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A Data Mining-based Exploration of Antecedents of Voluntary Knowledge Contribution to Organizational Repositories

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Abstract

Knowledge Management systems are often based on the assumption that employees will contribute their job related knowledge to electronic knowledge repositories, though organizations can't force its employees to do so. In a previous work Stewart & Osei-Bryson (2013) developed and tested a research model that was based on the theory of planned behavior. In this paper we use a data mining approach to explore the same data in order to see if there could be additional hypothesis that could be worthy of future exploration.

Keywords

Knowledge Management; Knowledge Contribution; Data Mining; Exploratory Data Analysis; Decision Tree; Abduction

1. Introduction

Knowledge management systems (KMS) are aimed at facilitating the management of an organization's knowledge (Alavi and Leidner 2001; Shin, et al. 2001). Hansen et al (1999) suggested that organizations choose one of two approaches in creating their KMS, i.e. either a codification approach where the organization creates technology-based repositories of knowledge, or a personalization approach where the organization creates directories pointing to human knowledge repositories. Whichever approach is chosen, the success of the KMS and by extension the success of the knowledge management endeavor is dependent on the willingness of those employees who constitute the firm's human knowledge repositories to contribute their knowledge to the organization's non-human (e.g. electronic knowledge) repositories (Kankanhalli, et al. 2005). The Knowledge Management (KM) effort will fail if the creators of knowledge cannot be motivated to contribute their knowledge (Alavi and Leidner 2001, Gibbert and Krause 2002, Renzl 2006).

In this paper, as in Stewart & Osei-Bryson (2013), the term *Knowledge Contribution* is defined as an employee's non-perfunctory contribution of knowledge to an electronic knowledge repository of their employing organization as opposed to a community of practice (e.g. e.g. Fahey et al., 2007). Our focus is on the exploration of factors that impact voluntary knowledge contribution in organization's without an explicit reward system that applies to knowledge contribution. Sutton (2001) suggested that "*people are critical elements in any knowledge* *management system*", which is consistent with Ruppel and Harrington's (2001) notion that social issues are important to knowledge sharing.

Stewart & Osei-Bryson (2013) formulated and tested a theoretical model to explain actual *Knowledge Contribution* of employees to organizational electronic knowledge repositories. In that paper a traditional positivist falsification approach was used, with the measurement and structural models being explored using PLS. Popper (1963) expressed the view that systematic testing should involve not only attempts to falsify a theory via repeated observation and experimentation, but to propose alternative hypotheses that would later also be subject to falsification. In this paper we use the measurement model developed in that work but will use a data mining technique, decision tree induction, to abduct new hypotheses that may be relevant to an explanation of actual *Knowledge Contribution*. We use an exploratory data analysis approach that is based on Osei-Bryson & Ngwenyama (2011), which is itself based on Pierce's perspective (cf 1867) that abduction is an approach to "*studying the facts and devising a theory to explain them*".

2. Overview on Relevant Research:

2.1 Research Model:

Stewart & Osei-Bryson (2013) presented a research model that is an adaptation and extension of the model of Kankanhalli et al. (2005), and include constructs posited or known to impact knowledge sharing in other contexts (Bock, et al. 2005, Ko, et al. 2005, Sharratt and Usoro 2003, Wasko and Faraj 2005, Ye, et al. 2006). Complementing theories, such as Social Exchange Theory, Social Network Theory, Cognitive Dissonance Theory, and excerpts from the Ease of Use, Organizational Commitment, Self-efficacy, Organizational Climate, Top Management Support literature are employed to establish the relationships between constructs, while framing the model within an adapted Theory of Planned Behavior (TPB) framework. This model posits constructs influencing *Intention to Contribute Knowledge* organized in three categories: (i) behavioral beliefs - *Intrinsic Motivation*, *Extrinsic Motivation*, and *Organizational Commitment*, (ii) normative beliefs – *Organizational Climate*, *Social Inclusion*, and *Top Management Support*, and (iii) control beliefs – *Perceived Ease of Use*, *Knowledge Self-efficacy*, and *Knowledge Sharing Cost*. Additional, the independent constructs can be organized along a four-dimensional schema: personal psychological, system-related psychological, organizational contextual and social factors.

The aforementioned control beliefs and *Intention to Contribute Knowledge* were posited to directly influence *Knowledge Contribution*. It is worthwhile to note that all the constructs were assessed as perceptions of the individual, making the level of theory the individual (Klein, et al. 1994). The constructs *Organizational Climate*, and *Top Management Support* require special mention as they are sometimes operationalized at different levels of theory in the literature, but for the purposes of this model these two constructs were at the individual level of theory.

2.2 Data Collection

The survey method of data collection was adopted. Items for the questionnaire were adapted from prior validated instruments (Bock, et al. 2005, Kankanhalli, et al. 2005, Ko, et al. 2005, Lin 2007, Park, et al. 2007, Randel and Ranft 2007, Thong, et al. 1996, Venkatesh 2000) to enhance validity (Stone 1978).. The final instrument in the form of an online web-based questionnaire was used to collect data from organizations, in Jamaica, that had implemented a help-desk solution for their technical support departments. A total of 72 completed questionnaires of 119 were received from 20 organizations (60.5% response rate, the web-based questionnaire would only accept completed questionnaires).

2.3 Validity Assessments

Assessment of the convergent validity and discriminant validity was conducted in order to validate the measurement model. Composite reliability and average variance extracted (AVE) were examined to assess convergent reliability from the measures (Hair, et al. 1998) using 0.7 as the lower threshold for a reliable construct as suggested by Chin (1998) for composite reliability, and 0.5 for the AVE as suggested by Fornell and Larcker (1981), respectively. Items with low loadings (i.e. < 0.60) were dropped. All constructs were found to be reliable with composite reliability ranging from 0.805 to 0.974 for the constructs Extrinsic Motivation (EXTM) and Knowledge Contribution (KNCT), respectively. The AVE for all constructs exceeded the threshold values of 0.50, with values ranging from 0.580 for EXTM to 0.949 for KNCT, thereby establishing convergent validity for each construct. As reported in our earlier paper, discriminant validity was assessed by comparing the square root of the AVE for each construct against the level of correlation with that construct (Fornell and Larcker 1981). The results indicated that each construct is more correlated with itself than any other construct, thereby establishing discriminant validity of each construct.

2.4 Results of Factor Analysis

Table 1 shows the weights and loadings of the items, with all being significant at the p = 0.01 level on their path loadings. Additionally, the loading and cross-loading were examined and the results indicated that each item loaded more on its intended construct than any other, further establishing discriminant validity.

Construct	Item	Loading	Weight	Standard Error	t-statistic
KNCT	KNCT1	0.973	0.506	0.009	106.775
	KNCT2	0.975	0.520	0.008	120.948
INCK	INCK1	0.862	0.309	0.046	18.693
	INCK2	0.871	0.303	0.034	25.293
	INCK3	0.816	0.295	0.081	10.066
	INCK4	0.797	0.288	0.087	9.125
SINC	SINC1	0.929	0.564	0.093	10.020
	SINC2	0.916	0.520	0.037	24.491
ORCL	ORCL2	0.793	0.153	0.090	8.769
	ORCL3	0.842	0.201	0.074	11.420
	ORCL4	0.821	0.197	0.079	10.391
	ORCL5	0.794	0.207	0.081	9.851
	ORCL6	0.687	0.138	0.140	4.902
	ORCL8	0.773	0.191	0.081	9.568
	ORCL9	0.773	0.184	0.069	11.187
TPMG	TPMG1	0.787	0.230	0.087	9.083
	TPMG2	0.923	0.416	0.037	24.864
	TPMG3	0.893	0.378	0.063	14.264
	TPMG5	0.782	0.126	0.122	6.429
COMM	COMM1	0.766	0.344	0.093	8.264
	COMM2	0.839	0.293	0.075	11.239
	COMM3	0.779	0.166	0.206	3.788
	COMM4	0.777	0.219	0.180	4.327
	COMM5	0.772	0.248	0.160	4.824

Construct	Item	Loading	Weight	Standard Error	t-statistic
EXTM	EXTM2	0.715	0.282	0.181	3.953
	EXTM6	0.761	0.478	0.208	3.658
	EXTM1	0.807	0.539	0.133	6.055
INTM	INTM1	0.885	0.267	0.029	30.854
	INTM2	0.893	0.232	0.025	36.437
	INTM3	0.790	0.204	0.066	11.980
	INTM4	0.842	0.264	0.059	14.206
	INTM5	0.834	0.207	0.037	22.511
KNSE	KNSE1	0.803	0.494	0.171	4.697
	KNSE2	0.899	0.672	0.041	22.079
PEOU	PEOU1	0.896	0.438	0.028	32.057
	PEOU2	0.806	0.362	0.064	12.658
	PEOU3	0.852	0.370	0.052	16.401
COST	COST1	0.719	0.310	0.236	3.048
	COST2	0.731	0.287	0.234	3.121
	COST3	0.740	0.474	0.157	4.720
	COST4	0.764	0.284	0.185	4.124

Table 1. Weights and Loadings of Items

Variable	MinValue	MaxValue
COMM	-4.0957	1.5627
INCK	-4.1443	1.7904
INTM	-3.4377	1.3582
KNCT	-2.5516	1.5943
KNSE	-3.1999	1.3369
ORCL	-2.2016	2.0039
PEOU	-2.9481	1.3725
SINC	-3.4012	1.6484
TPMG	-2.1421	2.0029

Table 2. Factor Scores

3. Data Analysis using Decision Tree Induction

The following steps form the Methodology that is based on Osei-Bryson & Ngwenyama (2011):

1. Use existing theory to select Potential direct & indirect Predictor Variables for Knowledge Contribution.

2. Collect relevant data.
3. Use Decision Tree Induction technology to do recursive partitioning of the given dataset resulting in rulesets.
4. Abduct Hypotheses from the results of the DT Induction. Both Single Rule Hypotheses & Sibling Rules Hypotheses (e.g. Osei-Bryson & Ngwenyama, 2011) will be generated.

3.1 Overview on Decision Tree Induction

A DT is a tree structure representation of the given decision problem such that each non-leaf node is associated with one of the decision variables, each branch from a non-leaf node is associated with a subset of the values of the corresponding decision variable, and each leaf node is associated with a value of the target (or dependent) variable. There are two main types of DTs: 1) classification trees and 2) regression trees. For a classification tree, the target variable takes its values from a discrete domain, and for each leaf node the DT associates a probability) for each class (i.e. value of the target variable). A regression tree (RT) is a decision tree (DT) in which the target variable takes its values from a continuous domain (numeric). For each leaf, the RT associates the mean value and the standard deviation of the target variable.

There are two major phases of the RT induction process: the *growth phase* and the *pruning phase* (e.g. Kim and Koehler, 1995). The *growth phase* involves a recursive partitioning of the training data resulting in a RT such that either each leaf node is pure (i.e. all observations have the same value for the target), further partitioning of the given leaf would result in at least one of its child nodes being below some specified threshold, or the split is not statistically significant at a specified level. The *pruning phase* aims to generalize the RT that was generated in the *growth phase* by generating a sub-tree that avoids over-fitting to the training data. The actions of the *pruning phase* is often referred to as *post-pruning* in contrast to the *pre-pruning* that occurs during the *growth phase* and which aims to prevent splits that do not meet certain specified threshold (e.g. minimum number of observations for a leaf).

In order to reduce over-fitting the generated RT to the data that was used to generate it, for large modeling datasets, the original dataset would be divided into mutually exclusive *Training* and *Validation* subsets, where the Training subset is used during the *Growth Phase* to generate the initial RT, and the *Validation* subset would be used during the Post-Pruning phase. For small modeling datasets, such an approach is not possible so techniques such as k-fold cross validation (e.g. 10-fold) are used where the original model dataset is divided into k mutually exclusive subsets (k-folds), and k runs are done each in involving a unique combination of (k-1) folds.

During the Growth Phase, the given dataset is recursively split into smaller & smaller datasets based on the selected splitting method. A splitting method is the component of the DT induction algorithm that determines both the attribute that is selected for a given node of the DT and also the partitioning of the values of the selected attribute into mutually exclusive subsets such that each subset uniquely applies to one of the branches that emanate from the given node. It is well known that there is no single splitting method that will give the best performance for all datasets. While some datasets are insensitive to the choice of splitting methods, other datasets are very sensitive to the choice of splitting methods. Given that it is never known beforehand which splitting method will lead to the best DT for a given dataset, it is advisable that the data miner explore the effects of different splitting methods (e.g. Variance Reduction, F-Test, Entropy, Gini).

3.2 Application of Decision Tree Induction

To generate a DT from a given dataset, a single variable must be identified as the *Target* (or dependent) variable and the potential predictors must be identified as the I*nput* variables. Commercial data mining software (e.g. C5.0, SAS Enterprise Miner, IBM Intelligent Miner) provide facilities that make the generation of RTs a relatively easy task. In our case the SAS Enterprise Miner data mining software was applied to this dataset, resulting in the RTs that are displayed in Figures 1 & 2. Since our dataset is small we used 10-fold cross validation. We set the maximum number of splits per node to 3; the maximum number of predictors per rule to 3; and the minimum number of observations associated with a rule to 10. To generate RTs we used both available splitting methods; similarly for the2 CTs (see Figures 3 & 4).

Variable	Role
KNCT	Target
COMM	Input
INTM	Input
KNSE	Input
ORCL	Input
PEOU	Input
SINC	Input
TPMG	Input

Table 3: Variables used in DT Induction

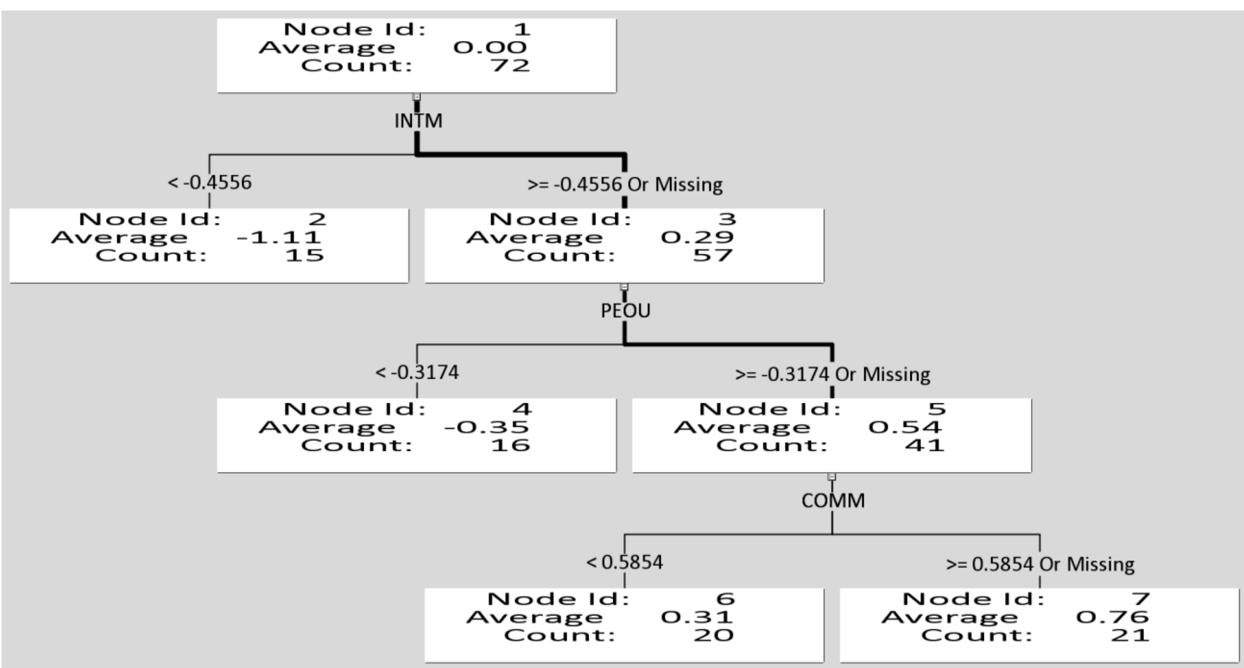

Figure 1: RT_F - RT derived using F-Test Splitting Method

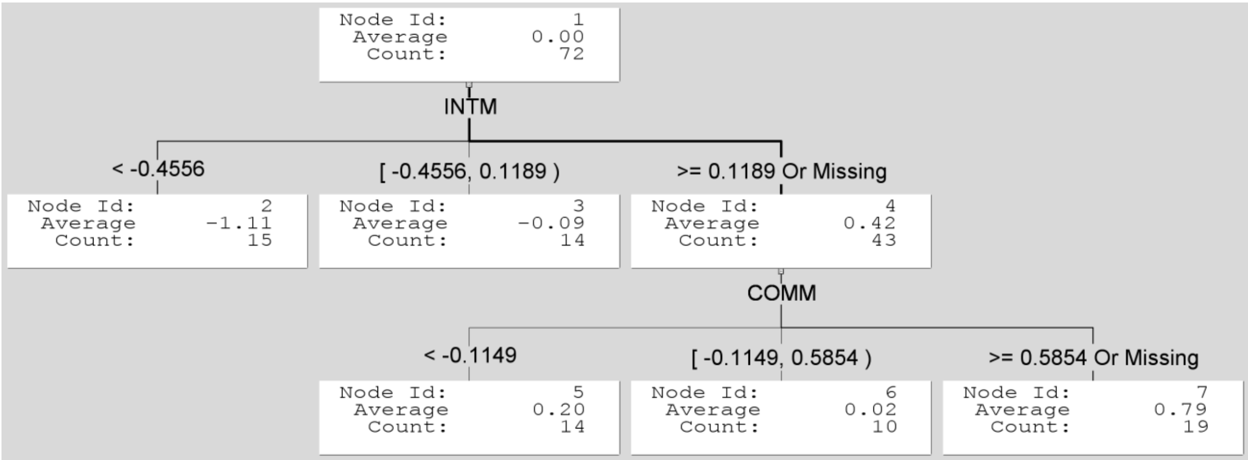

Figure 2: RT_V - RT derived using Variance Reduction (VR) Splitting Method

Tentative Inference from RT_F:

- On average, higher levels of *Knowledge Contribution* (KNCT) can be achieved simply by having an individual with a high level of *Intrinsic Motivation* (INTM) whose *Perceived Ease of Use* (PEOU) of the system is high, within the context of a high level of *Organizational Commitment* (COMM). This suggests that high levels of a specific aspect of personal characteristics (INTM), a specific aspect of organizational characteristics (COMM), and a system factor (PEOU) could be sufficient for achieving a high level of KNCT.

Tentative Inference from RT_V:

- On average, higher levels of *Knowledge Contribution* (KNCT) can be achieved simply by having an individual with a high level of *Intrinsic Motivation* (INTM) within the context of a high level of *Organizational Commitment* (COMM) irrespective of system factors such as PEOU.
- At higher levels of *Intrinsic Motivation* (INTM), *Organizational Commitment* (COMM) appears to have an approximately U-shaped impact on KNCT. This tentative inference is based on the 3 RT nodes associated with COMM when INTM > 0.1189. The reader may observe that for COMM < -0.1149 that Average KNCT = <u>0.20</u>; for COMM $\in$ [-0.1149, 0.5854) that Avg KNCT = <u>0.02</u>; and for COMM $\geq$ 0.5854 that Avg KNCT = <u>0.79</u>. The averages of KNCT for the two outer intervals are greater than for the inner interval, thus suggesting the possibility of U-shaped impact rather than strictly linear impact of COMM on KNCT when INTM > 0.1189.

Table 2 provides the range of values for each of the variables. We thought it would be useful to also explore the conditions that would result in the highest level of knowledge contribution. We therefore discretized each variable into 3 intervals (bins) of equal width based on the range of the given variable. Using this transformed data we generated 2 DTs, which are actually classification trees (CTs) since the transformed variables are ordinal while the original variables were interval. These 2 CTs are presented in Figures 3 & 4.

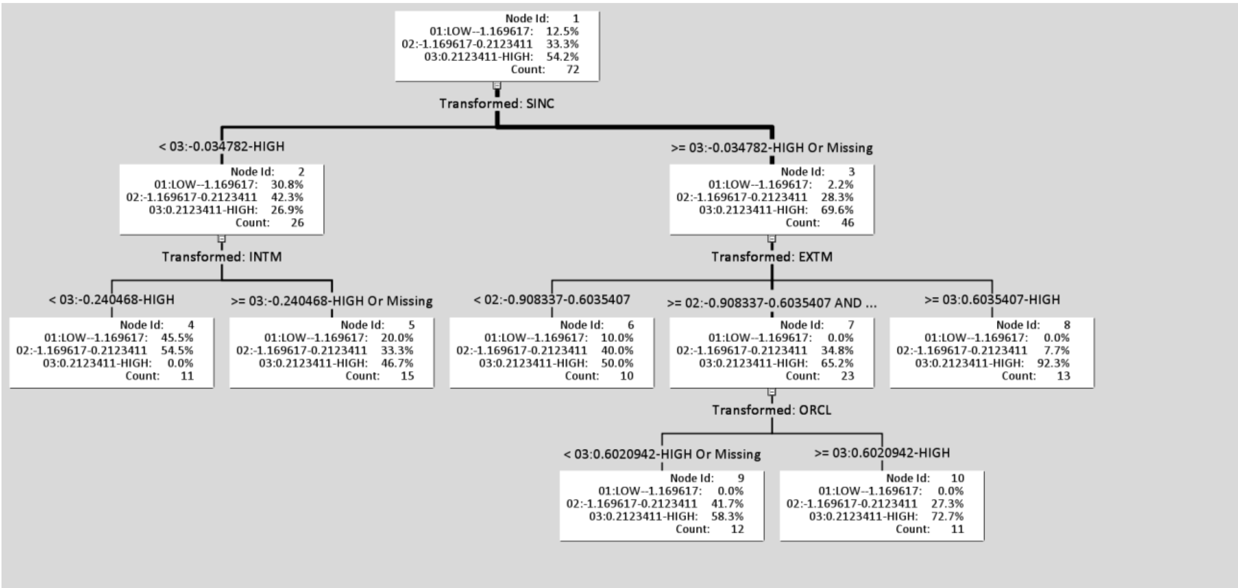

Figure 3: CT_E - CT derived using Entropy SM on Binned Variables

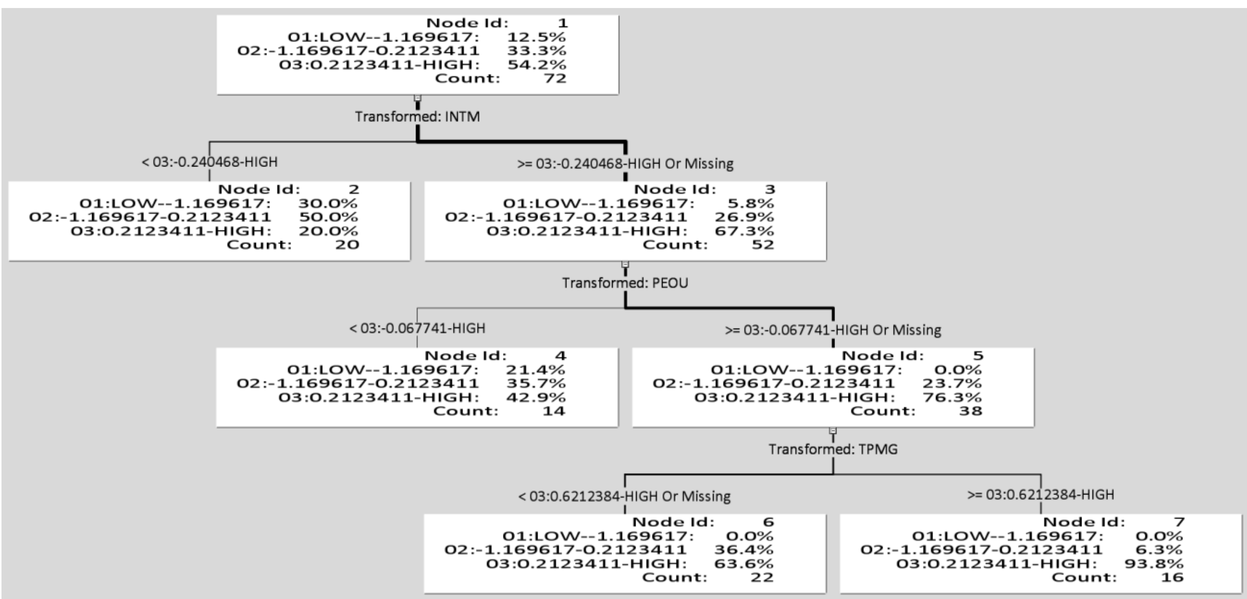

Figure 4: CT_GX1 - CT derived using Gini SM on Binned Variables with SINC excluded

Tentative Inference from CT_E:

- The reader may observe that when SINC is High, the relative frequency of high KNCT (i.e. bin 3) is 69.6%; but if both SINC is High & EXTM is High then the relative frequency of high KNCT increases to 92.3%.
- Thus IF the individual employee experiences a highest level of social inclusion (SINC) and the organization applies the highest level of *Extrinsic Motivation* (EXTM) THEN

irrespective of system factors such as *Perceived Ease of Use* (PEOU), it is highly likely that the *Knowledge Contribution* (KNCT) will be *High*.

Tentative Inference from CT_GX1:

- The reader may observe that when INTM is High, the relative frequency of high KNCT (i.e. bin 3) is 67.3%; if both INTM is High & PEOU is *High* then the relative frequency of *high* KNCT increases to 76.3%; and if INTM is *High* & PEOU is High & TPMG is *High* Then the relative frequency of high KNCT increases to 93.8%.
- If the individual employee has high *Intrinsic Motivation* (INTM), his/her *Perceived Ease of Use* (PEOU) of the system is *high*, and there is high *Top Management Support* (TPMG) then it is highly likely that the *Knowledge Contribution* (KNCT) will be High (*Source: RT_F*).
- IF the individual employee has *high Intrinsic Motivation* (INTM), his/her *Perceived Ease of Use* (PEOU) of the system is *high*, THEN *Top Management Support* (TPMG) has a positive impact on *Knowledge Contribution* (KNCT). This tentative inference follows from the fact that the relative frequency of a High KNCT level that is associated with TPMG being in its top bin (i.e. High) is significantly different than when TPMG is in its lower 2 bins (i.e. 93.8% vs 63.6%).

3.3 Abducted Hypotheses

Given the tentative inferences from the previous section, the following hypotheses appear to be worthy of exploration in future research:

- COMM has an approximately U-shaped impact on KNCT. This is based on comparison of the average values of KNCT that is associated with the 3 bins of COMM i.e. 0.20 vs 0.02 vs 0.079 - *Source: RT_V*). This is an example of a sibling rules hypothesis since it is based on the 3 child nodes of Node 4 of RT_V (see Figure 2).
- IF the individual employee experiences a highest level of *Social Inclusion* (SINC) and the organization applies the highest level of extrinsic motivation (EXTM) THEN it is highly likely that the *Knowledge Contribution* (KNCT) will be High (*Source: CT_E*). This is an example of a strong single rule hypothesis.
- IF the individual employee experiences a highest level of *Social Inclusion* (SINC) THEN *Extrinsic Motivation* (EXTM) THEN has a positive impact on *Knowledge Contribution* (KNCT). This is based on comparison of the relative frequencies for High KNCT that is associated with the 3 bins of EXTM (i.e. 50% vs 65.2% vs 93.2% - *Source: CT_E*).
- IF the individual employee has high *Intrinsic Motivation* (INTM), and his/her *Perceived Ease of Use* (PEOU) of the system is high, THEN *Top Management Support* (TPMG) has a positive impact on *Knowledge Contribution* (KNCT).

4. Conclusion

In this paper we used a data mining based exploratory data analysis approach to abduct some new hypotheses that should be subjected to future empirical analysis This approach has implications for practice as it describes multiple paths, each involving no more than 2 variables, to achieve a high level of *Knowledge Contribution* including:

- The occurrence of a high level of *Social Inclusiveness* (SINC) & a high level of *Extrinsic Motivation* (EXTM) is likely to result in a high level of *Knowledge Contribution* (KNCT).

- The occurrence of a high level of *Intrinsic Motivation* (INTM) & a high level of *Perceived Ease of Use* (PEOU) is likely to result in a high level of *Knowledge Contribution* (KNCT).
- The occurrence of a high level of *Intrinsic Motivation* (INTM) & a high level of *Organizational Commitment* (COMM) is likely to result in a high level of *Knowledge Contribution* (KNCT).

For example, the last two of the paths above provide guidance on what an organization should look for in a potential employee before he/she is hired (i.e. high INTM), and what the organization should do after the employee is hired (e.g. high PEOU, and/or high COMM). The first path above could be considered as providing guidance on what the organization should do with regards to existing employees (e.g. high EXTM).

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