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A Study of Medical Insurance With Big Data in Taiwan

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The structures of numerous industries, including the insurance industry, have been altered by the ongoing development of associated technologies. As the insurance industry undergoes this period of technology transformation, it is important to recognize the key role that big data play in the industry. Most critically, the industry could not function without the utilization of big data, which explains to a large extent why every insurance company maintains its own numeric database. Relatedly, Taiwan's Bureau of National Health Insurance recently established the Information Integration Application Service Center, to which qualified companies and institutions can submit applications for permission to analyze the bureau's collected disease data according to stipulated regulations. In effect, access to the center's data provides insurance companies with a further means of improving their operational effectiveness through the analysis of big data, with targets for potential improvements including the various strategies utilized to react to changes in the environment, such as those involved in marketing, administrative management, and product pricing and services. The foundation of the present study consisted of a literature review and survey, with the key objective being to determine and discuss the effects of big data analysis on the medical insurance industry, including the changes that the utilization of big data results in for the customers of medical insurance companies. With the issues discussed above in mind, the survey was designed to determine whether medical insurance consumers know about and understand the effects of big data. The survey data indicated the following key findings: (1) The two concepts exhibit clear differences in terms of population statistic variables; (2) The two concepts exhibit clear differences in terms of insurance purchasing variables; and (3) The two concepts exhibit clear differences in terms of the level of understanding regarding big data.

Keywords: big data, medical insurance, questionnaire survey

Introduction

On January 9, 2009, Barack Obama was made president and on that day he also signed the *Transparency and Open Government Memorandum*. Then he declared three major policies—transparent government, citizen participation, and public collaboration. Since then information transparent policies has begun. In the same year, the government opened an online information platform called "Data.gov"; this is a free platform for the people to gain government's information resource, hoping that through reusing information it could influence

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innovative applications and the development of economy (“6 zhan lücheng”, 2016).

In 2012 the Taiwanese government also passed “Government Open Data Development Strategy”, beginning the open data strategies in Taiwan. The next year, “Government Open Data Platform” was complete (Board of Science and Technology, 2015). In 2015, the National Development Council proposed “ide@Taiwan 2020 (creative Taiwan) white paper policy”, and the main govern concepts are based on “people-oriented”, “public- private partnership”, and “innovated governance”, hoping to widely use cloud computing and big data analysis, etc., these online resources and tools to explore the voice of the public and combining the power of online social media to prefect governance. Then “financial technology development strategy white paper policy” proposed that the insurance industry will use big data analysis on purchasing insurance, insurance claims, and determination of rate, etc., allowing the risk evaluation to be more precise Financial Supervisory Commission (Financial Supervisory Commission, 2016).

In the big data that Taiwan uses, the percentage of people that purchased the national health insurance is over 99% (National Health Insurance Administration, 2016). Thus, the big data that this database covers became the main representing data on medical and health related study. Is it possible for these data to be used on medical insurance? If we are able to obtain the citizen’s disease occurring data, will it bring any change to medical insurance? Do the consumers in this tide of change have any knowledge on this? Therefore, this study’s purpose is to discuss:

(1) The effect of big data on medical insurance;

(2) The effect on consumers when medical insurance is run by big data;

(3) The knowledge of consumers on the effects of big data on medical insurance;

(4) The knowledge of consumers on the effects of medical insurance run by big data.

Literature Review

In recent years, big data have become a topic of discussion in the IT and marketing industries, as well as in academia. However, the scope of big data is too broad and the varying definitions that are used to describe it are numerous and ambiguous, leading to a foggy understanding of its concepts and practical application. Big data are high-volume, high-velocity, and high-variety information assets that demand innovative forms of information processing for enhanced insight, decision making, and optimization (Beyer & Laney, 2012). Instead of simply using stochastic analysis (survey sampling), big data are an analytical approach that utilizes all of the data (Mayer-Schönberger & Cukier, 2013).

The big data environment will bring changes to life insurance companies. In the past, actuaries utilized historical data to make risk sharing estimations. However, through the use of big data, these estimations can now be made according to individual characteristics. When medical insurance fails to extend its coverage to new medical technologies derived from improvements in the field, disputes often occur. By utilizing big data to understand and analyze the actual treatment costs for covered diseases, medical insurance will be able to keep up with the improvements to medical technology, and to a reasonable extent, provide patients with the coverage that they need. With the support of big data, insurance companies can focus on their customers and formulate personalized solutions for each and every customer. In this manner, they can implement different rates for different customers, which will allow them to reduce the rates for low-risk customers and raise the rates for or reject high-risk ones, thereby bringing about genuine competitive differentiation (Brat, Clark, Mehrotra, Stange, & Boyer-Chammard, 2014). As big data methods can quickly research and understand information pertaining to the unreasonable claims payouts and history of patients, the costs associated with manually processed claims can thus be reduced. Moreover, the automated underwriting and distribution processes enabled by big data technology (Dorans & Kendrick, 2012) will allow insurance companies to sell their products at higher profit margins.

In one of Davenport's (2014) works, he mentioned that the insurance industry is the leaders in the data analysis. This means that there are many industries that are able to process data. With having these data, the data that life insurance companies need most are data that involve privacy issues, such as health and personal information. This information is under strict control for use in some countries (Brat, Clark, Mehrotra, Stange, & Boyer-Chammard, 2014). The consumers will want to know the use of their information, such as America, Austria, Canada, etc. (Rose, Barton, Souze, & Platt, 2014). Under these circumstances, the analyses that every life insurance company has done are relatively lower and also have the possibility of difference. Therefore, if the data that the insurance companies have are combined with the data of people's disease occurrence rate from the National Health Insurance and analysis them together, is it able to create more value for these huge forms of data?

Under the circumstances of clients agreeing for insurance companies to use their data, when clients become mobile and arrive at their destination, insurance companies are able to use big data to analyze their clients immediately and find out what kind of products their clients they need most (such as accident insurance, or search and rescue services), sending the information to their clients and making the experience of insurance purchasing easier for the clients. Also, this new marketing method can provide specific insurance product for those clients that have come to this region (Chiu, 2017). In some insurance incidents when there is need of insurance claims, the investigation of whether there is actually need of a claim is done manually and sometimes with an automatic analysis.

In 2016, Taiwan's National Health Insurance Administration established an information integration and application service center. Through the center, qualified institutions that have made the necessary applications and received approval for them may analyze disease-related data in accordance with existing regulations. This means that insurance companies now have a firmer basis for determining actuarial rates and pricing, as well as the ability to make more precise risk assessments. These advantages will then enable them to better promote innovation with respect to medical insurance products and raise the competitiveness of these products (Ministry of Health and Welfare, 2016).

Operating an insurance company through big data will enable more suitable insurance products for the need of the buyer. It will increase the precision of rate actuarial and insurance premium prices, solving the dilemma of the saturation of Taiwan's health insurance market. It will also solve the lack of rational judgements in medical clinical services of the past claims management. Therefore, it will miss out on most frauds and the monitoring of the unsuitable medical behavior. Modern health insurance institutions will be able to focus on these problems and communicate with related medical institutions, finding a way to reduce the cost and the possibility of increase in the management level (Chiu, 2017).

According to our nation's *Insurance Act* Article 126 section, one says "An insurer may, before entering into an insurance contract, require the insured to undergo a medical examination". From there we can tell that before the insurance company and the insurer sign the contract, the insurance company has the right to ask the applicant to undergo a medical examination, allowing the insurance company to evaluate the risk of the insurer's health status. But when the consumer chooses to share their personal information or agree others to save their personal information, they need to understand that this information is already out of the original person's control. Even if this information has let down the original person's trust or will, there is nothing that the person could do. Now there are many anonymous technologies to protect people's privacy, but actually an anonymous technology can be back tracked and the information can be traced.

With technological developments, insurance companies can access its customer's medical data for analytical purposes more easily and cheaply. However, from the public's perspective, this may render the protection of private medical information inadequate (Huang, 2014). Although the *Personal Information Protection Act* is already in place in Taiwan, the new analytical and application technologies of the big data era may present new privacy risks that fall outside the scope of the act (Ting, 2015).

In an interview with the *Risk Management & Insurance Magazine* (2016), Professor Jhih-Ling Chiu said that the increasing precision of medical testing (such as gene decoding technologies) and the emergence of big data-based underwriting screening processes will lead to the creation of blacklists (containing individuals to be rejected) by insurance companies. When insurance companies utilize big data technologies to build insurance claim forecasting systems, they will be able to not just uncover potential cases of fraud, but also identify customers with high payout rate, which will then enable them to raise the insurance rates for these customers or designate them as non-key marketing targets (Chiu, 2017).

Study Design and Method

This study focuses on the knowledge of general consumers on big data influenced medical insurance and the effect on big data operated medical insurance, discussing, analyzing, and using surveys to collect information and research. After that, using the SPSS (statistical product and service solutions) statistical system to discuss whether there is an obvious difference in the cognitions of different background information. Target customers are people that are capable to make juridical acts which are of 20 years old, discussing the effects of big data on medical insurance and the effect on big data operated medical insurance, designing the structure of the research according to the study motive, research motive, and literature review.

Research Results

After analyzing the 325 surveys that the participants filled out, the demographic variables are as follows: In the 325 surveys, 117 are male, which is 36.0% of the sample; 208 female, which is more than the male standing 64.0%. There are 181 participants at the age of 20-25, which stands the most participants of the survey and has the proportion of 55.7% of all; aged 26-30 has 50 participants and stands 15.4%. On education level, high school and below has 20 participants and stands 6.2%, junior college 37 participants and stands 11.4%, university 204 participants and stands 62.8%, and graduate school and above 64 participants and stands 19.7% , government employees have 24 participants and stand 7.4%, service industries have 74 participants and stand 22.8%, technology and electronics industries have 15 participants and stand 4.6%, students have 85 participants and stand 26.2%, and other occupations have 40 participants and stand 12.3%. On monthly incomes, 30,000 NT or less average a month has 167 participants and stands 51.4%, 30,001-40,000 NT has 76 participants and stands 23.4%, 40,001-50,000 NT has 37 participants and stands 11.4%, and 50,001 NT and above has 45 participants and stands 13.8% (see Table 1).

Insurance Underwriting Experience

According to Table 2, of the 325 participants, the characteristics of insurance underwriting experience variables are as follows: 229 participants have purchased insurance before and stand 70.5%; have not purchased insurance before 96 participants and stands 29.5%. The number of purchased medical insurance is as follows: 1 medical insurance has 96 participants and stands 41.9%; 2 medical insurance has 73 participants and stands 31.9%; and 3 medical insurance has 60 participants and stands 26.2%. The level of understanding of the insurance bought is as follows: Completely do not understand has 12 participants and stands 5.2%; somewhat understand has 107 participants and stands 46.7%; and completely understand has 110 participants and stands 48.0%.

Table 1

*Demographics Variables Analysi*s

Demographics variables	Classification	Number of participants	Percentage
Age	20-25 years old	181	55.7%
	26-30 years old	50	15.4%
	31-35 years old	19	5.8%
	36-45 years old	37	11.4%
	46 years & above	38	11.7%
Education level	High school & lower	20	6.2%
	Junior college	37	11.4%
	University	204	62.8%
	Graduate school & above	64	19.7%
Occupation	Finance and insurance industries	87	26.8%
	Government employees	24	7.4%
	Service industry	74	22.8%
	Technology	15	4.6%
	Students	85	26.2%
	Others	40	12.3%
Monthly average income	30,000 NT & below	167	51.4%
	30,001-40,000 NT	76	23.4%
	40,001-50,000 NT	37	11.4%
	50,001 NT & above	45	13.8%

Source: Organized by this research (2017).

Table 2

Insurance Underwriting Experience Variables Frequency Distribution

Insurance underwriting experience	Classification	Number of participants	Percentage
Purchase status	Purchased	229	70.5%
	Have not purchased	96	29.5%
The number of medical insurance purchased	1 medical insurance	96	41.9%
	2 medical insurance	73	31.9%
	3 medical insurance & above	60	26.2%
The level of understanding of the insurance policy	Completely do not understand	12	5.2%
	Somewhat understand	107	46.7%
	Completely understand	110	48.0%

Source: Organized by this research (2017).

The Level of Understanding on Big Data

According to Table 3, of the 325 participants, the characteristics of level of understanding on big data variables are as follows: Have heard of big data has 226 participants, which are over half and stand 69.5%;

participants who have not heard of big data have 99 participants and stand 30.5%. The level of understanding on the meaning and definition of big data is as follows: Do not understand has 10 participants and stands 4.4%; somewhat understand has 119 participants, which are over half and stand 52.7%; and completely understand has119 participants and stands 52.7%. Understanding the effects big data will bring to the consumer is as follows: Do not understand has 32 participants and stands 14.2%; somewhat understand has 96 participants and stands 42.5%; completely understand has 98 participants and stands 43.4%.

Table 3

Level of Understanding on Big Data Frequency Distribution Table

Level of understanding on big data	Classification	Number of participants	Percentage
Heard of big data	Yes	226	69.5%
	No	99	30.5%
Understand the meaning and definition of big data	Do not understand	10	4.4%
	Somewhat understand	119	52.7%
	Completely understand	97	42.9%
Understand the effects big data will bring to the consumer	Do not understand	32	14.2%
	Somewhat understand	96	42.5%
	Completely understand	98	43.4%

Source: Organized by this research (2017).

Analysis of Variance

Age

According to the two tables below (see Tables 4 & 5), the significance of Factors 1-1 and 2-1 in F-test is 0.018 and 0.014, which are both less than 0.05. This means that the age in the group distribution difference has significant difference of cognition. Among them who are 20-25 years old and 26-30 years old, the cognition significance is higher than those of 36-45 years old consumers.

Table 4

Age

	F	Significance
Factor 1-1	3.022	0.018
Factor 1-2	0.907	0.460
Factor 2-1	3.162	0.014
Factor 2-2	1.045	0.384

Source: Organized by this research (2017).

Table 5

Multiple Comparison—Age

Scheffé's method	(I) Age	(J) Age	Average value difference (I-J)	Standard error	Significance
Factor 1-1	20-25 years old	36-45 years old	0.65268	0.20817	0.046
	26-30 years old	36-45 years old	0.78955	0.25021	0.043
Factor 2-1	20-25 years old	36-45 years old	0.67579	0.20890	0.035
	26-30 years old	36-45 years old	0.80264	0.25109	0.039

Source: Organized by this research (2017).

The significance of Factors 1-2 and 2-2 in F-test is 0.460 and 0.384, which are both larger than 0.05. This means that the age in the group distribution difference has insignificant difference of cognition.

Education Level

According to the two tables below (see Tables 6 & 7), the significance of Factors 1-1 and 1-2 in F-test is 0.392 and 0.138, which are both larger than 0.05. This means that the education level in the group distribution difference has insignificant difference of cognition.

Table 6

Education

	F	Significance
Factor 1-1	1.033	0.392
Factor 1-2	1.852	0.138
Factor 2-1	7.792	0.000
Factor 2-2	7.443	0.000

Source: Organized by this research (2017).

Table 7

Multiple Comparison—Education Level

Scheffé's method	(I) Education level	(J) Education level	Average value difference (I-J)	Standard error	Significance
Factor 2-1	University	High school & below	1.13072	0.26664	0.001
	Graduate school & above	High school & below	1.17708	0.29151	0.001
Factor 2-2	University	High school & below	1.02451	0.25257	0.001
	Graduate school & above	High school & below	1.15104	0.27614	0.001

Source: Organized by this research (2017).

The significance of Factors 2-1 and 2-2 in F-test are 0.000 and 0.000, which are both less than 0.05. This means that the education level in the group distribution difference has significant difference of cognition. Among them who are education level university and graduate school and above, the cognition significance is higher than consumers with education level high school and below.

Occupation

According to the two tables below (see Tables 8 & 9), the significance of Factors 1-1 and 2-1 in F-test is 0.000 and 0.000, which are both less than 0.05. This means that the occupation in the group distribution difference has significant difference of cognition. Among them who are occupations of finance and insurance industries, the cognition significance is higher than those consumers with occupations of government employees, service industries, technology and electronic industry, students, and others.

The significance of Factor 1-2 in F-test is "0.000 < 0.05". This means that the occupation in the group distribution difference has significant difference of cognition. Among them who are occupations of finance and insurance industries, the cognition significance is higher than those consumers with occupations of government employees and students.

The significance of Factor 2-2 in F-test is "0.000 < 0.05". This means that the occupation in the group distribution difference has significant difference of cognition. Among them who are occupations of finance and insurance industries, the cognition significance is higher than those consumers with occupations of service industries, students, and others.

Table 8

Occupation

	F	Significance
Factor 1-1	15.531	0.000
Factor 1-2	6.687	0.000
Factor 2-1	11.626	0.000
Factor 2-2	6.990	0.000

Source: Organized by this research (2017).

Table 9

Multiple Comparison—Occupation

Scheffé's method	(I) Occupation	(J) Occupation	Average value difference (I-J)	Standard error	Significance
Factor 1-1	Finance and insurance industries	Government employees	1.44708	0.24341	0.000
		Service industries	1.25282	0.16695	0.000
		Technology & electronic industry	1.27625	0.29515	0.003
		Students	0.93899	0.16100	0.000
		Others	0.92625	0.20168	0.001
Factor 1-2	Finance and insurance industries	Government employees	1.22773	0.25599	0.000
		Students	0.71180	0.16932	0.004
Factor 2-1	Finance and insurance industries	Government employees	1.20195	0.25072	0.000
		Service industries	1.16629	0.17196	0.000
		Technology & electronic industry	1.17880	0.30401	0.011
		Students	0.77662	0.16584	0.001
		Others	0.72973*	0.20773	0.033
Factor 2-2	Finance and insurance industries	Service industries	0.81811	0.16788	0.000
		Students	0.56538	0.16191	0.034
		Others	0.93793	0.20281	0.001

Source: Organized by this research (2017).

Individual Monthly Average Income

According to the table below (see Table 10), the significance of Factors 1-1, 1-2, 2-1, and 2-2 in F-test is 0.710, 0.774, 0.313, and 0.436, which are all larger than 0.05. This means that the monthly average income of the individual in the group distribution difference has insignificant difference of cognition.

Table 10

Individual Monthly Average Income

	F	Significance
Factor 1-1	0.461	0.710
Factor 1-2	0.371	0.774
Factor 2-1	1.191	0.313
Factor 2-2	0.910	0.436

Source: Organized by this research (2017).

Numbers of Medical Insurance Purchased

According to the table below (see Table 11), the significance of Factors 1-1, 1-2, 2-1, and 2-2 in F-test is 0.153, 0.956, 0.067, and 0.225, which are all larger than 0.05. This means that the number of medical insurance purchased in the group distribution difference has insignificant difference of cognition.

Table 11

Number of Medical Insurance Purchased

	F	Significance
Factor 1-1	1.891	0.153
Factor 1-2	0.045	0.956
Factor 2-1	2.739	0.067
Factor 2-2	1.501	0.225

Source: Organized by this research (2017).

Level of Understanding on the Policy

Table 12

The Level of Understanding on the Policy

	F	Significance
Factor 1-1	13.596	0.000
Factor 1-2	18.590	0.000
Factor 2-1	10.086	0.000
Factor 2-2	4.055	0.019

Source: Organized by this research (2017).

Table 13

Multiple Comparison—The Level of Understanding on the Policy

Scheffé's method	(I) The level of understanding on the policy	(J) The level of understanding on the policy	Average value difference (I-J)	Standard error	Significance
Factor 1-1	Completely understand the policy	Somewhat understand the policy	0.76282	0.14895	0.000
Factor 1-2	Completely understand the policy	Somewhat understand the policy	0.81922	0.13731	0.000
Factor 2-1	Completely understand the policy	Somewhat understand the policy	0.67533	0.15040	0.000
Factor 2-2	Completely understand the policy	Somewhat understand the policy	0.36007	0.14251	0.043

Source: Organized by this research, 2017.

According to the two tables above (see Tables 12 & 13), the significance of Factors 1-1, 1-2, 2-1, and 2-2 in F-test is 0.000, 0.000, 0.000, and 0.019, which are all less than 0.05. This means that the level of understanding on the insurance purchased in the group distribution difference has insignificant difference of cognition. Among them who are the consumer that completely understand the insurance purchased, the cognition significance is higher than those consumers that somewhat understand the insurance they purchased.

Understanding the Meaning and Definition of Big Data

According to the two tables below (see Tables 14 & 15), the significance of Factors 1-1, 1-2, and 2-2 in F-test is 0.003, 0.001, and 0.000, which are all less than 0.05. This means that the understanding of the meaning and definition of big data in the group distribution difference has significant difference of cognition. Among them who are the consumers that completely understand the meaning and definition of big data, the cognition significance is higher than those consumers that somewhat understand the meaning and definition of big data.

The significance of Factor 2-1 in F-test is “0.00 < 0.05”. This means that the understanding of the meaning and definition of big data in the group distribution difference has insignificant difference of cognition. Among them who are the consumers that completely understand the meaning and definition of big data, the cognition significance is higher than those consumers that somewhat understand the meaning and definition of big data.

Table 14

Understanding the Meaning and Definition of Big Data

	F	Significance
Factor 1-1	5.891	0.003
Factor 1-2	6.734	0.001
Factor 2-1	11.633	0.000
Factor 2-2	8.375	0.000

Source: Organized by this research (2017).

Table 15

Multiple Comparison—Understanding the Meaning and Definition

Scheffé’s method	(I) Understanding the meaning and definition of big data	(J) Understanding the meaning and definition of big data	Average value difference (I-J)	Standard error	Significance
Factor 1-1	Completely understand	Somewhat understand	0.51827	0.15105	0.003
Factor 1-2	Completely understand	Somewhat understand	0.50531	0.14363	0.002
Factor 2-1	Completely understand	Do not understand	0.98958	0.33987	0.016
		Somewhat understand	0.61675	0.13998	0.000
Factor 2-2	Completely understand	Somewhat understand	0.48748	0.12742	0.001

Source: Organized by this research (2017).

Understand the Effect of Big Data on Consumers

Table 16

Understand the Effect of Big Data on Consumers

	F	Significance
Factor 1-1	8.181	0.000
Factor 1-2	6.772	0.001
Factor 2-1	7.457	0.001
Factor 2-2	8.952	0.000

Source: Organized by this research (2017).

Table 17

Multiple Comparison—Understand the Effect

Scheffé’s method	(I) Understand the effect of big data on consumers	(J) Understand the effect of big data on consumers	Average value difference (I-J)	Standard error	Significance
Factor 1-1	Completely understand	Somewhat understand	0.62897	0.15704	0.000
Factor 1-2	Completely understand	Somewhat understand	0.54735	0.15075	0.002
Factor 2-1	Completely understand	Do not understand	0.58418	0.21197	0.024
		Somewhat understand	0.52284	0.14950	0.003
Factor 2-2	Completely understand	Do not understand	0.76233	0.18919	0.000
		Somewhat understand	0.34914	0.13343	0.034

Source: Organized by this research (2017).

Based on the two tables above (see Tables 16 & 17), the significance of Factors 1-1 and 1-2 in F-test is 0.000 and 0.001, which are all less than 0.05. This means that the understanding the effect of big data on consumers in the group distribution difference has significant difference of cognition. Among them who are the consumers that completely understand the effects of big data, the cognition significance is higher than those consumers that somewhat understand the effect of big data.

The significance of Factors 2-1 and 2-2, in F-test is 0.001 and 0.000, which are all less than 0.05. This means that the understanding the effect of big data on consumers in the group distribution difference has significant difference of cognition. Among them who are the consumers that completely understand the effects of big data, the cognition significance is higher than those consumers that somewhat understand the effect of big data.

Conclusion and Recommendation for Future Research

Based on the survey, consumers with occupations that are in finance and insurance industries have higher cognitions than other occupations. Consumers that completely understand the insurances they purchased have higher cognitions than consumers that somewhat understand the insurances they purchased. Consumers that have heard of big data have higher cognitions than those who have not heard of big data. Consumers that understand the definition and meaning of big data have higher cognitions than those who somewhat understand the definition and meaning of big data. Consumers that understand the effect of big data on consumers have higher cognitions than those who somewhat understand and do not understand the effect of big data on consumers.

Although insurance companies are eager to use big data to aid them with decision making, they have met many obstacles along the way. With this research we can tell the how familiar consumers are to big data influenced life insurance: (1) Insurance companies can strength their product services and improve their relationships with their clients. This will be a win-win scenario for both sides; and (2) most insurance companies deal with the use of privacy and data with a supervision perspective and limited regulations. When insurance companies are data collecting and managing, they emphasize complying with the law and discloser requirements. But what consumers really want is how the insurance companies collect and protect their related data and how the insurance companies use this data. This means that the expiation for the use of this data is different. This causes trust issues and insurance companies should make up a perfected big data strategy. Let there be no more trust issues between consumers and insurance companies and start a good relationship.

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