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Exploring Users' Self-Disclosure Intention on Social Networking Applying Novel Soft Computing Theories

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Abstract: In recent years, users have increasingly focused on the privacy of social networking sites (SNS); users have reduced their self-disclosure intention. To attract users, SNS rely on active platforms that collect accurate user information, even though that information is supposed to be private. SNS marketers must understand the key elements for sustainable operation. This study aims to understand the influence of motivation (extrinsic and intrinsic) and self-disclosure on SNS through soft computing theories. First, based on a survey of 1108 users of SNS, this study used a dominance-based rough set approach to determine decision rules for self-disclosure intention on SNS. In addition, based on 11 social networking industry experts' perspectives, this study validated the influence between the motivation attributes by using Decision-Making Trial and Evaluation Laboratory (DEMATEL). In this paper, the decision rules of users' self-disclosure preference are presented, and the influences between motivation attributes are graphically depicted as a flow network graph. These findings can assist in addressing real-world decision problems, and can aid SNS marketers in anticipating, evaluating, and acting in accord with the self-disclosure motivations of SNS users. In this paper, practical and research implications are offered.

Keywords: social networking sites; self-disclosure; DRSA (dominance-based rough set approach); DEMATEL (Decision-Making Trial and Evaluation Laboratory); flow network graph

1. Introduction

Social networking sites (SNS) are popular multimedia communication channels that collect user profiles; registered members can use their profiles to share information or express opinions and attitudes [1]. Nowadays, websites such as Facebook are at the forefront of online social networking, attracting more than two billion monthly active users. Because of the increasing importance of SNS, several organizations have begun to manage their SNS to build relationships with users, promote services, improve communication, and stimulate users to share real information. Based on the shared details, personalized advertisements are presented to the users [2]. However, in 2018, the Facebook–Cambridge Analytica data scandal (which involved nearly a million users' personally identifiable information) reduced users' willingness to share personal information. Because personal

privacy is a crucial factor of self-disclosure behaviors on SNS, SNS managers should carefully formulate strategies encouraging users to provide accurate information about themselves on SNS [3,4].

Notably, SNS required to launch new services continues to increase involvement at a substantial pace for competitiveness. This is primarily because users demand more functions, entertainment, and better quality new service. In addition, the dramatic growth in popularity on SNS has promoted the advent of many new SNS. To sustain development becomes an important issue for SNS marketers. Prior studies have discussed SNS business sustainability, such as sustainable development of online communities [5], attitudes expressed in online comments of the hotel industry [6,7] and big social network data of sustainable development [8]. The results show that managers who succeed in understanding users' characteristics can improve business sustainability.

Self-disclosure intention is defined as the degree of willingness to distribute an individual's private information through a specific medium [9]. In social media, motivation plays an essential role in influencing consumer actions [10]. Motivation can be divided into extrinsic and intrinsic motivation [11]. Extrinsic motivation is driven by several attributes of wealth, fame, and image, which emphasize the individual's desire for external rewards; intrinsic motivation is driven by several attributes of self-esteem, personal growth, community feeling, self-directed pleasure, and relatedness, which emphasize the individual's desire for inherent qualities [12,13]. Numerous studies of self-disclosure have measured motivation on SNS [14–16]. The size and growth of the Internet has attracted increasing research for addressing prestige related to self-disclosure on SNS. However, compared with other research sectors, few studies are available regarding the application of a systemic decision model in SNS.

The main concerns in application of a systemic decision model are as follows: (1) What motivation influences users' self-disclosure intention on SNS? (2) What is the relationship between extrinsic and intrinsic motivation attributes? (3) What are the key extrinsic and intrinsic motivation attributes that influence users' self-disclosure intention on SNS? To gain new insights regarding self-disclosure, this research presents a multiple criteria decision-making (MCDM) model by using soft computing theories to examine the key attributes of extrinsic and intrinsic motivation to understand how the predictors influence users' self-disclosure on SNS. Some published studies have concluded that application of MCDM for business sustainability can have implications for marketers [17]. However, such studies have adopted either secondary data or domain experts' experience, or both [18,19], rather than user psychology data.

Thus, to extend the application area, we collected user psychology data through a questionnaire and then applied a dominance-based rough set approach (DRSA) to infer decision rules from the preference orderings of attributes [20]. These decision rules have the form: *if* (premise) *then* (decision) [21]. Hence, data mining the questionnaires to examine the attributes may explain users' self-disclosure preferences.

Through collection of user psychology data using a similar survey of a questionnaire, SNS marketers can better understand the attributes influencing self-disclosure. However, marketers would not have a clear conception of the relationship between attributes for strategic decision making. Therefore, the next step involves applying decision-making trial and evaluation laboratory (DEMATEL) to evaluate the relationships between the attributes from the domain experts' perspective to enhance our understanding of complex systems.

Although the decision rules derived through DRSA and the relationships between attributes established through DEMATEL can be directly translated into a path dependency graph [14], most studies have not yet adequately translated the users' and experts' perspectives into a diagram. A flow network graph is easy for SNS marketers to understand and depicts the main attributes and relationships between the attributes simultaneously. Hence, this study applied a flow network graph to present the results.

Building an effective model to improve users' self-disclosure on SNS has become a vital aspect of SNS survival in today's competitive environment. Therefore, unlike prior studies focusing

on statistical hypotheses to understand the relationship between motivation and self-disclosure, this study constructed a cause-and-effect model. This study explains the extrinsic (wealth, fame, and image) and intrinsic motivations (self-esteem, personal growth, community feeling, self-directed pleasure, and relatedness) of self-disclosure on SNS by combining the DRSA, DEMATEL, and a flow network graph.

The remainder of this paper is organized as follows. Section 2 introduces some soft computing theories. Section 3 illustrates an empirical example of SNS to demonstrate the proposed methods. Finally, Section 4 presents conclusions and remarks.

2. Literature Review

2.1. Motivation for Self-Disclosure Intention on Social Networking Sites

Social networking sites (SNSs) provide a user-friendly platform that involves collecting and communicating considerable amounts of information by encouraging users to disclose details about themselves [22]. “Disclosure” refers to revealing some form of private and protected information to the public [23]. Although some researchers define disclosure to be identical to self-disclosure [24], self-disclosure can be more specifically defined as voluntary and intentional disclosure of personal information [25]. Numerous studies have provided evidence that users’ self-disclosure intention on SNSs are driven by several benefits, including building new relationships [26], social capital [27], need for affiliation [28], enjoyment [26] and entertainment [14]. Moreover, SNSs are been deemed as an entertainment media or tools for killing time [29], which satisfy their users’ need to establish and manage online relationships with family, friends, or strangers [30]. Thus, to probe self-disclosure intentions on SNS, marketers must understand methods to continually drive users’ motivation.

Motivation is crucial in encouraging users toward intentional self-disclosure on SNSs [22]. Studies have classified motivation into extrinsic and intrinsic motivation [11]. Extrinsic motivation involves engaging in an activity leading to some separate consequence. For instance, extrinsically motivated behaviors are those performed to obtain a substantial reward or to avoid a punishment [31]. Extrinsic motivation is generally referred to as the motivation keeping individuals at a task through the application of external rewards [12]. In addition to rewards, the elements of extrinsic motivation include sanctions, praise, feedback, and obtaining good grades [32]. By contrast, intrinsic motivation involves embarking on an interesting and satisfying behavior. When intrinsic motivation occurs, performance engenders positive feelings. People are interested in what they are doing and are curious to explore novel stimuli and undertake challenges [31]. Intrinsic motivation is generally referred to as the motivation enabling individuals to persevere with a task through the inherent qualities of that task [12]. Furthermore, the elements of intrinsic motivation include being involved in an enthusiastic task, desiring to experience adventure, attempting to understand something and wishing to improve, and moving toward a goal [33].

2.2. Soft Computing Theories for Sustainability

Most studies of self-disclosure on SNS adopted statistical methods to examine the assumption for finding the positively or negatively relationship among variables (or attributes). However, by the results from probabilistic or regression, it is hard for the decision maker to understand the real relationship among attributes, especially those variables in real-world problems which are hard totally independent [20]. Therefore, using soft computing theories to consider relevant and interrelated attributes is more practical [34].

The foremost key factor for competitiveness in the SNS industry is the ability to attract and keep users with low cost. Based on limited resources when making decisions, prior studies have concluded that soft computing theory is an effective method for sustainability related subjects. For instance, soft computing theory has been applied on improving service quality [20], financial performance [35] and R&D performance [19] to pursue sustainability. Additionally, to solve practical problems in a rapid

change market in a more natural way, soft computing theories are usually combined or integrated for identifying the interrelationship among attributes [36] or improving the alternative on hand [18].

Dominance-based rough set approach (DRSA) is an extension of the rough set theory (RST) based on the dominance principle, which incorporates the ordinal nature of the preference data into the classification problem [37]. The DRSA derives a set of decision rules from preference-ordered data [38] that are then used in a classifier [39]. Recently, DRSA has been applied to solve practice problems in marketing [20], group decision [40] or finance [41].

Studies have combined RST (or DRSA) and a flow network graph to directly translate the decision rules in a more natural way for marketers to easy understand [42,43]. However, the main restriction of this combined method is that the decision rules by RST (or DRSA) just can present the relationship between the condition attributes and decision attributes, rather than presenting the relationship among condition attributes. Thus, the result of the flow network graph hardly shows the cause-and-effect among condition attributes. To fill this gap, recently studies have added decision-making trial and evaluation laboratory (DEMATEL) to this combined method to evaluate the influence among attributes [43].

3. Relevant Soft Computing Theories

To understand the influence of extrinsic and intrinsic motivation on the users' self-disclosure intention on SNS, this study applied DRSA to infer decision rules from preference-ordered data, then adopted DEMATEL to examine the relationships between motivation attributes, and finally used a flow network graph to depict the results as a diagram. This section reviews some relevant soft computing theories.

3.1. The Dominance-Based Rough Set Approach

Step 1: Construct the information system to the survey

DRSA is derived from classical rough set theory; DRSA infers decision rules from the preference orderings of attributes. The preference orderings of attributes use an ordered information system $IS = (U, Q, V, f)$, where U is a finite set representing the universe of discourse (i.e., the participants in the survey); $Q = \{a_1, a_2, \dots, a_m\}$ is a finite set of ordered attributes, which is further divided into C (condition attributes, i.e., extrinsic and intrinsic motivation in this study) and D (decision attributes, i.e., self-disclosure intention in this study); V_a is the value domain of attribute a , where $f : U \times Q \rightarrow V$ is the total information function, in which $f : U \times Q \rightarrow V$ for every $a \in Q$ and $x \in U$ [16]. The first empirical step is to construct the information system by completing a questionnaire.

Step 2: Approximation of the dominance relation

In approximation, first, $\geq_a$ indicates an outranking relation on set U regarding to some criterion for each $a \in Q$ (i.e., $x \geq_a y$ denotes that x is at least not worse than y on attribute a). Here, $Cl = \{Cl_t, t = 1, \dots, t\}$ is defined as a set of decision classes of U . Assuming that for all $r, s \in T$, $r > s$ indicates that $Cl_r > Cl_s$. Then, upward and downward unions of classes are defined as follows:

$$Cl_t^{\geq} = \bigcup_{s \geq t} Cl_s, Cl_t^{\leq} = \bigcup_{s \leq t} Cl_s, t = 1, \dots, n \quad (1)$$

In addition, for the preference-ordered condition attributes, the knowledge to be approximated uses a dominance relation instead of indiscernibility. In this case, $D_p^+(x) = \{y \in U : y \geq x\}$ and $D_p^-(x) = \{y \in U : y \leq x\}$ represent sets of objects dominating or being dominated by x respectively.

The P -lower of $\underline{P}(Cl_t^{\geq})$ can be defined as $\underline{P}(Cl_t^{\geq}) = \{x \in U : D_p^+(x) \subseteq Cl_t^{\geq}\}$ for $t \in \{2, 3, \dots, n\}$, and similarly the P -upper of $\overline{P}(Cl_t^{\geq})$ can be defined as $\overline{P}(Cl_t^{\geq}) = \{x \in U : D_p^-(x) \cap Cl_t^{\geq} \neq \emptyset\}$ for $t \in \{1, 2, \dots, n\}$ with the P -boundaries of $Cl_t^{\geq}$ defined as $Bn_p(Cl_t^{\geq}) = \overline{P}(Cl_t^{\geq}) - \underline{P}(Cl_t^{\geq})$ and the P -boundaries of $Cl_t^{\leq}$ defined as $Bn_p(Cl_t^{\leq}) = \overline{P}(Cl_t^{\leq}) - \underline{P}(Cl_t^{\leq})$.

With each set of $P \subseteq U$, the approximation of $Cl_t^{\geq}$ and $Cl_t^{\leq}$ can be estimated with the following expression:

$$\alpha_P(Cl_t^{\geq}) = \left| \frac{P(Cl_t^{\geq})}{\overline{P}(Cl_t^{\geq})} \right| \quad \alpha_P(Cl_t^{\leq}) = \left| \frac{P(Cl_t^{\leq})}{\overline{P}(Cl_t^{\leq})} \right| \quad (2)$$

The quality of approximation of classification (or the quality of classification) Cl by the set of attributes P is called $\gamma_P(Cl)$. The quality of classification indicates the ratio of all of the P -correctly classified objects (i.e., the ratio of all of the non-ambiguous participants to all of the participants in the system).

Step 3: Extraction of the decision rules

The end result of the DRSA is to infer significant information in the considered information system. The decision table is a deterministic or exact decision rule expressed logically in the form: *if* (premise) *then* (decision). There are two types of decision rules:

- (1) The “at least decision rule” is supported only by objects from P -lower approximations of the upward unions of classes $Cl_t^{\geq}$, using the following expression: *If* $f(x, a_1) \geq r_{a_1}$ and $f(x, a_2) \geq r_{a_2}$ and ... $f(x, a_p) \geq r_{a_p}$, *then* $x \in Cl_t^{\geq}$.
- (2) The “at most” decision rule” is supported only by objects from P -lower approximations of the upward unions of classes $Cl_t^{\leq}$, using the following expression: *If* $f(x, a_1) \leq r_{a_1}$ and $f(x, a_2) \leq r_{a_2}$ and ... $f(x, a_p) \leq r_{a_p}$, *then* $x \in Cl_t^{\leq}$.

In general, the decision rule reflects a relationship between a set of conditions attributes and a decision attribute. Hence, in this study, the decision rules were generated based on upper and lower approximations extracted from the information system by using dominance relations.

3.2. DEMATEL

DEMATEL can analyze complicated cause-and-effect societal problems between dimensions and attributes. The results of these analyses can be used verifying independence and finding influence relationships [44]. To deal with the ambiguities of SNS user psychology, this study evaluated user preferences regarding the extrinsic and intrinsic motivation attributes by using DEMATEL. This methodology can be summarized as follows:

Step 4: Calculate the direct-influence matrix

First, each expert was asked to indicate the direct effects they believed attribute i exerted on attribute j , as indicated by a_{ij} , with a scale from 0 (no influence) to 4 (very high influence), and then an average matrix A was produced from Equation (3). In matrix A , each element was the mean of the same elements in the experts’ various direct matrices.

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & & \vdots & & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & & \vdots & & \vdots \\ a_{n1} & \cdots & a_{nj} & \cdots & a_{nn} \end{bmatrix} \quad (3)$$

Step 5: Calculate the normalize matrix

The initial direct influence matrix M was obtained by normalizing the average matrix A . Specifically, the matrix M can be calculated through Equations (4) and (5), in which all the principal diagonal attributes are equal to zero, and constant s could be normalized for matrix A .

$$M = s \times A \quad (4)$$

$$s = \text{Min} \left[\frac{1}{\max_{1 \leq i \leq n} \sum_{j=1}^n |a_{ij}|}, \frac{1}{\max_{1 \leq j \leq n} \sum_{i=1}^n |a_{ij}|} \right], ij \in \{1, 2, \dots, n\} \quad (5)$$

Step 6: Total influence relation matrix

After the normalized direct relation matrix has been calculated, I denotes the identity matrix in the total influence matrix T . As a result of continuous decrease in the indirect effects of problems along the powers of M , the total influence relation matrix T can be calculated through Equation (6):

$$\begin{aligned} T &= M + M^2 + \dots + M^K = M(I - M^K)(I - M)^{-1}, \text{ and} \\ T &= M(I - M)^{-1} \text{ where } k \rightarrow \infty, \quad M = [0]_{n \times n} \end{aligned} \quad (6)$$

Step 7: The cause-and-effect relationships of attributes

According to Equation (6), we derive r and c from row and column sums within the total relation matrix T as:

$$r = [r_i]_{n \times 1} = \left(\sum_{j=1}^n t_{ij} \right)_{n \times 1} \quad (7)$$

$$c = [c_j]_{n \times 1} = \left(\sum_{i=1}^n t_{ij} \right)_{1 \times n} \quad (8)$$

Furthermore, when $i = j$ and $i, j \in \{1, 2, \dots, n\}$, the sum $(r_i + c_j)$ indicates the index of the degree of influences given and received by the attribute i . Similarly, $(r_i - c_j)$ denotes the net effect that the attribute i contributes to the system. If $(r_i - c_j)$ is positive, then the attribute i primarily influences the strength of some other attribute; on the contrary, if $(r_i - c_j)$ is negative, then the attribute i primarily is a net receiver. Therefore, in this study, the cause-and-effect influence between the extrinsic and intrinsic motivation attributes is analyzed using DEMATEL to produce a flow networking graph.

3.3. The Flow Network Graph

Step 8: The cause-and-effect of decision rules based on the flow network graph

Flow network graphs can describe the nature of decision processes. In addition, a flow network graph is an excellent tool to describe the decision rules and the relationships between the attributes [42,43]. With a flow network graph and decision rules of user self-disclosure intention characteristics, this research derived a cause-and-effect path-dependent figure. The resultant figure depends on the rules and relationships between attributes of self-disclosure intention potential.

4. The Empirical Example of Facebook

Facebook, a free social network site, has gained more than two billion monthly global active users, among whom university students are especially well represented (Facebook Statistics). Facebook has various functions that enable individuals to disclose personal information, such as posting personal anecdotes, sharing new information, and connecting acquaintances. In this section, we build a novel model by combining the DRSA, DEMATEL, and a flow network graph of self-disclosure on Facebook. The results confirm the influence of extrinsic and intrinsic motivations on the intention to disclose private information on Facebook. The proposed approach was successfully employed in this academic empirical study. The conceptual framework of this study is illustrated in Figure 1.

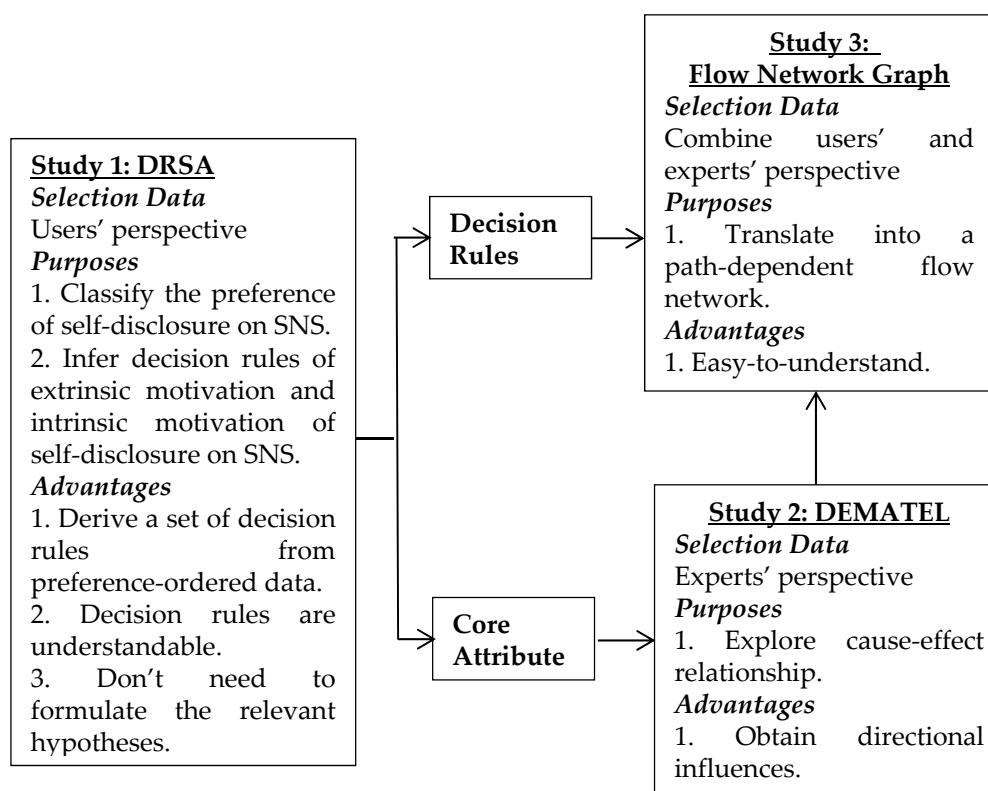


Figure 1. Conceptual framework of the proposed approach.

4.1. Rules for Self-Disclosure Intention on SNS

In this study, a total of 1108 students and faculty members from three universities in Northern Taiwan participated in a survey and completed a questionnaire pertaining to their self-disclosure intention on SNS. Within the sample population, by gender, 585 (52.8%) were female and 523 (47.2%) were male; by occupation, 786 (70.9%) (age from 18 to 22 years) were students and 322 (29.1%) (age from 30 to 60) were faculty.

The condition attributes of extrinsic motivation (wealth, fame and image) and intrinsic motivation (self-esteem, personal growth, community feeling, self-directed pleasure, and relatedness) were measured through a scale in which each motivation had three items; participants rated the degree to which they were motivated to disclose personal information on SNS. Furthermore, the self-disclosure intention decision attribute was posed to the participants using three scales. We measured all these condition attributes and decision attributes with five-point Likert scales (ranging from 1 = completely disagree to 5 = completely agree). The domain values and the definitions of these attributes are shown in Table 1.

JAMM software was used to infer the decision rules. Accuracy and quality of classification were calculated for the objects in the information system. This study classified objects into four classes: at most 3, at most 4, at least 4, and at least 5. The accuracy values of the classification were 0.94, 0.98, 0.99, and 0.96. The accuracy results indicated that most objects in this information system were correctly classified. The overall quality of approximation was 0.97; extrinsic and intrinsic motivations had considerable influence on self-disclosure intention. The results of accuracy and quality of classification are shown in Table 2.

Table 1. Attribute specification for self-disclosure intention on social networking sites (SNS).

Attribute Name	Attribute Values	Preference	Brief Explanations
Condition Attributes			
Extrinsic motivation			
Wealth (a_1)	1: Completely disagree; 2: Disagree; 3: Neutral; 4: Agree; 5: Completely agree	Ordered	It represents individuals attain wealth and material success.
Fame (a_2)			It represents individuals been recognized in the society.
Image (a_3)			It represents individuals have an attractive viewing.
Intrinsic motivation			
Self-esteem (a_4)	1: Completely disagree; 2: Disagree; 3: Neutral; 4: Agree; 5: Completely agree	Ordered	It represents individuals have a subjective self-assessment which reflect on the attitude.
Personal growth (a_5)			It represents individuals achieve psychological growth, autonomy, and self-regard.
Community feeling (a_6)			It represents individuals can improve the world through activism.
Self-directed pleasure (a_7)			It represents individuals' satisfied needs with which they can please themselves.
Relatedness (a_8)			It represents individuals have satisfying relationships with family and friends.
Decision Attributes			
Self-disclosure intention (d_1)	1: Completely disagree; 2: Disagree; 3: Neutral; 4: Agree; 5: Completely agree	Ordered	

Table 2. Accuracy of classification and quality of classification.

Self-Disclosure Intention	Numbers of Objects	Lower Approximation	Upper Approximation	Accuracy of Classification	Quality of Classification
d_1	-	-	-	-	0.97
At most 3 ($d_1 \leq 3$)	282	273	291	0.94	-
At most 4 ($d_1 \leq 4$)	566	559	573	0.98	-
At least 4 ($d_1 \geq 4$)	826	820	826	0.99	
At least 5 ($d_1 \geq 5$)	542	531	553	0.96	

In addition, this study applied a “minimum cover rules” approach to generate a total of 37 decision rules. To improve the importance of decision rules, this study assumed a threshold value of 100 for each decision class; thus, the reduced rule set only considered 6 rules, as illustrated in Table 3.

Table 3. Rules on the self-disclosure intention on SNS.

Rules	Decision	Support	Certainty	Strength	Coverage
The user has self-disclosure intention on SNS ($d_1 \geq 4$)					
1	$(a_1 \geq 4) \& (a_3 \geq 4) \& (a_7 \geq 4) \& (a_8 \geq 4)$	$d_1 \geq 4$	430	1	0.39
2	$(a_2 \geq 4) \& (a_6 \geq 4) \& (a_8 \geq 4)$	$d_1 \geq 4$	332	1	0.30
3	$(a_4 \geq 4) \& (a_7 \geq 4) \& (a_8 \geq 4)$	$d_1 \geq 4$	174	1	0.16
4	$(a_2 \geq 4) \& (a_7 \geq 4)$	$d_1 \geq 4$	147	1	0.13
The user has no or weak self-disclosure intention on SNS ($d_1 \leq 3$)					
1	$(a_3 \leq 3) \& (a_8 \leq 3)$	$d_1 \leq 3$	416	1	0.38
2	$(a_2 \leq 3) \& (a_7 \leq 3)$	$d_1 \leq 3$	174	1	0.16

As Table 3 demonstrates, the top ranking frequencies attributes were self-directed pleasure (a_7) (4 times), relatedness (a_8) (4 times), and Fame (a_2) (2 times). These attributes possessed high importance and could influence users’ self-intention on SNS more than other attributes. Given these classes of rules, SNS marketers could formulate marketing strategies based on at least 4 classes (Rules 1 to 4). The results indicate that if SNS marketers wish to increase user self-disclosure intention, they must achieve a rating of four or better on extrinsic and intrinsic motivation. In addition, the support of a rule corresponds to the number of surveyed participants supporting that rule. Because Rule 1 had higher support than did Rule 2, SNS marketers should work to satisfy the conditions in Rule 1 before working on Rule 2.

4.2. The Influence of Dimensions and Attributes of Motivation

To analyze the relationships between extrinsic and intrinsic motivations, we invited 11 experts from various social networking industry domains for a face-to-face questionnaire interview. Every expert had extensive knowledge and solid work experience in social networking. In the interviews, we requested the experts to rate the influences of dimensions and attributes by using scales (ranging from 0 = no influence to 4 = very high influence). Moreover, the experts’ perspectives and the levels of their portfolio offerings were noted. The completed questionnaires used for statistical analysis demonstrated that each of these industrial practitioners had more than five years of administrative experience in social networking.

DEMATEL was utilized in the decision problem formulation. We evaluated two dimensions and eight attributes. The DEMATEL results are presented in Appendix A. The influences between dimensions and attributes are shown in Tables 4 and 5.

In Table 4, the results demonstrate that extrinsic motivation ($r_i - c_j$) = 1 was a positively-affected dimension, and intrinsic motivation ($r_i - c_j$) = −1 was a negatively-affected dimension. In Table 5, by observing ($r_i + c_j$) values, we discover that relatedness (a_8) ($r_i + c_j$ = 7.212) was the most critical criterion, whereas wealth (a_1) ($r_i + c_j$ = 5.73) was the least important criterion. Furthermore, by observing ($r_i - c_j$) values, between all factors in the cause attributes, wealth (a_1) has the highest value ($r_i - c_j$ = 0.876). By contrast, relatedness (a_8) ($r_i - c_j$ = −1.006) was the smallest value between the effect attributes. This suggests that relatedness (a_8) is minimally affected by other factors.

Table 4. Directional influences between dimensions.

Dimension	r_i	c_j	$(r_i + c_j)$	$(r_i - c_j)$
Extrinsic motivation (d_1)	45	44	89	1
Intrinsic motivation (d_2)	44	45	89	−1

Table 5. Directional influences among attributes.

Attributes	r_i	c_j	$(r_i + c_j)$	$(r_i - c_j)$
Wealth (a_1)	3.303	2.427	5.73	0.876
Fame (a_2)	3.443	2.888	6.331	0.555
Image (a_3)	3.557	3.447	7.004	0.11
Self-esteem (a_4)	3.149	3.369	6.518	−0.22
Personal growth (a_5)	3.08	2.979	6.059	0.101
Community feeling (a_6)	3.072	3.104	6.176	−0.032
Self-direct pleasure (a_7)	3.146	3.53	6.676	−0.384
Relatedness (a_8)	3.103	4.109	7.212	−1.006

4.3. The Cause-and-Effect Flow Network Graph of Self-Disclosure on SNS

To further interpret the decision rules in Table 3 and study the influences of dimensions and attributes listed in Tables 4 and 5, this study used a flow network graph to illustrate the cause-and-effect relationship between motivation and self-disclosure intention as depicted in Figure 2. Extrinsic motivation had a positive influence on intrinsic motivation and the attributes on the left influenced those on the right. This flow network graph is easy for SNS-related marketers to understand.

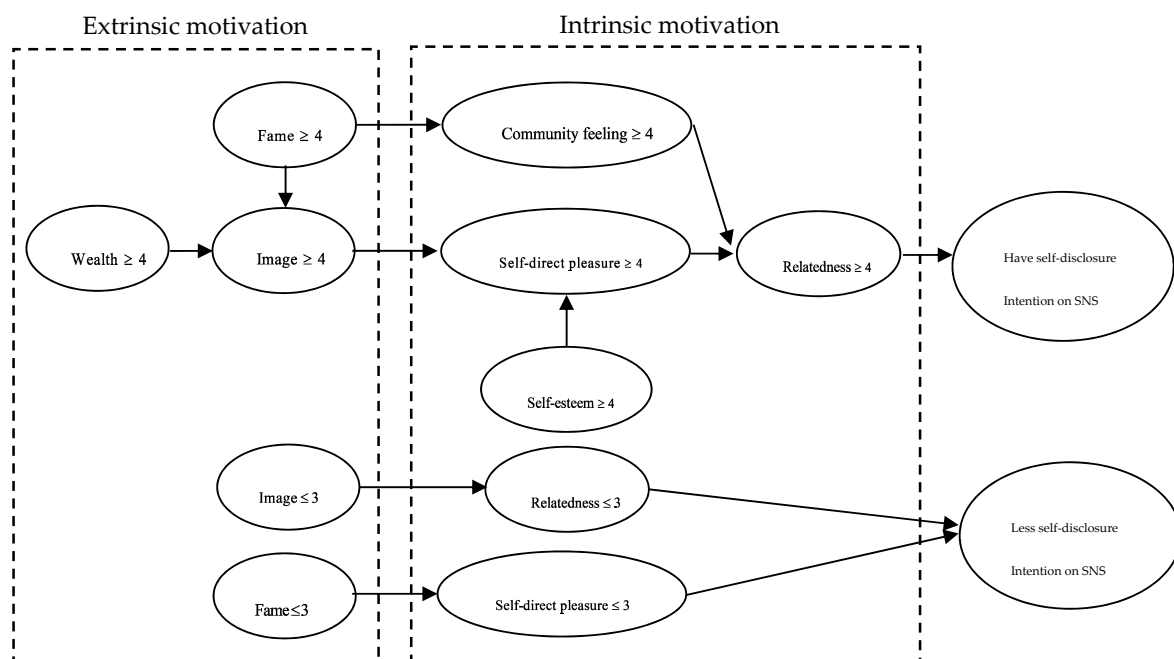


Figure 2. Flow network graph based on the rules for the user has or weak self-disclosure intention on SNS.

5. Discussions Managerial Implications and Concluding Remarks

5.1. Implications For Marketers

The results of this study have implications for marketers. As mentioned previously, motivation plays an important role in self-disclosure on SNS. This study draws several conclusions.

First, unlike numerous empirical studies that have confirmed that motivation is conducive to self-disclosure and have formulated relevant hypotheses regarding the relationship, this study applied DRSA, a data mining technique, to infer decision rules from the users' perspectives. Our findings elucidate that self-directed pleasure, relatedness, and fame are highly associated with self-disclosure intention on SNS. These findings support the argument that enjoyment, relationship [26] and social capital [27] would positively affect self-disclosure on SNS. Thus, SNS marketers must be explicitly aware that those motivation attributes act as a catalyst for improving self-disclosure intention.

Second, the main contribution of the study is the identification of the influence of dimensions and attributes of motivation by DEMATEL. To the best of our knowledge, this study represents the first effort to identify a relationship between extrinsic and intrinsic motivation attributes. The result shows that extrinsic motivation has a positive influence on intrinsic motivation. Prior empirical research also indicated that extrinsic motivation induced greater willingness to share information on SNS [45,46]. In addition, the results suggest that the eight attributes can be divided into a cause group and an effect group. The cause group consists of wealth, fame, image, and personal growth. The effect group includes self-esteem, community feeling, self-directed pleasure, and relatedness. The cause-and-effect structure implies that the cause group has the main core attributes for attracting self-disclosure intentions in users on SNS.

Then, in addition to extrinsic and intrinsic motivation, demographics might also impact self-disclosure. By the survey, our findings are in accord with [22] who concluded that age and gender have no significant role or difference in self-disclosure on SNS. Although, prior studies showed that younger users have more self-disclosure on computer-mediated communication [47], and males have more self-disclosure intention than females on SNS [29]. A plausible explanation for these findings is that there is no gender or age difference on the SNS environment, such as Facebook, where users are just being themselves.

Finally, from a practical viewpoint, this study offers guidance on how motivation influences self-disclosure intention on SNS and provides useful information by a flow network graph. Our findings suggest that on SNS, if users possess a crucial concern for extrinsic–intrinsic motivation, then they must have considerable self-disclosure intention. In addition, extrinsic motivation has a positive influence on intrinsic motivation that can lead to self-disclosure intention. Therefore, users' extrinsic motivations should be SNS marketers' first priorities.

5.2. Implications for Academics

Past studies have seldom combined DRSA, DEMATEL, and flow network graph by using questionnaire data to predict self-disclosure intention on SNS [14,22,23,29]. Thus, this research presents a new approach by using soft computing theory to identify self-disclosure decision rules. The advantages of combining soft theories for motivations are summarized in two points. The first point is that SNS marketers can discover hidden information regarding extrinsic and intrinsic motivations and predict and act on the new information arising from the scale information. The second point is that the model's ability to capture the influence of extrinsic and intrinsic motivations on behavioral intentions and turn that information into useful marketing strategies would be appreciated and should eventually improve users' self-disclosure intention on SNS.

The results of this study should be interpreted with caution because of certain limitations. First, we built the information system by completing a questionnaire from only 1108 participants, which limited our ability to make causal predictions. Therefore, SNS-related marketers could build a larger database to infer more accurate and meaningful decision rules, and increase correctness in the results. Second, we applied soft computing theories, such as DRSA, DEMATEL, and flow network graph, to understand the relationship between motivation and self-disclosure. Future studies could adopt similar theories to fill the gap between users' and experts' perspective.

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Appendix

Refer to Step 4 to 6, an average matrix A , direct relation matrix M , indirect relation matrix N and indirect influence matrix T of dimensions and attributes can be produced in Equations (3)–(6) respectively. The results are shown as Tables A1–A8.

Table A1. Initial average matrix A of dimension.

Dimension	Extrinsic Motivation	Intrinsic Motivation	Sum
Extrinsic motivation	0	2.706	0
Intrinsic motivation	2.588	0	2.588
Sum	0	2.706	2.706

Table A2. Direct relation matrix M of dimension.

Dimension	Extrinsic Motivation	Intrinsic Motivation	Sum
Extrinsic motivation	0	1	1
Intrinsic motivation	0.957	0	0.957
Sum	0.957	1	-

Table A3. Indirect relation matrix N of dimension.

Dimension	Extrinsic Motivation	Intrinsic Motivation
Extrinsic motivation	23	23
Intrinsic motivation	22	23

Table A4. Total influence matrix T of dimension.

Dimension	Extrinsic Motivation	Intrinsic Motivation	r_i
Extrinsic motivation	22	23	45
Intrinsic motivation	22	22	44
c_j	44	45	

Table A5. Initial average matrix *A* of attributes.

Attributes	Wealth	Fame	Image	Self-Esteem	Personal Growth	Community Feeling	Self-Direct Pleasure	Relatedness	Sum
Wealth	0	2.294	2.706	2.059	1.765	1.941	2.471	3.118	16.354
Fame	1.882	0	3	2.176	1.882	2.412	2.824	2.941	17.117
Image	1.882	2.588	0	2.471	2.294	2.588	2.765	3.235	17.823
Self-esteem	1.412	1.765	2.412	0	2.059	2.059	2.647	3.235	15.589
Personal growth	1.471	1.765	2.176	2.412	0	2.353	2.235	2.824	15.236
Community feeling	1.588	2.176	2.353	2.235	2.059	0	2	2.706	15.117
Self-direct pleasure	1.941	2.059	2.353	2.529	2	1.765	0	2.882	15.529
Relatedness	1.529	1.588	2.294	2.706	2.411	2.176	2.647	0	15.351
Sum	11.705	14.235	17.294	16.588	14.470	15.294	17.589	20.941	20.941

Table A6. Direct relation matrix *M* of attributes.

Attributes	Wealth	Fame	Image	Self-Esteem	Personal Growth	Community Feeling	Self-Direct Pleasure	Relatedness	Sum
Wealth	0	0.110	0.129	0.098	0.084	0.093	0.118	0.149	0.781
Fame	0.090	0	0.143	0.104	0.090	0.115	0.135	0.140	0.817
Image	0.090	0.124	0	0.118	0.110	0.124	0.132	0.154	0.852
Self-esteem	0.067	0.084	0.115	0	0.098	0.098	0.126	0.154	0.742
Personal growth	0.070	0.084	0.104	0.115	0	0.112	0.107	0.135	0.727
Community feeling	0.076	0.104	0.112	0.107	0.098	0	0.096	0.129	0.722
Self-direct pleasure	0.093	0.098	0.112	0.121	0.096	0.084	0	0.138	0.742
Relatedness	0.073	0.076	0.110	0.129	0.115	0.104	0.126	0	0.733
Sum	0.559	0.68	0.825	0.792	0.691	0.73	0.84	0.999	

Table A7. Indirect relation matrix N of dimension.

Attributes	Wealth	Fame	Image	Self-Esteem	Personal Growth	Community Feeling	Self-Direct Pleasure	Relatedness
Wealth	1.245	0.389	0.461	0.429	0.378	0.397	0.461	0.543
Fame	0.337	1.303	0.487	0.448	0.396	0.429	0.489	0.554
Image	0.345	0.422	1.373	0.471	0.422	0.446	0.499	0.579
Self-esteem	0.296	0.354	0.433	1.324	0.376	0.387	0.451	0.528
Personal growth	0.293	0.348	0.416	0.420	1.280	0.392	0.427	0.504
Community feeling	0.297	0.364	0.423	0.412	0.369	1.291	0.418	0.498
Self-direct pleasure	0.317	0.365	0.431	0.431	0.373	0.375	1.339	0.515
Relatedness	0.297	0.343	0.423	0.434	0.385	0.387	0.446	1.388

Table A8. Total influence matrix T of attributes.

Attributes	Wealth	Fame	Image	Self-Esteem	Personal Growth	Community Feeling	Self-Direct Pleasure	Relatedness	r_i
Wealth	0	2.294	2.706	2.059	1.765	1.941	2.471	3.118	16.354
Fame	1.882	0	3	2.176	1.882	2.412	2.824	2.941	17.117
Image	1.882	2.588	0	2.471	2.294	2.588	2.765	3.235	17.823
Self-esteem	1.412	1.765	2.412	0	2.059	2.059	2.647	3.235	15.589
Personal growth	1.471	1.765	2.176	2.412	0	2.353	2.235	2.824	15.236
Community feeling	1.588	2.176	2.353	2.235	2.059	0	2	2.706	15.117
Self-direct pleasure	1.941	2.059	2.353	2.529	2	1.765	0	2.882	15.529
Relatedness	1.529	1.588	2.294	2.706	2.411	2.176	2.647	0	15.351
c_j	11.705	14.235	17.294	16.588	14.470	15.294	17.589	20.941	20.941

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