercely competitive as insurers strive to attract more profitable, low-risk drivers. 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.

Although the use of telematics has accelerated globally in recent years, one important barrier for insurers attempting to adopt or expand a telematics-enabled UBI program is the need to build predictive loss cost models that can identify behaviors indicative of unsafe vehicle operation (Harbage, 2015).

From the perspective of auto insurance underwriters, compare to the driving data collected by a traditional auto insurance application form , the data collected from a telematics devices more effective or not is a question and to answer.

Because there has been little objective scientific research focused on telematics-enabled UBI in Taiwan, insurers have limited information to judge if the driving behaviors data collected from telematics devices can totally replace the data collected by a traditional auto insurance application form or not. Therefore, the purposes of this study are to explore:

1. Can the Telematics-enabled UBI totally replace the traditional auto insurance?
2. Is the importance level of the underwriting data collected from Telematics-enabled UBI higher than that collected by a traditional auto insurance application form?

2 Literature Review

2.1 Factors That Affect Auto Insurance Rates

The first automobile liability insurance was sold in the U.S. 116 years ago, and the same underwriting model has been used for decades. Rejda (2011) claimed that the major rating factors for determining private passenger auto premiums are territory, age, gender, marital status, use of the auto, driver education, number and types of cars, individual driving record, and insurance score. In practice, there are a number of key factors most insurance companies use to calculate how much drivers will end up paying for their auto insurance. The key factors include what drivers drive, coverage and deductibles, territory, driving record, insurance score, age, gender, and marital status (State Farm, 2012).

Generally speaking, the traditional auto insurance 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.

2.2 A Fundamental Change

UBI has been in development since the1990s. 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).

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.

2.3 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 Agnik Analytics 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).

2.4 The Differences between UBI and Traditional Insurance

Telematics-enabled 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 1).

Table 1: SWOT Analysis of Traditional and Telematics-enabled UBI

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

This study refers to the practice of the traditional auto insurance market and experience of markets that have implemented telematics-enabled UBI and conclude different kinds of data collected by Telematics-enabled UBI or traditional auto insurance (view table 2).

Table 2: Data Collected from Telematics Device and Insurance Application Form

	Data Collected from	Collected Data for Underwriting
1	Telematics Device	Fast Lane Change
2		Miles Driven
3		Daily Number of Drives
4		Rapid Acceleration
5		Hard Braking
6		Hard Cornering
7		Air Bag Deployment
8		When of Usually Driving
9		Where the Vehicle Is Driven
10		The Weather
11		Traffic Information
12	Insurance Application Form	Territory
13		Age
14		Gender
15		Marital Status
16		Use of the Auto
17		Driver Education
18		Number and Types of Cars
19		Individual driving Record
20		Insurance Score

3 Methodology

This study's purposes are to explore (1) if the data collected from Telematics-enabled UBI can totally replace the data collected by traditional auto insurance; (2) is the importance level of the underwriting data collected form Telematics-enabled UBI higher than that collected by a traditional auto insurance application form. To satisfy the purposes of this research, this study first reviews prior studies to identify the underwriting data considered by telematics-based UBI or traditional auto insurance. Then, this study employs the grey relational analysis (GRA) to identify the weight of each considered underwriting data (figure 1). To compare the weight of each underwriting data, this study identifies if the importance level of the underwriting data collected form Telematics-enabled UBI higher than that collected by a traditional auto insurance application form.

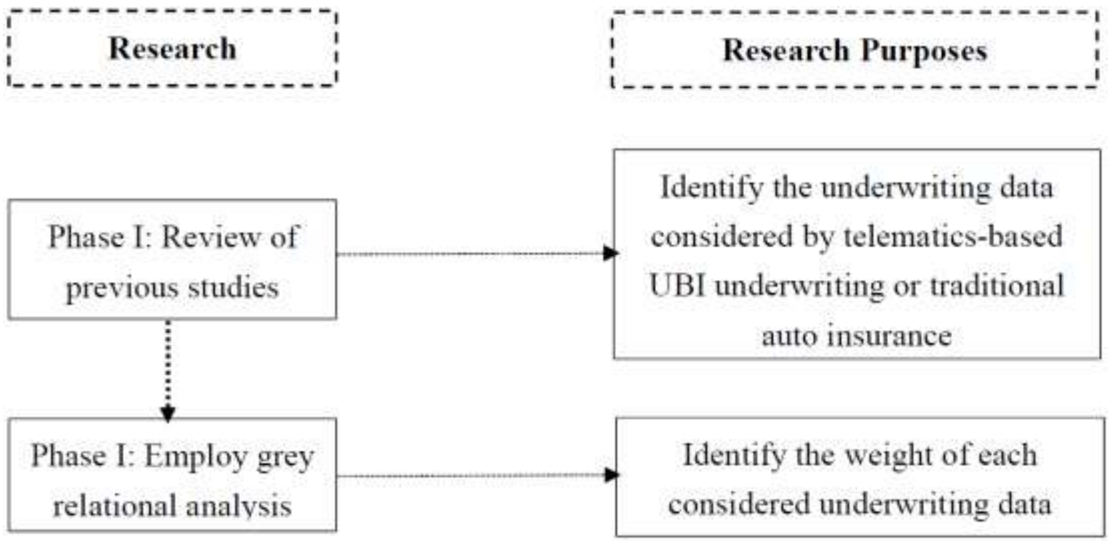

Figure 1. Research Procedure

The grey system method, as developed by Deng (1989), has been extensively applied in various fields, including decision science. The GRA is calculated as follows:

Let X_0 be the referential series with k entities (or criteria) of X_1, X_2, …, X_i, …, X_N (or N measurement criteria). Then

$$X_0 = \{x_0(1),\ x_0(2),\ ...,\ x_0(j),\ ...,\ x_0(k)\},$$
$$X_1 = \{x_1(1),\ x_1(2),\ ...,\ x_1(j),\ ...,\ x_1(k)\},$$
$$\vdots$$
$$X_i = \{x_i(1),\ x_i(2),\ ...,\ x_i(j),\ ...,\ x_i(k)\},$$
$$\vdots$$
$$X_N = \{x_N(1),\ x_N(2),\ ...,\ x_N(j),\ ...,\ x_N(k)\}.$$

The grey relational coefficient between the compared series X_i and the referential series of X_0 at the *j*-th entity is defined as

$$\gamma_{0i}(j) = \frac{\Delta\min + \Delta\max}{\Delta_{0j}(j) + \Delta\max}, \tag{1}$$

where $\Delta_{0j}(j)$ denotes the absolute value of difference between X_0 and X_i at the *j*-th entity, that is

$\Delta_{0j}(j) = |x_0(j) - x_i(j)|$, and $\Delta\max = \max_i \max_j \Delta_{0j}(j)$,

$\Delta\min = \min_i \min_j \Delta_{0j}(j)$.

The grey relational grade (GRG) for a series of X_i can be expressed as

$$\Gamma_{0i} = \sum_{j=1}^{K} w_j \gamma_{0i}(j), \tag{2}$$

Where w_j represents the weight of *j*-th entity. If the weight does not need to be applied, take $\omega_j = \frac{1}{K}$ for averaging.

Before calculating the grey relation coefficients, the data series can be treated based on the following three kinds of situation and the linearity of data normalization to avoid distorting the normalized data. They are:

3.1 Upper-bound effectiveness measuring (i.e., larger-the-better)

$$x_i^*(j) = \frac{x_i(j) - \min_j x_i(j)}{\max_j x_i(j) - \min_j x_i(j)}, \tag{3}$$

where $\max_j x_i(j)$ is the maximum value of entity *j* and $\min_j x_j(j)$ is the minimum value of entity *j*.

3.2 Lower-bound effectiveness measuring (i.e., smaller-the-better)

$$x_i^*(j) = \frac{\max_j x_i(j) - x_i(j)}{\max_j x_i(j) - \min_j x_i(j)}, \tag{4}$$

If $\min_j x_i(j) \le x_{ob}(j) \le \max_j x_i(j)$, then $x_i^*(j) = \dfrac{|x_i(j) - x_{ob}(j)|}{\max_j x_i(j) - \min_j x_i(j)}$, (5)

If $\max_j x_i(j) \le x_{ob}(j)$, then $x_i^*(j) = \dfrac{x_i(j) - \min_j x_i(j)}{x_{ob}(j) - \min_j x_i(j)}$, or (6)

If $x_{ob}(j) \le \min_j x_i(j)$, then $x_i^*(j) = \dfrac{\max_j x_i(j) - x_i(j)}{\max_j x_i(j) - x_{ob}(j)}$. (7)

where $x_{ob}(j)$ is the objective value of entity *j*.

4 Estimation Model and Results

The estimation model in this study consists of two phases. In the first phase, the underwriting data considered by telematics-based UBI underwriting or traditional auto insurance are identified using the literature reviewing. The second phase, the weight of each considered underwriting data is evaluated by employing the GRA method. The second phase is described in detail as follows.

There are 22 non-life insurance companies in Taiwan in 2016. Twenty auto insurance underwriting managers of non-life insurance companies are selected to comprise the group of experts under the condition that each experts has: (a) at least 10 years of professional experience in the non-life insurance sector, and (b) participated in the decision-making process of underwriting in non-life insurance companies. However, only 11 qualified auto insurance underwriting managers agreed to share their opinion and answered the questionnaire, and 10 questionnaires were completed in the survey (Table 3).

Table 3: Descriptive Statistics of Expert Attitude toward underwriting data

Underwriting Factors	SA	A	UD	D	SD	N	Mean	Std. Deviation
Fast Lane Change	5	5	0	0	0	10	4.5	0.52705
Miles Driven	3	7	0	0	0	10	4.3	0.48305
Daily Number of Drives	8	2	0	0	0	10	4.8	0.42164
Rapid Acceleration	9	1	0	0	0	10	4.9	0.31623
Hard Braking	6	4	0	0	0	10	4.6	0.51640
Hard Cornering	4	6	0	0	0	10	4.4	0.51640
Air Bag Deployment	0	0	3	7	0	10	2.3	0.48305
When of Usually Driving	7	3	0	0	0	10	4.7	0.48305
Where the Vehicle Is Driven	0	0	9	1	0	10	2.9	0.31623
The Weather	3	5	2	0	0	10	4.1	0.73786
Traffic Information	0	0	8	2	0	10	2.8	0.42164
Territory	0	6	4	0	0	10	3.6	0.51640
Age	0	0	6	4	0	10	2.6	0.51640
Gender	0	4	6	0	0	10	3.4	0.51640
Marital Status	0	1	9	0	0	10	3.1	0.31623
Use of the Auto	2	5	3	0	0	10	3.9	0.73786
Driver Education	0	0	0	7	3	10	1.7	0.48305
Number and Types of Cars	0	0	2	7	1	10	2.1	0.56765
Individual driving Record	0	0	5	5	0	10	2.5	0.52705
Insurance Score	0	0	1	4	5	10	1.6	0.69921

Note: strongly agree (SA) = 5, agree (A) = 4, undecided (UD) = 3, disagree (D) = 2, and strongly disagree (SD) = 1.

The numerical illustration follows the procedure previously discussed.

1. Sample 10 attitude tendency toward underwriting data are graded based upon 10 experts' opinions (see Table 4).

Table 4: 10 Attitude Tendency toward underwriting data

	EP T1	EP T2	EP T3	EP T4	EP T5	EP T6	EP T7	EP T8	EP T9	EP T10
Fast Lane Change	5	4	4	4	4	5	5	4	5	5
Miles Driven	4	4	4	4	4	4	5	4	5	5
Daily Number of Drives	5	4	5	5	5	5	5	4	5	5
Rapid Acceleration	5	5	5	5	5	5	5	5	5	4
Hard Braking	5	5	5	4	4	5	5	5	4	4
Hard Cornering	4	4	4	4	5	4	5	5	5	4
Air Bag Deployment	2	2	2	2	3	3	3	2	2	2
When of Usually Driving	5	5	5	4	4	5	5	4	5	5
Where the Vehicle Is Driven	3	3	3	3	3	3	2	3	3	3
The Weather	4	4	4	3	4	4	5	3	5	5
Traffic Information	3	3	3	3	3	3	3	2	3	3
Territory	3	4	4	4	3	4	3	3	4	4
Age	2	3	2	3	3	3	3	2	2	3
Gender	4	3	3	3	3	4	3	3	4	4
Marital Status	3	3	3	3	3	3	3	3	4	3
Use of the Auto	3	4	4	3	4	4	4	3	5	5

Driver Education	2	1	1	2	2	1	2	2	2	2
Number and Types of Cars	2	2	2	2	1	2	3	2	2	3
Individual driving Record	3	2	2	3	3	2	3	2	2	3
Insurance Score	1	1	1	2	2	1	1	2	3	2

Note: EPT=Expert

2. According to literature reviewing, 20 underwriting data are important equally. Moreover, the underwriting data are nominal-the-best response. Therefore, the referential series can be X_0 = (5,5,5,5,5,5,5,5,5,5,5,5,5,5,5,5,5,5,5,5) and the underwriting data of compared series are X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8 X_9, X_{10}, X_{11}, X_{12}, X_{13}, X_{14}, X_{15}, X_{16}, X_{17}, X_{18}, X_{19}, X_{20}.
3. Data normalization are obtained by using Eq. (3). The results are tabulated in Table 5.

Table 5: Summary of Data Normalization

	EPT 1	EPT 2	EPT 3	EPT 4	EPT 5	EPT 6	EPT 7	EPT 8	EPT 9	EPT 10
Fast Lane Change	1.00	0.75	0.75	0.67	0.75	1.00	1.00	0.67	1.00	1.00
Miles Driven	0.75	0.75	0.75	0.67	0.75	0.75	1.00	0.67	1.00	1.00
Daily Number of Drives	1.00	0.75	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00
Rapid Acceleration	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.67
Hard Braking	1.00	1.00	1.00	0.67	0.75	1.00	1.00	1.00	0.67	0.67
Hard Cornering	0.75	0.75	0.75	0.67	1.00	0.75	1.00	1.00	1.00	0.67
Air Bag Deployment	0.25	0.25	0.25	0.00	0.50	0.50	0.50	0.00	0.00	0.00
When of Usually Driving	1.00	1.00	1.00	0.67	0.75	1.00	1.00	0.67	1.00	1.00
Where the Vehicle Is Driven	0.50	0.50	0.50	0.33	1.00	0.50	0.25	0.33	0.33	0.33
The Weather	.075	0.75	0.75	0.33	0.75	0.75	1.00	0.33	1.00	1.00
Traffic Information	0.50	0.50	0.50	0.33	0.50	0.50	0.50	0.00	0.33	0.33
Territory	0.50	0.75	0.75	0.67	0.50	0.75	0.50	0.33	0.67	0.67
Age	0.25	0.50	0.25	0.33	0.50	0.50	0.50	0.00	0.00	0.33
Gender	0.75	0.50	0.50	0.33	0.50	0.75	0.50	0.33	0.67	0.67
Marital Status	0.50	0.50	0.50	0.33	0.50	0.50	0.50	0.33	0.67	0.33
Use of the Auto	0.50	0.75	0.75	0.33	0.75	0.75	0.75	0.33	1.00	1.00
Driver Education	0.25	0.00	0.00	0.00	0.25	0.00	0.25	0.00	0.00	0.00
Number and Types of Cars	0.25	0.25	0.25	0.00	0.00	0.25	0.50	0.00	0.00	0.33
Individual driving Record	0.50	0.25	0.25	0.33	0.50	0.25	0.50	0.00	0.00	0.33
Insurance Score	0.00	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.33	0.00

Compute Δ0i (j). The results are tabulated in Table 6.

Table 6: The result of$\Delta 0i$ (j)

		EPT1	EPT2	EPT3	EPT4	EPT5	EPT6	EPT7	EPT8	EPT9	EPT10
Fast Lane Change	Δ_{01}=	0.00	1.00	1.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00
Miles Driven	Δ_{02}=	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	0.00	0.00
Daily Number of Drives	Δ_{03}=	0.00	1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
Rapid Acceleration	Δ_{04}=	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
Hard Braking	Δ_{05}=	0.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	1.00	1.00
Hard Cornering	Δ_{06}=	1.00	1.00	1.00	1.00	0.00	1.00	0.00	0.00	0.00	1.00
Air Bag Deployment	Δ_{07}=	3.00	3.00	3.00	3.00	2.00	2.00	2.00	3.00	3.00	3.00
When of Usually Driving	Δ_{08}=	0.00	0.00	0.00	1.00	1.00	0.00	0.00	1.00	0.00	0.00
Where the Vehicle Is Driven	Δ_{09}=	2.00	2.00	2.00	2.00	2.00	2.00	3.00	2.00	2.00	2.00
The Weather	Δ_{010}=	1.00	1.00	1.00	2.00	1.00	1.00	0.00	2.00	0.00	0.00
Traffic Information	Δ_{011}=	3.00	3.00	3.00	3.00	3.00	3.00	3.00	2.00	3.00	3.00
Territory	Δ_{012}=	3.00	3.00	3.00	3.00	2.00	4.00	3.00	2.00	4.00	4.00
Age	Δ_{013}=	1.00	2.00	1.00	2.00	2.00	2.00	3.00	1.00	2.00	3.00
Gender	Δ_{014}=	4.00	2.00	3.00	3.00	3.00	4.00	3.00	2.00	4.00	4.00
Marital Status	Δ_{015}=	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	4.00	2.00
Use of the Auto	Δ_{016}=	3.00	4.00	4.00	2.00	3.00	4.00	4.00	3.00	4.00	4.00
Driver Education	Δ_{017}=	1.00	0.00	0.00	1.00	2.00	0.00	2.00	2.00	2.00	1.00
Number and Types of Cars	Δ_{018}=	1.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00	1.00	0.00
Individual driving Record	Δ_{019}=	3.00	2.00	2.00	2.00	2.00	2.00	3.00	1.00	2.00	3.00
Insurance Score	Δ_{020}=	1.00	1.00	1.00	0.00	0.00	1.00	2.00	0.00	1.00	0.00

4. Compute the relational coefficient, $\gamma 0i$ (j) of compared series by using Eq. (1) and the results are tabulated in Table 7.

Table 7. The result of Relational Coefficient $\gamma 0i$ (j)

		EPT1	EPT2	EPT3	EPT4	EPT5	EPT6	EPT7	EPT8	EPT9	EPT10
Fast Lane Change	γ_{01}=	1.00	0.67	0.67	0.67	0.67	1.00	1.00	0.67	1.00	1.00
Miles Driven	γ_{02}=	0.67	0.67	0.67	0.67	0.67	0.67	1.00	0.67	1.00	1.00
Daily Number of Drives	γ_{03}=	1.00	0.67	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00
Rapid Acceleration	γ_{04}=	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.67
Hard Braking	γ_{05}=	1.00	1.00	1.00	0.67	0.67	1.00	1.00	1.00	0.67	0.67
Hard Cornering	γ_{06}=	0.67	0.67	0.67	0.67	1.00	0.67	1.00	1.00	1.00	0.67
Air Bag Deployment	γ_{07}=	0.40	0.40	0.40	0.40	0.50	0.50	0.50	0.40	0.40	0.40
When of Usually Driving	γ_{08}=	1.00	1.00	1.00	0.67	0.67	1.00	1.00	0.67	1.00	1.00
Where the Vehicle Is Driven	γ_{09}=	0.50	0.50	0.50	0.50	0.50	0.50	0.40	0.50	0.50	0.50
The Weather	γ_{010}=	0.67	0.67	0.67	0.50	0.67	0.67	1.00	0.50	1.00	1.00
Traffic Information	γ_{011}=	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.50	0.40	0.40
Territory	γ_{012}=	0.40	0.40	0.40	0.40	0.50	0.33	0.40	0.50	0.33	0.33
Age	γ_{013}=	0.67	0.50	0.67	0.50	0.50	0.50	0.40	0.67	0.50	0.40
Gender	γ_{014}=	0.33	0.50	0.40	0.40	0.40	0.33	0.40	0.50	0.33	0.33
Marital Status	γ_{015}=	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.40	0.33	0.50
Use of the Auto	γ_{016}=	0.40	0.33	0.33	0.50	0.40	0.33	0.33	0.40	0.33	0.33
Driver Education	γ_{017}=	0.67	1.00	1.00	0.67	0.50	1.00	0.50	0.50	0.50	0.67

Number and Types of Cars	γ_{018}=	0.67	0.67	0.67	0.67	0.67	1.00	0.67	0.67	0.67	1.00
Individual driving Record	γ_{019}=	0.40	0.50	0.50	0.50	0.50	0.50	0.40	0.67	0.50	0.40
Insurance Score	γ_{020}=	0.67	0.67	0.67	1.00	1.00	0.67	0.50	1.00	0.67	1.00

5. Compute the related grade, Γ0i, by using Eq. (2) to determine the attitude tendency grade. The result reported in Table 8

Table 8 Summary of the GRG Γ0i.

NO.	Underwriting Data	Γ_{0i}	Rank
1	Fast Lane Change	0.4167	5
2	Miles Driven	0.3833	8
3	Daily Number of Drives	0.4833	2
4	Rapid Acceleration	0.4833	1
5	Hard Braking	0.4337	4
6	Hard Cornering	0.4000	6
7	Air Bag Deployment	0.2150	15
8	When of Usually Driving	0.4500	3
9	Where the Vehicle Is Driven	0.2450	13
10	The Weather	0.3667	9
11	Traffic Information	0.2050	16
12	Territory	0.2000	18
13	Age	0.2650	12
14	Gender	0.1967	19
15	Marital Status	0.2017	17
16	Use of the Auto	0.1850	20
17	Driver Education	0.3500	11
18	Number and Types of Cars	0.3667	10
19	Individual driving Record	0.2433	14
20	Insurance Score	0.3917	7

From Table 8 this study decided the grey relation analysis was following: $\Gamma0_4(0.4833)>\Gamma0_3(0.4833)>\Gamma0_8(0.4500)>\Gamma0_5(0.4337)>\Gamma0_1(0.4167)>\Gamma0_6(0.4000)>\Gamma0_{20}(0.4000)>\Gamma0_2(0.3833)>\Gamma0_{10}(0.3667)>\Gamma0_{18}(0.3667)>\Gamma0_{17}(0.3500)>\Gamma0_{13}(0.2650)>\Gamma0_9(0.2450)>\Gamma0_{19}(0.2433)>\Gamma0_7(0.2150)>\Gamma0_{11}(0.2050)>\Gamma0_{15}(0.2017)>\Gamma0_{12}(0.2000)>\Gamma0_{14}(0.1967)>\Gamma0_{16}(0.1850)$.

In other words, after conducting the GRA, this research showed the experts' attitude tendency toward the 20 underwriting data from the most important to the least important as followings:(1) Rapid Acceleration, (2) Rapid Acceleration, (3) When of Usually Driving, (4) Hard Braking, (5) Fast Lane Change, (6) Hard Cornering, (7) Insurance Score, (8) Miles Driven, (9) The Weather, (10) Number and Types of Cars, (11) Driver Education, (12) Age, (13) Where the Vehicle Is Driven, (14) Individual driving Record, (15) Air Bag Deployment, (16) Traffic Information, (17) Marital Status, (18) Territory, (19) Gender, and (20) Use of the Auto.

5 Conclusion

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

1. There are 20 kinds of collected underwriting data totally put in the grey relation analysis. Eleven kinds of underwriting data collected from telematics devices. The rest underwriting data collected by a traditional auto insurance application form. According to the results of the grey relation analysis, not all the underwriting data collected from telematics devices are before the 10th rank. In other words, there are two kinds of underwriting data, such as Insurance Score as well as Number and Types of Cars, are the 7th rank.
   General speaking, from a perspective of an auto insurance underwriter, although most of driving behavior data collected from telematics devices is very helpful for auto insurance underwriting, some traditional data collected by an application form is still necessary for underwriters to make a well underwriting decision.
2. The important level of each underwriting data, no matter where they are collected, are different. The most six important underwriting data, including Rapid Acceleration, Daily Number of Driven, When of usually Driving, Hard Braking, Fast Lane Change, and Hard Corning, are collected from telematics devices. The least three important data, including Use of the Auto, Gender, and Territory, are collected by a traditional auto insurance application form. The implication is, in order to improve the effective of an underwriting decision making, insurance companies in Taiwan need to take advantage of Iot (Internet of Things) tech to collect more helpful underwriting data as well as adjust their underwriting policy accordingly.

References

[1] D. Karapiperis, B. Birnbaum, A. Brandenburg, R. Harbage, A. Obersteadt, “Usage-based Insurance and Vehicle Telematics Insurance Market and Regulatory Implications,” The Center for Insurance Policy and Research, 2015. https://zh.scribd.com/doc/310430063/Cipr-Study-150324-Usage-Based-Insurance-and-Vehicle-Telematics-Study-Series

[2] Marsh & McLennan Companies, Asia Insurance Market Report 2014, Insurance Market Report, Marsh & McLennan Companies, 2015.

[3] R. Harbage, “Telematics UBI Modeling and Analytics,” The Center for Insurance Policy and Research, March, Cipr 150324, 2015, p.p. 15-17.

[4] G.E. Rejda, Principles of Risk Management and Insurance, Pearson Education, Inc. Prentice Hall: New Jersey, 2011.

[5] State Farm, Seven Factors Affecting Your Car Insurance Premiums, Auto Learning Center, 2012. https://learningcenter.statefarm.com/auto/7-factors-affecting-your-auto-insurance-premiums/

[6] SIERRA WIRELESS, Capturing the Usage-Based Insurance Opportunity, 2015 . http://www.gsma.com/membership/wp-content/uploads/2015/10/Whitepaper-UBI_FINAL_3.pdf.

[7] J. Reifel, M. Hales, G. Ku, S. Lala, Telematics: The Game changer-Reinventing Auto Insurance, A. T. Kearney, Inc: Chicago, Illiois, 2010.

[8] INSLY, Innovation Key to Ideal Usage Based Insurance Solutions, 2015. https://www.insly.com/en/blog/innovation-key-to-ideal-usage-based-insurance-solutions

[9] NAIC, “Usage-Based Insurance and Telematics,” The Center for Insurance Policy and Research, 2015. http://www.naic.org/cipr_topics/topic_ysage_based_insurnce.htm

[10] A. Cohen, “Mileage Unfairly Excluded From Car Insurance Quotes,” Consumer Group Says, Vehicle Insurance, May 21, 2015. http://www.Nerdwallet.com/blog/insurance/2015/05/21/insurers-excluding-mileage-from-car-insurance-quotes/

[11] M. Voelker, “Telematics: Carriers expanding tools beyond usage- based insurance,” National Underwriter Property & Casualty, August 2014. http://www.propertycasualty360.com/2014/08/12/telematics-carriers-expanding-tools-beyond-usage-b

[12] Allstate, “Canadians Skeptical About the Benefits of Usage-Based Insurance,” Allstate Insurance Company of Canada, 2015. http://www.allstate.ca/webpages/about/newsroom-auto.aspx?article=usage-based

[13] J. L. Deng, Introduction to grey system. Journal of Grey System, 1(1): 1-24, 1989.