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Using Ontology to Incorporate Social Media Data and Organizational Data for Efficient Decision-Making

Tengku Adil Tengku Izhar[1], Torab Torabi[2] and M. Ishaq Bhatti[3]

[1] Faculty of Information Management
Universiti Teknologi MARA, UiTM
Shah Alam, Selangor, Malaysia
tengkuadil4540@salam.uitm.edu.my

[2] Department of Computer Science and Information Technology
La Trobe University
3086, Victoria, Australia

[3] La Trobe Business School
La Trobe University
3086, Victoria, Australia

Abstract: **People have access to more data in single day than most people that have access to data in the previous decade. Data are created in many forms and it highlights the development of big data. Big data in organizations have transformed the way organizations across industries implement new approach to handle huge amount of data. It means change in skills, structures, technologies and architectures. Organizations rely to this data to achieve specific business priorities. The challenge is how to capture this data to be considered relevant for the specific organization activities because determining relevant data is a key to delivering value from massive amounts of data. The aim of this paper is to evaluate the level of organizational goals achievement by incorporating social data and organizational data using an ontology. We investigate on how external data such as social media can support internal data such as organizational data for better decision-making in relation to the organizational goals. The results show that an ontology provides a platform to incorporate social data and organizational data.**

Keywords: big data, ontology, organizational data, social data, NodeXL, Twitter

I. Introduction

Big data is a new way of thinking about enterprise data and how it can drive business value. The amount of data that is available to businesses is increasing, with social media and machine-to-machine as just two of the leading sources. The central role of business services in today's enterprises, and the more complex architecture through which they are delivered, make it important to manage big data solutions from a business perspective. Business perspective focuses on business objectives and benefit, and prioritizes resources and activities according to the needs of the business. Business model elements also have been studied in different types of organization, especially in software business [1]. This has lead to difference definition in business model. In this way, effective evaluation of the big data can ensure optimal relevance of data for more effective decision-making to support the business goals. Provision of big data analysis, with ease and affordable cost to a wide range of customers and businesses is still a big challenge for data scientists [2].

This paper discusses a holistic approach to evaluation big data to help researchers to automate, accelerate and integrate the existing types of data in the organizations. The approach to evaluate the big data will depend on how organizations specific their business priorities. The most likely organizational structures to initiate big data technologies are either existing analytics groups or innovation or architectural groups within IT organizations. In many cases these central services organizations are aligned in big data initiatives with analytically-oriented functions or business units [3].

Even though there are many recent studies have been done on big data in the context of the organizations [4-7]. There is still little debate these days about the importance of the big data in supporting the goals of an organization [3, 6, 8]. There is yet no consensus about how best to incorporate big data in the organizations and how the process of incorporating the big data can identify the relevance of data to assist decision-making process in relation to the organizational goals.

In order to achieve the organizational goals, organizations rely on data [9]. For example, information retrieval model is used to incorporates dependency relationships between different type of data [10]. Organizational data such as data on sales and profits can assist domain experts with decision-making process in relation to the organizational goals [9]. The aim of this paper is to evaluate the achievement level of the organizational goals by incorporating organizational data and social media. We demonstrate how to capture relevant data from huge social media to support organizational data for better decision-making process. We present a guideline to filter this data in order to identify relevant data that relate to the organizational goals.

The ideas of using an ontology and visual structuring in organization applications were discussed in many works and now are implemented in many sectors [11-15]. However, much of the research in this field did not receive much attention in the literature on incorporating the big data for social media to assist the organizations with the decision-making process in relation to the organizational goals.

An ontology provides explicit and formal specifications of knowledge, especially implicit or hidden knowledge [16]. By incorporating the big data, an ontology make the process to identify the relevance of data more easily consumable to address which data from the datasets are more important in evaluating the goals. The outcome of this paper can establish an analytics of big data structure for the organizations to ensure that analytics processes are supported by the specific organizational priorities.

Big data provides significant opportunities for organizations to impact a wide range of practices and processes in the organization. However, there is still little debate these days on the role and importance of big data for efficient decision-making. While most people take such technologies for granted, our understanding about external data such as social media, mobile data and sensor data are still very limited. Most existing studies on this topic only focus on knowledge extraction from each data source independently, and the outcomes are then combined and co-relation is investigated [17, 18]. However, in this proposed research we argue that these external data sources need to be semantically linked and integrated before any meaningful data analytics or knowledge extraction can be performed. Furthermore, we proposed a framework to find a correlation between internal and external data for efficient decision-making. Although there are studies on statistics correlations and machine learning based correlations, but as to our knowledge, there is a lack of study on using a semantic underpinning such as an ontology to perform correlation of heterogeneous data in a cloud infrastructure. The aims of this research are:

1. To develop a framework that underpins a seamless integration of organizational data and heterogeneous external data pertinent to the organizational focus area.
2. To develop a mechanism that allows seamless consolidation of knowledge from external sources will enrich the capability of the organization to make accurate decision-making.

The availability of heterogeneous external sources are growing very significantly in the last few years, especially due to the availability of wireless and mobile technologies, crowd-sourcing facilities, Internet of Things, sensor networks, and other social media and web data. The focus of our research is to generate huge amount of data that can be extracted to generate values to the organization and to establish situational awareness of the community or market trends.

II. Big Data in Organization

Today people have access to more data in single day than most people that have access to data in the previous decade. Big data provides significant opportunities for enterprises to impact a wide range of business processes in the organizations. Organizations create huge amount of data in their daily business activities. The problem is this data is created and found in many different forms. All this data captures in different formats and makes it almost impossible to understand the existing relationship between different data. As a result, this data might be redundant with huge volume of data and make it hard to identify which data is relevant to the organizational goals. Although big data does not refer to any specific quantity, this data might create petabytes and exabytes of data, much of which cannot be integrated easily. For example, government agencies and large, medium and small private enterprises in many domains, such as engineering, education, manufacturing, are drowning in an ever-increasing deluge of data. Companies like Google, eBay, LinkedIn, and Facebook were built around big data from the beginning [3].

Even though the professional such as data scientists are trained to analyse this data but the huge capacity of data created everyday make it hard to identify which data is relevant for the specific organization activity. As a result, it poses an issue on how effective this data to support decision-making process [9]. Data scientists must somehow get along and work jointly with mere quantitative analysts [3]. Thus, having an ability to analyse the data in a timely fashion can ensure organizations have a competitive edge to improve productivity in relation to the organizational goals. However, the trustworthiness of data in relation to the organizational goals is often questionable due to the huge amount of data within the organizations.

A. Social Media

In recent years, the rapid development of Internet, Internet of Things, and Cloud Computing have led to the explosive growth of data in almost every industry and business area. Big data has rapidly developed into a hot topic that attracts extensive attention from academia, industry, and governments around the world. There are many challenges in harnessing the potential of big data today, ranging from the design of processing systems at the lower layer to analysis means at the higher layer, as well as a series of open problems in scientific research. Big data processing systems suitable for handling a diversity of data types and applications are the key to supporting scientific re-search of big data [19].

Social media are transforming the way information travels within and between networks of individuals [20]. Although the research on social networks dates back to early 1920s, nevertheless, social media analytics is a nascent field that has emerged after the advent of Web 2.0 in the early 2000s. The key characteristic of the modern social media analytics is its data- centric nature. Social media analytics refer to the analysis of structured and unstructured data from social media channels. Social media is a broad term encompassing a variety of online platforms that allow users to create and exchange content. User-generated content (e.g., sentiments, images, videos, and bookmarks) and the relationships and interactions between the network entities (e.g., people, organizations, and products) are the two sources of information in social media [21].

Social media have profoundly changed our lives and how we interact with one another and the world around us [22, 23]. Recent research indicates that more and more people are using social media applications such as Facebook and Twitters for various reasons such as making new friends, socializing with old friends, receiving information, and entertaining themselves [24-27]. Social media analysis will extract value from vast amount of social media data to detect and discover new knowledge to understand how industry is changing, and use the findings and improved understanding to achieve competitive advantage against their competitors [28, 29]. Social media competitive analysis allows a business to gain possible business advantage by analyzing the publicly available social media data of a business and its competitors [29]. As social media have become a topic of interest for many industries, it is important to understand how social media data can be harvested for decision-making [29].

With the development of smart devices and cloud computing, more and more public data can be collected from various sources and can be analyzed in an unprecedented way. The huge social and academic impact of such developments caused a worldwide buzz for big data [30]. Data flow is an ordered sequence which is consecutive, high-speed, infinite and time varying. It's also of great importance in internet management, internet security and internet experiment. However, with the rapid development of internet technology, the number of internet applications and users keeps rising, and the internet data is growing exponentially [31]. As a result, there is a stricter requirement about the efficiency, expandability and stability of the data flow in social media.

B. Challenge

Big data may be as important to business because more data can lead to more accurate analyses. More accurate analyses may lead to more confident decision-making and better decision can mean greater operational efficiencies in the organization [3].

Taking advantage of big data opportunities is challenging for the organizations [7]. Firms and other organizations have been using large databases and analytics for the last couple of decades. Transactions are stored in data warehouses and analyzed with data-mining algorithms to extract insights [4]. In order to ensure the effectiveness of the data, organizations need to be able to store data reliably across a number of databases. Once data need to be distributed, organizations need a way to get it out again and they need to identify which data is needed, assemble it and analyse it. The challenge is how to capture this data to be considered relevant for the specific organization activities because determining relevant data is a key to delivering value from massive amounts of data as shown in Figure 1. The real issue is not how the organizations acquiring large amount of data but how they do with the data that counts [3]. The technologies and concepts behind big data can allow organizations to achieve a variety of objectives.

This paper provides an approach on how data can be identified by incorporating the relationship between different types of data using an ontology. We structure this data to filter the existing data that might be relevant to support the decision-making process in relation to the specific organizational goals.

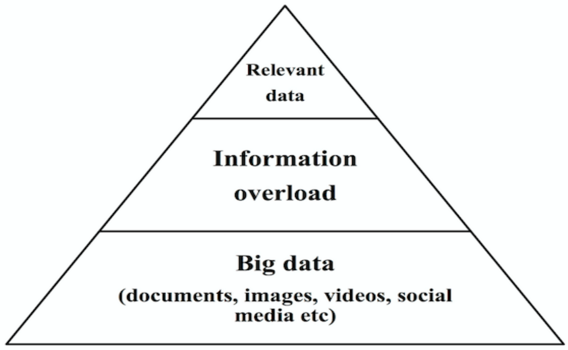

Figure 1. Relevant data from large amounts of data.

III. The Need for an Ontology

The contribution of an ontology is to improve the creation of model ultimately takes place through the organizational goals and it works as a type of relationship to represent the dependency relationship between data and organizational goals. In Section I, the problems covered the limitation in structuring big data in the context of the organizational goals. It prevents the solution to identify the important of this data from being practical and implement in relation to the organizational goals. Therefore, it is important to develop a model for organizational goals in order to show the dependency relationship between data and organizational goals [9].

Despite the various existing methodologies to evaluate the organizational process based on an ontology [12, 13, 32-35], this paper focuses on structuring the relationship between social data and organizational data in relation to the organizational goals. This process consists of identifying which data are relevant in achieving the organizational goals that will be used by domain experts and entrepreneurs who contribute to the decision-making process. They are also responsible for identifying to what extent the organizational goals have been achieved.

Ontology architecture as presented in Figure 2 consists of ontology design and ontology application. Ontology design is a stage where we apply the ontology to identify the goals and different types of data. After we identify the data, we develop the relationship between data and organizational goals.

Ontology application is a stage where we analyse this data to support decision-making process in relation to the organizational goals. We come out with the decision-making process to evaluate the organizational goals achievement. In this paper, an ontology is applied for big data to:

- be applicable in a wide range of domain.
- successfully develop the dependency relationship between different types of data.
- successfully develop the dependency relationship between data and goals.

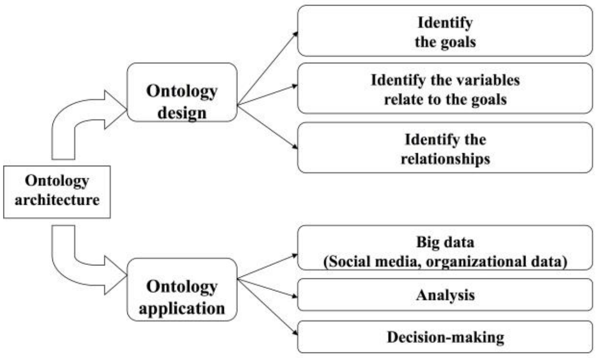

Figure 2. Ontology architecture.

The originality of this research lies in the creation of the big data integration 'road-map' in the form of an organizational goal ontology that contains references to concepts and properties from external sources relevant to the organization. This road-map will enable accurate integration of the datasets for decision-making as it will serve as a meta-data for the connectivity of the integration process. This approach will enable the organization to have an overall view of data connectivity within and outside the organizations, and to enable the data scientists to harvest interconnected information for analytics purposes.

Previously, a study has been done on organizational data and social media data using an ontology to capture relevant information and to resolve the issue in identifying and evaluating relevant data for better decision-making that covers the characteristics of good quality relevant data. In the current research, we proposed an organizational goal ontology that can capture the concepts of complexity and use it as a basis for data integration processes suitable for efficient correlative decision-making. We will develop an incremental approach to extend the ontology with relevant external knowledge bases by clustering and annotating the external data to concepts and properties within the ontology.

IV. Organizational Goals Ontology

Organizational goals are defined as the most important targets to be achieved in every organization [9]. Even though the concept of the organizational goals has been in the existence for some time, modeling the structure of the organizational goals is much more difficult [9, 36]. For example, one way to develop a common understanding of the organizational goals structure is based on an ontology [9]. An ontology provides explicit and formal specifications of knowledge, especially implicit or hidden knowledge [16]. An ontology is considered as an approach to support data sharing [37]. Therefore, an ontology assists with part of the integration problem in relation to the organizational goals and can be used to improve the communication and collaboration between the decision makers and the users [38], which is, in this paper, the decision makers in relation to the organizational goals.

In Izhar et al [9], organizational goals ontology is developed based on the work of Rao et al. [12], Sharma & Osei-Bryson [34] and Fox et al. [33]. Despite many research efforts and established model for the organizational goals using an ontology, they have not yet been systematically applied for decision-making to support the evaluation of the organizational goals achievement. This is important because decision-support is one of the main objectives of an ontology [39]. In this paper, we extend the organizational goals ontology developed in Izhar et al. [9], in order to develop the relationship between social data and organizational goals, as shown in Figure 3.

Several structures that were proposed in the previous models are combined [12, 33, 34] for the organizational goals ontology in Izhar et al. [9]. These models are adapted as a reference for the organizational goals ontology. However, the scope of the proposed organizational goals ontology in this methodology do not cover all the organizational processes as discussed in Sharma & Osei-Bryson [34], Fox et al. [33] and Rao et al. [12].

Fox et al. [33] 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 [34] 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. [33], where the authors discussed the physical resources and role of the organizational model.

Recently, Rao et al. [12] 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 [34]. Another aspect that is similar to Sharma & Osei-Bryson's work is that both models include business processes. However, Rao et al. [12] discussed business processes from the organizational goals point of view and Sharma & Osei-Bryson [34] discussed business processes from the organizational activity point of view. Most of these studies focused on the organizational structure and performance. In Izhar et al. [9], the authors developed the organizational goals ontology that consists of organizational goals, sub-goals, and organizational data. They developed the dependency relationship for the organizational goals and dependency relationship between organizational data and organizational goals. However, they evaluate the organizational goals by identifying the organizational goals first and then they identify the organizational data that relate to the organizational goals.

Table 1 shows the results from the previous models on the organizational goals using an ontology but none of these studies focus on structuring the big data in the organizations in order to develop the dependency relationship between data and organizational goals. In this paper, we extend the organizational goals ontology from Izhar et al. [9] to incorporate social data and organizational data in relation to the organizational goals.

Table 1. Previous scope of the existing models on organizational goals ontology.

Authors	Organizational goals ontology		Resources		Develop the relationships
	Organizational goals	Sub-goals	Organizational data	Social media	Big data
Fox el al. [33]	✓	✓	×	×	×
Sharma & Osei-Bryson [34]	✓	✓	×	×	×
Rao et al. [32]	✓	✓	×	×	×
Izhar et al. [36]	✓	✓	✓	×	×

In organizations, it is extremely important for the manager to have access to the most relevant data in relation to the organizational goals [9]. Simsek et al. [40] 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 domain experts and entrepreneurs to use the most relevant data to successfully achieve the organizational goals.

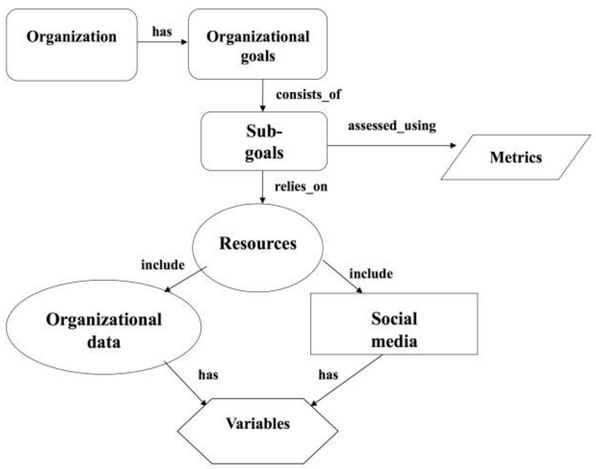

Figure 3. Proposed organizational goals ontology (adapted from Izhar et al. [9])

In contrast to Izhar et al. [9], the proposed organizational goals ontology can be verified to:

- Identify the organizational goals.
- Identify the sub-goals that relate to the organizational goals.
- Identify which data domain experts want to evaluate.
- Incorporate different types of data in relation to the organizational goals.
- Analyse this data.
- Evaluate the decision-making process in relation to the organizational goals.

A. *Metrics to measure the level of the organizational goals achievement*

Metrics is defined to evaluate the extent to which the organizational goals have been achieved by measuring the dependency organizational data elements that relate to the organizational goals. It is important to identify the value of the organizational data that relate to the organizational goals to support decision-making. In the metrics, the factors may include:

- frequency
- percentage
- rank

The weight to analyse the dependencies of organizational data can be defined in many ways, such as percentage and frequency based on different situations. For example, domain experts and entrepreneurs might want to identify the percentage of data that relate to organizational goals. After we identify this value, it can be presented on the dashboard to show a graphical presentation of value. The comparison of this value can be presented to support the decision-making process in relation to the organizational goals.

Varghese & Sundar [41] evaluated the weight of the matching data for metrics evaluation that used various types of databases [42]. For example, we assumed two organizational data, data a and data b, from two organizational datasets, dataset A and dataset B, relate to the same organizational goals, $a \in A$ and $b \in B$.

For example, if both organizational data *a* and *b* relate to the same organizational goals, then

$M = \{(a, b): a \in A, b \in B, (a, b)\}$ is matching organizational data between data *a* and *b* to the same organizational goals.

Even though values such as percentage, rank and frequency are discussed in this section, but how domain experts and entrepreneurs want to define their own metrics is not the main objective of the research. This is because they might want to evaluate the organizational data and define the metrics in different ways, as in the case study.

V. Case Study

This case study is presents to evaluate the relationship between organizational data and social data. The aim is to investigate how data from social media can incorporate with the organizational data for better decision-making in relation to the organizational goals. In order to achieve this aim, we present a case study from La Trobe University Student Support Services. In this case study, we evaluate internal data, which is data that have been collected in the university and external data, which is data that have been collected from Twitter in relation to the case study goal.

A. *Identify the goals*

The case study used in this research aims to evaluate the level of student satisfaction in the La Trobe Student Support Services at La Trobe University, Melbourne Australia. The aim of the La Trobe University Support Services is to improve the students' university experience by providing services that encourage students to socialize and become involved in things other than academic activities. This case study is important as it provides a way to t evaluate the extent to which the data are relevant to the decision-making process in terms of achieving the case study goals.

In this case study, we examined the goals from La Trobe University Student Support Services Experiment Report in 2011. In this Student Support Service Report, student satisfaction is the main goal of this case study. We aim to look at the level of student satisfaction to assess to what degree students believe the services at La Trobe University have been of benefit to them.

We identify the possible sub-goals and variables in relation to the main goal. The experiment aims to identify the main goal and examine the dependency relationship between different backgrounds of the students who used the particular service and their level of satisfaction in the La Trobe Student Support Services. We define that the goal of the case study is to determine the level of satisfaction of students who have used the services. Therefore, in order to achieve this goal, the evaluation is based on the service satisfaction and service popularity as we defined these two variables as sub-goals. Service satisfaction shows the number of students who were satisfied with the service. Service popularity shows the level of usage of the services. We identify the sub-goals in this case study as follows:

Sub-goal: Level of service satisfaction
Sub-goal: Level of service popularity

B. Dependency relationship for the goals

We identify the relationship for the goal and sub-goals. For example, Student Support Service is part of La Trobe University. Student Support Service has goal which is to evaluate the level of student satisfaction. This goal is assessed using metrics. Student satisfaction has sub-goals. The sub-goals are service popularity and service satisfaction. These sub-goals rely on resources, which includes organizational data and social data, as shown in Figure 4. We identify the relationships are:

- *part_of*(student support service, La Trobe University)
- *has_goal*(student support service, student satisfaction)
- *assessed_using*(student satisfaction, metrics)
- *consists_of_sub-goal*(student satisfaction, service popularity)
- *consists_of_sub-goal*(student satisfaction, service satisfaction)
- *relies_on*(service popularity, resources)
- *relies_on*(service satisfaction, resources)

1) Dependency relationship for organizational data

We identify the relationship for organizational data. In Fig. 7, organizational data access the Student Support Service Report and this report includes student background. In this case study, we only evaluate the background based on campus. The relationships are defined as:

- *access_the*(organizational data, student support service report)
- *includes*(student support service report, student background)
- *based_on*(student background, campus)

2) Dependency relationship for social data

Social media has a potential to be used as a professional and social networking to share interest [2]. Users to share similar interests on the Internet can use social media such as Twitter. In order to support the evaluation of organizational data in relation to the goal in this case study, we evaluate external data which is data from social media. In this case study, we present data from Twitter. Data is selected based on LaTrobe username. People in LaTrobe network discuss about student satisfaction. In this user network, somewhere there might be someone who mentions the word "student satisfaction". Then, we filter our search from student satisfaction to the service popularity and service satisfaction. This includes people who tweet, mentions and replies to the word student satisfaction.

The relationships shows when the person in the user network who tweet, mentions or replies to one another tweet about student satisfaction. In this case study, we summarise all these relationships as discuss about. It means people tweet, replies and mention about certain topic. The relationships are defined as:

- *such_as*(social media, Twitter)
- *include_username*(Twitter, LaTrobe)
- *has*(LaTrobe, followers)
- *has*(LaTrobe,following)
- *discuss_about*(followers, student satisfaction)
- *discuss_about*(following, student satisfaction)
- *includes*(student satisfaction, service popularity)
- *includes*(student satisfaction, service satisfaction)

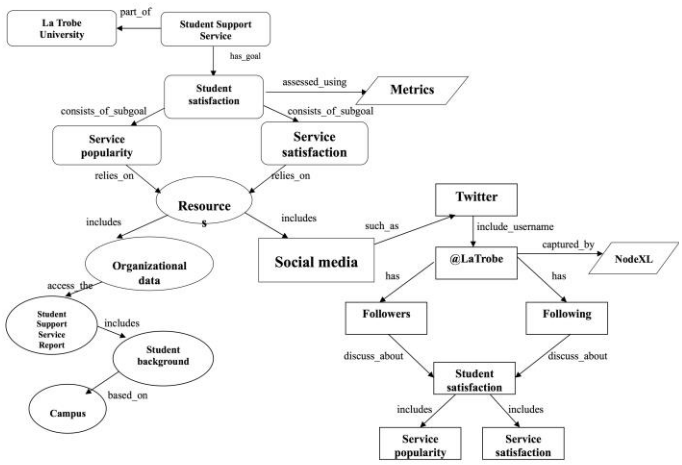

Figure 4. Ontology for La Trobe Univesity.

C. Metrics

In this section, we identifies the different weights which were assigned to the dependency variables to measure the level of student satisfaction in the La Trobe Student Support Services based on service satisfaction and service popularity. The case study used in this experiment provides an approach to show how the data relating to the case study goal can be analysed. However, we are mindful of the fact that domain experts and entrepreneurs might want to analyse data in a different way to the way we have undertaken the analysis in this case study, which would require a different approach to define the metrics. The overall student satisfaction based on service satisfaction and service popularity is calculated based on total rank and percentage using the following metrics:

$$\text{Total rank } (\text{Total} \times \text{Rank})$$

$$\text{Percentage } \left(\frac{\text{Total}}{\text{Total rank}} \times 100\right)$$

In this case study, this metrics will be applied for both organizational data and social data. For example, we evaluate data on students who have used the services which means these services are considered popular. Metrics is applied to evaluate the level of service satisfaction from the total number of students who have used the services. For example, in Table 2, we evaluate the level of service satisfaction of students on the Bundoora campus. The evaluation shows that the level of service satisfaction is 32% of the total number of students who used the services. Therefore, the level of service popularity is 68%. The results show that even if the popularity of the services is high among the students, this does not mean that the students are satisfied with the services.

As an explanation of how the metrics for student satisfaction is calculated, consider the following example using the data from the Bundoora campus, shown in Table 2. The total number of students who used the service *career events* is 441 which gives this service a rank of 3, hence the value for this rank is [441(3)]. Then, the rank of the next service listed in the table, *career information and resources,* is calculated in a similar fashion, [464(2)]. This process continues until all the services in the list have been assigned a value, hence the service satisfaction of students from the Bundoora campus can be calculated as follows:

$$\text{metrics} = \text{count(Bundoora campus)} \left(\frac{4002}{441(3) + 464(2), \ldots, 1656(1)} \times 100\right)$$

D. Evaluation of Organizational Data

1) Sample and data collection

We applied dataset from La Trobe University Student Support Services Experiment Report in 2011 [1]. A survey was conducted online and the students were invited to participate by completing an anonymous questionnaire, as guaranteed confidentiality helps ensure that the true concerns of the students are identified. The survey firstly asked students to provide some demographic information regarding the La Trobe University Services which were considered critical to the satisfaction of students. Students were asked to indicate whether:

- they had not used the services but were aware of them.
- they had used the services but believed the services could be improved.

In this dataset, we select 11 different services provided by La Trobe University. It is important to note that we do not mean to imply that the entire services are not important but we suggest that these numbers of services are enough to test the flexibility of the framework with respect to the La Trobe University Student Support Services. A value is assigned to each La Trobe Student Support Service to identify the degree of student satisfaction of the student support services and to identify which service was considered the most important in increasing student satisfaction. In this case study, we only evaluate the satisfaction of the students in the La Trobe Student Support Services based on campus (Albury Wodonga, Bendigo, Bundoora, City, Mildura, Shepparton).

2) Analysis

Data is evaluated in an effort to identify the level of student satisfaction in the La Trobe University Student Support Services. The results show the evaluation of service satisfaction and service popularity among students who used the services by campus, as shown in Table 2 and Table 3. After we evaluate the percentage for every campus, we then evaluate total percentage of service popularity and service satisfaction, as shown in Table 4. We summarize the results to evaluate the level of student satisfaction.

Table 2 and Table 3 summarizes the student satisfaction by campus based on service satisfaction and service popularity. For the service popularity we can see that student from the Albury-Wodonga campus have the highest percentage at 70%. The results show that even though student from this campus used the services but their satisfaction of the services are only at 30%. The results in Table 2 and Table 3 also show the popularity of services among student from the Bundoora campus is at 68% but their satisfaction of these services only at 38%, followed by the service popularity from the students from the Bendigo campus at 67% but their satisfaction only at 33%. Service popularity among student from Mildura campus is 66% and their satisfaction only 34%. At the same time, student from the Shepparton campus have 63% for service popularity and 37% for service satisfaction, followed by student from the City campus with only 59% of the service popularity and 41% for the service satisfaction.

Table 2 and Table 3 also shows the relative importance of each service, as ranked by the students who have used each service. For example, the *faculty office* is ranked first by students from every campus while *childcare* is ranked last by students from the Bundoora campus, Bendigo campus, Shepparton campus and the City campus. However, the students from Albury-Wodonga ranked *discrimination and harassment support services* in the last place. The results show that several student support services are ranked equally. For example, *chaplaincy and religious services* and *discrimination and harassment support services* are ranked last by the students from the Mildura campus. In conclusion, the results show that the numbers of student who use the services are high in every campus. They use the services many times. However, their satisfactions of these services are still low.

[1] http://www.latrobe.edu.au/student-services/student%20survey/index.html

Table 2. Level of student satisfaction by campus.

Services/ Campuses	Student satisfaction					
	Bundoora	Rank	Bendigo	Rank	Albury Wodonga	Rank
Career events	441	3	138	4	46	2
Career information and resources	464	2	189	2	36	5
Career planning and advice	315	5	91	6	18	6
Chaplaincy and religious services	139	8	34	8	9	7
Childcare	32	11	7	11	8	8
Clubs, collectives & societies	366	4	167	3	37	4
Counselling	296	6	120	5	43	3
Disability support	91	9	37	7	7	9
Discrimination and harassment support services	33	10	11	10	1	11
English language support	169	7	25	9	6	10
Faculty office	1656	1	517	1	93	1
TOTAL/TOTAL RANK	4002	12512	1336	4037	304	1011
Level of service satisfaction	32%		33%		30%	
Level of service popularity	68%		67%		70%	

Table 3. Level of student satisfaction by campus.

Services/ Campuses	Student satisfaction					
	Mildura	Rank	Shepparton	Rank	City	Rank
Career events	9	5	9	5	4	2
Career information and resources	20	2	16	2	2	5
Career planning and advice	12	3	12	3	3	3
Chaplaincy and religious services	2	10	0	9	1	8
Childcare	4	7	0	9	0	11
Clubs, collectives & societies	3	8	4	6	2	5
Counselling	11	4	11	4	2	5
Disability support	3	8	3	8	1	8
Discrimination and harassment support services	2	10	0	9	1	8
English language support	5	6	4	6	3	3
Faculty office	54	1	41	1	24	1
TOTAL/TOTAL RANK	125	365	100	270	43	104
Level of service satisfaction	34%		37%		41%	
Level of service popularity	66%		63%		59%	

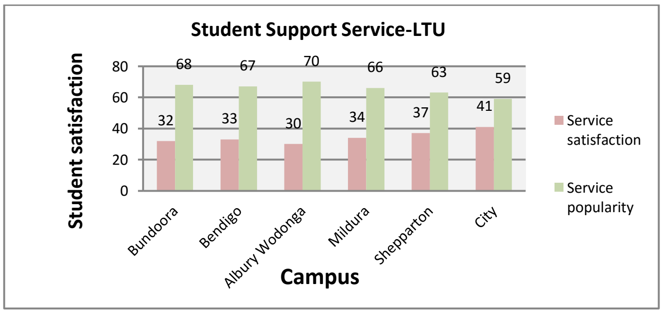

Figure 5. Level of student satisfaction by campus.

Table 4. Total score of service popularity and service satisfaction based on campus

Campus	Service popularity	Rank	Service satisfaction	Rank
Bundoora	68	2	32	5
Bendigo	67	3	33	4
Albury Wodonga	70	1	30	6
Mildura	66	4	34	3
Shepparton	63	5	37	2
City	59	6	41	1
Total/ Total rank	393	1340	207	689
Percentage	29%		30%	

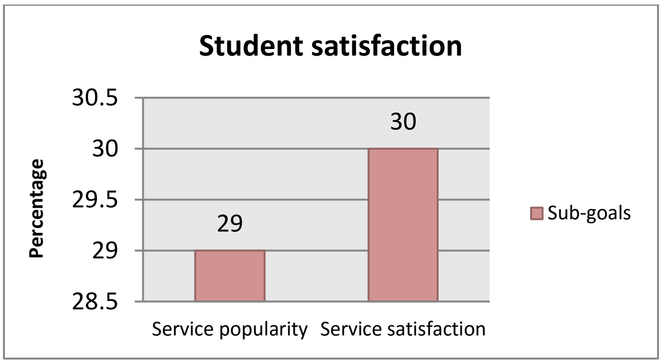

Figure 6. Total score of service popularity and service satisfaction.

Table 4 shows the total percentage of service popularity and service satisfaction based on campus. The results show that service satisfaction has the highest percentage with 30% and service popularity with 29%. Based on these campuses, we can make a decision that student believe that service satisfaction is important when they use the services in the university.

E. Evaluation of Social Media Data

1) Sample and data collection

In order to identify participants, we used the sampling pool of Twitter that appears in the NodeXL, a software tool that import data from outside data providers. We apply NodeXL, an extendible toolkit for network overview, discovery and exploration implemented as an add-in to the Microsoft Excel 2007 spreadsheet software. NodeXL is applied to retrieve data from social media and import this data. NodeXL demonstrate data analysis with a social media data sample drawn from an enterprise intranet social network.

Users create data on Twitter every second and data is collected based on the date of the tweet is created in order to avoid huge volume of data. NodeXL import data from Twitter username LaTrobe into the spreadsheet, as shown in Figure 7. In this case study, we aim to evaluate data for two week from 17 November 2014 to 30 November 2014. Therefore, data is filter and capture within this period of time using NodeXL.

The name is removed in order to protect the privacy of the users.

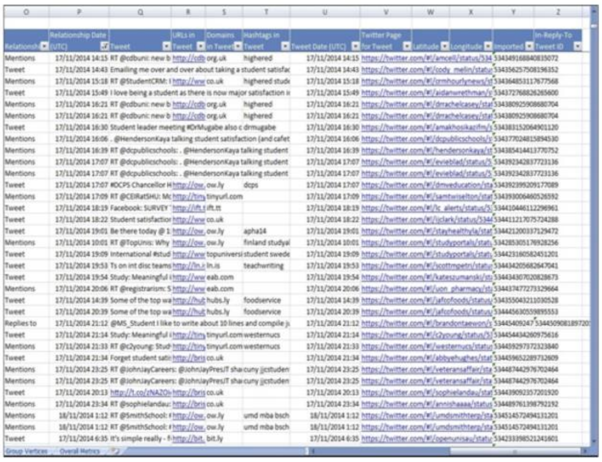

Figure 7. Example of imported Twitter data into spread sheet using NodeXL from 17/11/2014 to 30/11/2014.

2) *Mapping Diagram for Twitter*

In social media, users create data every second and minute. As a result, number of social data keep changing all the time and make it hard to evaluate. For example, today data might be important but tomorrow this data might not be important anymore. In LaTrobe network, we capture data that match to the query of people who discuss about student satisfaction. We expand this query by looking at people who discuss about service popularity and service satisfaction. This data based on people who tweet, mention and replies about the query. Data mapping for social media is illustrated as shown in Figure 8.

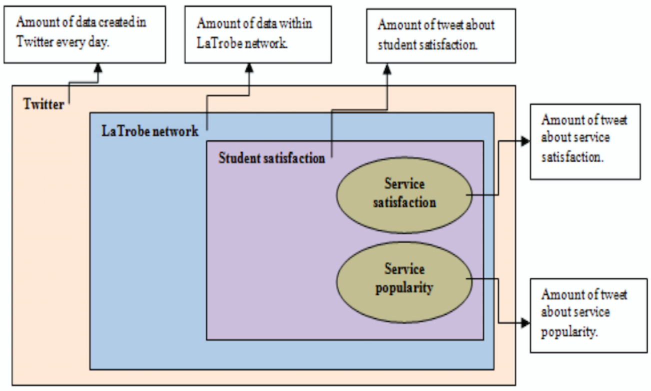

Figure 8. Mapping diagram for Twitter to capture data that relate to service popularity and service satisfaction.

In Figure 8, data is mapped for the case study as follows:

- Twitter has many users.
- We capture data from LaTrobe username.
- Within LaTrobe network, we capture data from people who tweet about student satisfaction.
- Within student satisfaction, we capture data from people who tweet about service popularity and service satisfaction.

3) *Data Filtering*

This section will provide steps to demonstrate how we filter data from large amount of data from the social media to allow us to evaluate specific query in relation to the goals. These preferences are used to configure the steps in filtering the data from Twitter using NodeXL.

1. Import from Twitter users network, as shown in Figure 9.
   1.1. It optionally clear the NodeXL workbook, then get the network of specified Twitter users.

2. Specify the Twitter users with specific username.
   2.1. We interested in username @LaTrobe.

3. Import basic network plus followers and following who replies, mentions and tweet.
   3.1. Limit it to 100 recent tweets per user.

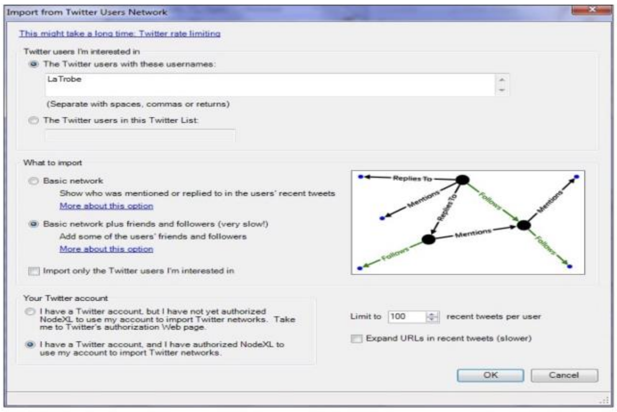

Figure 9. Import Twitter username

4. Import from Twitter search network, as shown in Figure 10.
   4.1. It optionally clear the NodeXL workbook, then get the network of people who tweets certain specified word.

5. Search for the tweets that match to the specific query. For example, we want to identify the level of student satisfaction. Therefore, the main query is student satisfaction.
   5.1. We search for student satisfaction.

6. Import basic network to specifically show who replied or mentioned in the tweets.
   6.1. Limit to 100 tweets.
7. Filter by relationships (tweet, mentions and replies).

8. Filter by specific date (day, week, month).
9. We apply the steps for tweet that match to service popularity and service satisfaction in user network.

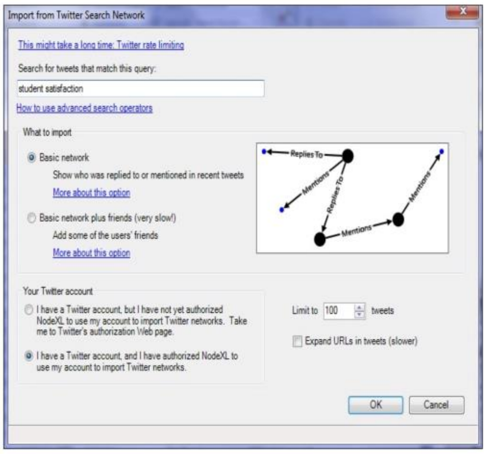

Figure 10. Import tweet from Twitter network.

The step-by-step guideline explains how we select data from huge volume of social data that relate to the goals. Using NodeXL as a tool to capture this data, this guideline provide systematic steps for domain experts to capture which data they want to evaluate to assist their decision-making in relation to the organizational goals. However, in other case, domain experts might use different tool to capture this data and the process to identify relevant data might be different.

4) Analysis

Data for two weeks are summarised in Table 5. The tables show the number of tweet about service satisfaction and service popularity. Full description of this data can be referred in the appendix. Based on these datasets, we evaluate the percentage of tweet in relation to the student satisfaction in the LaTrobe network. Therefore, we can make a decision of what people think about La Trobe University Student Support Services.

Table 5. Score of tweet that relate to student satisfaction.

Weeks	Service popularity	Rank	Service satisfaction	Rank
Week 1	121	1	726	1
Week 2	120	2	524	2
Total/Total rank	241	361	1250	1774
Percentage	67%		70%	

The results show that service satisfaction has the highest percentage with 70% and service popularity with 67%. Total number of tweet for week 1 and week 2 also shows that service satisfaction has the highest number of tweet. The results can be concluded that people from LaTrobe network believe that service satisfaction is important to them when they use any services in the university.

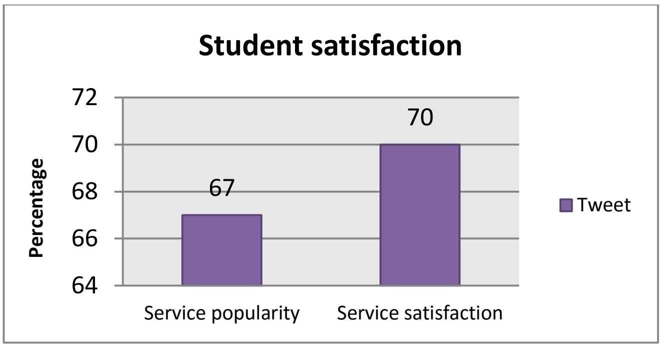

Figure 11. Score of tweet that relate to student satisfaction.

This section evaluates data from social media in relation to the goal. The results in this section are evaluated to investigate how this data can incorporate with organizational data in relation to the goal in the case study. At this stage, we can conclude that the results are consistent with the results from student who have used the services based on campus.

F. Evaluation of Social Media Data and Organizational Data

In order to evaluate social data and organizational data, we improve the metrics to incorporate both data in relation to the goal. In this metrics, we evaluate the data based on the overall rank. Overall rank is a total rank for both sub-goals. For example, total rank for service popularity is 125 and service satisfaction is 130, as shown in Table 6. Therefore, overall rank is 255. The definition of overall rank is as follows:

$$\text{Overall rank (sub-goal 1(total rank)} + \text{sub-goal 2(total rank))}$$

In Table 6, we incorporate the value from social data and organizational data for every sub-goal and we evaluate the percentage based on total and overall rank. For example, total value for service popularity after we incorporate social data and organizational data is 96. Therefore, the percentage of service popularity in relation to the student satisfaction is 38. The definition of this metrics is as follow:

$$\text{Percentage } \left(\frac{\text{Total}}{\text{Overall rank}} \times 100\right)$$

Table 6. Evaluation of social data and organizational data in relation to the student satisfaction.

Data	Service popularity	Rank	Service satisfaction	Rank
Social data	67	1	70	1
Organizational data	29	2	30	2
Total/Total rank	96	125	100	130
Total/ Overall rank	96	255	100	255
Percentage	38%		39%	

In Table 6, the results show that service satisfaction has the highest percentage compare to service popularity. These results are consistent with the results from organizational data in Table 4 and the results from social data in Table 5. The results show that service satisfaction is important toward student satisfaction of La Trobe Student Support Services.

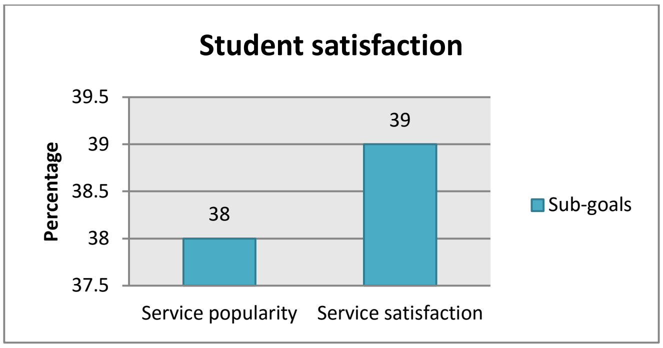

Figure 12. Rank of service popularity and service satisfaction in relation to the student satisfaction.

This case study is presents to investigate how social data incorporate with organizational data for better decision-making in relation to the organizational goals. After we identify the goal and sub-goals, we identify the relationship between goal and sub-goals. Based on this relationship, we identify data that relate to the goal. In this paper, we incorporate internal data (survey from La Trobe University Student Support Service Report) and external data (social data from Twitter). The results show the relationship between social data and organizational data in relation to the case study goal. In conclusion, social data can contribute for better decision-making process.

VI. Discussion

Most organizations today are fundamentally dependent on their data and information handling services facilitated by their information technology to collect, store, flow, manage and analyze data better. This paper addressed the relationship between different types of data and organizational goals. We proposed the organizational goals ontology to develop this relationship so we can identify the goals, sub-goals and data that relate to the organizational goals. A unique contribution of this paper is its perspective on how data from social media can support organizational data for better decision-making. The paper demonstrated the challenges to identify data that relate to the goals, especially social data. When we analyse both organizational data and social data, we see that these two data provide consistent results. The results assist decision-making process for consistent outcome, which may lead to achieving the organizational goals.

Evidence has shown that organizational goals ontology can be effectively developed the relationship between organizational data and social data in relation to the organizational goals. We found that, for example, despite the challenges in capturing relevant data from social media, filtering this data would be a better solution to store and analyse this data as they could incorporate with organizational data for better decision-making. Also, as larger volumes of social data are unstructured, data becomes more complex to analyse. NodeXL has been found to deal better with complex and unstructured social data, in which it can import social data in basic spreadsheet.

A. Contribution of the Proposed Organizational Goals Ontology

The analysis and evaluation of the data assisted our decision-making process in evaluating the level of student satisfaction based on service satisfaction and service popularity based on organizational data and social data. The case study was implemented and proves the applicability of the organizational goals ontology. In contrast to Rao et al. [12], Fox et al. [33] and Sharma & Osei-Bryson [34], the final results of the organizational goals ontology achieved the aim of being flexible and applicable in assisting decision-making in relation to the organizational goals.

- *Flexible to identify the organizational goals*

In this paper, we explained how to define the organizational goals. The usage of ontology assists the flexibility to define the organizational goals. By using an ontology, the process to identify the set of the organizational goals becomes flexible. The results in the case study proved the flexibility how we want to define the main goal.

- *Flexible to identify the dependency relationship*

The organizational goals ontology developed the dependency relationship between organizational data and organizational goals. At the same time, we developed the relationship between social data and organizational goals. We explained how to identify organizational data from organizational datasets that relate to the organizational goals. The organizational goals ontology provides this flexibility to develop this dependency. We proved this flexibility in the case study in which we developed the dependency relationship between data (internal and external data) and case study goals. This flexibility assists the process to identify which data to be consider relevant to the organizational goals.

- *Flexible to define the metrics after the main goals are identified*

We then test the flexibility to define the metrics. In this paper, the organizational goals ontology gives domain experts and entrepreneurs the flexibility on how they want to define the metrics after they identified the main goals. Domain experts and entrepreneurs have this flexibility on how they want to evaluate the data that relate to the organizational goals. This flexibility was tested in the case study. This proves that the organizational goals ontology assist the process to define the metrics in different way after we identified the goals that we want to evaluate.

- *Organizational goals ontology assists the decision-making and provide feedback in relation to the organizational goals*

The main objective of data analysis is to evaluate data from the vast amount of datasets. In this paper, data analysis is important to identify the value of data that relevant to the goals to support decision-making process in relation to the organizational goals [9].

After we analyse the data based on the metrics, the values of this analysis are presented to evaluate the level of the organizational goals achievement. Organizational goals ontology aims to provide a platform to analyse this value and assist domain experts and entrepreneurs to evaluate this value. Therefore, they can evaluate the level of the organizational goals achievement.

VII. Limitation and Future Work

In this paper, the evaluation of external data only limited to social media. There are other external data that can support the internal data for efficient decision-making such as mobile data and sensor data. Therefore, it is important to evaluate this data to see if this data can be used for decision-making process.

In the future, we will take this framework to the next level by building a Global Ontology that can capture the concepts of complexity and use as a basis for data integration processes suitable for efficient correlative decision-making. This Global Ontology will reside on the cloud and it will initially contain the local organizational ontology. We will develop an incremental approach to extend the ontology with relevant external knowledge bases by clustering and annotating the external data to concepts and properties within the ontology.

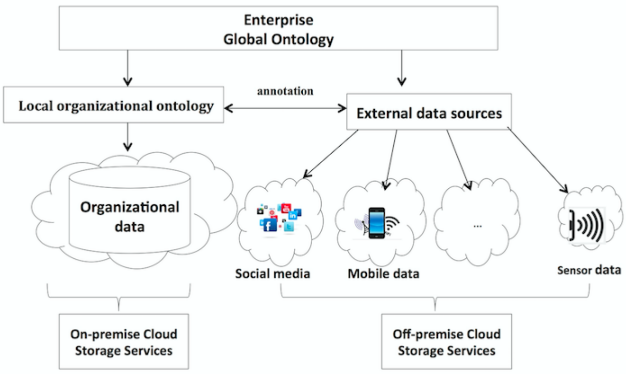

Figure 13. Future work.

The originality of our proposal lies in the creation of the Big Data integration 'road-map' in the form of an Enterprise Global Ontology that contains references to concepts and properties from external sources relevant to the organization. This road-map will enable accurate integration of the data sets for decision making as it will serve as a meta-data for the connectivity of the integration process. This approach will enable the organization to have an overall view of data connectivity within and outside the organizations, and to enable the data scientists to harvest interconnected information for analytics purposes.

In Figure 13, the Enterprise Global Ontology will be built on a cloud computing environment. The on-premise storage services will house the organizational data and the different off-premise storage services will house the external data, which we consider the Big Data. This Big Data is basically dynamic and its relation/connectivity to the organizational data needs to be incrementally and timely updated based on-demand from the user. Enterprise Global Ontology will contain the local organizational ontology and it will be extended by clustering and annotating the relevant external data in a timely manner. The first focus of this research will be on the development of the local organizational ontology to show the flow of data in the organization. After that, we will focus on the relationship between local ontology and external data. This local ontology will be extended by clustering the external data to define the degree of relevance of the particular data. In this research, Enterprise Global Ontology will extract knowledge through the correlation between local ontology and external data. In doing correlation, there are few issues that we want to resolve. For example, finding the most efficient clustering methodology to extract external data. Likewise, it is important to find the best way to link the local organizational ontology to the matched data which was derived after clustering the external data. Experiments will be conducted taking into consideration business enterprises as a proof of concept.

The ability to draw correlation and extract knowledge from relevant internal and external data will provide accurate situational awareness that supports effective decision making. The outcome of this research includes (i) consolidated decision-making process, (ii) cloud services for data matching and integration techniques, and (iii) incremental global ontology expansion. Beside business enterprise, the Global Ontology concept can also be applied to other areas which are highly impacted by things that are external to the organization (environmental conditions, weather, public sentiments, etc.), such as the agricultural industry, health care systems, transport industry, animal husbandry, and other industries in which decision-making is critical.

Finally, the results will be published in major scientific journals, and presented in domestic/international conferences during the first and second years. Currently, I am conducting literature reviews on related researches pertaining to the above-mentioned research plan. Also, I am identifying and selecting possible tools and software to capture and analyse different types of data.

VIII. Conclusion

In this paper, we have described the main features of the organizational goals ontology when developed the relationship between organizational data and social data in relation to the organizational goals. In addition, we have proposed an alternative approach to capture social data using NodeXL. We extend the application of the organizational goals ontology for better decision-making in relation to the organizational goals by evaluating both organizational data and social data. In conclusion, organizations can rely on external data such as social data to support their decision-making in evaluating the organizational goals achievement. This paper shows that the evaluation of the organizational goals achievement is better by incorporating social data and organizational data.

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Author Biographies

Tengku Adil Tengku Izhar, Ph.D., is a lecturer at the Faculty of Information Management, Universiti Teknologi MARA, Malaysia. His teaching and research interests are in big data, ontology, information management, social media and organizational knowledge assets.

Torab Torabi, Ph.D., is Senior Lecturer at Department of Computer Science and Computer Engineering. His research interests include software engineering, case tools, process modelling, software quality, xml and metadata, location based services, context-aware mobile services, integration of mobile services, ontology, model driven specification, component-based simulation.

M. Ishaq Bhatti, Ph.D., is Associate Professor and the founding director of Islamic Banking and Finance Programme at La Trobe University (LTU); the first ever in Australasian region. His major areas of research, scholarship and teaching are in quantitative finance, islamic finance, applied econometrics and statistics.