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A factor-identifying study of the user-perceived value of collective intelligence based on online social networks

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Abstract

Purpose – An important issue for researchers and managers of organizations is the understanding of user-perceived values of collective intelligence (UPVoCI) in online social networks (OSNs) with the purpose of helping organizations identify the values that cause internet users and members of OSNs to share information and knowledge during they participate in collective intelligence (co-intelligence) activities. However, the development of measurement instruments and predictive models and rules for predicting UPVoCI are inadequate. The paper aims to discuss these issues.

Design/methodology/approach – A novel measurement scale was developed to measure UPVoCI using a user-oriented research strategy that is based on qualitative and quantitative research methods. This work also identified critical indicators and constructed predictive models and rules for forecasting UPVoCI by multivariate statistical methods and data mining.

Findings – A 17-item scale of UPVoCI was developed and 17 measurement items were associated with two major dimensions, which are the user-perceived social value of co-intelligence and the user-perceived problem-solving value of co-intelligence. Ten critical indicators of UPVoCI that are important in predicting UPVoCI and 12 rules for predicting UPVoCI were identified and a refined model for predicting UPVoCI was constructed.

Research limitations/implications – The results in this work allow organizations to determine the perceived value of members of OSNs and the benefits of their participating in co-intelligence activities, as a basis for adjusting user-oriented online co-intelligence and service strategies with the goal of improving collaborative innovation performance.

Originality/value – This work systematically developed a novel scale for measuring UPVoCI in OSNs and constructed new models and rules for predicting UPVoCI in OSNs.

Keywords Online social networks, Collective intelligence, User-perceived value

Paper type Research paper

1. Introduction

Online social media services allow customers and organizations conveniently to interact and share experiences with each other (Cheung and To, 2016). Recently, the deployment of collective intelligence (co-intelligence) to solve organizational problems, such as product and service quality problems, is an important internet strategy for companies. In 2015, only 1.8 percent of Fortune 500 corporations did not use any social media platform and up to 74 percent of corporations had a fan page on Facebook (Barnes *et al.*, 2015). These companies have recognized the need to focus on what customers want from a website; what they want to communicate consumers, and the potential role of a fan page in communicating messages.

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A major success factor of community-based innovation is to identify and motivate community members who are qualified to contribute to a specific development task (Chu and Chan, 2009). Mačiulienė and Skaržauskienė (2016) revealed that an online community has a greater potential for the emergence of co-intelligence when managers create appropriate mechanisms to motivate the participants of the online community, and when a balance exists between the participants' goals and the community's goals. Therefore, the use of online social networks (OSNs) (such as Facebook fan pages) to connect with consumers and to strengthen their identification with companies and participation in co-intelligence activities to generate value through collaborative innovation is important for companies. The internet user-perceived value of collective intelligence (UPVoCI) affects his or her intention to participate in co-intelligence activities for the purposes of collaborative innovation in OSNs. However, the development of instruments for measuring UPVoCI does not suffice for the academic determination of the perceived value of participating in co-intelligence activities to internet users and members of an OSN.

What causes an internet user to be open to sharing his/her intelligence, including information and knowledge, with others in an OSN? Motivation theory states that individuals offer knowledge when they perceive that it improves their professional standing (Wasko and Faraj, 2005). When individuals believe that their experiences are valuable and useful, they are more willing to share them (Senge, 1999; Wasko and Faraj, 2005). Perceived benefit is a factor that affects self-disclosure in OSNs (Cheung *et al.*, 2015). Tang *et al.* (2016) demonstrated that intrinsic motivations (e.g. sense of self-worth and socializing) and extrinsic motivations (e.g. economic reward and reciprocity) positively influence users' intention to share mobile coupons in OSNs. Individuals have high intention to share information with their strong-tie friends in OSNs (Choi *et al.*, 2017). Social identification and trust in a workplace also have a mediating effect on online knowledge sharing within organizations (Ho *et al.*, 2012). Social identity has significant effects on the participation of users in online communities (Zhou, 2011). In a study on online consumer behavior, customer identification toward a corporate OSN can trigger customer citizenship behavior in the OSN (Wu *et al.*, 2017). Furthermore, community members are typically motivated by achievement when sharing information, and those with high levels of motivation to achieve enjoy performing challenging tasks and a feeling of accomplishment upon task completion (Wu and Sukoco, 2010). However, negative motivation also influences the provision of valuable knowledge and experiences, which takes time and mental effort, likely reducing willingness to share. Hoarding knowledge and guarding it against others are common human tendencies. Extensive knowledge sharing in organizations remains the exception rather than the rule (Davenport and Prusak, 2000). Chen *et al.* (2016) demonstrated that the cognitive dimensions (such as shared vision and social norm) are not directly related to the self-disclosure behavior of social network site users. These theories may explain why internet users are or are not willing to share the understandings or knowledge that their intelligence gives them with others in OSNs.

Co-intelligence facilitates intellectual cooperation within communities that create, innovate, or invent (Lévy, 1999). The concept of co-intelligence has been widely extensively applied in sociology, business, computer science, and mass communications (Wikipedia, 2014). In commerce, online social networking service platforms have been used to link customers with companies. Companies face the increasing challenge of determining how to develop an effective OSN for interactions that consolidate customer relationships and responds rapidly to changes in the market and customer demand. As part of a modern business model, a company may have a Facebook fan page as a platform for co-intelligence, supporting win-win outcomes of two-way interactions (Small and Medium Enterprise Administration, Ministry of Economic Affairs, 2009). For example, ASUSTeK Computer Inc., a Taiwanese company, has a Facebook page that presents information about its latest products and allows members to share and discuss relevant experiences. The success of an OSN depends on the participation of its members and their investment in the development of knowledge (Tedjamulia *et al.*, 2005).

Based on the above discussion, one important issue for researchers and managers of organizations is the measurement of UPVoCI in OSNs to help organizations to identify the perceived values that drive internet users and members of OSNs to share information and knowledge when they participate in co-intelligence activities and thereby determine their expected motivation to participate. Therefore, this work develops a novel scale for quantifying UPVoCI in OSNs using quantitative and qualitative methods. Furthermore, this work includes a pioneering empirical study of a systematic method for constructing predictive models and rules for predicting UPVoCI in OSNs. The results in this work may elucidate a means by which organizations can improve online collaborative innovation through the effective management of online co-intelligence activities. If these indicators and predictive models and rules for predicting UPVoCI in OSNs can be effectively managed, then the quality of participation and cohesion of OSNs may be increased, markedly improving collaborative innovation. More importantly, from monitoring to mastering, the critical predictive indicators of UPVoCI are essential to the success of co-intelligence in OSNs. The scale on which UPVoCI is measured may also allow online social media service providers to evaluate the limitations of the services that they provide, and thereby enhance the quality of the services that are provided by social networking platforms.

2. Literature review

2.1 Collective intelligence

Co-intelligence can be defined as seeming intelligence in the collective activities of groups (Malone *et al.*, 2009). Heylighen (1999) defined co-intelligence as the ability of a group to solve problems faster than its members can, such that a group's capacity to perform a wide range of tasks is critical to successful collaboration (Chikersal *et al.*, 2017). Anderson (2012) posited that the term co-intelligence has replaced "wisdom of the crowd" in recent years. The concept of co-intelligence encompasses and transcends many other associated concepts, such as open innovation, crowd-sourcing, peer-production, the wisdom of crowds, and Wikinomics (Wise *et al.*, 2012). Co-intelligence allows actors to solve specific problems in cooperation (Bonabeau, 2009), so co-intelligence, which supports decision making by the collaboration of, and exchange of information among, actors (Trigo and Coelho, 2011), is associated with mass collaboration (Tapscott and Williams, 2010), and aggregate knowledge or collective knowledge (Vossen and Hagemann, 2007; Tapscott and Williams, 2010). A crowd of volunteers with a wide range of backgrounds can be smarter than the best expert (Matzler *et al.*, 2016). Steffes and Burgee (2009) demonstrated that the information that is gained from an online word of mouth forum influences the decisions of participants in the forum to a greater extent than speaking with friends in person. Haltofová (2016) also showed that participatory crowdsourcing solutions innovatively contribute to knowledge management and public policy making, and that the co-intelligence of online communities can be leveraged in the public sector.

Information and knowledge can be effortlessly shared around the world. Co-intelligence commonly determines the competitiveness, creativity, and human development of organizations in today's knowledge-based or information economy (Benkler, 2006). For example, P&G drives innovation by collaborating with external partners in at least 50 percent of instances (Dodgson *et al.*, 2006). According to Tapscott and Williams (2010), co-intelligence is mass collaboration, and its occurrence depends on openness, peering, sharing, and global action. Web 2.0 technologies support co-intelligence by enabling users to share quickly, easily, and securely their ideas, combining flexibility with the ability to control and manage parts of an interaction (Wagner and Majchrzak, 2007). O'Reilly (2007) argued that a critical characteristic of Web 2.0 is its ability to harness co-intelligence, transforming the Web into a "global brain." Web 2.0 has many popular applications, including Flickr, Wikipedia, YouTube, MySpace, and Facebook (Hendler, 2009). Bothos *et al.* (2009) also indicated that in the Web 2.0 era, the appropriate software tools and method can support co-intelligence for community-based idea management and internet-based idea generation and evaluation. For example, 3M Company established a Facebook fan page that provided fans all relevant information about their products. Its Facebook page enables 3M to survey consumers, initiate discussions that facilitate dialogue, develop and nurture relationships with influential community members, and elicit feedback about products (Treadaway and Smith, 2012). Additionally, companies can use online social networking platforms (e.g. Facebook or Twitter) to enable employees to interact and share ideas as well as promote collaboration among employees across the company (Wu *et al.*, 2016).

2.2 Perceived value of collective intelligence

Perceived value is typically the outcome of comparing perceived benefits and perceived costs (Lovelock and Wirtz, 2010). In the literature, the value is typically regarded as a subjective perception of a trade-off between benefits and sacrifices – both monetary and non-monetary (Lapierre, 2000; Walter *et al.*, 2001). Non-monetary rewards are improvement in competence, improved market position, and social rewards (Walter *et al.*, 2001). The non-monetary benefits may be quality, delivery, personal interaction, and service support (Ulaga, 2003). Non-monetary costs may be time, effort, and energy spent, including in conflict resolution, by a customer to obtain a product or service. Personal values typically reflect an individual's behavioral standards, including his/her degree of engagement (Kim *et al.*, 2013). Lykourentzou *et al.* (2009) stated that a co-intelligence system comprises a sufficiently large group of people, each of whom acts for his/her benefit, but as a group – facilitated by technology – exhibits increased intelligence, benefitting the entire community.

3. Development of scale and predictive model

The works of Wagner and Majchrzak (2007), Malone *et al.* (2009), and Tapscott and Williams (2010) were considered in defining UPVoCI as the value of posting photographs, videos, and related data; of writing opinions; and of participating in discussions to solve problems or clarify confusion in OSNs, as perceived by internet users. The OSNs were defined as networks built on social media sites, such as Facebook. Previous works have not developed a suitable scale for measuring UPVoCI; therefore, following the work of Churchill (1979) and other work on scale development (Netemeyer *et al.*, 1995; Yang *et al.*, 2014), the UPVoCI scale herein was developed using qualitative and quantitative research methods. Table I summarizes the

Study 1	Study 2	Study 3	Study 4
Qualitative research ($n = 134$)	Pretest ($n = 179$)	Formal test ($n = 558$)	Predictive research ($n = 751$)
Initial scale item generation and item pool	Initial scale item purification	Scale refinement	Predictive models and association rules
Open-ended elicitation procedure	Item analysis	Reliability analysis	Cluster analysis
Generate initial pool of items	Reliability analysis	Exploratory factor analysis	Independent sample *t*-test
Focus group method	Exploratory factor analysis	Confirmatory factor analysis	Decision tree algorithm
Expert judgment method		Discriminant and convergent validity analysis	Logistic regression analysis

Notes: n, number of samples under study

Table I. The development process of the UPVoCI scale and predictive models development of the UPVoCI scale and predictive models. The focus group method and the expert judgment method were used in Study 1 to develop an initial scale. A pool of items for measuring UPVoCI was identified using an open-ended questionnaire survey to determine the perception of UPVoCI by qualified participants. The subjects were asked about the value they perceived in participating in co-intelligence activities in OSNs. Study 2 focused on pretesting and conducting an initial scale item purification. Study 3 refined the developed scale. Study 4 identified critical prediction indicators (critical measurement items), and constructed predictive models and rules for predicting UPVoCI using multivariate statistical methods and data mining techniques.

4. Methods and results

4.1 Study 1: qualitative research and generation of initial scale item

4.1.1 Participants in qualitative research. A qualitative questionnaire about UPVoCI with an open-ended question item was developed for collecting the perceived value of participating in co-intelligence activities in OSNs. InsightXplorer's report of February 2014 found that more than 29.9 percent of internet users are aged 15-24, which is the age range with most users (InsightXplorer, 2014). The Pew Research Center reported that 90 percent of young adult internet users in the USA of ages 18-29 use social networking sites and the adoption rate for social media is 76 percent for users with a college or graduate degree (Perrin, 2015). Therefore, copies of the qualitative questionnaire were distributed to undergraduate and graduate students at a university in Taiwan. A convenience sampling method was adopted and the participants were selected from four different departments included Business Administration, Journalism and Communication, Mass Communication, and Computer Science and Information Engineering because of the backgrounds of these departments accord with this work.

Out of 154 qualitative questionnaires distributed, 20 were invalid, so the valid response rate was 87.0 percent. Of the 134 participants who returned valid questionnaires, 134 (100 percent) had Facebook account. The most common social networking platforms were Facebook, YAHOO!Kimo knowledge+, and Wretch. Additionally, the frequency of participating in online discussions, 95 (70.9 percent) averaged at least once a week. Regarding the average hours per day spent in participating in online discussions, 113 (84.4 percent) averaged less than 2 hours daily.

4.1.2 Qualitative research findings and initial generation of scale items. Two qualitative research methods – the focus group method and the expert judgment method – were used to generate categories of UPVoCI. After data were collected, the validity of 439 items of UPVoCI was assessed. A data classification team was assembled for this assessment from five professionals, comprising two IT managers, one professor, and two undergraduate students with the extensive experience of participating in co-intelligence activities. The team of five experts systematically discussed classifications of the 439 items and generated names for categories using the focus group method. In total, 32 categories of items for UPVoCI were identified from 439 items and these were divided into two dimensions – the user-perceived social value of co-intelligence and the user-perceived problem-solving value of co-intelligence. The user-perceived social value of co-intelligence concerned expanding interpersonal networks by joining in co-intelligence activities. The user-perceived problem-solving value of co-intelligence concerned solving problems in co-intelligence activities. In this work, these 32 categories were used to construct an item pool for measuring UPVoCI in OSNs.

4.2 Study 2: pretest and initial scale item purification

The 32 items of UPVoCI that were obtained from Study 1 were purified in Study 2. Facebook, which bundles co-intelligence activities with social functions, was the research target.

Participants were required to have experience of Facebook. After the initial 32-item UPVoCI scale was developed, a quantitative research questionnaire was completed by two qualified undergraduate students, who provided opinions and ensured that the wording of each item was clear and concise. As recommended by Reynolds *et al.* (1989) and Yang *et al.* (2014), a pretest was performed to assess the items with respect to discrimination and clarity and to evaluate the reliability and validity of the scale.

4.2.1 Participants in pretest and data collection. A total sample of 205 students with Facebook accounts as participants were randomly selected from the College of Management, College of Science and Engineering, College of Human Ecology, College of Communication, and College of Art at the same university as in Study 1. A total of 179 responses were valid, and 26 were invalid, so the response rate was 87.3 percent. Table II shows the detailed pretest participants profile.

4.2.2 Analytical results of pretest and initial scale item purification. Item analysis separately assesses each measurement item to determine if the item is good or poor and to increase both the reliability and validity of instrument (Kerlinger and Lee, 2000). After ranking each test score from highest to lowest, a *t*-test was performed to identify the 28.5 and 26.8 percent most frequent and least frequent answers, respectively, to each item on the 32-item UPVoCI scale. In total, 32 items with the *t*-values were in the range 4.619-9.305 (>3.000), and the *p*-values of the all items were 0.000 (<0.001), existed adequate discrimination and effectiveness.

Reliability is the degree of consistency to which a set of measurements or measuring instrument is dependable and reliable. A Cronbach's α value exceeding 0.7 is considered sufficient for the reliability analysis (Kerlinger and Lee, 2000). The scale had a Cronbach's α value of 0.925 (>0.7), and the value could not be increased even after excluding any of 32 items. Furthermore, the item-total correlations of items were between 0.345 and 0.625 and the criterion of 0.3 as an acceptable corrected item-total correlation (Nunnally and Bernstein, 1994), indicating that the scale existed satisfactory reliability.

Validity measures the accuracy of the extraction of the important characteristics of content (Triola, 2009). Kaiser (1974) indicated that the KMO between 0.80 and 0.89 is meritorious.

Characteristics	Descriptions	Pretest Number	Pretest %	Formal test (scale development) Number	Formal test (scale development) %	Predictive research (prediction model) Number	Predictive research (prediction model) %
Gender	Male	77	43.0	263	47.1	344	45.8
	Female	102	57.0	295	52.9	407	54.2
Frequency of participating in online discussions	Less than once per month	31	17.3	80	14.3	115	15.3
	Once per month	27	15.1	48	8.6	67	8.9
	Twice per month	23	12.8	78	14.0	96	12.8
	Once per week	19	10.6	68	12.2	89	11.8
	Twice per week	44	24.6	119	21.3	159	21.2
	Once per day (including over once)	35	19.6	165	29.6	225	30.0
Average hours per day spent in participating in online discussions	Less than 0.5	61	34.1	141	25.3	213	28.3
	More than 0.5 but less than 1	70	39.2	215	38.5	289	38.5
	More than 1 but less than 2	36	20.1	102	18.3	120	16.0
	More than 2 but less than 3	4	2.2	42	7.5	50	6.6
	More than 4 but less than 5	4	2.2	31	5.6	44	5.9
	5 or more	4	2.2	27	4.8	35	4.7
Years of using Facebook	Less than 3			39	7.0	59	7.9
	More than 3 but less than 7			477	85.5	641	85.3
	7 or more			42	7.5	51	6.8

Table II. Profile of participants

When using principle component analysis to obtain the factors, the standards for choosing variables are an eigenvalue larger than 1 and a factor loading larger than 0.5 after varimax rotation. Analytical results herein demonstrated that KMO = 0.848, and Bartlett's test of sphericity had a p-value less than 0.001. Six items had factor loadings of < 0.5 and so were excluded. Seven factors were extracted and the values of eigenvalue were 2.819, 2.041, 1.751, 3.102, 1.872, 2.058, and 3.400; and the values of variance explained were 10.843, 7.850, 6.735, 11.931, 7.200, 7.913, and 13.075 percent, respectively; hence, the explained cumulative variance was 65.548 percent, indicating that the UPVoCI scale with the remaining 26 items exhibited acceptable construct validity.

4.3 Study 3: formal test and scale refinement

Based on the 26 items that were purified using the results of Study 2, a purified 26-item UPVoCI scale (see Appendix), with Facebook as the research target, for use in a quantitative research questionnaire, was developed to collect data for refining the UPVoCI scale in Study 3.

4.3.1 Participants in formal test. The simple random sampling method and convenience sampling method were used. The quantitative research questionnaire was distributed to undergraduate and graduate students in three universities located in northern, central, and southern Taiwan. Furthermore, the participants were required to have experience joining 3C (computer, communications, and consumer electronics) solution providers' Facebook fan pages. A total of 760 questionnaires were distributed; 558 responses were valid, and 202 were invalid, so the valid response rate was 73.4 percent. Table II shows the detailed participants profile.

4.3.2 Analysis of results of formal test and scale refinement. The purified 26-item UPVoCI scale had a Cronbach's α value of 0.925, which did not increase even when items were excluded. The item-total correlations of items were between 0.305 and 0.658, and the criterion of 0.3 as an acceptable corrected item-total correlation, which indicated that the scale existed satisfactory reliability. For exploratory factor analysis of the scale, analytical results indicated that KMO $= 0.918$, and Bartlett's test of sphericity had a p-value less than 0.001. Four items had factor loadings < 0.5 and were excluded. All 22 items factor loadings were in the range 0.543-0.770 (> 0.5), which indicated that the scale had satisfactory construct validity. Four new factors were extracted, indicating that the scale had acceptable construct validity (see Table III). To solve the problem of cross-loading when the difference between the highest and second highest factor loadings of a measurement item across factors was less than 0.1, that item was deleted (Ramayah *et al.*, 2009; Snell and Dean, 1992). Then, the differences between the highest and second highest factor loadings of the remaining 22 items were in the range 0.161-0.593, demonstrating that these 22 items did not suffer from cross-loading. Common method bias was also evaluated using the single factor test (Podsakoff *et al.*, 2003). Since the first factor explains 36.540 percent of the variance, and this value is below the threshold of 50 percent (Podsakoff and Organ, 1986), indicating that common method bias was not a significant problem in this study.

This work further applied confirmatory factor analysis (CFA) to analyze the four different measurement models of UPVoCI and compare the goodness-of-fit of those measurement models to identify the best structure. Comparative analysis results demonstrated that the one-factor of first-order and the two-factor of first-order CFA measurement models found a poor fit. The four-factor of first-order CFA measurement model (Model 3) had acceptable goodness-of-fit and that the evaluated indices of three measures were better than the Model 4, and no offending estimates were found (see Table IV).

Additionally, although the Model 3 obtained a better fit, all of the standardized factor loadings of 22 items of UPVoCI are statistically significant ($p < 0.001$) and all of them exceeded 0.5 (range 0.563-0.787), but five items were further excluded for improving the

Dimensions/factors/measurement items		Item-to-total correlation	Communality	Factor 1	Factor 2	Factor 3	Factor 4
User-perceived social value of co-intelligence							
User-perceived value of enhancing interpersonal relationship (UPV-IR)							
Participants help each other	X_4	0.609	0.654	*0.751*	0.226	0.187	0.052
Conveniently interacting with other participants	X_1	0.502	0.554	*0.721*	0.080	0.128	0.110
Learning with and from each other	X_5	0.588	0.603	*0.720*	0.231	0.171	0.054
Finding and recognizing trends and fads	X_3	0.576	0.507	*0.598*	0.138	0.175	0.316
Sharing knowledge	X_{14}	0.591	0.496	*0.590*	0.267	0.267	0.070
Intelligence is open to all	X_{15}	0.478	0.410	*0.585*	0.203	0.157	0.035
Stating opinions freely	X_2	0.507	0.406	*0.543*	0.135	0.281	0.118
User-perceived value of enhancing personal reputation (UPV-PR)							
Earning private profit	X_9	0.388	0.646	−0.046	0.191	0.129	*0.768*
Improving reputation	X_8	0.375	0.561	0.120	0.145	−0.021	*0.725*
Promoting the publicity effects through co-intelligence activities	X_{10}	0.450	0.534	0.122	0.131	0.233	*0.669*
Expanding interpersonal networks	X_7	0.469	0.433	0.251	0.161	0.127	*0.573*
User-perceived problem-solving value of co-intelligence							
User-perceived value of improving cooperative environment (UPV-CE)							
Supporting the accumulation of intelligence	X_{16}	0.624	0.693	0.180	0.335	*0.732*	0.112
Correcting possible errors made by a single person	X_{13}	0.575	0.618	0.313	0.192	*0.692*	0.066
Cooperating to generate effective intelligence	X_{12}	0.636	0.638	0.337	0.216	*0.671*	0.166
Sharing intelligence at any time and at any place	X_{11}	0.506	0.616	0.385	−0.046	*0.658*	0.181
Strengthening problem management	X_{17}	0.623	0.604	0.131	0.443	*0.604*	0.161
User-perceived value of problem-solving effectiveness (UPV-PE)							
Improving decision-making efficiency	X_{23}	0.602	0.663	0.221	*0.770*	0.090	0.113
Helping to solve problems rapidly	X_{24}	0.647	0.674	0.293	*0.748*	0.109	0.128
Presentation of collective intelligence	X_{26}	0.595	0.622	0.082	*0.718*	0.241	0.203
Establishing objectivity of intelligence	X_{25}	0.586	0.595	0.114	*0.708*	0.173	0.225
Increasing the accuracy of intelligence	X_{21}	0.599	0.583	0.207	*0.700*	0.180	0.135
Reducing cost of solving problems	X_{22}	0.583	0.490	0.372	*0.565*	0.140	0.111

Factor		Eigenvalue	Variance explained (%)	Cumulative variance explained (%)	Cronbach's α value
User-perceived value of enhancing interpersonal relationship	UPV-IR	8.039	36.540	36.540	0.835
User-perceived value of enhancing personal reputation	UPV-PR	1.182	5.372	41.912	0.704
User-perceived value of improving cooperative environment	UPV-CE	1.484	6.763	48.675	0.833
User-perceived value of problem-solving effectiveness	UPV-PE	1.889	8.586	57.261	0.864

Notes: KMO = 0.918. Bartlett's test of sphericity p-value = 0.000

Table III. Results of exploratory factor analysis for formal test

Table IV. Specification of measurement models of UPVoCI: a comparative analysis

Absolute-fit measures					Incremental-fit measures		Parsimonious-fit measures			
χ^2	df	*p*-value	GFI	RMSEA	AGFI	NNFI	CFI	IFI	χ^2/df	Offending estimates
Model 1: one-factor of first-order CFA measurement model										
16,890.3	209	0.000	0.715	0.113	0.685	0.685	0.715	0.716	8.081	No
Model 2: two-factor of first-order CFA measurement model										
1,468.67	208	0.000	0.770	0.104	0.720	0.730	0.757	0.758	7.061	No
Model 3: four-factor of first-order CFA measurement model										
823.648	203	0.000	0.876	0.074	0.845	0.864	0.880	0.881	4.057	No
Model 4: four-factor of second-order CFA measurement model										
827.899	204	0.000	0.875	0.074	0.845	0.864	0.880	0.880	4.058	Yes
Refined model: scale refinement model										
370.713	113	0.000	0.923	0.064	0.895	0.918	0.932	0.932	3.281	No
Suggested										
–	–	> 0.05	0.80-0.90	0.05-0.08	0.80-0.90	> 0.90	> 0.90	> 0.90	< 3.0	–

model fit (see Table IV and the refined model). Figure 1 shows that the four-factor of first-order CFA model of UPVoCI (the refined model) had an appreciated goodness-of-fit; hence, this model was considered well-supported.

The correlations among the four factors in Figure 1 were statistically significant. The high standardized regression loadings supported the four factors. The four factors were appropriate metrics of the UPVoCI in OSNs.

This work also applied the average variance extracted (AVE) method developed by Fornell and Larcker (1981) to examine the convergent validity and discriminant validity of the four factors of UPVoCI. Analytical results indicated that for all factors, AVE exceeded 0.5 (range 0.529-0.692), which indicated adequate convergent validity. Since the squared Pearson correlation coefficients between factor pairs (range 0.065-0.359) were lower than the AVEs of the four factors, all factors had adequate discriminant validity. Finally, the composite reliability of each factor exceeded 0.7 (range 0.765-0.899), which indicated adequate internal consistency (Hatcher, 1994) (see Table V).

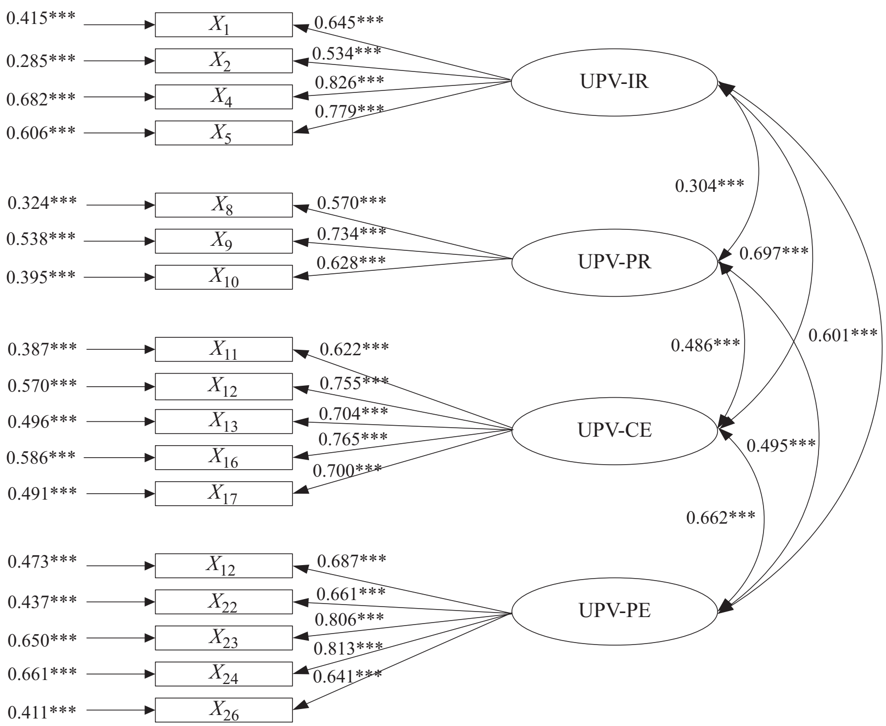
Based on the result of a formal test in Study 3, the refined UPVoCI scale included 17 measurement items and a four-factor model of UPVoCI with a favorable goodness-of-fit was constructed (see Figure 1).

4.4 Study 4: predictive models and rules

Based on the refined 17-item UPVoCI scale, a quantitative questionnaire survey of the UPVoCI was developed to collect data to construct predictive models and association rules of UPVoCI in Study 4.

4.4.1 Participants in predictive research. The simple random sampling method and convenience sampling method were adopted. The participants in predictive research were selected the undergraduate and graduate students who joined 3C solution providers' Facebook fan pages in three universities located in northern, central, and southern Taiwan. A total of 791 questionnaires were distributed; 751 responses were valid, and 40 were invalid, so the valid response rate was 94.9 percent. Table II shows the detailed participants profile.

4.4.2 Analysis of results of predictive research. 4.4.2.1 Clusters in predictive analysis. For constructing predictive models and association rules, the target variable and the input



Notes: χ^2=370.713; df=113; *p*-value=0.000; χ^2/df=3.281; IFI=0.932; AGFI=0.895; GFI=0.923; TLI=0.918; CFI=0.932; RMSEA=0.064. ****p*-value<0.001

Figure 1.
Four-factor model of the UPVoCI (the refined model)

Factors	Mean	SD	Composite reliability	UPV-IR	UPV-PR	UPV-CE	UPV-PE
UPV-IR	4.078	0.499	0.897	*(0.692)*			
UPV-PR	3.490	0.638	0.765	0.065	*(0.529)*		
UPV-CE	3.924	0.585	0.899	0.359	0.144	*(0.642)*	
UPV-PE	3.716	0.643	0.889	0.257	0.162	0.326	*(0.620)*

Notes: Values on the diagonal (in italics) are the average variance extracted (AVE) and the others are the squared correlation coefficients

Table V.
Results of correlation analysis and average variance extracted

variables were used in the predictive analysis techniques should be determined and defined. To determine the target variable of the decision tree (DT) algorithm and logistic regression (LR) analysis, cluster analysis was performed on the sample of 751 participants. The K-means method of non-hierarchical clustering analysis was adopted to classify the UPVoCI in OSNs. This work further applied discriminant analysis to validate the analytical results of cluster analysis, and found that they agree with the K-means method, and the cluster analysis had an accuracy of 100.00 percent.

Table VI presents the results of cluster analysis for group 1, comprising 435 participants, and group 2, comprising 316 participants, that were obtained using four factors of the UPVoCI. A *t*-test is performed to demonstrate the significant difference in the four factors between the two groups. Analytical results yielded that the *t*-values were in the range

16.588-23.879 and the p-values of all factors were 0.000 (< 0.001), indicating significance. The means of the four factors in group 1 were lower than that of those in group 2, revealing that group 1 had the lower UPVoCI and so was called the "low UPVoCI group", while group 2 had the higher UPVoCI and so was called the "high UPVoCI group". The result was the target variable of the DT algorithm and LR analysis.

4.4.2.2 Prototype of predictive model: LR model. Overfitting refers to the phenomenon whereby the numerous input variables of the DT algorithm and LR analysis make it easy to select unrelated variable categories. This work conducted the independent sample t-test to select meaningful input variables of statistics as the input variables of the DT algorithm and LR analysis to avoid deviation of the analysis results. Analytical results revealed that the p-values of 17 items were all below 0.05, and the t-values were in the range 11.366-17.828, achieving significance, and thus these 17 items were adequate as input variables of the DT algorithm and LR analysis.

The LR analysis was conducted to model dichotomous outcome variables and predicts relationships between the dependent variable and a set of independent explanatory variables. In this step, LR analysis was first used to model the influence and explanatory power of predictive variables. Analytical results demonstrated that the value of Cox-Snell R^2 was 0.744 and that of Nagelkerke R^2 was 1.000, suggesting that the model had receivable prediction power. Nevertheless, the 17 predictive variables (i.e. input variables) were in the range 48.168-105.785, and the p-values of the all variables exceeded 0.05 (range 0.911-0.993), indicating poor explanatory power. Under the prototype model, all 17 predictive variables had even less explanatory power. To improve the prototype model, the critical predictive variables were identified and the refined LR model then constructed to enhance the predictive power and accuracy of model of the UPVoCI.

4.4.2.3 Refined predictive model and rules: DT structure. The DT algorithm is used for mining data for knowledge discovery. Data are analyzed to identify rules and relations for use in data classification and prediction (Han and Kamber, 2006). Model accuracy is assessed using the actual DT performance to calculate the proportion correctly classified as judgment. This work administered the CART algorithms, the splitting criteria, impurity measures, and Gini criterion.

Analytical results herein demonstrated that the structure of DT that yielded the most accurate classification, including the minimum number of cases, two branching nodes, and the maximum DT depth was five hierarchies (see Figure 2). The performance measures, accuracy rate, precision rate, recall rate, and F1-measure rate, of the structure of DT were 90.1, 93.1, 89.7, and 71.2 percent, respectively (see Table IX).

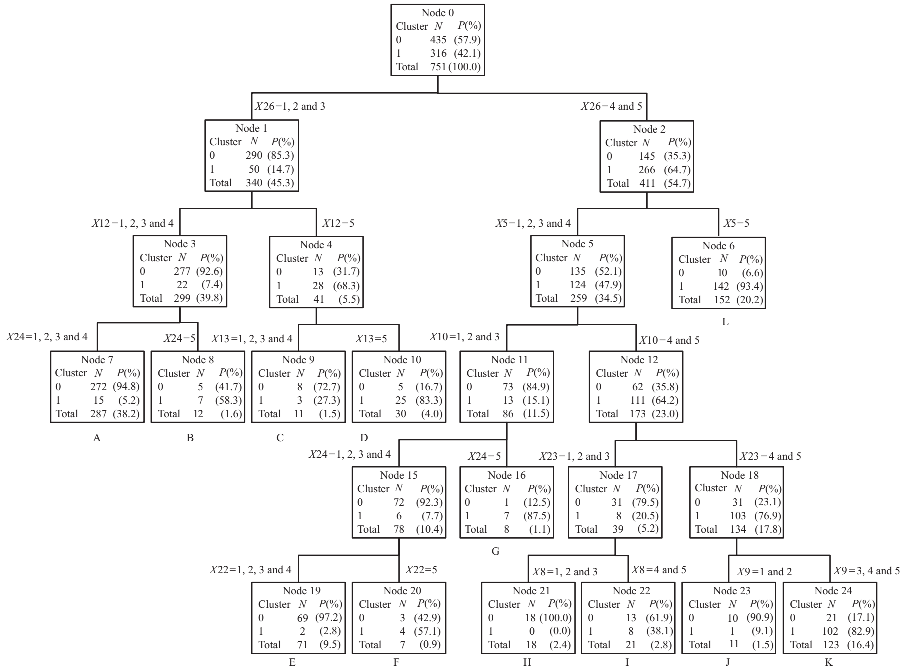
In Table VII and Figure 2, the tree structure was such that 12 predictive paths (association rules) existed from the root node to the leaf nodes. Analyzing all 12 predictive rules demonstrated that the ten critical determining indicators of UPVoCI were the items X_{26}, X_{12}, X_{24}, X_{13}, X_5, X_{10}, X_{22}, X_8, X_{23}, and X_9 (see Table VII).

4.4.2.4 Refined predictive model and rules: LR model. To improve the prototype predictive model that was constructed based on the first LR analysis, ten critical predictive

Groups	Participants	UPV-IR Mean	UPV-IR t-value	UPV-PR Mean	UPV-PR t-value	UPV-CE Mean	UPV-CE t-value	UPV-PE Mean	UPV-PE t-value
Low UPVoCI group	435	3.873	17.267***	3.201	16.588***	3.648	21.308***	3.346	23.879***
High UPVoCI group	316	4.417		3.894		4.383		4.236	

Note: ***p-value < 0.001

Table VI. Results of cluster analysis



Notes: Cluster 0: low UPVoCI; Cluster 1: high UPVoCI; *N*: number; *P*: purity of predictive association rule

Figure 2. The tree structure of the DT algorithm

Table VII. The prediction rules of DT algorithm

Rules	Purity (%)
Rule A: If $X_{26}=\{1,2,3\}$, $X_{12}=\{1,2,3,4\}$, and $X_{24}=\{1,2,3,4\}$, then low UPVoCI	94.8
Rule B: If $X_{26}=\{1,2,3\}$, $X_{12}=\{1,2,3,4\}$, and $X_{24}=\{5\}$, then high UPVoCI	58.3
Rule C: If $X_{26}=\{1,2,3\}$, $X_{12}=\{5\}$, and $X_{13}=\{1,2,3,4\}$, then low UPVoCI	72.7
Rule D: If $X_{26}=\{1,2,3\}$, $X_{12}=\{5\}$, and $X_{13}=\{5\}$, then high UPVoCI	83.3
Rule E: If $X_{26}=\{4,5\}$, $X_5=\{1,2,3,4\}$, $X_{10}=\{1,2,3\}$, $X_{24}=\{1,2,3,4\}$, and $X_{22}=\{1,2,3,4\}$, then low UPVoCI	97.2
Rule F: If $X_{26}=\{4,5\}$, $X_5=\{1,2,3,4\}$, $X_{10}=\{1,2,3\}$, $X_{24}=\{1,2,3,4\}$, and $X_{22}=\{5\}$, then high UPVoCI	57.1
Rule G: If $X_{26}=\{4,5\}$, $X_5=\{1,2,3,4\}$, $X_{10}=\{1,2,3\}$, and $X_{24}=\{5\}$, then high UPVoCI	87.5
Rule H: If $X_{26}=\{4,5\}$, $X_5=\{1,2,3,4\}$, $X_{10}=\{4,5\}$, $X_{23}=\{1,2,3\}$, and $X_8=\{1,2,3\}$, then low UPVoCI	100.0
Rule I: If $X_{26}=\{4,5\}$, $X_5=\{1,2,3,4\}$, $X_{10}=\{4,5\}$, $X_{23}=\{1,2,3\}$, and $X_8=\{4,5\}$, then low UPVoCI	61.9
Rule J: If $X_{26}=\{4,5\}$, $X_5=\{1,2,3,4\}$, $X_{10}=\{4,5\}$, $X_{23}=\{4,5\}$, and $X_9=\{1,2\}$, then low UPVoCI	90.9
Rule K: If $X_{26}=\{4,5\}$, $X_5=\{1,2,3,4\}$, $X_{10}=\{4,5\}$, $X_{23}=\{4,5\}$, and $X_9=\{3,4,5\}$, then high UPVoCI	82.9
Rule L: If $X_{26}=\{4,5\}$ and $X_5=\{5\}$, then high UPVoCI	93.4

Notes: The extent of promotion of or support for *Xi*; very low = 1, low = 2, medium = 3, high = 4, very high = 5

indicators of UPVoCI were derived from the classification and predictive model after the DT algorithm was used to refine the prototype model to improve its predictive power and accuracy.

Analytical results demonstrated that the value of the Cox-Snell R^2 was 0.675 and that of the Nagelkerke R^2 was 0.908, indicating that the refined LR model to compare with the prototype model was constructed by the first LR analysis had good predictive and explanatory capability. The omnibus test χ^2 was 843.857 and the p-value was 0.000 (< 0.001), revealing that the model predicted the UPVoCI (Table VIII).

The suggested predictive equation was as follows:

$$p = \frac{e^{f(x)}}{1+e^{f(x)}}$$

$$\text{In}\left(\frac{p}{1-p}\right) = f(x) = -95.437 + 2.270 \times X_5 + 2.457 \times X_8 + 1.934 \times X_9 + 2.955 \times X_{10} + 3.173 \times X_{12} + 2.220 \times X_{13} + 2.787 \times X_{22} + 2.344 \times X_{23} + 2.119 \times X_{24} + 2.446 \times X_{26}$$

The probability (P) in the range 0-1 was used to identify the UPVoCI in OSNs, where the value of P is close to 1 means high the UPVoCI and the value of P is close to 0 means low the UPVoCI. Ten critical prediction indicators included X_5, X_8, X_9, X_{10}, X_{12}, X_{13}, X_{22}, X_{23}, X_{24}, and X_{26}, and achieved the good explanatory power (see Table VIII). The predictive indicators of X_{12}: cooperating to generate effective intelligence, X_{10}: promoting the publicity effects through co-intelligence activities, and X_{22}: reducing cost of solving problems had higher predictive power than others.

Additionally, Table IX lists the results of the four predictive performance measures – accuracy, precision, recall, and F1-measure of the refined LR model, and the comparison between actual conditions and test results of the two LR models and the structure of DT. For the refined LR model, the total predictive accuracy, precision, recall, and F1-measure were 95.1, 95.6, 95.9, and 95.8 percent, respectively. The results demonstrated that the refined LR model exhibited a better predictive performance than the prototype LR model, and the same predictive performance as the structure of DT.

5. Conclusions and suggestions

5.1 Conclusions

Recently, the number of organization-related OSNs has increased. Therefore, organizations should develop effective online service strategies to simulate the perceived values of members

Indicators (measurement items)	Estimate	SE	Wald χ^2	p-value
Constant	−95.437	10.300	85.861	0.000***
X_5	2.270	0.468	23.568	0.000***
X_8	2.457	0.390	39.631	0.000***
X_9	1.934	0.335	33.241	0.000***
X_{10}	2.955	0.443	44.474	0.000***
X_{12}	3.173	0.494	41.279	0.000***
X_{13}	2.220	0.439	25.532	0.000***
X_{22}	2.787	0.542	26.450	0.000***
X_{23}	2.344	0.433	29.246	0.000***
X_{24}	2.119	0.440	23.194	0.000***
X_{26}	2.446	0.390	39.310	0.000***
Model fit properties	Omnibus test $\chi^2 = 843.857$, p-value $= 0.000$*** Cox-Snell $R^2 = 0.675$ Nagelkerke $R^2 = 0.908$			

Note: ***p-value < 0.001

Table VIII. Results of the refined LR analysis

Methods		Groups	Actual condition Low UPVoCI group	High UPVoCI group
LR model (prototype)	Test result	Low UPVoCI group	–	–
		High UPVoCI group	–	–
		Accuracy	Poor model	
		Precision	Poor model	
		Recall	Poor model	
		F1-Measure	Poor model	
DT structure	Test result	Low UPVoCI group	390(TP)	29(FP)
		High UPVoCI group	45(FN)	287(TN)
		Accuracy	90.1%	
		Precision	93.1%	
		Recall	89.7%	
		*F*1-Measure	71.2%	
LR model (refined)	Test result	Low UPVoCI group	417(TP)	19(FP)
		High UPVoCI group	18(FN)	297(TN)
		Accuracy	95.1%	
		Precision	95.6%	
		Recall	95.9%	
		F1-Measure	95.8%	

Notes: TP, true positive; FP, false positive; FN, false negative; TN, true negative

Table IX. Results of predictive accuracy of the DT algorithm and the LR model

of OSNs and to increase their participation in co-intelligence activities, promoting interest, and intention to engage in collaborative innovation. Identifying UPVoCI is important as doing so can elucidate the relationships among the perception of value of co-intelligence, attitudes toward co-intelligence and intention to engage in collaborative innovation, with the goal of setting online service strategies.

This work offers many important findings. First, a novel scale of UPVoCI is developed and its effectiveness is demonstrated using qualitative and quantitative research methods. Based on the results in this work, which incorporates a user-oriented research strategy, the refined 17 measurement items on the UPVoCI scale are associated with two major dimensions, which are the user-perceived social value of co-intelligence and the user-perceived problem-solving value of co-intelligence, and four factors. A structural scale for measuring UPVoCI can enable companies to identify the perceived values and benefits of participating in co-intelligence activities and to modify user-oriented online co-intelligence and service strategies to attract and retain members of OSNs. Furthermore, this measurement scale can enable online social media service providers to evaluate the limitations of online social media services, and thus to improve and to develop popular social networking functions and platforms.

Second, two models for predicting UPVoCI – the DT structure and the LR equation – are constructed. These two models provide different rules for forecasting UPVoCI. Ten critical predictive indicators that determine the UPVoCI are also identified. The results in this work further reveal that the most important predictive indicator of UPVoCI is the extent to which OSN members perceive that cooperation in online co-intelligence activities may yield effective intelligence. A stronger perception thereof corresponds to greater UPVoCI. The extent to which OSN members perceive that co-intelligence favors the publicity effects is the second most important predictive indicator. UPVoCI would be improved when members of an OSN perceive that participating in co-intelligence activities could strengthen the effects of publicity. A stronger association between co-intelligence activities and publicity effects corresponds to higher UPVoCI. The third most important predictive indicator of UPVoCI is the extent to which OSN members perceive that co-intelligence reduces the costs of solving problems. As OSN members increasingly perceive that co-intelligence activities reduce the costs of solving problems, UPVoCI increases. These important predictive indicators of UPVoCI are critical to the success of co-intelligence in OSNs for companies.

5.2 Implications

The findings in this work have several theoretical and practical implications. With respect to theoretical implications, the scale for measuring UPVoCI resolves weaknesses in quantitative research in the field of co-intelligence and allows researchers to examine the context of the motivation of participants in the collective behavior of intelligence sharing by members of an OSN. Little previous research has sought to measure UPVoCI and investigations of online co-intelligence tend to address this issue technically (Lévy, 2010; Lykourentzou *et al.*, 2010; Schut, 2010; Trappey *et al.*, 2015; Sadasivam *et al.*, 2016). This work fills a gap in the literature by developing a measurement scale that is based on qualitative and quantitative research, which can be used in future work on behavioral decision making by members of OSNs who participate in online co-intelligence activities.

The results herein also have implications for online social media service providers. This work systematically identifies 17 items that must be considered in measuring UPVoCI. Managers of online social media services can use these items as references to identify new online service strategies that improve their service capabilities and competitiveness by innovating online social media services and functions. They can also be used to add value to online social media services and better satisfy the needs of members of OSNs and companies use online social media platforms to interact and share knowledge and experiences with a view to solving organizational problems.

With respect to practical implications for companies, the outcomes of applying the predictive models and rules of UPVoCI can effectively help companies to recognize and master the perceived values of members of their OSNs that induce them to participate in innovative activities. Most companies are today addressing dramatic changes in their competitive environments and should effectively use online social networking platforms to connect with consumers and leverage the power of co-intelligence to form an effective collaborative environment. Those platforms can also be used to collect customers' opinions to help to identify new marketing opportunities. Other advantages include increasing the efficiency of the problem-solving process and the quality of products and services.

5.3 Limitations and suggestions

This work has various limitations, which suggest avenues for further research. The first limitation is that only undergraduate and graduate students were involved. Although they form a large part of the populations of OSNs, further studies that involve a broader range of participants, such as white-collar workers, are recommended. The UPVoCI scale may be applicable to many groups of users of online social media and so may help organizations better understand the differentiating UPVoCI.

Another limitation is that this work uses qualitative and quantitative research methods and attempts systematically to develop a novel scale of UPVoCI from a user-oriented perspective, which it then uses as a basis to construct a model of the relationship between co-intelligence and collaborative innovation. This is used to explore the relationships among the user-perceived value of, and attitude toward, co-intelligence, intention to engage in collaborative innovation which will be useful in enhancing the participation of internet users in co-intelligence activities with the goal of improving collaborative innovation. The results in this work can also help online social media service providers to understand how users utilize an online social networking platform to participate in co-intelligence and collaborative innovation activities.

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Appendix

Questionnaire items for formal test

The items investigate your opinions. According to your experiences of joining 3C (computer, communications, and consumer electronics) solution providers' Facebook fan pages, to what extent do you agree or disagree with the values of participating in online co-intelligence activities about the following (5 = strongly agree, 4 = agree, 3 = neutral, 2 = disagree, and 1 = strongly disagree):

(1) conveniently interacting with other participants (X_1);

(2) stating opinions freely (X_2);

(3) finding and recognizing trends and fads (X_3);

(4) participants help each other (X_4);

(5) learning with and from each other (X_5);

(6) establishing emotional contact (X_6);

(7) expanding interpersonal networks (X_7);

(8) improving reputation (X_8);

(9) earning private profit (X_9);

(10) promoting the publicity effects through co-intelligence activities (X_{10});

(11) sharing intelligence at any time and at any place (X_{11});

(12) cooperating to generate effective intelligence (X_{12});

(13) correcting possible errors made by a single person (X_{13});

(14) sharing knowledge (X_{14});

(15) intelligence is open to all (X_{15});

(16) supporting the accumulation of intelligence (X_{16});

(17) strengthening problem management (X_{17});

(18) enhancing self-defined abilities of participants (X_{18});

(19) receiving feedback and solving problems promptly (X_{19});

(20) brainstorming and producing ideas to solve problems (X_{20});

(21) increasing the accuracy of intelligence (X_{21});

(22) reducing cost of solving problems (X_{22});

(23) improving decision-making efficiency (X_{23});

(24) helping to solve problems rapidly (X_{24});

(25) establishing objectivity of intelligence (X_{25}); and

(26) presentation of collective intelligence (X_{26}).

Note: (Xi: item code).

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