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Article

Probabilistic and deterministic data linkage for data goals model in relation to the organization goals

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Probabilistic and deterministic data linkage for data goals model in relation to the organization goals

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Abstract

Data is an important asset to assist organization in decision making in order to achieve the organization goals. However, the trustworthiness of organization data in achieving the organization goals is questioned because of the vast amount of organization data. Therefore, it is important to develop a model that links organization data and organization goals. Structuring organization goals for small organization is less complicated compare to the large organization. This is because large organization have large structure, thus it is difficult to identify relevance data in relation to the organization goals. This paper propose data goals model in the context of the organization goals ontology. Ontology is important to improve a common understanding for the organization goals. We suggest data goals model is important to identify the relationship between organization data and organization goals. After that, we generalize organization goals ontology and data goals model to set a standard model so it can be applied in different domains. In this paper, we apply probabilistic analysis and deterministic analysis to analyze organization data in relation to the organization goals. The contribution of this paper may serve as a first step in understanding the evaluation of organization data for the achievement of the organization goals.

Keywords: Data goals model, Data linkage, Organization goals, Ontology

1. Introduction

Companies CEO have certain requirement from the information they receive as they use this information to support decision making process to achieve the organization goals. However, CEO requires an additional knowledge to support the information they receive especially toward problem resolution. For example, in a business environment, there are several causes of sales decrease such as economic turndown or ineffective planning. Therefore, data is collected and analyzed as an effort to resolve such issue. CEO uses this data as a backbone for the problem solution and decision making. However, the amount of organization resources such as data, information, knowledge and tools are very vast and the amount of data continues to grow and information technology also has changed beyond storage, transmission and processing (Seng & Chen 2010). Thus, it becomes a major problem for CEO to apply any organization data in the decision making process because they do not have enough relevance data to assist the decision making in relation to the organization goals. Organization goal is the important

achievement target in every organization. Organization goals consist of sub goals, actions, tasks and resources. Even though the concept of organization goal is developed but modelling the structural of the organization goals always questionable. Thus, we suggest that ontology is important to develop a common understanding of the organization goals structure. At the same time, ontology is explicit and formal specifications of the knowledge, especially implicit or hidden knowledge (Cho et al., 2006). Ontology also supports data sharing (Pundt & Bishr, 2002). Therefore, ontology assists with part of the integration problem in relation to the organization goals.

Even though the organizations have a vast amount of data but at the same time, they do not have the data that they really need. Thus, the trustworthiness of organization data in relation to meeting the organization goals is questioned and it poses an issue that how optimally the selected data may be used for better decision making and fully achieving the organization goals. Data is the most important organization resource and it is important to identify the relevance data for the achievement of the organization goals. At the same time, we suggest that organization data is important as information and knowledge in every decision making process. Therefore, it is important to understand the relationship between organization data and organization goals.

However, there is shortcoming when it comes to evaluating data in relation to the organization goals during the organization modelling development. Modelling the organization goals limited to the business process and organization process (Fox et al., 1996; Mansingh et al., 2009; Rao et al., 2012; Sharma & Osei-Bryson, 2008; Fox et al. 1998). At the same time, most of the previous studies argued that the need for and benefits from goal modeling are focus on process modelling, workflow analysis, computer supported cooperative work and design problem solving (Popova & Sharpanskykh). Despite of this shortfall, there are a number of tools for modelling the organization process where most of these tools support the mathematical modelling (Vergidis et al., 2008). In organization, structuring small organization is less complicated compare to large organization. Different organization structures, processes, amount of data and attributes make it more difficult to identify relevance data in relation to the organization goals. In this paper, we develop the concept by looking at the approach which can incorporate the relationship between organization data and organization goals. Therefore, it is important to develop a model to evaluate organization data for the achievement of the organization goals.

In this paper, we tackle the problem of analyzing organization data in relation to the organization goals based on the following aims. We propose data goals model in the context of the organization goals ontology. In order to propose this model, we discuss the concept of the organization goals ontology (Izhar et al., 2012). Ontology is important to improve a common understanding for the organization goals. We suggest data goals model is important to identify the relationship between organization data and organization goals. After that, we generalize organization goals ontology and data goals model. The process is important to generalize the concept as an effort to standardize the model so it can be apply in the real environment. We suggest that data goals model is important to develop the linkage between organization data and organization goals. In the end, we apply probabilistic analysis and deterministic analysis to analyze organization data in relation to the organization goals. The contribution of this paper may serve as a first step in modelling the organization data in achieving the organization goals.

The remainder of this paper is organized as follows. In Section 2, we discuss the background on the organization goals conformance. We propose the organization goals ontology and data goals linkage model in Section 3. In this section, we discuss the process for data attributes identification. In Section 4, we generalize the organization goals ontology for both goals model and data goals model. Section 5 discusses the methods. Discussion and future research are discusses in Section 6. In this section, we highlight the gaps to be considered for the future research. Section 6 is a conclusion.

2. Background on the organization goals conformance

Study on organization goals have been actively carried out previously and most of the previous studies comparing and evaluating the organization goal modelling focused on the goal structure, goal performance and goal processes. There are numbers of modelling techniques, for example Enterprise

Ontology and Unified Modelling Language (UML). Even though there are studies have been done on organization goals, all the studies do not focus on the evaluation of organization data as a main resource for organization to achieve its goal conformance. Thus, it is very difficult to identify the relationship structure within organization goal. In order to show the organization goals structure and relationship, ontology approach is proposed. Ontology model is important to develop organization modelling concept. Ontology development approach has been proposed which consisting of a number of steps for organization modelling (Fox et al., 1996). There are number of ontology exist such as Enterprise Ontology, TOVE, OWL and UML. However, the most important work on ontology development is briefly discussed to identify the existing gaps in the current research in order to present a conceptual view.

2.1 Organization goals

Organization goal is defined as organization main target. It is the higher and important achievement target in every organization and it consist the process of identifying the aim of the organization. Thus, it is important to understand the organization goals structure. The structure of the organization is important to develop the efficiency and flexibility of the organization to cope with unpredictable (Salerno 2009). For example organization structure is develop to achieve the performance of the organization (Earley & Kanfer, 1985; Bouskila-Yam et al., 2011) or goal structure is develop to achieve the performance of goal (Barlas & Yasarcan, 2006; Sholihin, et al. 2011; Lepmets et al., 2012). The example shows a number of studies look at the organization structure toward the performance. This is because organization performance depends on the organization structure. Same with goal structure and goal performance, where organization goal depends on goal structure toward goal performance. There are number of organization goal studies that focus on the performance such as system performance (Kang & Norton, 2004; Ceresia, 2011), goal performance (Barlas & Yasarcan, 2006; Dillard, 1981; Sholihin et al., 2011) and organization performance (Salerno, 2009; Earley & Kanfer, 1985; Bouskila-Yam et al., 2011; Lepmets et al., 2012). It is important to identify the entire organization modelling process as an effort to look at the organization performance and goal performance. However, the process can be very large and it is very difficult to evaluate organization data as an effort to achieve the organization goals. Compare to the previous study, we develop the organization modelling in the context of the organization goals. It is important to identify the elements of the organization goals conformance based on ontology.

2.2 Organization ontology

In the context of the organization goals, ontology is developed to improve the understanding of the organization structure and relationship within the organization goals. Ontology is developed to categories some domain within the concept and it is important to improve understanding of structure of data or information among people or software. Despite the vast amount of research on ontologies, there remains relatively little research on applying ontology for the organization goals. Ontology enables to show the flow of organization knowledge as how the organization store, share and use knowledge (Rao et al., 2012). Rao et al. (2012) studied the important of knowledge in the organization. In this study, the authors developed organization ontology based on knowledge map. The authors also addressed the issues of lack understanding of environment within the business process. Thus, it is suggested the need for knowledge ontology based on knowledge mapping in order to show the flow of knowledge within an organization. In contrast with this study, we develop an ontology based on the organization goal as an effort to evaluate organization data in relation to the organization goals. In our work, we narrow down the organization ontology in (Rao et al., 2012; Fox et al., 1998; Sharma & Osei-Bryson, 2008). Fox et al. (1998) addressed an organization to be a set of constraint on the activities performed by organizations. This study has been extended in Sharma & Osei-Bryson (2008), who discussed the relationships such as business process with a various types of resources.

In contrast of our work, we evaluate organization resources including data. In this paper, we do not interpret the overall business process that includes the overall organization activities and performance.

The development of the organization goal ontology is based on the organization goal, sub-goal, action, task and organization resource which is data. Instead of evaluating the information and knowledge, we argue that organization data also important and must be consider during the decision making process. This is because it is very important to identify the relevant and current organization data in order to achieve the organization goal. Metrics is important to evaluate the vast amount of data within the organization. Albino et al. (2001) defined the metrics provides important indications of the organization process efficiency and effectiveness which are directly related to the knowledge codification and consequently of the organization learning processes to be implemented. Quality metrics has been studied to look at the quality of data and information. Burton-Jones et al. (2005) studied on the ontology quality using metrics. However, the authors look at the importance of ontology in knowledge engineering and they present a suite of metrics that can be used to access the quality of ontology.

The limitation of metrics model is mostly studied on system performance. There are very limited studies have been done to look at the organization goals achievement. The development of metric to evaluate the organization data in relation to achieve the organization goals is important as an effort to identify the relevant of organization data.

3. Organization goals ontology

In this section, we propose organization goals ontology (Izhar et al., 2012). There are steps that we consider during developing the organization goals ontology. Firstly, ontology must improve understanding of the organization goals structure. Secondly, ontology must be able to integrate with the organization goal elements. Thirdly, the organization goal elements is arrange in a hierarchy. Lastly, ontology is able to validate organization goals. Later in this section, we propose data goals model in the context of the organization goals ontology. We suggest that this model is important in order to improve the understanding between organization data and organization goals. There are steps that we consider during the data goals model. Firstly, we identify the data sets. Secondly, we identify the possible attribute based on data sets. Thirdly, we develop data goals model based on ontology in order to improve the understanding between data and the goals.

Ontology is developed to categories some domain within the concept and it is important to improve the understanding of the structure of data or information among people or software. It also enables the use of knowledge within domain and to analyze domain knowledge. Thus, in the context of the organization goal, ontology is developed to improve the understanding of the organization structure and relationship between the organization goals. It creates the knowledge for the domain experts and entrepreneurs to identify the relevance organization data in relation to the organization goals conformance.

In order to propose our organization goals ontology, we compare the previous models in (Rao et al., 2012; Fox et al., 1998; Sharma & Osei-Bryson, 2008). Rao et al. (2012) developed organization ontology in order to build up a knowledge map within the organization. The authors studied the flow of knowledge within the organization in the context of knowledge sharing. Fox et al. (1998) focused in structuring the linking between organization structure and behavior. This is critical for enterprise model development. Meanwhile, Sharma & Osei-Bryson (2008) developed a framework of organization ontology as an effort to implement the business understanding. Most of the previous studies focus on the organization structure and performance and it is very little study has been done in evaluating the organization data in relation to the organization goals. In contrast, we evaluate organization resource which is data and we do not interpret the overall business process that includes the entire organization activities and performance. It is very important to identify the relevant and current organization data in order to achieve the organization goals.

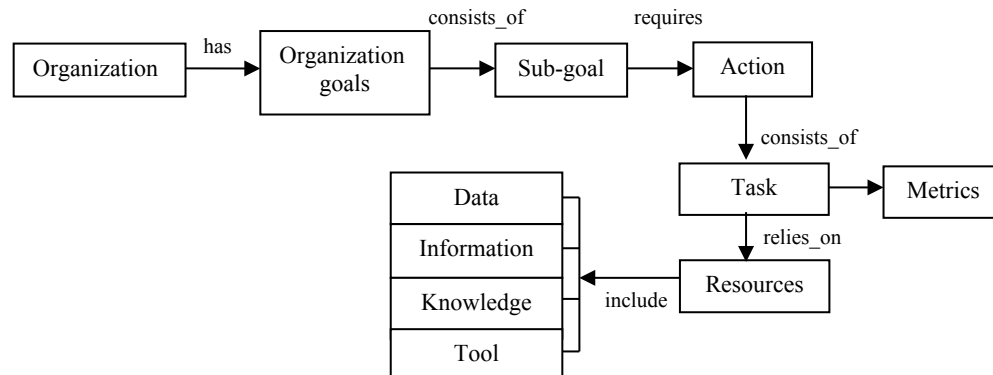


Fig. 1. Organization goals ontology

Based on above discussion, we proposed the organization goals ontology as shown in Fig. 1. In this figure organization has many organization goals. Each of the organization goals consists of sub-goal. This sub-goal requires actions. Each action consists of tasks. These are the organization goal elements and these elements rely on organization resources such as tool, knowledge, information and data. In this model, we added new elements such as action. Sharma & Osei-Bryson (2008) shows the relationship between activity and task in their model but we expand the concept of activity in our model. We define action as an activity performed by task. Thus, it is important to understand all the activities between action and task. Another is we focus at the usage of organization data instead of knowledge, information or tool. This is because organization data is a major resource in every organization and it is important to evaluate this data to achieve the organization goals. At the same time, we suggest that organization data also important as information and knowledge in every decision making process. There is also limitation of metric in (Sharma & Osei-Bryson, 2008; Fox et al., 1998). Only Rao et al. (2012) included a metrics in their model but the authors used the metrics to measure the knowledge within the organization. In this paper, we attempt to identify a metrics to analyze organization data in relation to the organization goals. There are two possible data analysis that can be used such as probabilistic analysis and deterministic analysis. At this stage, we test both methods to identify a metrics to analyse organization data.

3.1 Sub-goals, actions and tasks

In Fox et al. (1998) and Sharma & Osei-Bryson (2008), the authors discussed the element of task and activity. Fox et al. (1998) incorporated the element of activity from the physical point of view. The model show the activity that performed by the organization agent. At the same time, Sharma & Osei-Bryson (2008) also discussed the element of activity from the physical point of view. However, the authors include the element of task performed by activity. In this study, the authors comprise three sub-tasks such as human task, tool task and system task. The authors discussed the relationship between activity and task but they did not discuss the relationship between task and organization goal in particular. At the same time, Mansingh et al. (2009) defined task as an action that a role takes or the decision that the role makes and interactions are communication forums that can occur between roles and groups.

In the proposed organization goals ontology, we expand the concept of action, task and activity. We define action depends on task and task is an activity in the achievement of the organization goal. In addition, action provides a systematic organizational plan which must be followed to achieve its goals. In organization, in order to achieve the organization goals, it consists of action. Thus, we define that activity is performed by a task in order to achieve action. We use example from the university and library goal in order to expand the understanding between actions and tasks (see <http://www.lib.latrobe.edu.au/about/strategic-plan.php>). In the example, we look at La Trobe University Library's Strategic Plan for 2010 to 2015. In this plan, we can see the relationship between La Trobe University Library goal and action in relation to the La Trobe University's goal.

Sub-goal is defined as an out-come to achieve the organization goals. It is very important for the organizations to identify the sub-goals which are necessary to achieve in order to meet the organization goals. Sub-goal is used as a platform by which to examine the organization's progress toward achieving its main goal. However, action is required to perform sub-goal. For example, the main goal is to *Transform Student Lives Through Learning* and the sub-goal is to *Create Pathways for Underrepresented Students*. Here action to achieve this goal is 'to work with relevant university staff to develop programs to support under-prepared students' or 'review and further develop the library website in order to create more effective gateways for diverse client groups'.

Other example, if action is 'to work with relevant university staff to develop programs to support under-prepared students' then the possible task is to 'identify the student background in order to identify the most suitable program'. Based on the university and library goal, we can see the relationship between goal, sub-goal, action and task.

In the proposed organization goals ontology, we suggest the usage of the organization data as the important organization resource in relation to the organization goals. Thus, it is important to further the understanding of organization data compare to other organization resources such as information, knowledge and tools.

3.1.1 Data as an important organization resource to the organization goals

Organization goal is a main target for every organization. In order to perform the organization daily business activity in relation to the organization goals, it relies on the organization data. In organizations, data is important as a strategic asset that can be leveraged into a competitive advantage. This is because many organization recognize the value and the need of the data within the organization as an effort to assist decision making (Karim & Hussein, 2008). However, such data is too large though not all of this data is relevance to the organization goals. The difficulty in identifying the relevance of organization data become an issues. Even though information system and technology has been recognize to manage such data, the relevancy of organization data in relation to the organization goals always questionable.

Data provide detailed information about specific needs while service or system such as databases execute processes involving data and returning an informative result. In the knowledge society as today, user needs both data and system to systematically provide a value to all users. In order to make decision, organization depends on the amount of data to make a fact based decision. Organization uses this data for analysis. This is noted that, even though we live in organization business information but very little process has been work on data.

In one organization, the usage of data is very important for manager to share. It is important for manager to receive the relevance data in relation to the organization goals. Recent studies by Simsek et al. (2009) discussed that sharing of importance data and information can develop a knowledge to successful decision making. It is very crucial for the organization to create and generate new data and evaluate it for a better decision making. Differences in generating new idea, information and knowledge will help in term of decision-making and will enable such team within organization to use relevance data for the organization goals success. Data is presented in many forms such as documents and statistics. This data are the most important resource in relation to the organization goals.

3.2 Data goals linkage model

Even though there are many studies have been carried out in the context of data process such as data mining (Liao et al., 2008; Kum et al., 2009), limited study has been observed in evaluating organization data in relation to the organization goals (Izhar et al., 2012). Therefore, it is important to identify the relationship between organization data and organization goals. The relationship is important to identify the relevance of organization data from the vast amount of data. However, organizations have a huge set of organization data that might be relevance to the organization goals. At the same time, this large set of organization data might be redundant with respect to the organization goals. Thus, the first step to identify the relevance of organization data is to recognize the matching set of organization data for the achievement of the organization goals as illustrate in Fig. 2.

Data linkage approach is applied to identify the possibility linkage between organization data and organization goals. Data linkage is highly used to identify the data being linked, so all data sets under consideration should ideally undergo a matching process prior to data linkage. Many key identifiers for the same data can be presented quite differently between data sets, which can greatly complicate data linkage unless understood ahead of time. For example, as shown in Fig. 2, key identifiers for goal 1, goal 2 and goal 3 might appear in four different datasets (dataset A, dataset B, dataset C and dataset D).

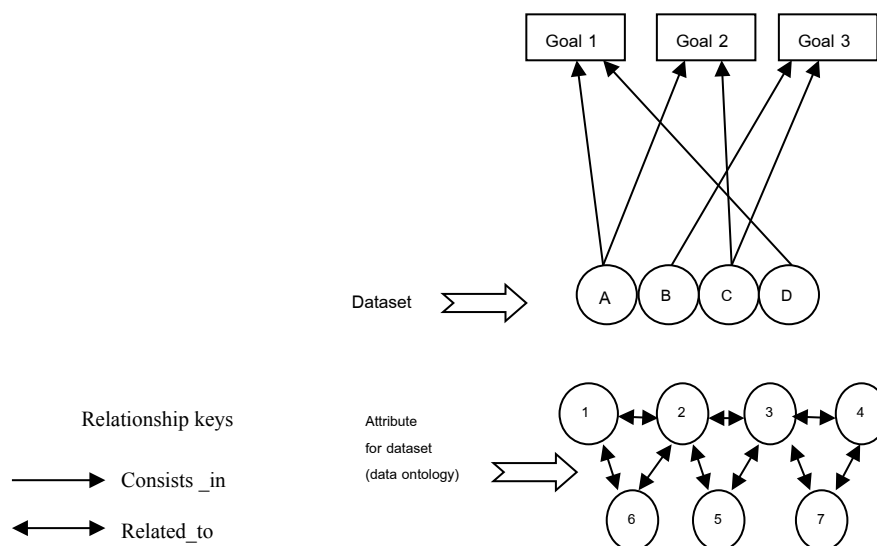


Fig. 2. Data-goals relationship

In Fig. 2, dataset A is linked with dataset D for goal 1 and data set A also linked with dataset C for goal 2. For goal 3, dataset B is linked with dataset C. However, most of the dataset is based on the question (see Table 1 and Table 2) and it is important to identify the possible attribute from each of dataset. It is important to identify the possible attribute that link data and goals. As shown in Fig. 2, we assume that each dataset might include the attributes. For example, dataset A may have attribute 1, 2, 3, 4, 5, 6 and 7, respectively.

3.2.1 Data attributes identification

Attribute identification is important in order to develop the link between organization data and organization goals. At the same time, it is important to avoid any redundant data for achieving the organization goals. For example, let's take La Trobe Library University as an example. In this example, data is collected every two years based on the Insync Survey¹. Library use this data to assist any decision

making process in relation to the library goals. In this example, library wants to look at “how students think the library is performing?” and “how students think the library is important?” Therefore, data sets for these questions are based on library’s performance and importance as shown in Table 1 and Table 2.

Table 1. Dataset for library’s importance

No	How students think library is important?	Data and attributes
1	Library staffs are approachable and helpful	Library staffs , <i>approachable, helpful.</i>
2	I can get wireless access in the library when I need to	Library , <i>wireless access.</i>
3	When I am away from campus I can access the library resources and services I need	Away from campus , <i>library resources, library services.</i>
4	Library staffs are readily available to assist me	Library staffs , <i>available, assist.</i>
5	The library web site is easy to use	Library web site , <i>easy to use.</i>

Bold= Data
Italic= Attributes

Based on Table 1, we identified the goal is the library's importance and we identified data and attributes for this goal. We recognized five sub-goals (no 1 to 5 in the table) in order to achieve library's importance and we develop data structure within the goal and sub-goal. However, some of this sub-goal might be related to other sub-goal as shown in Figure 3. We classified data (in bold) and attributes (in italic) for the sub-goals for the achievement of the library's importance. We develop data structure based on ontology for library's importance and this data structure is important to improve understanding of data goals structure of library's importance. Let's take one example in Table 1, in order to achieve library's importance, the possible sub goal is library staffs must be approachable and helpful.

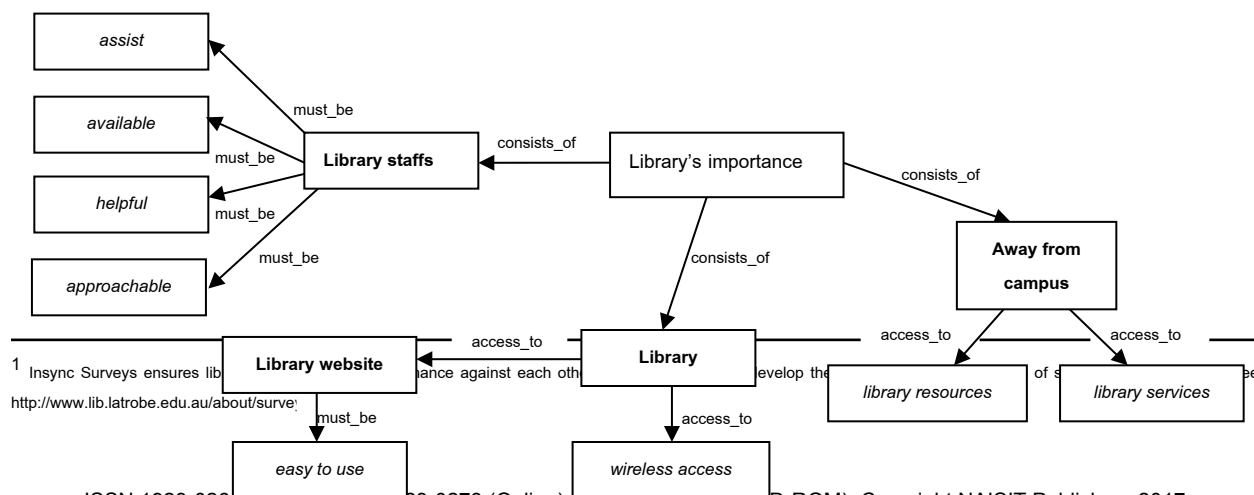


Fig. 3. Data goals structure for library's importance

Table 2. Dataset for library's performance

No	How student think library is performing?	Data and attributes
1	Library staff are approachable and helpful	Library staff , <i>approachable, helpful.</i>
2	Self Service (eg. Self check loans, requests, renewals, holds) meets my needs	Student needs , self service , <i>check loans, requests, renewals, holds.</i>
3	When I am away from campus I can access the library resources and services I need	Away from campus , <i>library resources, library services.</i>
4	The library web site is easy to use	Library web site , <i>easy to use.</i>
5	I can get wireless access in the library when I need to	Library , <i>wireless access.</i>

Bold= Data
Italic= Attributes

Based on Table 2, we identified the goal is the library's performance and we identified data and attributes for this goal same as in Table 1. We develop data structure based on ontology for library's performance as shown in Fig. 4. This data structure is important to define the relationship and the link between data and goals. Let's take one example in Table 2, in order to achieve library's performance, the possible sub goal is student can get wireless access in the library.

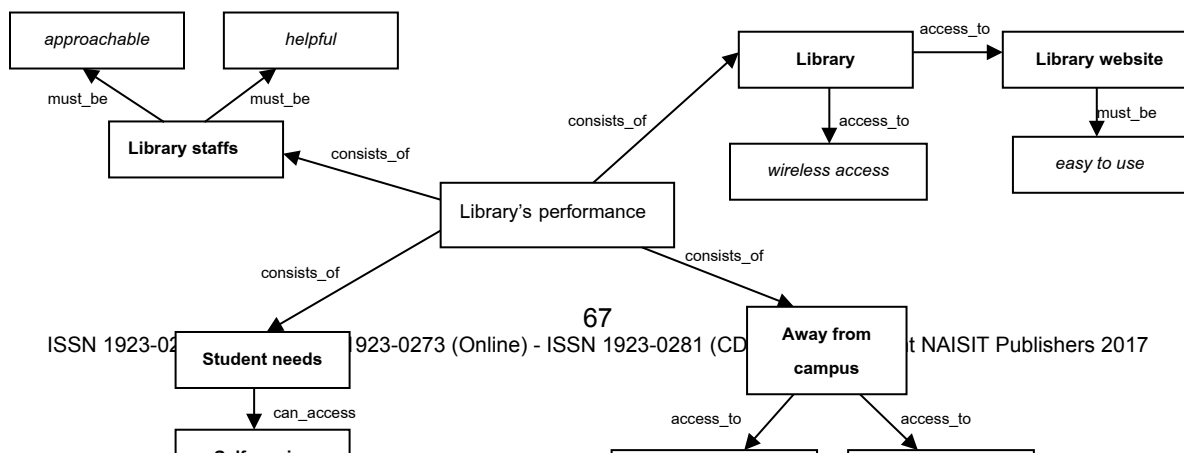


Fig. 4. Data goals structure for library's performance.

Based on Table 1 and Table 2, we can see the similar data and attributes between dataset of library's performance and data set of library's importance. It is important to identify matching data and attributes based on these two data sets in order to avoid redundancy of data and attribute. This process important to identify which data is been used more for the achievement of the library's performance and importance. We list down number of data and attributes for library's performance and importance as shown in Table 3.

Table 3. Attributes for library's performance and importance

List of attributes for library's performance and importance	
Library staffs	Assist
Approachable	Library website
Wireless access	Easy to use
Library resource	Self-service
Library service	Away from campus
Available	Request
Renewals	Holds
Helpful	Check loans
Student needs	Library

Based on Table 3, we identified eighteen attributes values are distributed. These eighteen attributes values are based on library data sets for library's performance and importance and it is important to apply these attributes for data goals linkage in order to identify the relevancy between data and the goals.

4. Generalizing the organization goals ontology

In this section, we attempt to generalize the sets of model for the organization goals ontology. We suggest that this process is important as a first step to develop a model that can be apply in the real world situation. In small organization, the process of identifying the organization goals structure is less complicated compare to the large organization. This is because large organizations have large structures and may involve more than one goal. Therefore, it is important to generalize a model for the organization goals that can be applied in any organization. This section has two aims. Firstly, we generalize the model for the organization goals. Secondly, we generalize the model for data goals model.

4.1 Generalizing the goals model

The first step is to generalize the organization goals. It is important to look at the entire organization goals before we generalize it into a data goals model. The process is to categorize the goals and the relationship between the goals. At the same time, it is important to avoid the duplication of attribute as discussed in Section 3.2. At this stage, we suggest four categories for generalizing the goals model and we explain the process as shown in Table 4.

Four categories of goals model:

- Type of goals,
- Data and attributes,
- Relationships, and
- Description.

Table 4. Generalizing the goals model.

Type of goals	Data and attributes	Relationships	Descriptions
(Identify the possible goals)	(Identify the possible attribute based on existing data)	(Identify the possible relationship in relation to the goals)	(Description for the goals)

For example, based on Table 1, Table 2 and Table 3, we generalize the goals model for the library's performance and importance. In Table 5, we identified library's performance and importance as the types of goals and we identified the entire data and attributes for library's performance and importance based on Table 3. Then, we identified the relationships for the goals based on ontology as in Fig. 4 and Fig. 5.

Table 5. Generalizing the goals model for library's performance and importance.

Type of goals	Data and attributes	Relationships	Descriptions
Library's important. Library's performance.	Library staffs. Assist. Approachable. Library website. Wireless access. Easy to use. Library resource. Self-service. Library service. Away from campus. Available. Request. Holds. Renewals. Check loans.	Consists_of Must_be Access_to Can_access Example_of	Library staffs are approachable and helpful. I can get wireless access in the library when I need to. When I am away from campus I can access the library resources and services I need. Library staffs are readily available to assist me. The library web site is easy to use. Self Service (e.g. self check loans, requests, renewals, holds) meets my needs.

	Student needs. Library. Helpful.		
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The process in Table 5 shows the overall goals for library's performance and importance. The process is important to avoid any redundancy that might happen during the process of identifying the goals. At the same time, the process standardizes the sets of model for the organization goals. Based on this model, it is important to develop the same approach to identify the relationship between organization data and organization goals.

4.2 Generalizing data goals model

The second step is to generalizing the goals model for data goals model. The process is important to categorize the goals model in order to improve the understanding of the relationship between data and organization goals based on ontology. At this stage, we suggest three categories for generalizing the data goals model and the process is explained in Table 6.

Three categories for data goals model:

- Concept,
- Types of entity, and
- Descriptions.

Table 6. Generalizing data goals model.

Concept	Types of entity	Descriptions
(Relationships for the goals)	(Type of entity for the goals)	(Description for the goals)

For example, we generalize data goals model for library's performance and importance as shown in Table 7 and Table 8.

Table 7. Generalizing data goals model for library's importance.

Concept	Types of entity	Descriptions
Library's importance	Goal	What student believes to be important for the library.
<i>consists_of</i>	Relationship	Goal consists of sub goal 1, sub goal 2 and sub goal 3.
Library staffs	Sub goal 1	Library staffs are approachable and helpful; and library staffs are readily available to assist student.
<i>must_be</i>	Relationship	Relationship of attribute.
Approachable	Attribute	Library staffs must be approachable.
Helpful	Attribute	Library staffs must be helpful.
Available	Attribute	Library staffs must be available.
Assist	Attribute	Library staffs must be available for assistant.
Library	Sub goal 2	Student can access to wireless in library when they need to.
<i>access_to</i>	Relationship	Relationship of attribute
Wireless access	Attribute	Library has access to wireless.

<i>access_to</i>	Relationship	Relationship of attribute.
Library website	Sub goal to sub goal 2	Student can access to the library website.
<i>must_be</i>	Relationship	Relationship of attribute.
Easy to use	Attribute	Library website must be easy to use.
Away from campus	Sub goal 3	Students can access to library resources and services when they are away.
<i>access_to</i>	Relationship	Relationship of attribute.
Library resource	Attribute	Students can access to the library resources.
Library service	Attribute	Students can access to the library services.

Table 8. Generalizing data goals model for library's performance.

Concept	Types of entity	Descriptions
Library's performance	Goal	How student think library is performing?
<i>consists_of</i>	Relationship	Goal consists of sub goal 1, sub goal 2, sub goal 3 and sub goal 4.
Library staffs	Sub goal 1	Library staffs are approachable and helpful; and library staffs are readily available to assist student.
<i>must_be</i>	Relationship	Relationship of attribute.
Approachable	Attribute	Library staffs must be approachable.
Helpful	Attribute	Library staffs must be helpful.
Available	Attribute	Library staffs must be available.
Assist	Attribute	Library staffs must be available for assistant.
Library	Sub goal 2	Student can access to wireless in library when they need to.
<i>access_to</i>	Relationship	Relationship of attribute
Wireless access	Attribute	Library has access to wireless.
<i>access_to</i>	Relationship	Relationship of attribute.
Library website	Sub to sub goal 2	Student can access to the library website.
<i>must_be</i>	Relationship	Relationship of attribute.
Easy to use	Attribute	Library website must be easy to use.
Away from campus	Sub goal 3	Students can access to library resources and services when they are away.
<i>access_to</i>	Relationship	Relationship of attribute.
Library resource	Attribute	Students can access to the library resources.
Library service	Attribute	Students can access to the library services.
Student	Sub goal 4	Student can access library self service.
<i>can_access</i>	Relationship	Relationship of attribute.
Self service	Sub to sub goal 4	Self service meets student needs.
<i>example_of</i>	Relationship	Relationship of attribute.
check loans	Attribute	Check loan is an example of self service.
requests	Attribute	Request is an example of self service.
renewals	Attribute	Renewal is an example of self service.
holds	Attribute	Hold is an example of self service.

Table 7 and Table 8 show the relationships between the library goals and library data for the library's performance and importance. However, based on these tables, we can see some similarity of data and attributes for library's performance and importance. Therefore, it is difficult to identify relevance library data because this data is related to both library's performance and importance. Thus, it is important to analyze this data for library's performance and importance.

5. Method

5.1 Data preprocessing

In organization, organization create vast amount of data every day and some of this data is redundant and not relevance. Therefore, it is important to preprocess the data in highly sensitive to identify the relevance organization data in relation to the organization goals. At the same time, it is important to identify the matching data in datasets as shown previously in Table 1 and Table 2. For example, key identifier for library staff might appear in two difference datasets as:

Table 9. Example of key identifier

Datasets	Name	Goals
Dataset 1	Library staffs are approachable and helpful	Library's importance
Dataset 1	Library staffs are readily available to assist me	Library's importance
Dataset 2	Library staffs are approachable and helpful	Library's performance

In this example, library staff might appear as “Library staffs are approachable and helpful” or “Library staffs are readily available to assist me”. The goal for key identifier of library staff also might appear in “Library’s performance” or “Library’s importance”. In essence, there are two main types of analysis which could be used. Firstly is probabilistic analysis², which aims to provide an expectation measurement when we unsure about the attributes. Secondly is deterministic analysis, which aims to provide a measurement when the attributes are known.

5.2 Probabilistic data linkage

Data linkage defined as a task of finding data in a data set that refer to the same entities (organization goals) from the different data sources. In data linkage, probability is a measurement of the expectation that the attribute from data sets will occur or true. Therefore, the higher probability for an attribute, the more certain we are that the data is relevance for library’s performance and importance. Data linkage can be subsequently fed into a business intelligence system for reporting and analytics. Data linkage between the different sources of data becomes necessary to ensure that the information about a particular entity in one source system can be seamlessly compared with information about the same entity from another source system.

In order to evaluation the organization data in relation to the organization goals, it is very important to identify the probabilistic linkage between organization data and organization goals. The probabilistic is important to identify relevance attribute of data within the datasets in relation to the organization goals. For example in Figure 5, the total number of attribute is classified in order to identify the probabilistic value for datasets. The matching data in the attribute can add the probabilistic value of the data.

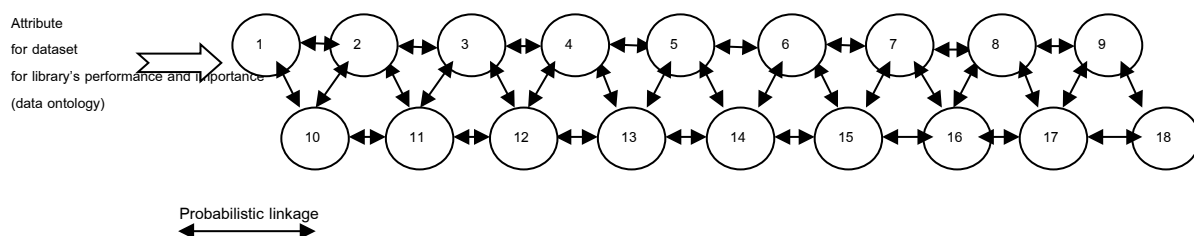


Figure 5: Data attributes

² The example of probabilistic analysis in this paper is based on Wikipedia (see http://en.wikipedia.org/wiki/Record_linkage). Wikipedia define data linkage as a record linkage.

Based on Table 3 in Section 3.2.1, we identified eighteen attributes values that are approximately uniformly distributed based on library's performance and importance. The probability for library's performance and importance is 1/18. Therefore, based from this example, if we want to identify the probability for library's performance, first we identify the total number of attribute for library's performance and importance. Now, we identify event E occur for library's performance.

$$P(E) = \frac{\text{Frequency attribute for library's performance}}{\text{Total attribute for library's performance and importance}}$$

$$= 16/18$$

If we want to identify the probability for library's importance, thus,

$$P(E) = \frac{\text{Frequency attribute for library's importance}}{\text{Total attribute for library's performance and importance}}$$

$$= 12/18$$

Even if probability for library's performance and importance is identified, many probabilistic data linkage algorithms assign match m and non-match u weights to identifiers by means of u probabilities and m probabilities. The u probability is the probability that an identifier in two *non-matching* records will agree purely by chance. The m probability is the probability that an identifier in *matching* pairs will agree.

For example, the non-match u probability for library's performance $1/18 = 0.055$ where the identifier with values that are not uniformly distributed will have different u probabilities for different value. The match m probability is the probability that an identifier in matching pairs will agree such as strings with high Jaro-Winkler distance or low Levenshtein distance. This value would be 1.0 in the case of perfect data, but given that this is rarely true, it can instead still be estimated. If a value of match m probabilities for library's performance is $16/18 = 0.88$, then the match/non-match weight for library's performance would be:

Table 10. Probabilities values of library's performance

Outcome	Proportion of links	Proportion of non-links	Frequency ratio	Weight
Match	$m = 0.88$	$u = 0.055$	$m/u = 16$	$\ln(m/u)/\ln(2) = 4$
Non-match	$1-m = 0.12$	$1-u = 0.945$	$(1-m)/(1-u) = 0.126$	$\ln((1-m)/(1-u))/\ln(2) = -2.98$

If a value of match m probabilities for library's importance is $12/18 = 0.66$, then the match/non-match weight for library's performance would be:

Table 11. Probabilities values of library's importance

Outcome	Proportion of links	Proposition of non-links	Frequency ratio	Weight
Match	$m = 0.66$	$u = 0.055$	$m/u = 12$	$\ln(m/u)/\ln(2) = 3.58$
Non-match	$1-m = 0.34$	$1-u = 0.945$	$(1-m)/(1-u) = 0.359$	$\ln((1-m)/(1-u))/\ln(2) = -1.474$

The existence of proposition in above table is disputed for data of being either true or false which applied for the existing links. It is important to refer to the meaningful data. In this paper, we define meaningful data as relevance data. To avoid the controversies of the ontology implication because the relationship between match and non-match link are developed based on ontology, proposition is applied for both match and non-match links where it is important to determine the frequency ratio for the existence data.

5.3 Deterministic data linkage

Based on the example of library's performance and importance, we identified eighteen attributes values that are distributed. The probability for library's performance and importance is 1/18. However, based on Table 1 and Table 2, we identified the attributes for both library's performance and importance. Meaning, the attributes for library's performance and importance are known. As discussed in Section 5.2, we identified the attributes for library's performance is 16/18 and library's importance is 12/18. Hence, we need to determine the expected value attributes for library's performance and importance.

We define some terms to determine the expected value³, where;

- Absolute frequency; how often a given measured value occurs within sample (≥ 0).
- Relative frequency; ratio between the numbers of certain events to the number of all events (≤ 1).
- Probability; measurement for the uncertainty of future events (between 0 and 1).
- Frequency; time related frequency (e.g. number of attribute) (≥ 0).

Based on the example in Section 5.2, we define the probability value for the attributes of library's performance and importance. We use this probability value to identify the expected value. This is because we know the number of attribute for library's performance and importance. It is important to identify the expected value for the attributes. We denote expected value as $E(x)$ and probability as $Pr.(x=x_i)$ as in Table 12, where

$$E(x) = \sum_{i=1}^2 x_i \cdot Pr(x = x_i)$$

³ Definition based on Department of Mechanical & Process Engineering, Swiss Federal Institute of Technology Zurich.

Table 12. Model definition

Model	Descriptions
E(x)	Expected value. Value from number of identified data and attributes.
X	Probability variable. Example link/non-link
Pr(.)	Relative frequency. Number of attribute from total number of attributes.

If we want to define expected value for library's performance, where "link attribute = 1 and non-link = 0", then it would be

$$X_i = \begin{cases} 1 & 16/18 = 0.88 \\ 0 & 2/18 = 0.11 \end{cases}$$

$$= E(x) = 0.88$$

The expectation for 1, closer to 100%.

If we want to define expected value for library's importance, then it would be

$$X_i = \begin{cases} 1 & 12/18 = 0.66 \\ 0 & 6/18 = 0.33 \end{cases}$$

$$= E(x) = 0.66$$

The expectation for 1, closer to 100%.

The example shows library expected value for its data in relation to the library's performance and importance. The evidence is clear and it shows the value of data and attributes. We conclude that deterministic can be acceptable for organizations that have smaller datasets and smaller attributes.

6. Discussion and future work

Different organizations create different data and because the complexity of data sources vary by organization, they need to decide which data linking strategy best suits their needs prior to implementation. The process can vary greatly depending on the types of matching method being used. In this paper, we applied data linkage to identify the linkage between organization data and organization goals. The process is important to identify relevance data and it important to analyze this data in relation to the organization goals. As discussed previously, there are essentially two methods available for data analysis, there are probabilistic and deterministic. Probabilistic matching uses likelihood ratio theory to assign comparison outcomes to the correct or more likely decision. This method can establish more accurate link between data and the goals. Deterministic matching have a relatively lower degree of accuracy compared to probability method.

In this paper, we developed data goals model based on the organization goals ontology. We suggest that the model is important to identify the link between organization data and organization goals. We applied probabilistic and deterministic methods in order to analyze the linkage between data and organization goals. The evidence from the examples is clear. Data driven decision tend to be better decision. In our example, the link between data and library's performance and importance are clear. We

identified existing data and attributes, and we identified the expected value for library's performance and importance. First, we defined the probabilities for library's performance and importance. However, in this example, library data is known. We identified number of data and attributes for both library's performance and library's importance. Therefore, we used these data and attributes to identify the expected value. Expected value for library's performance and importance shows the value between linked data. Therefore, we expected this value is important for the achievement of the library's performance and important where the value is closer to 100%.

Based on the observation, deterministic matching can be acceptable although it is less accurate. It is a lower-cost matching option for organizations that have smaller datasets, fewer attributes and require less complex rules. Others may favor probabilistic matching due to its flexibility and ability to check potential matches against a higher number of variables and very large data sets. Probabilistic solutions can provide enormous value for businesses in many industries. Businesses that require the highest levels of accuracy in real time, regardless of data volume, can fulfill their needs with a probabilistic solution, enabling them to limit the number of inaccurate matches and eliminate the costs and consequences associated with making them. Therefore, for small datasets, it is suitable to use deterministic and for large datasets, it is suitable to use probabilistic.

In summary, data goals model link the organization data in relation to the organization. The model assist the process of identifying the existing data and attributes, where we suggest that this data and attributes are important as an effort to identify the expected value of data in relation to the organization goals. However, we applied this model in a small structure of organization which is library goals. Structuring the small organization goals is less complicated compare to large organizations. Number of structure, volume of data and business process are difference compare to large organizations. Therefore, future works is needed.

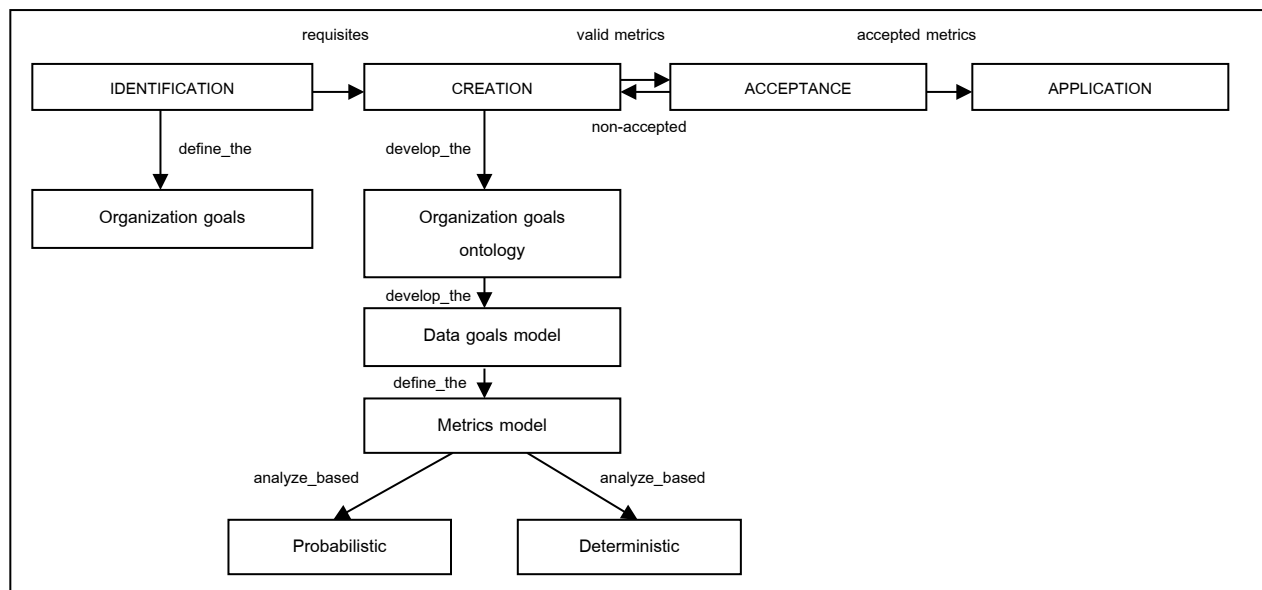


Fig. 6. Overall model process

In the future, we will attempt to extend the model illustrated in Fig. 6. In this figure, we develop a model for organization goals and we show the flow of organization data based on data goals model. In the case study, we applied small data from the library. In the future, it is important to apply our model to the larger organizations. It is important to make sure the model can be implemented at any size of

organizations. At the same time, it is important to identify the analysis method to analyze the data. In this paper, we applied both probabilistic and deterministic and we identified the gaps between the approaches. The process is important for us to identify the best approach that should be applied for data analysis. Lastly, it is important to identify variety of data to be implemented. For example, currently business intelligence talking about naked data and IBM is talking about big data. Therefore it is important to identify the various types of data in the organization in relation to the organization goals.

7. Conclusion

We have presented the design, implementation and evaluation of data goals model for the achievement of the organization goals. We developed this model based on the organization goals ontology. The purpose of data goals model is to identify the relationship between organization data and organization goals. In the first half of this paper, we discussed the background of the organization goals conformance. Then we discussed the concept of data goals model. In order to develop data goals model, we generalize organization goals ontology. We looked at the entire model of the organization goals and we narrow the process into organization data and organization goals. We applied library data for the model. In the second half of this paper, we discussed the methods to analyze the data in relation to the organization goals. We applied both probabilistic and deterministic methods and we identified the gaps between these methods. We conclude that expected value for data and attributes is important in relation to the organization goals. The process was important for use to identify the best analysis method that can be implemented for the future.

In conclusion, it is important to identify the relationship between organization data and organization goals for the achievement of the organization goals. Data is the most important organization resource and the organization can embrace the fact that it is important to have a relevance data to achieve the organization goals or facing the problem in identifying the relevance data from vast amount of it.

References

- Albino, V., Garavelli, A. C., & Schiuma, G. (2001). A metric for measuring knowledge codification in organisation learning. *Technovation*, 21, 413-422.
- Barlas, Y., & Yasarcan, H. (2006). Goal setting, evaluation, learning and revision: A dynamic modeling approach. *Evaluation and Program Planning*, 29, 79-87.
- Bouskila-Yam, O., & Kluger, A. N. (2011). Strength-based performance appraisal and goal setting. *Human Resource Management Review*, 21, 137-147.
- Burton-Jones, A., Storey, V. C., Sugumaran, V., & Ahluwalia, P. (2005). A semiotic metrics suite for assessing the quality of ontologies. *Data & Knowledge Engineering*, 55(1), 84-102.
- Ceresia, F. (2011). A model of goal dynamic in technology-based organizations. *Journal of Engineering and Technology Management*, 28, 49-76.
- Cho, J., Han, S., & Kim, H. (2006). Meta-ontology for automated information integration of parts libraries. *Computer-Aided Design*, 38(7), 713-725.
- Dillard, J. F. (1981). A longitudinal evaluation of an occupational goal-expectancy model in professional accounting organizations. *Accounting, Organizations and Society*, 6, 17-26.
- Earley, P. C., & Kanfer, R. (1985). The influence of component participation and role models on goal acceptance, goal satisfaction and performance. *Organizational Behavior and Human Decision Processes*, 36, 378-390.
- Fox, M. S., Barbuceanu, M., & Gruninger, M. (1996). An organisation ontology for enterprise modeling: Preliminary concepts for linking structure and behaviour. *Computers in Industry*, 29, 123-134.

- Fox, M. S., Barbuceanu, M., Gruninger, M., & Lin, J. (1998). An organization ontology for enterprise modelling. In *Simulation organizations: Computational models of institutions and groups* AAAI/MIT Press (pp. 131-152).
- Izhar, T. A. T., Torabi, T., Bhatti, I., & Liu, F. (2012). Analytical dependency between organisational goals and actions: Modelling concept. In *International Conference on Innovation and Information Management (ICIIM 2012)* (Vol. 36). Chengdu, China: IACSIT Press.
- Kang, S., & Norton, H. E. (2004). Nonprofit organizations' use of the World Wide Web: are they sufficiently fulfilling organizational goals. *Public Relations Review*, 30, 279-284.
- Karim, N. S. A., & Hussein, R. (2008). Manager's perception of information management and role of information and knowledge manager: The Malaysian perspectives. *International Journal of information Management*, 28, 114-127.
- Kum, H.-C., Duncan, D. F., & Stewart, C. J. (2009). Supporting self-evaluation in local government via Knowledge Discovery and Data Mining. *Government Information Quarterly*, 26(2), 295-304.
- Lepmets, M., McBride, T., & Ras, E. (2012). Goal alignment in process improvement. *The Journal of System and Software*, 85, 1440-1452.
- Liao, S.-H., Chang, W.-J., & Lee, C.-C. (2008). Mining marketing maps for business alliances. *Expert Systems with Applications*, 35(3), 1338-1350.
- Mansingh, G., Osei-Bryson, K.-M., & Reichgelt, H. (2009). Building ontology-based knowledge maps to assist knowledge process outsourcing decisions. *Knowledge Management Research and Practice*, 7, 37-51.
- Popova, V., & Sharpanskykh, A. (2011). Formal modelling of organisational goals based on performance indicators. *Data & Knowledge Engineering*, 70(4), 335-364.
- Pundt, H., & Bishr, Y. (2002). Domain ontologies for data sharing-an example from environmental monitoring using field GIS. *Computer & Geosciences*, 28(1), 95-102.
- Rao, L., Mansingh, G., & Osei-Bryson, K.-M. (2012). Building ontology based knowledge maps to assist business process re-engineering. *Decision Support Systems*, 52, 577-589.
- Salerno, M. S. (2009). Reconfigurable organisation to cope with unpredictable goals. *International Journal Economics*, 122, 419-428.
- Sharma, S., & Osei-Bryson, K.-M. (2008). Organization-ontology based framework for implementing the business understanding phase of data mining projects. In *International Conference on System Sciences* (pp. 27). Hawaii.
- Sholihin, M., Pike, R., Mangena, M., & Li, J. (2011). Goal-setting participation and goal commitment: Examining the mediating roles of procedural fairness and interpersonal trust in a UK financial services organisation. *The British Accounting Review*, 43, 135-146.
- Simsek, Z., Lubatkin, M. H., Veiga, J. F., & Dino, R. N. (2009). The role of an entrepreneurially alert information system in promoting corporate entrepreneurship. *Journal of Business Research*, 62, 810-817.
- Vergidis, K., Turner, C. J., & Tiwari, A. (2008). Business process perspectives: Theoretical developments vs real world practice. *International Journal of Production Economics*, 114, 91-104.