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Relationship between variables and attributes for organizational goals model

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Relationship between variables and attributes for organizational goals model

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Abstract

The purpose of this paper is to develop and validate the data- to- organization goal approach relationship. This is because data is very important for organization toward future performance. It is important to identify the type of data within organization in order to support the main organization goal. This paper concern the relationship involve between data and organization goal. In order to achieve this purpose, five main variables are identified: organization goal, sub-goals, actions, data input and data output. In additional, the paper focused on the possible relationship between variables and attributes within organization goal. The analytical concept of the relationship is developed and a simple case study is implemented to support the discussion.

Keywords: actions, attributes, organizational goals, sub-goals, variables

1. Introduction

Organization goal is very important in one organization. It is the target achievement that needs to be achieved by every organization. However, in order to achieve the goal, organization needs to understand the type of data that is important to achieve the performance toward goal. Data is a backbone for every organization and organization used data toward their organization action such as training, strategy and etc. Data also important in order to set up an approach toward organization goal which is used toward goal setting, evaluation, learning and revision (Barlas & Yasarcan, 2006).

In order to support the approach toward organization goal, data need to me identified. The process included the process of variable and attribute identification. The process shows the relationship between variables and attributes within organization goal. Data is important in order to support organization achieving their goal. In one organization, goal is set up as a primary target. This main goal is supported by several sub-goals. The sub-goals are supported by organization actions such as training, daily activity or strategy. In order to look at the organization goal, several variables are identified to support the organization goal. The variables are organization goal (Org_{goal}), sub-goals (Sub_{goals}), actions (A_{ctions}), data input (IN) and data output (OT). Data is very important as organization rely on data to perform. The

future discussion is depends on these main variables and the remaining paper as following ways. Section 2 discussed on the background, Section 3 is organization goal. Section 4 discusses on the variable concept, Section 5 discussed on the attribute concept, Section 5 discussed on the example on case study, Section 7 is case study and Section 8 is a conclusion.

2. Background

Organization goal the most important targets to be achieved in every organization (Izhar et al., 2013). It is the business perspective that focuses on business objectives and benefits and prioritizes resources and activities according to the needs of the organization. Even though the concept of organizational goals has been in existence for some time, modelling the structure of organizational goals is much more difficult (Izhar et al., 2012; Izhar et al., 2013). For example, one way to develop a common understanding of the structure of organizational goals is to use an ontology (Izhar et al., 2013).

An ontology provides explicit and formal specifications of knowledge, especially implicit or hidden knowledge (Cho et al., 2006). An ontology is considered as an approach to support data dependencies (Pundt & Bishr, 2002). Therefore, an ontology assists the creation of knowledge to develop a model in relation to the organizational goals and can be used to improve the communication and collaboration between the decision makers and the users (Selma et al., 2012), which is, in this research, the decision makers in relation to the organizational goals (Izhar et al., 2013).

There is a shortcoming when it comes to evaluating organizational data in relation to the organizational goals during the development of organizational modelling. Modelling the organizational goals is limited to business processes and organizational processes (Fox et al., 1996; Fox et al., 1998; Mansingh et al., 2009; Rao et al., 2012; Sharma & Osei-Bryson, 2008). Most of the previous studies focus on process modelling, workflow analysis, computer-supported cooperative work and design problem solving (Popova & Sharpanskykh, 2011).

Despite this shortfall, there are a number of tools for modelling organizational processes most of which support mathematical modelling (Vergidis et al., 2008). Structuring a small organization is less complicated than a large organization. This is because different organizational structures, processes and a vast amount of data make it more difficult to identify relevant organizational data in relation to the organizational goals. Therefore, it is also important to identify metrics that can measure the relevance of organizational data in relation to the organizational goals.

However, in many ontology studies, there is a lack of studies reporting on such metrics in relation to the organizational goals (Rao et al., 2012; Valiente et al., 2012). We suggest that metrics is important to enable both domain experts and entrepreneurs to evaluate the relevance of organizational data in relation to the organizational goals (Izhar et al., 2013) and measure the value of the analysed organizational data. Furthermore, the organizational goals ontology assists domain experts to apply such knowledge in relation to the organizational goals (Izhar et al., 2013).

Previous research in this area has mainly examined the issue from the data process point of view that addresses either software development or data mining (Lee et al., 2008). While many studies have examined the process of data collection, our main contribution is to develop a framework which can incorporate organizational data and can lead to reliable decision-making in relation to meeting the organizational goals. Therefore, it is important to develop a flexible and widely applicable framework to evaluate the relevance of organizational data to evaluate the extent to which the organizational goals could be achieved.

Most studies which have been conducted on this issue focus on business intelligence (BI) (Azma & Mostafapour, 2012; Nofal & Yusof, 2013; Popovic et al., 2012), data mining (Aghdaie et al., 2014; Weerdt, Schupp, Vanderloock, & Baesens, 2013; Zandi, 2014), data linkage (Christen, 2008; Durham et al., 2012; Ferrante & Boyd, 2012) and knowledge discovery in databases (KDD) (Cheng et al., 2012; Lin et al., 2008). Even though these studies focus on decision-making, they do not focus on the interaction between organizational data and organizational goals, as shown in Fig. 1. Therefore, it is difficult to identify the relevant organizational data that relate to the organizational goals.

For example, KDD is an interdisciplinary field that searches for valuable information in large volumes of data and has played an important role in identifying effective patterns from a vast amount of data (Lee et al., 2008). KDD is a concept of identifying new knowledge in the field of computer science that describes the process of searching a vast amount of data in order to produce knowledge but it misses the link to organizational goals. However, KDD applies the concept within the system instead of searching and evaluating the organizational data.

Another example is business intelligence (BI). BI is a computer-based technique to analyse business data which provide past and current information on the business strategies and business operation and has been utilized in competitive intelligence to support better decision-making. BI aims to analyse business data by providing past and current data as a strategy to assist decision-making. Meanwhile, data linkage is a process to identify data from different datasets. Christen (2012) defined data linkage as a process of data pre-processing to identify quality data.



Fig. 1. Problem scope.

3. Organizational goal

Organization goal is an outcome that organization developed to achieve. It is the higher achievement target in one organization. Organization goal is supported with several sub-goals. Sub-goals defined as the outcome set up to support the organization main goal. These sub-goals supported by several actions. Actions are the activities involved as organization strategy to achieve the goals. However, these actions rely on organization data. Past studies show many researchers discussed with an approach toward data usage within organization and business field (Aalst et al., 2005; Dijkman et al., 2011; Kock et al., 2009; Liu & Lai,

2011; Rozinat et al., 2009; Song & Aalst, 2008; Turetken & Schuff, 2007). This paper discusses the usage of data in relation to the organization goal with an approach to support the variable and attribute involved.

Nowadays, organization created new data almost every day. This data is kept in data storage such as database. The amount of data increase every day and this become a main issue for organization to identify the data toward their organization performance. The relationship is identified between the possible variable toward organization data. Early study has started to look at the relationship between goals as studied by Freeland and Baker,(Freeland & Baker, 1975) who looked at the partition aspects within organization goals. They emphases the goal as super-ordinate, which supported with several sub-ordinates. This paper present an approach to identify the possible variable exist and the relationship within the attribute. Simple discussion before show several main variables within organization goal such

Organization goal denoted as Org_{goal},

Sub-goals denoted as Sub_{goals}

and

Actions denoted as A_{ctions}.

 A_{ctions} required data which included data input and data output so denoted data input as IN and data output as OT. The main variables here are Org_{goal} , Sub_{goals} , A_{ctions} , IN and OT.

So assume the relationship here as

 $Org_{goal} = \{Org_{goal} (IN \in A_{ctions}) | x(OT \in Sub_{goals})\}.$

The approach is explained as as Org_{goal} rely on Sub_{goals} and A_{ctions} . But as we understand, organization relies on data to support achieving the goals. So, full relationship is defines as Sub_{goals} is an OT of A_{ctions} where Sub_{goals} and A_{ctions} are the requirement for Org_{goal} .

4. Variables: The relationship

The approach developed based on several variables. These variables are important as a basic structure for this approach. It is because the variables show the relationship involved toward the approach development. At the same time, the variables assist the focus of the approach.

Definition 1: Variables are the collection of attributes.

Example 1: One subject as STUDENT data is a variable and a collection of object such STUDENT_ID, STUDENT_ EMAIL and STUDENT_ADDRESS are group of attributes to support identify variable.

This study concerns the usage of data in order to support the organization goal. As discussed before, the concepts involved are organization goal and several sub-goals are developed to support organization main goal. These sub-goals are supported by organization actions such activity and strategy and these actions required data. Based from this simple



explanation, several main variables are identified such organization goal (Org_{goal}), sub-goals (Sub_{goals}), actions (A_{ctions}), data input (IN) and data output (OT). Below show simple example of possible variable exist

 $Org_{goal}(Org_{goal}^{1}, Org_{goal}^{2}.....Org_{goal}^{n})$

where the concept is the same to other variables

Sub_{goals} (Sub_{goals}¹, Sub_{goals}²...... Sub_{goals}ⁿ)

 $A_{\text{ctions}}(A_{\text{ctions}}^{1}, A_{\text{ctions}}^{2}, \dots, A_{\text{ctions}}^{n})$

 $IN (IN^1, IN^2....IN^n)$

and

OT (OT ¹, OT².....OTⁿ).

The discussion show simple relationship of selected variables. Here take Org_{goal} as an example, some organization may have several goals where here we divided the goal as Org_{goal}^1 , Org_{goal}^2 Org_{goal}^n where *n* is a number of variables. This Org_{goal} supported by several Sub_{goals} defined here as Sub_{goals}^1 support the Org_{goal}^1 and Sub_{goals}^1 is supported by A_{ctions}^1 as the process goes on with other variable.



The concept show where data output depend on data input as OT(IN) and organization goal depend on organization sub-goals and organization actions as Org_{goal} (Sub_{goals}, A_{ctions}). The discussion explain that data is the crucial variable for organization actions where the actions such training rely on organization data. This is important for organization to identify the types of data by analysing the existing data. The concept involved deeper understanding on the variable aspect and also the attribute aspect and the relationship between these two aspects.

Explaining that in one organization, several goals may be developed and the concept represent by $\text{Org}_{\text{goal}}^1$, $\text{Org}_{\text{goal}}^2$ $\text{Org}_{\text{goal}}^n$). This concept is similar with other

variables that involve toward organization goal. However, the process relies on the number of attribute toward the variable. The process must be separately defines as below.

 $Org_{goal} \{ V_{ariables} (A_{ttributes}) \}$

 $Sub_{goals} \{ V_{ariables} (A_{ttributes}) \}$

Actions {Variables (Attributes)}

The concept explain as

 $V_{ariables} = \{V_{ariables} (A_{ttributes}^{1}, A_{ttributes}^{2}, \dots, A_{ttributes}^{n})\}$

where variables rely on several subject of attributes. In this paper, we already defined variables as Org_{goal} , $\text{Sub}_{\text{goals}}$, A_{ctions} , IN and OT. These variables rely on data attributes involved within the variables.

5. Attribute concept: The relationship

We define the variables such IN, OT, A_{ctions} and Sub_{goals} , Org_{goals} . We understand that IN and OT is data process for A_{ctions} and Sub_{goals} . However, this process involves $A_{ttribute}$ which can help to assist the measurement process. Therefore, every variable must identify the $A_{ttribute}$ aspects.

Definition 2: Attributes are the collection of data toward variables.

Example 2: Assuming data input as STUDENT data. STUDENT is a variable and several attributes toward this variable are STUDENT_ID, STUDENT_EMAIL and STUDENT_ADDRESS.

Possible attribute need to be identified in order to support the relationship between variable and attribute. In order to support this, each variable identified is defined with possible attribute relationship. Assuming the process as below where IN is a variable.

IN= {IN ($A_{ttribute}^{1}$, $A_{ttribute}^{2}$, $A_{ttribute}^{3}$)}

IN rely on the number of $A_{ttribute}$ to support the IN process. Here, $A_{ttribute}$ is the type of data, data subject and data number

IN= { $A_{ttribute}^{1}$, $A_{ttribute}^{i}$,..... $A_{ttribute}^{n}$ }

where $1 \le i \le n$ and

 $OT = \{OT (A_{ttribute}^{1}, A_{ttribute}^{2}, A_{ttribute}^{3})\}$

OT rely on IN where OT is the $A_{ttribute}$ from IN. So the process still as

$$OT = \{A_{ttribute}^{1}, A_{ttribute}^{0}, \dots, A_{ttribute}^{n}\}$$

where $1 \le o \le n$.

Actions rely on IN and Subgoals rely on OT. Here, Attribute describes as

 $A_{ctions} = \{A_{ction}(A_{ttribute}^{1}, A_{ttribute}^{2}, A_{ttribute}^{3})\}$

$$\mathbf{A}_{\text{ctions}} = \{\mathbf{A}_{\text{ttribute}}^{1}, \mathbf{A}_{\text{ttribute}}^{a}, \dots, \mathbf{A}_{\text{ttribute}}^{n}\}$$

where $1 \le a \le n$ and

 $Sub_{goals} = \{Sub_{goal}(A_{ttribute}^{1}, A_{ttribute}^{2}, A_{ttribute}^{3})\}$

 $Sub_{goals} = \{A_{ttribute}^{l}, A_{ttribute}^{s}, \dots, A_{ttribute}^{n}\}$

where $1 \le s \le n$.

5.1. Data process

Data process involved the data flow. It is the process of data input and data output. However, data process involved the process input and the process output in order to identify the input and out of data. The relationship developed here:

 $D_{\text{process}}(P_i, P_o)$

and

D_{process} (IN, OT)

where full relationship is

 $D_{\text{process}} = \{P_i (IN), P_o (OT)\}$

The relationship explain as process input (P_i) rely on data input (IN) and process output (P_o) rely on data output (OT).

5.2. Process input

Processed or collected data is store into data storage. Every new data created must be store inside data storage and this process is an input process. Process input involve the process to identify the attribute involve within data input. This process assisted the output process in term of identifying the data existed.



5.3. Process output

Every data stored generate an output. This data is identified. In this study, this data is identified and measure in order to support the organization goal. This process is the process toward output. This output use as a final result for any future decision. The relationship for process input can be defined as

 $P_i(D_{process} \rightarrow IN)$

where

 $P_i = \{IN (IN^1, IN^2, \dots, IN^n)\}$ show that P_i involved several number of IN

and relationship for process output is

 $P_o (D_{process} \rightarrow OT)$

where

 $P_o = \{OT (OT^1, OT^2, \dots, OT^n)\}$ show that P_o involved several number of IN.

Relationships example,



Fig. 3. Variables and attributes.

Fig. 2 explain the number of variable involved several numbers of attributes and Fig. 3 show the relationship based on Org_{goal} , Sub_{goals} and A_{ctions} .



for the

6. Case Study

The case study is taken from Library Client Survey 2010 (insync surveys¹) toward library usage. One example from the survey is to look at the student background from the survey (http://www.lib.latrobe.edu.au/about/surveys.php).

6.1. Relationship development

Table 1 below showed a data from the survey which used as an example for this case. Based from Table 1, assume several variables such as *Campus library use*, *Study area*, *Student category* and *Academic category* as main variable.

Table 1. Library Survey.

¹ Insync Surveys is a survey that ensures the libraries can measure performance which in turn enables libraries to develop the highest possible standards of service for library users.

La Trobe University Library Client Survey September 2010 Response Statistics				
Total	4789			
Which Campus Library do you use most?	n	%		
Albury-Wodonga	220	4.6		
Bendigo	729	15.2		
Melbourne (Bundoora)	3550	74.1		
Mildura	89	1.9		
Shepparton	114	2.4		
In another Australian state	9	0.2		
Outside Australia	35	0.7		
Other	37	0.8		
Unspecified	6	0.1		
What is your major area of study, research or teaching?				
Education	412	8.6		
Health Sciences	1193	24.9		
Humanities and Social Sciences	893	18.6		
Law	267	5.6		
Management, Economics, Accounting and Tourism	863	18.0		
Science, Technology and Engineering	963	20.1		
Other	164	3.4		
Unspecified	34	0.7		
Which category describes you?				
Australian resident	3894	81.3		
Non-resident studying in Australia	720	15.0		
Off-shore student	118	2.5		
Other	42	0.9		
Unspecified	15	0.3		
What single category best describes you?				
Undergraduate	3421	71.4		
Postgraduate	894	18.7		
Academic/ Research Staff	894	18.7		
General Staff	114	2.4		
From another University	11	0.2		
TAFE	10	0.2		
Other	28	0.6		
Unspecified	14	0.3		

The example from Table 1 used to identify the different between variables and attributes. We assume the relationship as below figure.



Fig. 5. The relationship between variable and attribute.

Therefore, *Student background* is the main goal where several variables such as *Campus library use*, *Study area*, *Student category* and *Academic category* used to support *Student background*.

6.2. Relationship approach

As discussed in Section 1, simple relationship approach is developed within organization goals as $\text{Org}_{\text{goal}} = \{\text{Org}_{\text{goal}} (\text{IN} \in A_{\text{ctions}}) | x(\text{OT} \in \text{Sub}_{\text{goals}})\}$. Take first variable *Campus library use* as example in order to implement the approach. So here assuming attribute for *Campus library use* as ATT1, ATT2, ATT3, ATT4, ATT5, ATT6, ATT7. Thus

 $Org_{goal} = \{ n(220, 729, 3550, 89, 114, 9, 35) | 4.6 \in ATT1, 15.2 \in ATT2, 74.1 \in ATT3, 1.9 \in ATT4, 2.4 \in ATT5, 0.2 \in ATT6, 0.7 \in ATT7 \}$

where scale rate is as following, 1=0-20, 2=20-40, 3=40-60, 4=60-80, 5=80-100 and the rank is as following 0 = Very Low, 1-2 = Low, 3 = Medium, 4 = High 5 = Very High.

Attribute	Mean	Rate	Rank
ATT1	4.6	1	Low
ATT2	15.2	1	Low
ATT3	74.1	4	High
ATT4	1.9	1	Low
ATT5	2.4	1	Low
ATT6	0.2	1	Low
ATT7	0.7	1	Low
Total	99.1	5	Very High

Table 2. Result for campus library use.

Result from Table 2 show that the entire attributes for variable (Campus library use) is very high which is highly important toward achieving the goal (Student background). Here,

we attempt to look at the analytical dependency between data and organization goal based on variable and attribute. It is very important to identify the data in order to support the organization goal.

7. Discussion

In this paper, several variables are identified toward organization goal such as Org_{goal} , Sub_{goals} , A_{ctions} , IN and OT. These main variables show the dependent relationship between them. The process based on real scenario nowadays where organization created new data every day and this data is store in data storage such as database. Here the process involve process input (P_i) and process output (P_o). Both processes involve data input (IN) and data output (OT). Here, the overall process is discussed as Org_{goal} is the main target in every organization and several Sub_{goals} are developed in order to support the goal. However, these Sub_{goals} relies A_{ctions} which define as organization activity. A_{ctions} is important for organization toward achieving their organization goal but A_{ctions} rely on data. It is important to understand the type of data within organization in order to achieve the goal.

Based on the case study, we identify several variables in order to support the goal. The variables here are *Campus library use*, *Study area*, *Student category* and *Academic category*. These variables rely on several attributes and we took Campus library use in order to look at the data involve toward the attributes. The result show the entire attributes for variable (Campus library use) is very high. However, each of the attribute do not really impact the variable where ATT1 is Low, ATT2 is Low, ATT4 is Low, ATT5 is Low, ATT6 is Low and ATT7 is Low. Only ATT3 show High rate which we can see the usage of campus library is high in Melbourne campus because of their status as main campus.

8. Conclusion

The paper discussed on the relationship between variables and attributes which use to implement the relationship approach. Several main variables are identified such Org_{goal} , Sub_{goals} , A_{ctions} , IN and OT and variables are the basic structure for toward the approach. Case study is used to look at the relationship of variables and attributes where the overall process show the data involved within the attributes. In the future, it is very important to identify the variable that use toward real live activity and to analyse the data involve within the process.

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