Journal of Information and Knowledge Management (JIKM)
Volume 5 Number 2 (2015). pp 1-22

Identifying Information from Data Using an Organizational Goals Ontology: A Case of the Australian Economy

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Abstract
Organizational data is important to assist domain experts and entrepreneurs for decision-making process in relation to the organizational goals. The trustworthiness of organizational data in relation to achieving the organizational goals is often questioned because of the vast amount of organizational data. This paper proposes a methodology to evaluate organizational data that relates to the organizational goals. This refers to the importance of assisting the organization to utilize relevance of organizational data from the vast amount of datasets for decision-making in relation to the organizational goals. The aim of this paper is to evaluate the level of the organizational goals achievement. In order to achieve this aim, we identify the dependency relationship between organizational data and organizational goals. Based on this dependency relationship, we define a metrics to analyse organizational data to be considered relevant to the organizational goals achievement. The case study is present to test the applicability of the methodology to measure the level of the Australian economy. The results show the dependency relationship between the case study goal and its variables. The contribution of this paper will serve as a new approach in evaluating the level of the organizational goals achievement.

Keywords: Australian economy; organizational data; organizational goals ontology; metrics; dependency relationship

1. INTRODUCTION

Government agencies, public and private bodies are drowning in an ever-increasing deluge of data because they create and collect massive amount of data in their daily business activity (Christen, 2012). Thus, the ability to analyse their data in a timely fashion can provide a competitive edge to improve productivity in relation to the organizational goals. Data is the most important asset to assist the decision-making process in achieving the organizational goals. However, the trustworthiness of organizational data in relation to the organizational goals always questionable due to the huge data mining issue within the organization. Some of this data are not relevant to the organizational goals. Therefore, it is difficult to identify the relevance of organizational data even though the professional such as data analysts are trained to analyse this data but the increase amount of organizational data has become a major problem in applying this data in achieving the organizational goals. Thus, modelling the organizational goals structure is important to identify the dependency relationship of organizational data that relates to the organizational goals. For example, one approach to identify this dependency relationship is based on ontology to improve the understanding of the organizational goals structure as it shows the relationship between the organizational goal elements (Izhar et al., 2012; Izhar et al., 2013). Ontology captures data in the way that allow the relationship to become visible. It captures knowledge within the organization as a model. This model can be created by a user to answer complex questions and display relationship across the enterprise.

Organization relies on the resources to assist the process of a business plan, strategy and decision-making in relation to the organizational goals. Organizational resource such as organizational data must be relevant to assist domain experts or entrepreneurs with decision-making process. Typically, relevant data for decision-making is extracted from the organizational data sources (Romero & Abello, 2010). Therefore, it is important for the organization to manage its resources (Omerzel & Antoncic, 2008; Schalenkamp & Smith, 2008; Smith et al., 2007). This is because the growth in the amount of organizational resources available nowadays poses major difficulties as well as challenges in decision making (Mikroyannidis & Theodoulidis, 2010). 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 organizational data in relation to meeting the organization goals is questioned and it poses an issue of how optimally the selected data may be used for better decision-making and fully achieving the organizational goals.

However, there is a shortcoming when it comes to evaluating the organizational data in relation to the organizational goals. Modelling the organizational goals is limited to the business process and the organizational process (Fox et al., 1996; Mansingh et al., 2009; Rao et al., 2012; Sharma & Osei-Bryson, 2008). The aim of this paper is to present a methodology to measure organizational data that relates to the organizational goals as an effort to assist domain experts and entrepreneurs with decision making process in order to identify the level of the organizational goals achievement as shown in Figure 1. This paper is designed into three tasks.

1. Firstly, to identify dependency relationship of the organizational goals based on ontology (Izhar et al., 2012; Izhar et al., 2013). Ontology is important to define a specification of a conceptualization. In the context of the organizational goals, ontology is developed to improve the understanding of the organization structure and relationship of the organizational goals. It creates the knowledge for the domain experts and entrepreneurs to identify the relevance of organizational data in relation to the organizational goals. The concept of the organizational goals ontology is concerned with unifying organizational data from unrelated resource.

2. Secondly, to identify dependency relationship of organizational data that relates to the organizational goals. We suggest it is important to identify this relationship as the first step to identify organizational data to be analysed in relation to the organizational goals. In the mean time, this relationship is important to identify the relevance of organizational data from the vast amount of organizational datasets. Organizations have a huge set of organizational data that might not be relevant with respect to the organizational goals. Thus, the first step to analyse the relevance of organizational data is to identify organizational data that relates to the organizational goals.

3. Thirdly, the definition of a metrics as a measurement tool to analyse organizational data to be considered relevant in relation to the organizational goals.

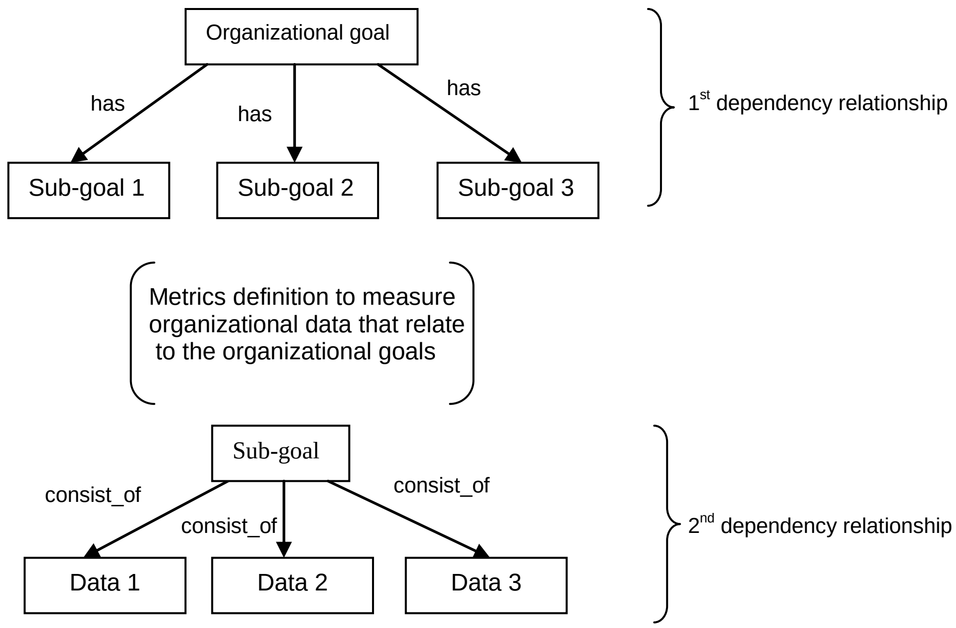

Figure 1 Concept development.

In Figure 1, we assumed the process of the organizational goals involves three sub-goals but in the real situation, the organization might have more than three sub-goals. In this figure, it is important to identify the value for every organizational data that relate to different sub-goals so this data can be considered relevant to the organizational goals. Therefore, metrics is defined to identify this value based on the requirement of domain experts and entrepreneurs. The process of measurement analysis become a nature of decision- making as the analysed data presents the value of organizational data that relate to the organizational goals.Even though the methodology is proposed with three main tasks, the concept and evaluation experimented in this paper is implemented so that the proposed methodology can be applied in any case with different datasets and different sets of the organizational goals.

1.1 Objective

The aim of this paper is to evaluate the level of the organizational goals achievement in the context of the Australian economy. This paper begins by identifying the organizational goals and the dependency relationship between organizational data and organizational goals and, finally, the measurement approach to analyse organizational data in order to consider which organizational data is relevant to assist domain experts and entrepreneurs with decision-making process in relation to the organizational goals.

The scope of the methodology consists of the deployment approach of the organizational goals ontology so domain experts and entrepreneurs can access available organizational data. As part of the organizational goals ontology, we introduce a measurement approach to analyse organizational data to consider whether this organizational data is relevant. In contrast to the works in Rao et al. (2012), Sharma & Osei-Bryson (2008) and Fox et al. (1998), the main challenge in this paper is to identify the dependency relationship between organizational data and organizational goals and to evaluate the weight of this dependencies. The process is to specify to what extent the organizational goals are achievable. This provides knowledge to improve the applicability of the methodology so future research can be suggested to address any gaps and issues in achieving the organizational goals.

2. LITERATURE REVIEW

Recently, there have been substantial growths in data linkage activities (Durham et al., 2012; Freire et al., 2012; Meray et al., 2007). Most of these studies focused on the task of identifying data from datasets in order to prevent any redundancies of data. To our knowledge, no studies have been carried out in the development of organizational data in relation to the organizational goals. Even though study on organizational goals have been carried out but most of the studies focus on the modelling concept for organization performance (Bouskila-Yam & Kluger, 2011; Earley & Kanfer, 1985; Lepmets et al., 2012; Salerno, 2009). Therefore, it is important to identify the linkage of organizational data and organizational goals as we suggest this data should be relevant to assist decision making process for the achievement of the organizational goals.

Organizational goals are defined as the 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 (Izhar et al., 2013). Thus, it is important to understand the organizational 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, organizational structure is developed to achieve the performance of the organization (Bouskila-Yam & Kluger, 2011) or the goal structure is developed to achieve the performance of goals (Barlas & Yasarcan, 2006); Earley & Kanfer, 1985; Lepmets, et al., 2012; Sholihin et al., 2011). The example shows a number of the studies that look at the organizational structure toward the performance. This is because the organizational performance depends on the organizational structure. Same with the goal structure and the goal performance, in which the organizational goal depends on the goal structure toward the goal performance.

There are number of the organizational goal studies that focus on the performance such as system performance (Ceresia, 2011; Kang & Norton, 2004), goal performance (Barlas & Yasarcan, 2006; Dillard, 1981; Sholihin et al., 2011) and organization performance (Bouskila-Yam & Kluger, 2011; Earley & Kanfer, 1985; Lepmets et al., 2012; Salerno, 2009). It is important to identify the entire organizational modelling process as an effort to look at the organizational performance and the goal performance. However, the process can be very large and it is very difficult to evaluate the organizational data as an effort to achieve the organizational goals. In contrast, it is important to identify organizational data that relates to the organizational goals. Therefore, the linkage of organizational data from datasets should be consistent to identify the relevance of organizational data, thus it can be evaluated in relation to the organizational goals.

Even though the concept of the organizational goals is developed but modelling the structural of the organizational goals is always questionable. Thus, we suggest that ontology is important to develop a common understanding of the organizational goals structure (Izhar et al., 2012). At the same time, ontology is explicit and formal specifications of the knowledge, especially implicit or hidden knowledge (Cho et al., 2006). Ontology also considered as an approach to support data sharing (Pundt & Bishr, 2002). Ontology assists with part of the integration problem in relation to the organizational goals. Therefore, ontology can be used to improve communication between decision makers and users collaborating (Selma et al., 2012), where in our case, the communication between the decision makers in relation to the organizational goals.

3. METHODOLOGY

The methodology is designed and developed specifically to address the issues in identifying the relevant organizational data to assist the decision-making process in relation to the organizational goals. Therefore, he/she can identify to what extent this organizational goals are achieved. The methodology is designed to:

- Successfully develop the dependency relationship between the organizational goals elements based on ontology.
- Capable to be applicable in wide range of domains.
- Successfully develop the dependency relationship between organizational data that relate to the organizational goals.
- Capable of defining a metrics to evaluate the level of the organizational goals achievement by evaluating organizational data that relate to the organizational goals.

The methodology focus on the development of the methodology associated with the organizational goals ontology (Izhat et al., 2012; Izhar et al., 2013).

3.1 Dependency relationship of the organizational goal elements using an ontology

The organizational goals ontology aim to develop the dependency relationship between the organizational goals elements and dependency relationship between organizational data and organizational goals (Izhar et al., 2013). An ontology is applied as a tool to develop the dependency relationship between the organizational goals elements which include sub-goals and organizational data (Izhar et al., 2012; Izhar et al., 2013). It provides the means to understand this dependency relationship, as shown in Figure 2. Therefore, domain experts and entrepreneurs can define the organizational goals based on their requirement.

An ontology shows the dependency relationship of the organizational goals, dependency relationship of organizational data that relate to the organizational goals and to evaluate the weight of this dependency between organizational data and organizational goals. The evaluation aims to test the flexibility of the ontology to develop these dependencies and to define the organizational goals. In order to develop the organizational goals ontology, several structures that were proposed in the previous models are combined (Fox et al., 1998; Rao et al., 2012; Sharma & Osei-Bryson, 2008). We adopted these models as a reference for the organizational goals ontology. However, the scope of the proposed organizational goals ontology in this methodology does not cover all the organizational processes as discussed in Sharma & Osei-Bryson (2008), Fox et al. (1998) and Rao et al. (2012).

Fox et al. (1998) focused on structuring the linkage between organizational structure and behavior. This is critical for enterprise model development. However, the authors do not emphasize any organizational resources such as data and information but they focus on the roles and activities within the organization. Meanwhile, Sharma & Osei-Bryson (2008) developed a framework for an organizational ontology in an effort to increase an understanding of the business. However, the authors do not specifically identify the relationship between organizational resources, such as data and the organizational goals. In this model, the authors adapted the work of Fox et al. (1998), where the authors discussed the physical resources and role of the organizational model.

Recently, Rao et al. (2012) developed an organizational ontology in order to build a knowledge map within the organization. The structure includes the flow of knowledge within the organization in the context of knowledge sharing and knowledge storage. In this model, the authors discussed the organizational resources, as in Sharma & Osei-Bryson (2008). Another aspect that is similar to Sharma & Osei-Bryson's work is that both models include business processes. However, Rao et al. (2012) discussed business processes from the organizational goals point of view and Sharma & Osei-Bryson (2008) discussed business processes from the organizational activity point of view. Most of these studies focused on the organizational structure and performance.

Table 1 shows the results from the previous models on the organizational goals using an ontology but none of these studies focus on the evaluation level of the organizational goals achievement. Table 1 also shows that these models do not focus on organizational data. At the same time, there is no study on metrics to evaluate the dependency relationship of organizational data that relate to the organizational goals. The gaps of these issues are important during the development of the methodology.

Table 1 Review of the issues.

Authors	Organizational goals ontology		Resources			Metrics
	Organizational goals	Sub-goals	Information	Knowledge	Organizational data	Dependency relationship
Fox el al. (1998)	✓	✓	x	x	x	x
Sharma & Osei-Bryson (2008)	✓	✓	✓	✓	x	x
Rao et al. (2012)	✓	✓	✓	✓	x	x

We proposed the organizational goals ontology as shown in Figure 2. In this figure, we show that each organization has many organizational goals and each organizational goal consists of sub-goals. In order to identify the level of the organizational goals achievement, organization relies on organizational resource which include organizational data to evaluate this level of the organizational goals achievement.

Compare to Sharma & Osei-Bryson (2008), our organizational goals ontology focus on the usage of organizational data instead of knowledge, information or tools because organizational data is a major resource in every organization and it is important to evaluate the relevance of this organizational data in achieving the organizational goals. We also suggest that organizational data is as important as information and knowledge to assist the decision-making process (Izhar et al., 2013).

In an organization, it is extremely important for the manager to have access to the most relevant organizational data in relation to the organizational goals. Simsek et al. (2009) pointed out that sharing important data and information can provide the required knowledge to assist successful decision-making. It is crucial for organizations to create and generate new data and evaluate it to enhance decision-making. Different ways of generating new ideas, information and knowledge will help in terms of decision-making and will enable teams within the organization to use the most relevant organizational data to successfully achieve the organizational goals.

Data is presented in many forms such as documents and statistics. The data is the most important resource in relation to the organizational goals. In this paper, we defined this data as organizational data and we refer to this term in the rest of this paper.

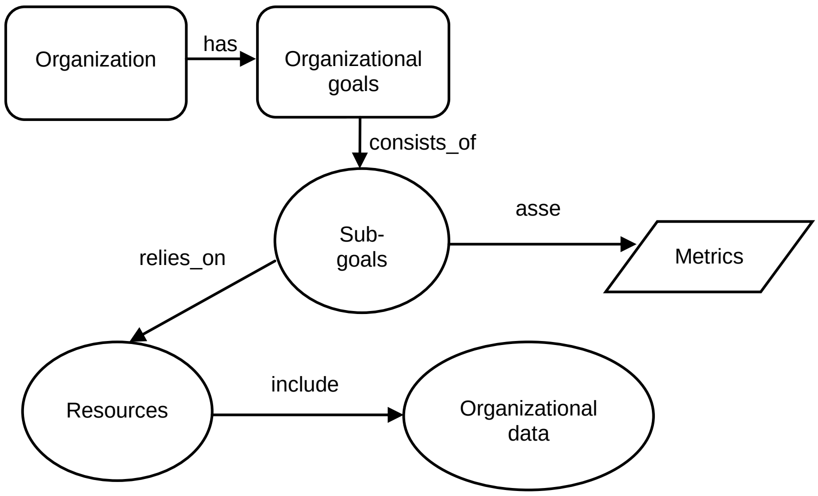

Figure 2 Organizational goals ontology.

Figure 2 is different to other studies which either did not include metrics at all (Fox et al., 1998; Sharma & Osei-Bryson, 2008) or only used the metrics to measure the knowledge within the organization (Rao et al., 2012). However, in this research we introduce metrics as a measurement tool to analyse organizational data that relate to the organizational goals.

3.2 Dependency relationship between organizational data and organizational goals

In order to develop the dependency relationship between the organizational data and organizational goals, record linkage is adapted. Record linkage is commonly used to identify data that is linked, so all datasets under consideration should ideally undergo a matching process prior to record linkage (Durham et al., 2012). Even though studies have been carried out on various issues such as software (Freire et al., 2012; Jutte et al., 2011) and data privacy (Abril et al., 2012; Karakasidis & Verykios, 2011), it is important to develop a standard set of approaches to show the relationship between the organizational data and organizational goals.

A large body of existing work uses the terms record linkage, data linkage, record matching, data matching (Abril et al., 2012; Christen, 2012; Ferrante & Boyd, 2012; Scannapieco et al., 2007; Su et al., 2010; Yakout et al., 2010), however, in this paper, we use the term data dependency in an effort to identify the dependency relationship between the organizational data and organizational goals because we attempt to identify dependency for all organizational data that relate to organizational goals.

We suggest data and goals dependency based on the organizational goals ontology to define the dependency relationship between the organizational data and organizational goals as shown in Figure 3. Data and goals dependency is a process to identify which organizational data in the organizational datasets is relevant to the organizational goals. Even though many studies have been carried out in the context of data processes such as data mining (Kum et al., 2009; Liao et al., 2008), a limited number of studies have been conducted to evaluate the dependency organizational data in relation to organizational goals (Izhar et al., 2012). Identifying the relationship between the organizational data and organizational goals is important to determine the relevant organizational data in the vast amount of organizational datasets.

Organizations have a huge set of organizational data that might be relevant to the organizational goals. However, not all of this might be relevant with respect to the organizational goals. Thus, the first step to identify the relevant organizational data is to recognize the matching set of organizational data to identify which organizational data relate to the organizational goals.

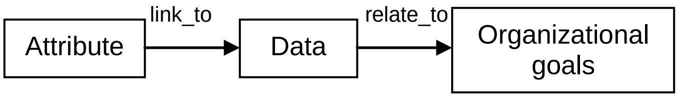

Figure 3 An example of data and goals dependency.

Figure 3 shows that data and goals dependency involves the organizational data, attributes, relationships and organizational goals. However, the example in this figure does not include any organizational goal elements because we just want to show the relationship between the organizational data and organizational goals.

3.3 Metrics definition to measure the level of the organizational goals achievement

At this stage of our research, we define a metrics to measure organizational data as an effort for domain experts to come out with decision-making process in relation to the organizational goals. Figure 1 shows the dependency relationship between organizational data and organizational goal. It is important to identify the value for every organizational data that relates to the organizational goals so this organizational data can be considered as relevance of organizational data in relation to the organizational goals.

For example, when the value is assigned to the number of data, the value of weight will change and this value can be defined in many ways such as percentage or frequency value as discussed in the case study. Assuming this value is identified and it can be presented in the dashboard to show a graphical presentation of value. Therefore, the comparison of this value can be presented to support the decision-making process in relation to the organizational goals.

3.4 Application tool of the methodology

We develop a tool associated from the organizational goals ontology to assist domain experts and entrepreneurs to be able to analyse and evaluate the level of the organizational goals. The tool assists the flexibility of the methodology to identify the dependency relationship between the organizational goals element and the dependency relationship between organizational data and organizational goals (Izhar et al., 2012; Izhar et al., 2013). This dependency relationship is important to identify which organizational data is relevant. In order to achieve this, we set a measurement tool based on the metrics in order to evaluate organizational data that relate to the organizational goals.

The application process of the methodology is based on two stages: planning and operational. These stages will allow the flexibility of the methodology. Based on these two stages, we develop five-steps during the application process. The steps will provide a systematic approach on how the organizational goals will be identified, the dependency relationship between organizational data and organizational goals, and how the metrics will be defined to evaluate the organizational data to assist the decision-making process in relation to the organizational goals.

Planning stage is to test the flexibility and applicability of the methodology. At this stage, domain experts and entrepreneurs can customize the methodology to identify the organizational goals together with its sub-goals and variables. At the same time, it is a stage to develop the dependency relationship between organizational data and organizational goals in order to identify which organizational data relates to the organizational goals. Therefore, we can define the metrics to evaluate this organizational data.

Operational stage is a stage to execute the application of the methodology. This stage is about identifying the measurement data and making effectiveness results to assist decision-making process in relation to the organizational goals. This means we need to identify the weight of analysed data based on the actual implementation. The operational stage is the process covering the evaluation of the framework in order to identify the value from the populated data. Based on this value, domain experts and entrepreneurs can identify to what extent the organizational goals might been achieved. Based on the planning and operational stages, we describe the five-steps of the application process as follows:

Planning stage:

- Step 1: Identify the organizational goals.
- Step 2: Identify the sub-goals and variables.
- Step 3: Identify the dependency relationship.
- Step 4: Identify the metrics.

Operational stage:

- Step 5: Analysis and feedback.

The first four steps define the organizational goals and how the organizational goals relate to each other. The last step defines the data to be measured to assist the decision-making process. This process identifies the right metrics to make sure the dependency organizational data will be evaluated in relation to the organizational goals. Even though the discussion is elaborated in general, the aim is to see how these steps can be proven to be flexible and applicable when the methodology is tested in different domains.

3.4.1 Tool design and implementation

This tool is presented as an instruction for domain experts to follow from Step 1 to Step 5. The steps include how to identify the goals, the organizational dataset and how domain experts evaluate the goals. After we identified the goals, we populate the data to the dataset and evaluate this data to assist the decision-making process. The implementation of the tool is based on the application process of the methodology, in which from the planning stage to the operational stage.

- **Planning stage**

The steps involve the process to identify the main goals and the metrics without populating any data to the main goals.

Step 1: Identify the organizational goals

- Domain experts identify the set of goals in the organization.
- They identify the goal they want to evaluate.
- They have the flexibility to identify and select the main goal.

Step 2: Identify the sub-goals and variables

- Domain experts identify the possible sub-goals and variables that relate to the main goal.
- They have the flexibility to identify these sub-goals and variables.

Step 3: Identify the dependency relationship

- Domain experts identify the dependency relationship between the goals and sub-goals.
- Domain experts identify the dependency relationship of data that they want to evaluate to the goals.

Step 4: Identify the metrics

- Domain experts define the metrics based on the dependency relationship they identified in Step 3.
- They define the metrics based on their evaluation requirement. For example, they can evaluate the data based on the frequency, rank and percentage.
- They select or remove data from dataset that they want to evaluate and analyse in relation to the main goals.
- Domain experts have the flexibility to change how they want to define the metrics based on how they define the main goals.

- **Operational stage**

This stage is about how data is populated from the datasets and how this data will be analysed based on the metrics in order to assist decision-making process in relation to the goal.

Step 5: Analysis and feedback

- Domain experts assign the value to the dataset and dataset is populated.
- The populated data is analysed based on the metrics.
- Final results will be shown in the dashboard to evaluate the level of the goals achievement.
- Using the framework, the evaluation process for the final results is flexible with the change of the value in the dataset.

The process discussed in this section explains how we use the tool to identify the main goals and sub-goals from the dataset and how we can define the metrics to evaluate the data that relate to the goals from Step 1 to Step 5 in the planning stage and operational stage.

The tool embedded in the methodology allows the five steps to be applied with any organizational goals and organizational data. We presented some examples to illustrate how this tool supports the application of the steps. This section discusses how domain experts implement the framework based on the five steps in order to evaluate the level of organizational goal achievement. Based on the tool discussed in this section, we summarise the benefits of the methodology as follows:

- Domain experts have the flexibility to identify and select the main goal.
- Domain experts have the flexibility to identify the sub-goals and variables.
- Domain experts are able to develop the dependency relationship between the goals and sub-goals.
- Domain experts have the flexibility to change how they want to define the metrics based on how they define the main goals.
- The evaluation process for the final results is flexible with changes in the values in the dataset.

4. CASE STUDY

In this section, we demonstrate the operation of the organizational goals ontology with an illustrative example to show its applicability.

4.1 Data collection

Data in this case study were prepared by the Australia Industry Policy and Economic Analysis Branch in the Industry and Small Business Policy Division of the Department of Innovation, Industry, Science and Research and is available through the Small Business Key Facts and Statistics Report on the department's website at www.innovation.gov.au. The aim of this report is to provide a comprehensive overview of Australia's small, medium and large sized businesses for, with an emphasis on how business size characteristics and performance affect the Australian economy.

In order to achieve this aim, the report provides information about the number of people employed in an organization and industry value added by looking at the contribution of business size to the Australian economy. According to the Small Business Key Facts and Statistics Report, businesses of all sizes are a vital part of the Australian economy, providing almost half the total industry employment and around a third of industry value added in 2010 to 2011. We used data from this report to test the methodology.

In this case study, data are used to evaluate the contribution of business size to the Australian economy. The experiment is conducted to test the framework to show the dependency relationship between industry sector and business size in relation to the Australian economy. Therefore, in this case study, the contribution of the number of employees and the value added by business size are analysed to provide a comprehensive overview of the Australian economy. The overall process of the case study is shown in Figure 4.

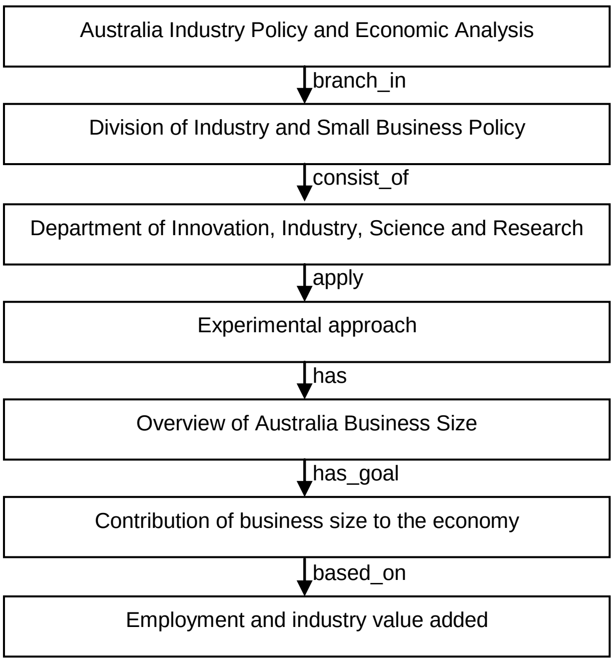

Figure 4 Case study process.

4.2 Application process of the organizational goals ontology

In this case study, we test the organizational goals ontology to define the goals, sub-goals and metrics in order to evaluate the case study goals. The flexibility and applicability of the organizational goals ontology will be tested by using the five main step of the organizational goals ontology.

4.2.1 Planning stage

In the planning stage, we identify the main goals and sub-goals for this case study. After this, we define the metrics in relation to the case study goal. The planning stage of the methodology is implemented from Step 1 to Step 4.

Step 1: Identify the organizational goals

The aim of this case study is to identify the contribution of employee numbers and value added of industry sectors by business size in relation to the Australian economy. Therefore, the goal of this case study is to evaluate the contribution of different sized businesses to the Australian economy.

- Goal: To measure the contribution of different sized businesses to the Australian economy.

Step 2: Identify the sub-goals and variables

The contribution of employees relates to the number of employees in an organization. Refered to as the Small Business Key Facts and Statistics Report, the measurement of value added relates to the contribution to Australia's gross domestic product by businesses in all industry sectors and indicates the value produced from employees (i.e wages plus salaries) and business owners (i.e. profits).

These variables are a vital part of the Australian economy, providing almost half the total industry employment and around a third of value added in 2010 to 2011. Therefore, we define this variable in order to evaluate the industry sectors by business size, based on the contribution of employee number and value added. The sub-goals and variables of this case study are as follows:

- Sub-goal: Contribution level of employee number.
- Sub-goal: Contribution level of value added.
- Variable: Industry sectors and business size.

Step 3: Identify the dependency relationship

In Step 3, we develop the dependency relationship in this case study using Protégé. Protégé is a tool to provide a graphic user interface to define the organizational goals ontology.Figure 6 shows the dependency relationship between the case study goal, sub-goals and the variables through the process of assigning a weight to the dependencies to measure the contribution level of employee number and value added by business size to the Australian economy.

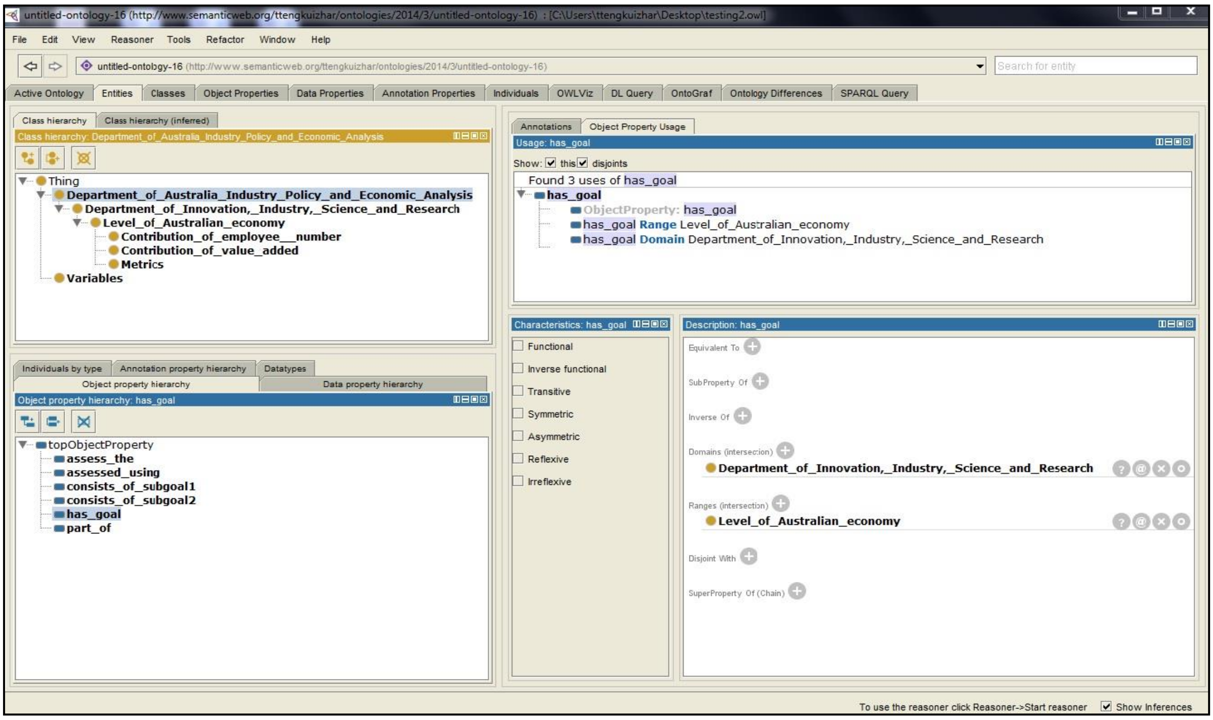

Figure 5 Classes and relationships.

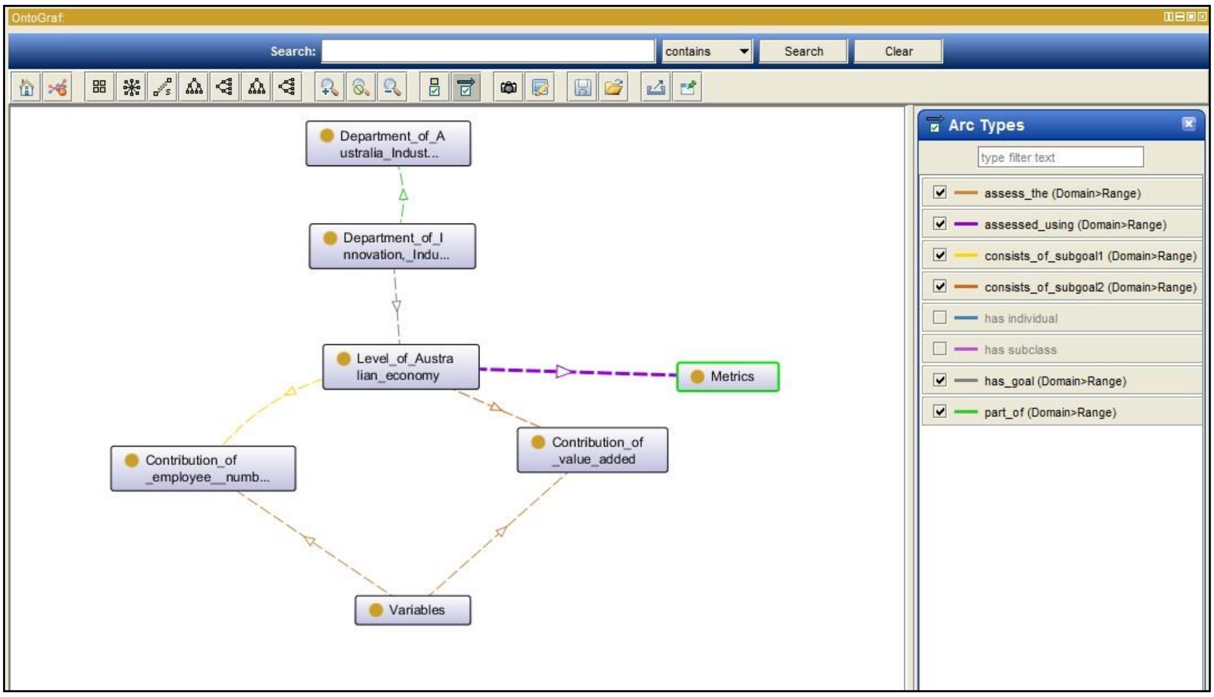

Figure 6 Ontology for the Australian economy using Protégé OntoGraf.

Step 4: Identify the metrics

In this case study, it is important to evaluate the performance of the Australian economy, based on the industry sectors, by observing which business size contributes more to the Australian economy.

The evaluation of business size is based on: 1) the contribution of employee number; and 2) the contribution of value added. It is important to evaluate both of these in order to identify which sub-goals make the highest contribution to the Australian economy. This case study uses the results from the Small Business Key Facts and Statistics Report which examines 18 industry sectors. We defined the metrics to show the overall contribution of employee numbers and value added to the Australian economy. The metrics is defined as:

$$\text{Metrics (Contribution level)} = \sum \frac{\text{Frequency}}{\text{Overall total}} \times 100$$

For example, Table 2 shows the overall contribution of business size to the Australian economy. Taking large businesses as an example, employee number contributes 3154, from the overall total of 10633, therefore, the calculation is as follows:

$$\text{Metrics (Contribution level)} = \sum \frac{3154}{10633} \times 100$$

In this case study, this is how we define the metrics in order to evaluate the extent to which different sized organizations contribute to the Australian economy. We demonstrate the flexibility of the organizational goals ontology in defining the metrics with a different definition of the goal and using a different data set.

4.2.2 Operational stage

After we defined the main goal and metrics, we populate the dataset and analyse this data in order to assist the decision-making process. This process is based on Step 5 of the methodology.

Step 5: Analysis and feedback

Data are evaluated in an effort to evaluate the contribution of employee numbers and value added to the Australian economy. The results in Table 2 to Table 4 show a comparison of business size (large, medium and small) by industry sectors. As shown in this table, there is a different value for every industry sector. We summarize this table for the decision-making process to evaluate the contribution of employee numbers and value added, as shown in Table 5.

The results in Table 5 summarize the contribution of employee number and value added to the Australian economy. The contribution of value added for medium business is only 14.90% and the contribution of employee number is only 25.04% which is the lowest compared to large business and small business. The contribution of employee number in small business is 45.30% and 21.44% of value added to the Australian economy.

The results presented in Figure 7 assist the decision-making to evaluate the contribution of different sized organizations to the Australian economy. The figure compares the different contributions to the Australian economy by business size. The figure shows that large businesses make the highest contribution in terms of value added compared to other business sizes but the contribution of employee number is not very high.

Table 2 Contribution level of employee number and value added for large businesses.

Business size	Industry sectors	Contribution of employee number		Contribution of value added	
Large business	Accommodation and food services	186	1.75%	33435	2.29%
	Administrative and support services	300	2.82%	45574	3.12%
	Agriculture, forestry and fishing	16	0.15%	22864	1.57%
	Arts and recreation services	67	0.63%	10467	0.72%
	Construction	159	1.50%	88516	6.07%
	Education and training	121	1.14%	18716	1.28%
	Electricity, gas, water and waste services	79	0.74%	36146	2.48%
	Health care and social assistance	373	3.51%	53235	3.65%
	Information media and telecommunication	107	1.01%	35664	2.44%
	Manufacturing	360	3.39%	101434	6.95%
	Mining	112	1.05%	126296	8.66%
	Other services	52	0.49%	25111	1.72%
	Professional, scientific and technical services	201	1.89%	90307	6.19%
	Public administration and safety	29	0.27%	4252	0.29%
	Rental, hiring and real estate services	31	0.29%	52998	3.63%
	Retail trade	559	5.26%	68228	4.68%
	Transport, postal and warehousing	240	2.26%	55462	3.80%
	Wholesale trade	162	1.52%	60110	4.12%
	Frequency	**3154**	**29.66%**	**928815**	**63.66%**

Table 3 Contribution level of employee number and value added for medium businesses.

Business size	Industry sectors	Contribution of employee number		Contribution of value added	
Medium business	Accommodation and food services	256	2.41%	11502	0.79%
	Administrative and support services	216	2.03%	11053	0.76%
	Agriculture, forestry and fishing	56	0.53%	3674	0.25%
	Arts and recreation services	60	0.56%	2517	0.17%
	Construction	238	2.24%	27688	1.90%
	Education and training	139	1.31%	8751	0.60%
	Electricity, gas, water and waste services	16	0.15%	3172	0.22%
	Health care and social assistance	248	2.33%	10163	0.70%
	Information media and telecommunication	37	0.35%	4018	0.28%
	Manufacturing	285	2.68%	28270	1.94%
	Mining	26	0.24%	23950	1.64%
	Other services	114	1.07%	7315	0.50%
	Professional, scientific and technical services	299	2.81%	22306	1.53%
	Public administration and safety	27	0.25%	1385	0.09%
	Rental, hiring and real estate services	61	0.57%	6121	0.42%
	Retail trade	273	2.57%	13102	0.90%
	Transport, postal and warehousing	94	0.88%	9661	0.66%
	Wholesale trade	217	2.04%	22760	1.56%
	Frequency	**2662**	**25.04%**	**217408**	**14.90%**

Table 4 Contribution level of employee number and value added for small businesses.

Business size	Industry sectors	Contribution of employee number		Contribution of value added	
Small business	Accommodation and food services	465	4.37%	13885	0.95%
	Administrative and support services	261	2.45%	16754	1.15%
	Agriculture, forestry and fishing	438	4.12%	18338	1.26%
	Arts and recreation services	79	0.74%	2847	0.20%
	Construction	679	6.39%	42207	2.89%
	Education and training	102	0.96%	3283	0.23%
	Electricity, gas, water and waste services	13	0.12%	3482	0.24%
	Health care and social assistance	325	3.06%	24089	1.65%
	Information media and telecommunication	39	0.37%	2678	0.18%
	Manufacturing	291	2.74%	20596	1.41%
	Mining	24	0.23%	11514	0.79%
	Other services	311	2.92%	14195	0.97%
	Professional, scientific and technical services	520	4.89%	41630	2.85%
	Public administration and safety	23	0.22%	1114	0.08%
	Rental, hiring and real estate services	301	2.83%	40357	2.77%
	Retail trade	519	4.88%	26403	1.81%
	Transport, postal and warehousing	235	2.21%	14057	0.96%
	Wholesale trade	192	1.81%	15410	1.06%
	Frequency	**4817**	**45.30%**	**312839**	**21.44%**

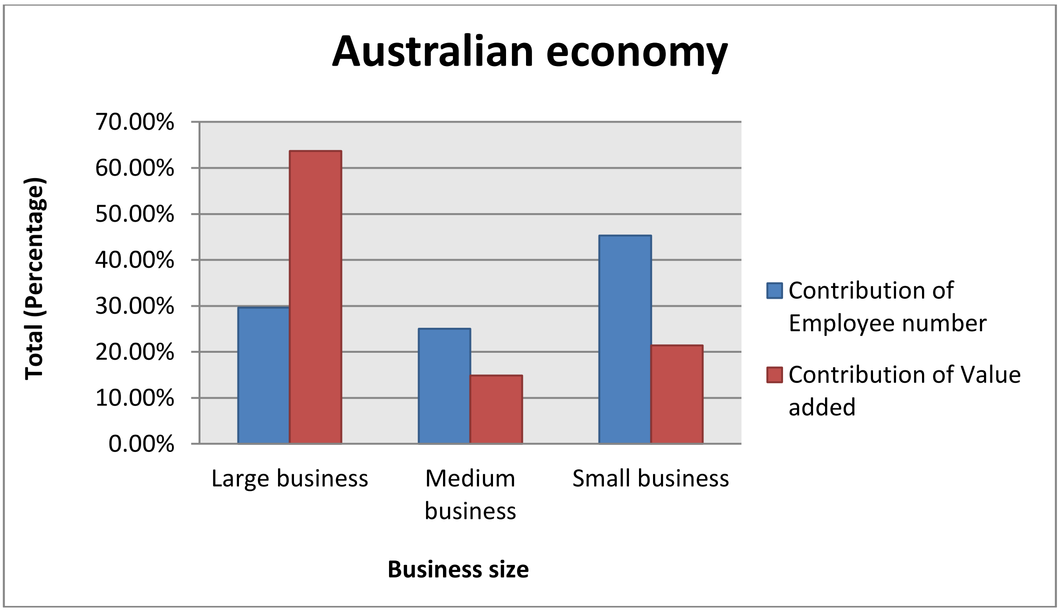

Figure 7. Contribution of employee number and value added to the Australian economy.

Table 5 Summary of the contribution of employee numbers.

Business size	Australian economy			
	Contribution of employee number		Contribution of value added	
Large business	3154	29.66%	928815	63.66%
Medium business	2662	25.04%	22760	14.90%
Small business	4817	45.30%	312839	21.44%
Frequency/ Overall total	10633	100.00%	1459062	100.00%

5. DISCUSSION

In this case study, the methodology is tested to prove its flexibility and applicability to assist the decision-making process in order to evaluate the extent to which different sized organizations contribute to the Australian economy. The outcome of the case study discussed in detail how the methodology is implemented in different domains. In the case study, we applied the case of Australian economy in which business size is evaluated based on the number of employees and the value added, so decision-making can be undertaken to decide the overall level of the Australian economy, as shown in Figure 7.

The methodology is tested in this case study to develop the understanding of the dependency relationship between the case study goal which is the Australian economy and the existing variables in which business size, industry sector, number of employees and value added, as shown in Figure 6. An ontology is applied in the case study which proves the flexibility of the methodology to build the dependency relationship between the case study goal, sub-goals and variables, as shown in Figure 6. This ontology advances the understanding of the organizational goals model in evaluating organizational data with respect to the models presented in (Fox et al., 1998; Rao et al., 2012; Sharma & Osei-Bryson, 2008).

In the case study, the methodology was successfully used to identify the dependency relationship between the case study goal and its variables. The methodology aims to provide this flexibility as to how the goal can be defined. The metrics was defined to analyse the data to evaluate the extent to which different sized organizations contribute to the Australian economy. The metrics is defined so it can be applied to evaluate the data from the datasets using different values. The results prove that the methodology is flexible in other domains.

5.1 The outcome from the case study

The case study discussed in detail how the goal is defined, the possible variables that relate to the goal and how we evaluated the data. Even though the evaluation process of data analysis could be done differently with different values, this case study discussed how the framework could be implemented and gives domain experts and entrepreneurs an overall idea as to how the data could be analysed to assist their decision-making. This case study only discussed one example as to how data could be analysed based on the dataset in this case study.

The application steps of the methodology are tested based on the planning and operational stage to further test the flexibility and applicability of the methodology.

5.1.1 Planning stage

- Step 1: Identify the organizational goals: Using methodology to facilitate the identification set of the case study goals based on ontology.

The aim of the methodology is to assist the decision-making process in relation to the goal. In the case study, the goal is identified, as shown in Figure 6. The main goal is to evaluate the extent to which different sized organizations contribute to the Australian economy.

- Step 2: Identify the sub-goals and variables: Generate the methodology to identify the sub-goals and variables that relate to the case study goals.

The relationship developed in Figure 6 based on an ontology improved the understanding of the relationship between sub-goals and variables in relation to the case study goal. Even though the background of the case study already discussed these variables, the implementation of the ontology advances the relationship between these variables that relate to the Australian economy.

In this step, we identified the sub-goals. The sub-goals are to identify the contribution of the number of employees and the contribution of value added by Australian businesses. Therefore, we can achieve the main goal in order to evaluate the extent to which different sized organizations contribute to the Australian economy.

- Step 3: Identify the dependency relationship: Develop the dependency relationship between data and case study goals from the methodology.

We develop the dependency relationship to show the relationship between the goal and sub-goals. This step also improves the understanding as to how the evaluation can be made based on this dependency relationship. Data in the case study show the dependency how this data relate to the case study goal. Therefore, the process of defining the metrics as a measurement tool for this data is defined based on the case study goal. The discussion shows how this data relate to the Australian economy and how metrics is defined to identify the value for this data.

- Step 4: Identify the metrics.

Metrics is defined based on the case study goal and how data is selected in relation to the case study goal, as discussed in Step 3. We analysed this data based on the metrics and obtain the value to assist the decision-making process. Based on this evaluation, we decide if the value is relevant in assisting our decision-making. The results from this case study prove the importance of the metrics definition in this methodology in order to evaluate data that relates to the goal.

5.1.2 Operational stage

- Step 5: Analysis and feedback for decision-making in relation to the case study goal.

Data in this case study are analysed and the values are discussed. The results from the data analysis create new knowledge to assist decision-making by identifying which business size contributes more to the Australian economy.

5.2 Limitations and future research

The main limitation of this paper is due to the lack of past definition of the organizational goals in order to identify the dependency relationship between organizational data and organizational goals. Although we applied ontology to drive the common understanding of this dependency relationship, the ability to identify this relationship is limited to organizational data only. It was unable to interact with external data such as social data in order to see how social data can play its parts in assisting the achievement of the goals.

In the case study, there is limitation in applying our methodology. We only identified one main goal in the case study. It was unable to interact with the main goals themselves so decision-making can be decided which main goals are achievable.There are several areas that can be investigated in the future. Further research could be done to improve the entire methodology as:

- Extending the ontology in the scope of the organizational goals. Organizational goals ontology is developed to identify the dependency relationship between the organizational goals elements (Izhar et al., 2013). In this organizational goals ontology, we only identified the elements of sub-goals and resources. Therefore, future work can be done by adding new elements such as human resources and organizational behaviours in order to identify the dependency relationship between the new elements in relation to the organizational goals.

- Extending the dependency relationship between organizational data and organizational goals. In this paper, data linkage is adapted from Christen (2012) to drive the understanding of the dependency relationship of organizational data that relate to the organizational goals. However, future research can be conducted to investigate the dependency relationship of external data such as social data in order to assist the decision-making process in relation to the organizational goals.

- Extending the metrics to measure the dependency relationship. In this research, we suggest that metrics is important as a measurement tool to evaluate organizational data that relate to the organizational goals (Izhar et al., 2013). In the case study, we evaluate the percentage of the business size to the Australian economy. However, in the future different number of value can be identified to evaluate organizational data that relate to the organizational goals.

- In the case study, there were limitations during the application of the methodology. We identified few sub-goals for the Australian economy. Even though we identified the sub-goals, the process to implement this methodology to the main goals will be the same. Therefore, it is important to apply this methodology with main goals in which in this thesis the framework was unable to interact with the main goals themselves.

The contribution of the methodology proposed in this paper serve as an approach for domain experts and entrepreneurs to drive the creation of new information and knowledge in assisting the decision-making process in relation to the organizational goals.

6. CONCLUSION

We have presented the design, implementation and evaluation of the methodology for the achievement of the organizational goals. In the first half of this paper, we discussed the methodology with three main tasks. The tasks are to identify the organizational goal elements, to identify the dependency relationship of organizational data that relates to the organizational goals and to define the metrics measurement in an effort to identify which organizational data is relevant in relation to the organizational goals. In the second half of this paper, we tested the methodology to the case study. We applied data from the Small Business Key Facts and Statistics Report in Australia to evaluate the contribution of employees and value added based on industry sectors for business size to the Australian economy.

The methodology is important as an approach to identify relevance of organizational data that relates to the organizational goals. It is considered as a first step in understanding the evaluation approach to analyse organizational data for better decision-making in relation to the organizational goals.

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