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Making an Insurance Underwriting Decision by Employing Social Media Networking Data

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Abstract – **Traditional techniques are labor intensive and very expensive. The new online social networking technology may help insurance companies to improve their underwriting profits and select prospective policyholders. However, insurers face obstacles that may impede the speed-to-market of applying social networking data to underwriting. This is because neither regulators nor insurers have developed guidelines for the overall use of social data, and scientific studies have not determined what types of social medial data are referable. To fill this research gap, this study conduct TOPSIS and CA methods to identify what underwriting factors underwriters prefer to search for in social media networking and explore the types of social media data that may offer the best insights on underwriting factors for insurers to make underwriting decisions. This study suggests Data derived from social media sites can serve to provide further confirmation of the information filled in an insurance application form, thereby assisting underwriting professionals to develop a proper social media underwriting guideline. The impact and influence of social media on underwriting handling, fraud preventing, and adverse selection avoiding cannot be ignored.**

Keywords – **Insurance Underwriting, Social Media Networking, Adverse Selection.**

I. Introduction

Insurance companies are charged, on the one hand, with taking policyholders' premiums to protect the insured from the risk of potential losses; on the other hand, insurance companies are charged with serving as gatekeepers to prevent policyholders from taking too much from the risk pool. Many functions can help insurance companies to take responsibility for this difficult task. One of the most important functions of an insurance company is the underwriting process, including selecting, classifying, and pricing applicants for insurance. The major objective of underwriting is to determine if an applicant is acceptable for the insurance under the conditions indicated. Through underwriting, an insurance company can produce a safe and profitable distribution of business. Insurance scholars, practitioners, and supervisors have a long history of evaluating insurance applicants' knowledge, skills, and ability directly through a wide variety of sources, including applications, agents' reports, inspection reports, physical inspections, physical examinations, and attending physicians' reports [1]. Unfortunately, many of these assessments are at risk of fraudulence and adverse selection. Insurance fraud hurts the insurance companies and everyone else because it adds 10% to the cost of the average policy [2].

To make appropriate underwriting decisions and prevent insurance fraud, insurance companies attempt to collect various sources of data to accurately rate the risk profile of certain classes of policyholders or applicants. Traditionally, underwriters rating loss exposure or those presented with potential adverse selection or moral risk tend to rely on tools for their inspection. The agent is told what types of applicants are acceptable, borderline, or prohibited. Underwriters also require certain information to decide whether to accept or reject an applicant for insurance. The required information includes the application, agent's report, inspection report, physical inspection, or physical examination [1]. In this context, underwriters will often cast a broad net in discovery requests, seeking as much documentation as possible to search for inconsistencies in the applicant or policyholder's story or indications of potential fraud. However, these traditional techniques are labor intensive and very expensive [3]. Fortunately, the new online social networking technology may help insurance companies to improve their underwriting profits and select prospective policyholders. Online social networking websites and micro blogging services allow users to post and read text-based messages of up to 140 characters, such as "Facebook" and "Twitter". There are more than 554 million active registered Twitter users and 1.11 billion people using Facebook, according to reports from Twitter statistics and Yahoo Finance in 2012. Almost 72% of all US Internet users are on now Facebook, and 70% of the entire user base is located outside of the US. In other words, Facebook is now used by one in every seven people on earth. Every 20 minutes, more than 2.7 million photos are uploaded, 2.7 million messages are sent, one million links are shared, and 10 million comments are posted on Facebook, based on information provided by "WWW.ONLINESCHOOLS. ORG" in 2011.

Because online social networking websites have both high frequency use and wide coverage, employers have arguably been quicker than organizational scientists to realize social media's assessment potential [4]. Numerous studies have examined employers' social media usage to select job candidates and observe employees [5]; [6]. Individuals have often been cautioned to watch what they post or otherwise divulge via social media because employers may base hiring and firing decisions in part on what they find online. Outside of the workplace, many job applicants use social media for personal communication that is unintended for employers [4], often leaving public traces of their social communication in cyberspace through forums such as blogs, tweets, and posts on social networking web sites such as Facebook [7]. In other words, job applicants' online activity, including Facebook activity, tweets, and online searches, can serve as background for employers making hiring decisions. There is now another group that may also be watching people's social networking and analyzing the data that they glean from it: insurance companies. Social media data will pay dividends for insurers in areas such as underwriting, claims, and subrogation [8].

Social media networks provide a rich source of data that insurers can use to improve a variety of operational processes [8]. However, insurers face obstacles that may impede the speed-to-market of applying social networking data to underwriting [9]. This is because neither regulators nor insurers have developed guidelines for the overall use of social data, and scientific studies have not determined what types of social medial data are referable [9]. To fill this research gap, the first purpose of this study is to identify what underwriting factors underwriters prefer to search for in social media networking. The second purpose of this paper is to explore the types of social media data that may offer the best insights on underwriting factors for insurers to make underwriting decisions. The findings may provide information for those who employing social media networking data to make underwriting decision to attain underwriting profits, select prospective policyholders, and provide equity among policyholders.

II. Literature Review

Information Provided by Social Popular Networking Sites

Facebook, Twitter, Google +, and LinkedIn will be the most popular social networking sites in the world by 2014 according to research conducted by eMarketer, a company located in New York that provides the most complete view of digital marketing available to the world's top brands, agencies, and media companies. The following is description of the type of information available from each site.

With 750 million active users on Facebook, it is almost certain that any applicants or policyholders will have a Facebook profile. A profile provides Facebook users with a forum for presenting their experiences, interests, and thoughts to a selected circle of friends or to the public at large. Because it provides a messaging feature that allows direct communication between Facebook users, the information on Facebook can be used to develop a picture of a person's activities before and after an insurance application [10].

A Twitter posting is a text-based post of up to 140 characters. Tweets are essentially text messages posted in real time for communication or discussion with a tweeter's followers. Usually, tweets contain links to other sources of information, such as photograph repositories or websites. Moreover, users have direct conversations with other users through tweets directed at individuals using the @ symbol. Searching Twitter may produce information relevant to whether an insured individual suffers from sickness or injuries [3].

Google + is a relatively new player introduced to the social networking field in June 2011. Google + is designed to integrate other Google services related to a user's Google profile that contain many discussion forums. Google + also contains new social networking features, including "Circles", "Hangouts", "Huddles", and "Sparks" [11], which may provide a wealth of information to insurance underwriters about a policyholder's friends, interests, group video chats, and text messages within various circles.

LinkedIn, with 225 million members in more than 200 countries, is business oriented and is the world's largest professional networking site. LinkedIn users post resume-type information about their current employment, work history, experience, and educational background. The information posted on LinkedIn may help insurance underwriters recognize policyholders' real working situation, experience, and environment [3].

The Role of Social Media in Insurance Underwriting

The immediacy of social media data enables insurers to shift underwriting from a static process that relies upon backward-facing data to a dynamic process that relies upon real-time data [8]. In the near future, insurers will be increasingly sensitive to the connection between an insured person's credit score and his or her potential risk for loss. The relation between the activities in which users engage online and their riskiness as policyholders is becoming an important issue [11]. The use of social media networking continues to grow in absolute numbers and to expand to all age groups, and new approaches are using social media data from online networking sites in operational applications for underwriting. Insurers should consider social networking because of who uses it and what is being posted [12].

As Ha predicted, automatically mined data from social networking sites may find their way into the underwriting pricing process [9]. Social media data may become a factor in determining premiums for both personal and business insurance.

Social Media Data Used as Sources of Evidence in Courts of Law in Claim Cases

Fraud is a significant challenge to the insurance business. The explosion of new Internet-based technology combined with a poor economy has encouraged unscrupulous individuals to find new ways to commit insurance fraud. In this context, insurers and lawyers have found ways to take advantage of online social media to fight fraudulent claims [13].

Scouring Facebook and other social networking pages of policyholders is a common practice on the claims side of the business. Many investigators report that navigating an insured individual's online social media page is one of the first things they do when looking into potentially fraudulent claims, according to a report from Boston-based research firm Celent in 2011. Online social media is a goldmine for the discovery of insurance fraud, particularly in the litigation process [3]. Chastain stated that social media is obviously an important factor in insurance fraud investigation [14]. There have been many situations in which the public information available through social media has been beneficial in insurance fraud investigations.

Social media network data are used extensively as sources of evidence in claim cases in courts of law. Underwriting will be the next area [9] if key techniques can be developed or enhanced, including reliable authentication methods, improved data extraction tools, and more advanced analysis tools [12]. Insurers have not yet provided guidelines in terms of the overall use of social data, and these data are not yet approved for use in the pricing process [9].

Important Underwriting Factors That Determine a Life Insurance Premium

The world of underwriting is evolving. Paramedical exams are used more often, and blood tests have become a staple of underwriting. However, the basic factors considered by insurers to make underwriting decision are similar to those in the past [15], according to many previous studies (e.g., [16]; [17]; [18]; [19]). The factors considered in making underwriting decisions include 11 determinants and can be framed as in the following structure (Figure 1).

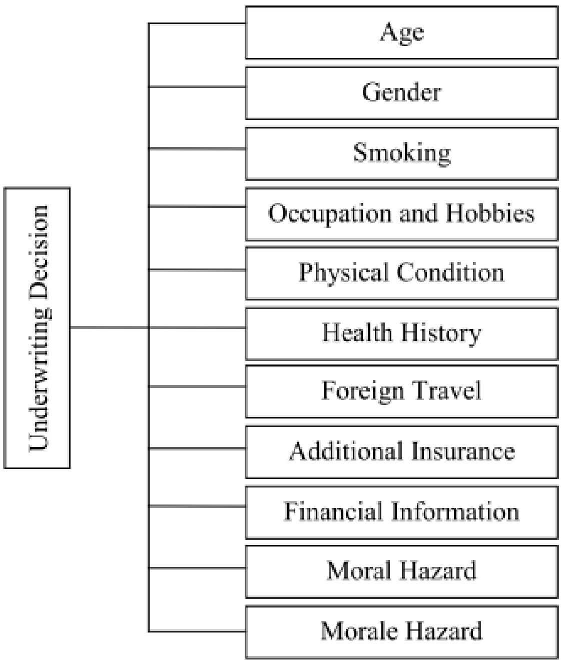

Fig.1. Determinants of Underwriting Decision Making

Useful Social Media Data in Underwriting

As users interact with multiple social networking sites, purchase items online, and communicate with others in public forums, they leave behind data about their preferences, lifestyle, operations, and habits. Another piece of useful information that social media data can provide is the "social graph", which shows how individuals or companies are linked together, providing a picture of who is friends with whom, who follows whom, and people's friends of friends. In addition to identifying fraud organizations, these graphs can give underwriters further insight into how an individual may perform in terms of risk based on the behavior of those to whom he or she is connected [20]; [9]. In general, useful information can be searched by underwriters through social media networking sites, including individuals' interaction with multiple social networking sites, purchase of items online, communication with others in public forums, and social graph.

The TOPSIS and Shortlist

According to the general rule of thumb developed by many studies [21]; [22], full-profile conjoint analysis (CA). is useful for measuring up to about six attributes. However, there was scant sufficient method suggested by prior studies which can be employed to select appropriate attributes in the CA. Fortunately, technique for order preference by similarity to ideal solution (TOPSIS) may be adopted for the shortlist selection of each considered factor. Followings are the introductions of TOPSIS and CA.

III. Methodology

TOPSIS

TOPSIS developed by Hwang and Yoon was conducted to rank the determinants of underwriting decision making [23]. The calculating procedure of TOPSIS is discussed as following:

1. Establishing the performance matrix

$$D = \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array} \begin{bmatrix} X_{11} & X_{12} & \cdots & \cdots & X_{1j} & X_{1n} \\ X_{21} & X_{22} & \cdots & \cdots & X_{2j} & X_{2n} \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots \\ X_{i1} & X_{i2} & \vdots & \vdots & X_{ij} & X_{in} \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots \\ X_{m1} & X_{m2} & \cdots & \cdots & X_{mj} & X_{mn} \end{bmatrix}, \quad (1)$$

where X_{ij} is the performance of attribute X_j for alternative A_i, for i=1, 2, ..., m, j=1, 2, ..., n.

2. Normalize the performance matrix.

Normalizing the performance matrix is an attempt to unify the unit of matrix entries.

$$\mathrm{X} = (X_{ij}) \ \forall i, j \ , \quad (2)$$

where X_{ij} is the performance of attribute i to criterion j.

3. Create the weighted normalized performance matrix

TOPSIS defines the weighted normalized performance matrix as

$$\mathrm{V} = (V_{ij}) \quad \forall i, j \ , \quad (3)$$

$$V_{ij} = w_j \times r_{ij} \quad \forall i, j \ .$$

where w_j is the weight of criterion j.

4. Determine the ideal solution and negative ideal solution

The ideal solution is computed based on the following equations:

$$A^* = \{(max\ V_{ij} \mid j \in J), (\min V_{ij}\ j \in J'), \quad i = 1, 2, \ ..., \mathrm{m}\}, \quad (4)$$

$$A^- = \{(min\ V_{ij} \mid j \in J), (\min V_{ij} \mid j \in J'), \quad i = 1, 2, \ ..., \mathrm{m}\} \ , \quad (5)$$

where

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$j = \{ j = 1, 2, \ldots, \text{n} \mid$

j belongs to benefit criteria$\}$,

$j' = \{ j = 1, 2, \ldots, \text{n} \mid$

j belongs to cost criteria$\}$.

5. Calculate the distance between idea solution and negative ideal solution for each alternative, using the n-dimensional Euclidean distance.

$$S_i^* = \sum_{j=1}^{n} (V_{ij} - V_j^*)^2 \qquad i = 1,\ 2,\ \ldots,\ \text{m}\ , \tag{6}$$

$$S_i^- = \sum_{j=1}^{n} (V_{ij} - V_j^-)^2 \qquad i = 1,\ 2,\ \ldots,\ \text{m}\ , \tag{7}$$

6. Calculate the relative closeness to the ideal solution of each alternative

$$C_i^* = \frac{S_i^-}{S_i^* + S_i^-} \qquad i = 1,\ 2,\ \ldots,\ \text{m}\ . \tag{8}$$

where $0 \le C_i^* \le 1$. That is, an alternative i is closer to A^* as C_i^* approaches to 1.

7. Rank the preference order

A set of alternatives can be preferentially ranked according to the descending order of C_i^*

The Conjoint Analysis Methodology

Conjoint analysis (CA) has been employed in research for many years. Panda and Panda have described CA as a "what if" experiment in which buyers are presented with different possibilities and asked which product they would buy [24]. In other words, CA is a multivariate technique used specifically to understand how respondents develop preferences for products or services [21]. Sudman & Blair emphasized that CA is not a data analysis process [25], such as cluster analysis or factor analysis; it can be regarded as a type of "thought experiment," designed to display how various elements, such as price, brand, and style, can be used to predict customer preferences for a product or service.

The basic CA model was computed with the ordinary least squares (OLS) regression parametric mathematic algorithm using dummy variable regression [26]. This basic model can be represented as follows [27]; [28] .

$$\text{U (X)} = \sum_{i=1}^{m} \sum_{j=1}^{ki} \alpha_{ij} \bullet \chi_{ij}$$

where

U(X) = Overall utility (importance) of an attribute

α_{ij} = Overall utility of the j level of the i attribute

i = 1, 2,………., m   j= 1, 2,………..ki

X_{ij} = 1, if the j^{th} level of the i^{th} attribute is present = 0, otherwise.

According to the CA basic model, Churchill & Iacobucci presented a six-stage model that is based on the more critical decision points in a conjoint experiment [29].

1. Select attributes: The attributes are those that the company can do something about and which are important to consumers. In other words, the company has the technology to make changes that might be indicated by consumer preferences.
2. Determine Attribute Levels: The number of levels for each attribute has a direct bearing on the number of stimuli that the respondents will be asked to judge.
3. Determine Attribute Combinations: This will determine what the full set of stimuli will look like.
4. Select Form of Presentation of Stimuli and Nature of Judgments: Typically, three approaches can be used: a verbal description, a paragraph description, and a pictorial representation. One method for characterizing judgments is to ask respondents to rank the alternatives according to preference or intention to buy. Another method that is gaining popularity among researchers is to use rating scales.
5. Decide on Aggregation of Judgments: This step basically involves the decision as to whether the responses from consumers or groups of consumers will be aggregated.
6. Select Analysis Technique: The final step is to select the technique that will be used to analyze the data. The choice depends largely on the method that was used to secure the input judgments from the respondents.

IV. Decision Model Application and Results

There are 30 life insurance companies in Taiwan in 2014. Twenty underwriting managers of 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 life insurance sector, and (b) participated in the decision-making process of underwriting in life insurance companies. However, only 11 qualified underwriting managers agreed to share their opinion and answered the questionnaire, and 6 questionnaires were completed in the survey.

The estimation model in this study consists of three phrases. In the first phrase, underwriting factors for underwriters are identified using the literature reviewing. The second phrase, underwriting factors for underwriters are shortlisted by using the TOPSIS method, The third phrase, in which the weights of the underwriting factors, also used as the decision evaluation criterion, are calculated and types of social media data, which may provide the best insights on underwriting factors for insurers to make underwriting decision, is evaluated- both by employing the CA method. The second phrase is described in detail as follows.

Based on the TOPSIS, a general consensus among experts can be reached to rate their level of agreement toward underwriting factors for CA. Those results are in Table 1.

Table 1. Descriptive Statistics of Expert Attitude toward underwriting factors

underwriting factors	SA	A	UD	D	SD	N	Mean	Std. Deviation
Age	0	2	3	1	0	6	3.167	0.69
Gender	0	1	5	0	0	6	3.167	0.37
Smoking	0	4	2	0	0	6	3.667	0.47
Occupation and Hobbies	1	3	2	0	0	6	3.833	0.69
Physical Condition	0	2	4	0	0	6	3.333	0.47
Health History	0	3	3	0	0	6	3.500	0.50
Foreign Travel	1	4	1	0	0	6	4.000	0.58
Additional Insurance	2	3	1	0	0	6	4.167	0.69
Financial Information	4	2	0	0	0	6	4.667	0.47
Moral Hazard	3	3	0	0	0	6	4.500	0.50
Morale Hazard	3	2	1	0	0	6	4.333	0.75

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 6 attitude tendency toward underwriting factors are graded based upon 6 experts' opinions (see Table 2).

Table 2: Attitude Tendency toward underwriting factors

Experts Underwriting Factors	Sub-criteria					
	EPT 01	EPT 02	EPT 03	EPT 04	EPT 05	EPT 06
Age	3.000	2.000	3.000	4.000	3.000	4.000
Gender	3.000	3.000	3.000	3.000	4.000	3.000
Smoking	4.000	3.000	3.000	4.000	4.000	4.000
Occupation and Hobbies	5.000	3.000	4.000	3.000	4.000	4.000
Physical Condition	4.000	3.000	3.000	3.000	4.000	3.000
Health History	3.000	3.000	4.000	4.000	3.000	4.000
Foreign Travel	5.000	4.000	4.000	4.000	3.000	4.000
Additional Insurance	4.000	3.000	4.000	5.000	4.000	5.000
Financial Information	5.000	4.000	5.000	5.000	5.000	4.000
Moral Hazard	4.000	4.000	5.000	4.000	5.000	5.000
Morale Hazard	4.000	4.000	5.000	3.000	5.000	5.000

Note: EPT=Expert

2. Calculate the normalized performance matrix and calculate the weighted normalized performance matrix, using formulae (1) and (2). Table 3 summarizes those results.

Table 3: Summary of Data Normalization

Experts Underwriting Factors	Sub-criteria					
	EPT 01	EPT 02	EPT 03	EPT 04	EPT 05	EPT 06
Age	0.222	0.181	0.227	0.310	0.222	0.291
Gender	0.222	0.272	0.227	0.233	0.296	0.218
Smoking	0.296	0.272	0.227	0.310	0.296	0.291
Occupation and Hobbies	0.371	0.272	0.302	0.233	0.296	0.291
Physical Condition	0.296	0.272	0.227	0.233	0.296	0.218
Health History	0.222	0.272	0.302	0.310	0.222	0.291
Foreign Travel	0.371	0.362	0.302	0.310	0.222	0.291
Additional Insurance	0.296	0.272	0.302	0.388	0.296	0.364
Financial Information	0.371	0.362	0.378	0.388	0.371	0.291
Moral Hazard	0.296	0.362	0.378	0.310	0.371	0.364
Morale Hazard	0.296	0.362	0.378	0.233	0.371	0.364

Note: EPT=Expert

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3. Determine the distance of the ith alternative from the ideal and negative-ideal solutions, using formulae (6) and (7). Table 4 displays those results.

Table 4. The Result of □ $\Delta_{0i}(j)$

Underwriting Factors	S_i^*	S_i^-
Age	0.056	0.018
Gender	0.054	0.020
Smoking	0.038	0.029
Occupation and Hobbies	0.037	0.036
Physical Condition	0.049	0.023
Health History	0.044	0.026
Foreign Travel	0.033	0.045
Additional Insurance	0.026	0.044
Financial Information	0.012	0.060
Moral Hazard	0.018	0.055
Morale Hazard	0.029	0.054

4. Calculate the relative closeness to the ideal solution and rank the preference order.
5. Calculate the relative closeness to the ideal solution of each alternative, C_i^*, using formulae (8) and rank the preference order (Table 5).

Table 5: Summary of the TOPSIS C_i^*

Underwriting Factors	Age	Gender	Smoking	Occupation and Hobbies	Physical Condition	Health History	Foreign Travel	Additional Insurance	Financial Information	Moral Hazard	Morale Hazard
C_i^*	0.24	0.27	0.43	0.49	0.32	0.38	0.58	0.63	0.83	0.76	0.65
Rank	11	10	7	6	9	8	5	4	1	2	3

From Table 5, this study decided the TOPSIS was following $C^*_9 > C^*_{10} > C^*_{11} > C^*_8 > C^*_7 > C^*_4 > C^*_3 > C^*_6 > C^*_5 > C^*_2 > C^*_1$.

In other words, after conducting the TOPSIS, this research showed the experts' attitude tendency toward the 11 underwriting factors from the most important to the least important as followings: (1) Financial Information, (2) Moral Hazard, (3) Morale Hazard, (4) Additional Insurance), (5) Foreign Travel, (6) Occupation and Hobbies, (7) Smoking, (8) Health History, (9) Physical Condition, (10) Age, and (11) Gender. Hair et al. (1998), this study decides to choose top six cross-buying intentions including: (1) Financial Information (0.832), (2) Moral Hazard (0.756), (3) Morale Hazard (0.652), (4) Additional Insurance (0.627), (5) Foreign Travel (0.576), (6) Occupation and Hobbies (0.494) as underwriting factors. The adjusted cross-buying intentions by TOPSIS used in this study are reported in Figure 2.

For a formal analysis, the different attribute levels have to be dummy-encoded in a binary manner. The lowest attribute level serves as a reference point and gets a binary code of 0 (Helm et al., 2003). For any other attribute level, a binary digit of 1 is given if the level is present, and 0 is given if it is not.

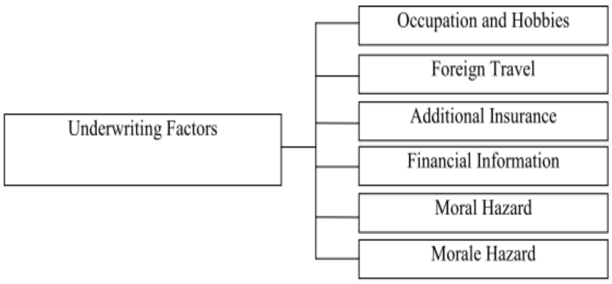

Fig.2. Shortlisted Underwriting Factors

Due to s of the attributes having two levels, the total number of possible combinations is 2^6 = 64 alternatives (stimuli). This is far too many possible combinations to be evaluated by any decision maker. Therefore, we had to construct a design of the inquiry that defined a restricted set of stimuli to be considered and the pairs of these stimuli to be compared.

Starting with a basic orthogonal plan generated by Addelman [30], 8 stimuli were determined (see Table 6). Using the stimuli of the orthogonal array, a difference design was constructed by a randomized procedure following the principles given by Hausruckinger & Herker [31].

Table 6: Attribute Level and Orthogonal Plan Card of Underwriting Factors

Factors	**Attribute Level**				**Card No.**							
					1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Occupation and Hobbies	1	Security	0	Danger	0	1	1	0	1	1	0	0
Foreign Travel	1	Rare	0	Usually	0	0	1	0	1	0	1	1
Additional Insurance	1	No	0	Yes	0	1	0	1	1	0	1	0
Financial Information	1	Good	0	Bad	1	0	1	1	1	0	0	0
Moral Hazard	1	Low	0	High	1	1	0	0	1	0	0	1
Morale Hazard	1	Low	0	High	0	0	0	1	1	1	0	1

The CA questionnaire was developed on the basis of some of the literature, planned with an orthogonal design, and distributed to 6 experts. 6 questionnaires were completed in the survey.

According to the CA report (see Table 7), the most important factor was financial information (relative importance = 20.200 %), the second most important factor was moral hazard (relative importance = 19.202 %) and the third most important factor was morale hazard (relative importance = 18.204 %).

Table 7: Relative Importance of Underwriting Factors

Factors	Variable		Part-Worth Utility	Relative Importance
Occupation and Hobbies	1	Security	0.267	0.11097
	0	Danger	0.000	
Foreign Travel	1	Rare	0.340	0.14131
	0	Usually	0.000	
Additional Insurance	1	No	0.413	0.17165
	0	Yes	0.000	
Financial Information	1	Good	0.486	0.20200
	0	Bad	0.000	
Moral Hazard	1	Low	0.462	0.19202
	0	High	0.000	
Morale Hazard	1	Low	0.438	0.18204
	0	High	0.000	
Total Utility			2.406	

V. Conclusions and Recommendations

As a result of the growing amount of information that is posted to social media networking sites, underwriting professionals, and the experts they engage, have discovered that social media can be a useful investigative tool for conducting research and uncovering relevant information on underwriting. Data derived from social media sites can serve to provide further confirmation of the information filled in an insurance application form, thereby assisting underwriting professionals to develop a proper social media underwriting guideline. The impact and influence of social media on underwriting handling, fraud preventing, and adverse selection avoiding cannot be ignored.

Life insurance underwriters prefer non-physical factors to physical factors searched on the social media networking sites. This is because most of the physical factors are declarations and required to fill in the application form. Therefore, this kind of physical factor is not necessary to be searched by underwriters on the social media networking sites. Moreover, through studying a body examination report, underwriters can indentify insured's physical condition and then makes the underwriting decision.

The non-physical factors, such as financial information, moral hazard, and morale hazard, are not required items to fill in the application form, but very important for underwriters to make underwriting decision accordingly. In order to improve underwriting profit, underwriters hope to search more information related to non-physical factors on the social media networking sites.

Financial Information, Moral Hazard, and Morale Hazard are the most three useful factors that underwriters want to search on the social media networking sites. On the other hand, age, gender, and physical condition are the factors that seldom need be identified by underwriters through social media networking searching. If underwriters want to search the useful information related to Financial Information, Moral Hazard, and Morale Hazard, the social media data type of "social graph" is the best choice. This is because "social graph" shows how individuals are linked together, providing a picture of who is friends with whom, who follows whom, and people's friends of friends. In other words, social graphs can give underwriters further insight into how an individual may perform in terms of risk based on the behavior of those to whom he or she is connected.

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