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Original Research

The Interactive Behavior in the Relation between Simple and Complex Structure of Concept and Semantic Relations in an Agricultural Ontology (VocBench)

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Abstract

The purpose of this empirical quantitative study is the measurement and evaluation of the relations between structural domains, including simple and complex structure of concepts and semantic relations. Our scientific guess is that there is a significant relation between the structure of concepts and the number of semantic relations. Moreover, there is the lack of investigation on assessing the behavioral interaction between structural domains to improve information retrieval (IR) performance for achieving cognitive results to generate theoretical argument. The mix-method of deductive and inductive approach is adapted in operating the research methodology, especially for data collection. The research data is selected from a complex and authoritative agricultural ontology (i.e., VocBench). Sample size out of 40000 concepts is around 1500 concepts, which were collected via stratified random sampling. The data analysis results were derived from SPSS and Excel software which employed proportional and inferential analysis. The expected relation is that an increase in the numbers of simple concepts causes the increase of semantic relations and vice versa.

Keywords: Ontology Evaluation, Structural Analysis, Structural Domains, Concept Structure, Simple Concepts, Compound Concepts, Semantic Relations, Quantitative Analysis, Proportional Analysis, Agricultural Ontology, Vocbench.

Introduction

Ontologies are generated for several diverse purposes and various types of evaluations are required Gomez-Perez, 1994). (Ontology evaluation can measure three major issues (Obrst, Ashpole, Ceusters, Mani, Steve & Smith, 2007) which include structural, functional and usability-profiling (Gangemi, Catenacci, Ciaramita & Lehmann, 2006). The majority of the literature on ontology evaluation have focused on functionality issues, rather than the structural ones (Gangemi, Catenacci, Ciaramita, & Lehmann, 2005) and usability. In spite of the limitation in applying structural analysis, the structural analysis plays a vital position in evaluating ontology structure (Dividino, Romanelli & Sonntag, 2008; Eynard, Matteucci &

Marfa, 2012) regarding the structure of concepts (Alani & Brewster, 2005) and the relationships among concepts (Assal, Pohl & Pohl, 2009) where entities are represented as nodes (Martín Chozas, 2018). Therefore, major parts of criteria and related measures have been proposed in the field of functional and usability analysis instead of focusing on structural issues, despite the importance of the structural analysis in ontology evaluation. Structural analysis, however, has a strong capacity to evaluate a domain independent approach (i.e., various domains of knowledge) in evaluating the structure of ontologies.

The structural domains can cover the analysis of the structure of concepts and semantic relations. Concepts, which play a major role in the construction of ontology structure (Alani & Brewster, 2005), include their own structure. Concepts structure can be evaluated as simple or complex structure. International standards have emphasized on splitting compound words into simpler concepts (International Organization for Standardization, ISO: 25964, 2011, 2013) which is expressed by a single-word term (National Information Standards Organization, NISO, 2005). Simple concepts cause the increase of recall and precision (Pohlmann & Kraaij, 1997; Airio, 2006; Lazarinis, Vilares, Tait & Efthimiadis, 2009; Leveling, Magdy & Jones, 2011) to improve IR performance (Leveling et al., 2011; Braschler & Ripplinger 2004; Hedlund, 2002) in knowledge organizations (Monz & De Rijke, 2002). Hence, simple concepts play a role in increasing IR performance (Amirhosseini & Salim, 2010). Consequently, simple or single concepts play a great role in increasing the performance of information and knowledge storage and retrieval.

The role of single or simple concepts to improve IR effectiveness can be more clearly observed by some examples which will then clarify our scientific guess in this research that is "concept structure affects the number of semantic relations". "Information", "Management", "Resources", "Sciences" and the like are some concepts or descriptors. In this matter, single descriptors consist of generic concepts to develop the rate of recall. Additionally, the composition of the single descriptors in IR time results in the making of semantic linkages between different subject fields, such as "Information Resources Management", "Information Management", "Management Information Resources", "Management Information", "Resources Management" and so on (Amirhosseini & Salim, 2015). Moreover, these compositions reason for the increasing of precision on the basis of syntactic relations in IR time. Furthermore, a few numbers of descriptors can be connected to one another through numerous linkages. In addition to the role of simple concepts in IR performance, our scientific guess is that simple concepts cause an increase in the number of semantic relations as well. Moreover, results of the literature review demonstrated a gap in structural analysis of concept structure and semantic relations regarding their interactive behavior in the structural analysis of ontologies. Therefore, there is a lack of investigation on behavioral interaction between structural domains to improve IR performance.

Analysis of behavioral interactions between structural domains constitutes a major reason for achieving cognitive results to generate theoretical arguments. The expected relations in structural domains may be explained in the relations between the amounts of simple or complex concepts and the amount of semantic relations. The expected relation is that an increase in the numbers of simple concepts causes the increase of semantic relations and vice versa. These relations lead ontology builders to maintain, validate and verify ontologies to increase IR performance. For the sake of this purpose, a specific method should operate in finding the relations between concept structure and semantic relations to realize their interactive behavior based on deductive and inductive logical reasoning to achieve cognitive results in generating theoretical arguments (Amirhosseini & Salim, 2011, 2019a, 2019b). The mixed method of logical reasoning is an appropriate method to analyze the iterative process to formulate, examine, reformulate and reexamine the research data and process in developing multiple measures and observations and reducing research errors to achieve cognitive results (Houston, 2009). Therefore, the research problem is derived from the lack of investigation on the relation between structural domains through a mixed method of logical reasoning to generate theoretical argument to achieve cognitive results. The aforementioned problem can be demonstrated in the form of sub-problems, which are described as follow:

- Lack of investigation into structural analysis of concepts in terms of their simple and complex structure on the basis of simplicity concept.
- Lack of investigation into the relations between concepts structure with semantic relations to operate a mixed-method of inductive and deductive approach to develop multiple measures and observations in achieving cognitive results to generate theoretical arguments.

In this research, concepts' structure and their relation with semantic relations have been taken into account as two major categories in data collection. The mix-method of deductive and inductive approach is adapted in operating the research methodology, especially for data collection. The research data is selected from a complex and authoritative agricultural ontology which is VocBench. The first efforts to reengineer AGROVOC for use as an ontology (Soergel, Lauser, Liang, Fisseha, Keizer & Katz, 2006) to develop semantic and lexical relations in more refined and precise ways to build domain specific ontologies in the agricultural domain, the Concept Server (CS), have been done since 2003 (Liang, Lauser, Sini, Keizer & Katz, 2006). VocBench was produced in the form of ontology from AGROVOC thesaurus that is AGROVOC moved to an OWL model in 2005 (Yves, 2011). VocBench, in fact, is the newest, latest version (Xian & Zhao, 2012) and the successor of AGROVOC Concept Server Workbench (ACSW) to focus on multilingualism, collaboration and on a structured content validation & publication workflow (Stellato, 2015). ACSW is the re-engineered version of AGROVOC thesaurus (Soergel, et al., 2006; Sabou, 2007). These vocabulary control tools have been originated by Food and Agricultural organization (FAO), United Nation (Xian & Zhao, 2012). Therefore, the data resource for examining our objectives and scientific guesses in ontology evaluation in terms of structural dimensions is VocBench.

The agricultural ontology, VocBench, includes around 40000 concepts. Sample size for 40000 concepts is around 1500 concepts based on Krejcie and Morgan (1970). The sampling technique used was stratified random sampling. The data analysis results were employed in the SPSS and Excel software to extract various statistical reports. Data analysis was divided into two main steps, deductive and inductive approaches to follow the eight research objectives. Firstly, in the deductive step, we find appropriate answers to the first four research objectives via operating proportional analysis and test two general hypotheses through comparing the means of semantic relations and concepts structure. Secondly, we struggle to evaluate the structural domains based on an inductive approach in the form of descriptive statistics, and examine two main hypotheses by using frequency analysis and inferential statistics through analyzing the last four research objectives. Therefore, the research data was analyzed by various statistical methods in order to achieve general and specific knowledge based on the deductive and inductive approach for finding cognitive results in VocBench.

Operational definition

In this section, the dependent variables of the research are explained to clarify their meaning or concept in analyzing the casual relation regarding concepts structure and semantic relations (Amirhosseini and Salim, 2019b).

1. *Taxonomic input*: Concepts usually receive taxonomic relations regarding hierarchical relations which is called taxonomic input, for example the concept of “Wheat” is a kind of or sub concept of “Cereals”. In the case, the relation between “Wheat” and “Cereals” is fulfilled by a such a relation as “IS_a_Sub_Concept”. It means that “Wheat” is linked to “Cereals via a taxonomic input and “Cereals” receives a taxonomic input from “Wheat”.

2. *Taxonomic output*: Concepts usually send or forward the hierarchical relations as Taxonomic outputs regarding part-whole or generic-specific relations. For instance, “Cereals” include some concepts such as “Rice”, “Barley” and “Wheat”. In other words, “Cereals” has been linked by the axiom of sub_concept to “Rice”, “Barley” and “Wheat” as a taxonomic output or Cereals sends semantic outputs to the mentioned concepts.

3. *Non-taxonomic input*: Sometimes, concepts link with each other through conceptual relations, which cannot be categorized based on hierarchical relations. Non-taxonomic input, as a kind of such relations, connects two concepts based on associative relations. In other words, non-taxonomic inputs result in receiving semantic relations concepts form other concepts. For instance, “Wheat Flour” links to “Wheat” through an axiom such as “*Product of”*. Thus, “Wheat” is accessible through the usage of a linkage (i.e., “Product of”) as non-taxonomic input from “Wheat Flour”.

4. *Non-taxonomic output*: Some concepts link with each other through the sending or forwarding of semantic relations from one concept to the other(s). This kind of association relation between concepts is fulfilled through non-taxonomic outputs. For instance, “Wheat” links to “Wheat Flour” via a semantic relation such as “*has Product*”, which means “Wheat” is associated to “Wheat Flour” by a non-taxonomic output. Thus, “Wheat Flour” is accessible by user through sending a non-taxonomic output from the concept of “Wheat”.

5. *Taxonomic number*: This factor demonstrates the number of taxonomic relations in semantic network. In other words, taxonomic number, which is the total number of taxonomic relations, is obtained by the sum of taxonomic inputs and outputs.

6. *Non-taxonomic number*: This factor is also obtained via calculating the number of not-taxonomic input and output to achieve the total number of associative relations between concepts.

7. *Semantic input*: Semantic input includes the total number of taxonomic input and non-taxonomic input.

8. *Semantic output*: This factor is obtained by the sum of the numbers of taxonomic output and non-taxonomic output.

9. *Concepts’ input and output*: Concepts send and receive some semantic relations. In this case, the total number of taxonomic input and output (i.e., Taxonomic number) and non-taxonomic inputs and outputs (and output (i.e., Non-taxonomic number) result in the fulfilling of the total number of concepts’ input and output. In other words, the concepts’ input and output includes the total number of semantic input and output.

Literature Review

The literature review focused on various investigations in analyzing concept structure and semantic relations as well as their relations through quantitative methods. The related researches on concept structure, in general, focused on concepts description (Navigli, Velardi, Cucchiarelli, & Neri, 2004) and terminology mapping between concepts in ontology (Mayr, Petras & Walter, 2007) or the correspondence between concepts in two different ontologies in similar domains based on concept similarity (Liu, Barnaghi, Moessner & Liao, 2010; Jiratthitikul, 2014). The related researches in analyzing the structure of semantic relations demonstrated that these relations were evaluated via several metrics and measures. Some early research focused on analyzing connectedness and accessibility in semantic relations (Kochen & Tagliacozzo, 1968). The others attempted to assess conceptual coherence, conceptual complexity (HIS, 2005), analyze content correctness and axioms verification (Rogers, 2006), evaluate average analysis in clarifying concept correctness (Blomqvist & Ohgren, 2008) and examine depth measure checking in terms of complexity in an ontology (Vrandecic, 2010; Calbimonte, García-Castro & Corcho,, 2011). Furthermore, some of the studies identified anonymous class count and class to property analysis to evaluate ontology design patterns (Hammar, 2013) to detect common pitfalls (Villalon, 2016) in operating ontology mapping (Chmielewski & Stapor, 2016) especially through using of a semiotic-inspired approach (Amith & Tao, 2017). Moreover, the evaluation of semantic association has been taken into account (Chmielewski & Stąpor, 2018) in ontology quality assurance work (Zhanga, Xingd & Cuia, 2018) to analyze semantic network (Holst, 2014) based on graph theory and ontology graph.

The relation between concepts and their semantic relations has been considered through preparation of a set of syntactic, semantic and pragmatic constructs (Burton-Jones, Storey, Sugumaran & Ahluwalia, 2003; Park, Cho & Rho, 2007). Moreover, regarding the relationship between concept and its relations, some methods were operated as designing weighted class dependent graphs (Kang, Xu, Lu & Chu, 2004), analyzing the string of path-to-term (Mungall, 2005), evaluating the complexity in semantic network (His, 2005; Zhang, Ye & Yang, 2006) in the ontology conceptual model (Mungall, 2005) and operating link analysis techniques and data mining algorithm (Furletti, 2009). Furthermore, some researches focused on analyzing the relation between concepts and semantic relations via comparing ontologies based on semantic similarity (Chmielewski, Paciorkowska, & Kiedrowicz, 2017) and concept similarity (Xamena, Brignole & Maguitman, 2017) to analyze navigability among concepts and their relations in clarifying the design pattern of ontologies for the sake of ontology development.

Among the researches related to structural analysis, Amirhosseini and Salim (2010; 2015) proposed a method in analyzing the number of words in structure of concepts. Moreover, the authors proposed ratios in measuring domains of taxonomic and non-taxonomic relations (Amirhosseini, 2010) through a mix-method of deductive and inductive approach (Amirhosseini & Salim, 2019b). Additionally, an investigation presented a theoretical method to propose a proportional analysis (Amirhosseini, 2007) based on proposed criteria and related measures (Amirhossini & Salim, 2011) to evaluate simplicity in concepts structure and unity in semantic network in identifying the interactive behavior of concept structure and semantic relations through the use of deductive/inductive approach (Amirhosseini, 2016; Amirhosseini & Salim, 2019b). The mentioned researches are closely related to the present study in terms of methodology and research topic in evaluating ontology structure. However, literature review showed that there is a gap in structural analysis of concept structure and semantic relations regarding the role of number of words in concept structure and its effect on the number of semantic relations in the structural analysis of ontologies.

Materials and Methods

Goal and objectives

This research consists of a major goal and other related specific objectives. The goal of this study is "to analyze and evaluate the structural domains and their interactive behavior in ontologies to generate a theoretical argument". The research objectives to achieve the mentioned goal are:

- To identify the condition of simplicity in the concepts' structure in VocBench.
- To find a relation between the mean number of semantic relations and a group of simple and complex concepts.
- To achieve a complement analysis as a supportive method in examining concepts' structure regarding simplicity.
- To find a relation between simple structures of concepts and the amount of semantic relations.

Research Hypotheses

The following research hypotheses are related to the last two research objectives:

- There is a relation between the mean numbers of semantic relations and a group of simple and complex concepts.
- There is a relation between the simple structures of concepts and the amount of semantic relations.

Method

This research is a quantitative investigation on the measurement and evaluation of structural domains in ontologies. Ontology evaluation has the capacity to be analyzed via qualitative and quantitative approaches (Velardi et al., 2005). Quantitative approach uses the principles of ontology construction (Brewster, Alani, Dasmahapatra & Wilks, 2004) for finding detailed information to extract and formalize knowledge which are derived from unstructured data (Velardi et al. , 2005). Since this research attempts to analyze the structural domains in the construction of ontologies, the proper approach to take, would be the quantitative method for the sake of evaluating the structural domains in ontologies. Literature review showed that there is a gap in structural analysis in ontology evaluation. This gap is the lack of structural analysis to assess structural domains in concepts structure and semantic relations as well as their interactions, by focusing on multiple measures and observations to create new knowledge based on the deductive and inductive logical reasoning. Consequently, the structural analysis of concepts and semantic relations and their interactional behavior are quantitatively evaluated based on a mixed-method of inductive and deductive approach to achieve cognitive results.

As stated previously, this research is conducted through quantitative evaluation based on deductive and inductive approach. The various steps of the research method incorporating the mixed method of logical reasoning are explained as follow:

Deductive approach

This step can be divided into two groups of investigations; firstly, there is the quantitative evaluation of the concepts' structure through proportional analysis using EXCEL. This investigation attempts to find information to answer the first research objective. Secondly, the examination of the general or deductive hypotheses, related to the second research objectives is to find a relation between the mean numbers of semantic relations and concepts' structure through descriptive analysis, especially the compare mean method that is carried out via SPSS.

Inductive approach

This step can categorize two groups; firstly, the structure of concepts is analyzed by descriptive analysis using SPSS, especially the frequency analysis. The third research objective is involved in this group .Secondly, the relation between concepts' structure and semantic relation is examined to test the fourth research objectives related to the main or inductive hypotheses by using inferential analysis, Pearson correlation method via SPSS.

Results

Data analysis and findings

As stated previously, the investigation has relied on the two main approaches, deductive and inductive, to present the research findings.

Deductive Approach

In this step, we intend to assess the first two research objectives. The first research objective focuses on analyzing the structure of concepts and the second one is related to the general or deductive hypothesis. Thus, the research data analysis and findings based on the deductive approach can be demonstrated in the following sections:

The first: Analysis of simplicity in concept structure via proportional analysis

The first research objective is related to the analysis of simplicity in the structure of concepts. Simplicity in concepts' structure can be analyzed by a proposed formula, namely The Simplicity Ratio (Amirhosseini, 2007). The indicators of this ratio are the number of simple, single and unitary concepts and the total number of concepts (Amirhosseini & Salim, 2010).

$$SR = \frac{\mathrm{a}}{\mathrm{b}}$$

$a = the\ number of simple\ concepts$

$b = the\ total\ number\ of concepts$

Operating the aforementioned indicators shows that the number of simple concepts in VocBench is equal to 810 in the research population. The total number of sample size, as stated previously, is equal to 1500. Therefore, the amount of simplicity in concepts' structure is equal to 0.53. It means that 53 percent of concepts in VocBench have simple structures. Figure 2: shows the domain of simplicity and complexity in the structure of concepts in VocBench.

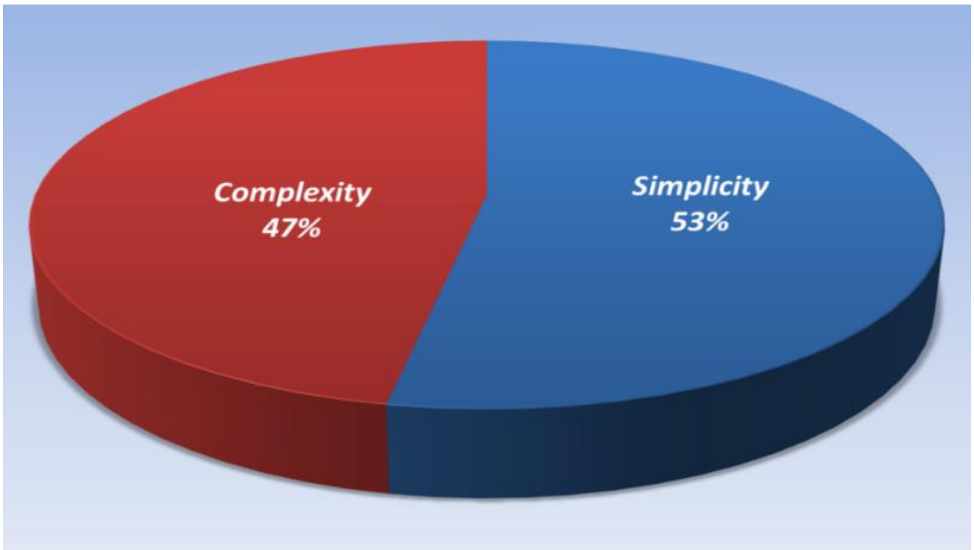

Figure 1: Simplicity and complexity domains of concept structure in VocBench

The above figure demonstrates that the amount of simple concepts (i.e., 53 percent) is more than the compound or complex ones (i.e., 47 percent) in VocBench.

The second: Testing the General Hypothesis

After the investigation and clarification of structural domains based on proportional analysis in examining the first research objective, general hypotheses are formulated to reach meaningful relations between concept structure and semantic relations. In this section, we intend to examine the general hypothesis, which is related to the second research objective for finding the relations between concept structure and semantic relations. The general or deductive hypothesis is stated as follow:

General Hypothesis: There is a relation between the mean numbers of semantic relations and a group of simple and complex concepts.

This hypothesis attempts to find the relation between concepts structure and the number of semantic relations through the use of descriptive analysis based on a deductive approach. In this case, our expectation is that an increase in the use of simple concepts causes the increasing of semantic relations and vice versa. For instance, simple concepts such as ‘art’ comprise of more semantic relations than complex concepts such as ‘Western art philosophy’. Testing of this hypothesis has been done by relying on SPSS reports in terms of comparison between means and is demonstrated as follow:

Table 1
Comparison between the mean numbers of semantic relations between the groups of simple and complex concepts

Concepts' structure		Taxonomic Number	Non Taxonomic Number	Semantic input	Semantic Output	Concepts' Input Output
Simple	Mean	5.11	1.56	2.11	4.56	6.67
	N	809	808	809	809	809
Complex	Mean	2.72	1.11	1.97	1.86	3.82
	N	691	692	691	691	691
Total	Mean	4.00	1.35	2.04	3.31	5.36
	N	1500	1500	1500	1500	1500

Table 1 Demonstrates that there exists a statistically meaningful relation between the mean number of taxonomic relations and semantic relation output, as well as concepts' input-output between simple and complex concepts. Results of the descriptive analysis of "means comparison", reveals that simple and complex concepts differ from each other in terms of the mean numbers of semantic relations. In other words, there is a significant difference in the mean numbers of taxonomic number (i.e., 5.11 & 2.72), semantic relations output (i.e., 4.56 & 1.86) and concepts' input-output (i.e., 6.67 & 3.82) regarding the two groups of simple and complex concepts. In contrast, there were no differences between the groups of simple and complex concepts in terms of the non-taxonomic number and semantic input. However, in the group of simple concepts the mean numbers of concepts input-output is equal to 6.67 that show a meaningful relation between the concept structure and the number of semantic relations. This means that each simple concept includes about seven semantic input-output or semantic relations. On the other hand, complex concepts consist of about 4 semantic input-output (i.e., 3.82). Thus, the above results have demonstrated that simple concepts cover more semantic relations than the complex ones. Simple concepts have sent and received more semantic relations than complex concepts. Consequently, the scientific guess of the first hypothesis has been confirmed by a comparison between the mean numbers of semantic relations with an exception of the results of the non-taxonomic number and semantic input.

Inductive Approach

The inductive approach in data analysis starts from a descriptive approach in clarifying the frequency analysis of structural domains in concepts' structure and continues to test the main hypothesis in analyzing the relation between concept structure and semantic relations to generate theoretical argument to achieve cognitive results in the structural analysis of ontologies. The research findings based on the inductive approach can be shown in the following sections:

The first: Descriptive Analysis of Concepts Structure and Semantic Relations

The structural analyses in the deductive approach had focused on proportional analysis of simplicity in concept structure for answering the research objectives to prepare a general knowledge about structural domains. On the contrary, the descriptive statistics in this section identify in-depth knowledge in evaluating the structure of concepts. In this section, descriptive analysis operates to follow the third research objective in assessing the frequency of the usage of simple & complex concepts structure through the analysis of SPSS report. Hence, the descriptive approach based on the inductive approach discovers in-depth knowledge in identifying structural domains as a complement to the proportional analyses in step one of the data analysis (i.e., deductive approach in data analyzing)

The frequency of the simple (i.e., one-word concepts) and complex concepts that have more than one word in their structure are presented in the following table based on the inductive approach.

Table 2

The frequency of the usage of simple & complex concepts structure in VocBench

Concept Structure		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Simple	810	53.4	53.7	53.7
	Complex	690	46.0	46.3	100.0
	Total	1500	99.4	100.0	
Missing	System	0	0		
Total		1500	100.0		

Table 2 displays the number and percentage of simple and complex concepts in VocBench. At first glance, the number of simple concepts is seen to be more than the complex ones. In this manner, the number of simple concepts is equal to 810 while the number of complex ones is 690. This means that more than 54 percent of concepts have a simple structure based on a valid percentage. Therefore, the frequency results of simple and complex concept usage, confirms the results of the simplicity ratio in the deductive step. Moreover, the results demonstrate that ontology builders move toward simplicity in constructing concepts in VocBench.

The second: Inferential Analysis

In the deductive step, we found the relations between concepts' structure and semantic relation by comparing their means in examining the general hypothesis. In contrast, the statistical analysis in the deductive step has focused on evaluating the relation between the structure of concepts and the numbers of semantic relations by applying inferential statistics. This kind of statistical analysis prepares precise knowledge in the field of structural domains to test the main hypothesis. In this matter, the related method in inferential statistics is the Pearson correlation. Thus, the accurate statistical method in this section prepares absolute knowledge in testing the inductive or main hypothesis related to the fourth research objective on analyzing structural domains based on the inductive approach. This hypothesis is stated as follow:

Main Hypothesis: There is a relation between the simple structures of concepts and the amount of semantic relations.

The Examination of the inductive or main hypothesis has been done through focusing on the SPSS reports based on Pearson correlation to test the linear relationships between the two quantitative variables, which are simple or complex structures of concepts and the amount of semantic relations. The results of Pearson correlation is presented in the following table.

Table 3

Correlation analysis between simple structures of concepts with the amount of semantic relations in VocBench

Correlations		Simple& Complex Concepts
Taxonomic Relations	Pearson Correlation	Reports
Taxonomic input	Pearson Correlation	.087**
	Sig. (2-tailed)	.001
	N	1500
Taxonomic output	Pearson Correlation	-.912**
	Sig. (2-tailed)	.000
	N	1500
Non-Taxonomic input	Pearson Correlation	-.040
	Sig. (2-tailed)	.124
	N	1500
Non-Taxonomic output	Pearson Correlation	-.63**
	Sig. (2-tailed)	.015
	N	1500
Taxonomic number	Pearson Correlation	-.804**
	Sig. (2-tailed)	.000
	N	1500
Non-Taxonomic number	Pearson Correlation	-.55*
	Sig. (2-tailed)	.034
	N	1500

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 3 displays the results of the linear relationships between simple structures of concepts and the amount of semantic relations. At first glance, the highlighted results clearly show that a majority of cases consist of meaningful correlations between their variables. In this matter, based on Pearson's results there exists a negative relationship between simple structure of concepts and semantic relations in taxonomic relations output ($r = -0.912$, p-value $0.000 < 0.05$). That is, as the number of complex or compound concept decrease the numbers of semantic relations increase. In this case, simple concepts result in increasing semantic relations. Similar relation can be seen in the results of taxonomic number ($r = -0.804$, p-value $0.000 < 0.05$) and non-taxonomic number ($r = -0.55$, p-value $0.034 < 0.01$) and non-taxonomic output ($r = -0.63$, p-value $0.015 < 0.05$). In contrast, there is a positive relationship between variables in taxonomic input ($r = 0.087$, p-value $0.001 < 0.05$). This means, as complex concepts increase, the semantic relation also increases. Moreover, the correlation test shows that the p-value is equal to 0.124 which is more than the 0.05 in non-taxonomic input. This concludes that there is no significant relation between structures of concepts and the amount of semantic relations. Thus, the scientific guess in hypothesis one is approved by relying on the correlations between variables in major parts of semantic relations. Subsequently, simplicity in concept structure reasons for the increasing of semantic relations with the exception of the correlation outcomes in taxonomic and non-taxonomic input. These groups of semantic relations express that complexity in concepts structure causes an increase in semantic relations.

Discussions

The discussions in this section are divided into two complementary sections. The first section relies on discussions on the findings of the deductive approach which follow the first two research objectives including the deductive or general hypotheses in analyzing the structure of concepts and examining the relation between concept structure as a casual factor and semantic relations as a factor. The second section discusses the findings based on the inductive approach to follow the research adjective no. 3 and 4, in explaining the results of the descriptive analysis and testing the inductive or main scientific guesses in analyzing concept's structure and semantic relations. The scientific guess on the structure of concepts and the number of semantic relations endeavors to clarify the correlation between casual factor (i.e., concept structure) and factors or semantic relations.

Deductive Approach

The discussions in this section focus on the results of the deductive step to clarify the results of analysis of the domain of simplicity in concepts' structure and to examine the deductive hypothesis in reaching general knowledge regarding structural analysis in VocBench. Thus, the discussions will allow us to capture a general knowledge in evaluating the structural domains through a deductive approach through the following sections:

The first: Concept Structure in Ontologies

The first research objective is to define the simplicity domain in the structure of concepts in ontologies. This objective was related to identifying the range of the usage of single, simple and unitary concepts in ontology. The result reveals that slightly more than half of the concepts are simple in structure. This means that ontology builders have given considerable attention to the construction of simple concepts as oppose to taking into account the more complex concepts (i.e., compound concepts which are conveyed by multi-word terms). Moreover, because absolute consistency in the admission of complex concepts is difficult to achieve and is not always necessary, ontology builders of VocBench have followed related standards to decrease the amount of complex concepts (ISO: 25964, 2011, 2013). Furthermore, other standards such as ISO 5964, British standard Institution BS (2005) 5723, 6723 and BS 8723 emphasize on construction of simple or unitary concepts or a single linguistic form (ANSI/NISOZ39.19, 2005) as far as possible (ISO: 25964, 2011), to compensate for the vocabulary control problems (ANSI/NISOZ39.19, 2005). In addition, simple concepts play a great role in improving IR. Braschler & Ripplinger (2004) reported that a single word has a maximum possible number of relations (Muñoz, 1997). In this case, construction of single concepts reasons for improving IR (Leveling, et al., 2011) with regard to increasing recall (Airio, 2006; Lazarinis, et al., 2009) and while precision does not deteriorate, (Pohlmann & Kraaij, 1997) it will increase as well (Airio, 2006). Subsequently, the domain of simple concepts is more than the complex ones, while additionally the domain of single concepts results in increasing the performance of IR in VocBench.

The second: Comparing the Means between Simple and Complex Concepts and Semantic Relations

In this section, the investigation tends to test the general hypothesis based on the deductive approach to achieve information about the second research objective. This scientific guess examined the comparison between means of simple and complex concepts and semantic relations. This study attempts to explain the presence of a relation between the mean numbers of semantic relations and a group of simple and complex concepts. In fact, the structure of concepts played a role as casual factors and semantic relations functioned as the research factors. The findings between the means of simple and complex concepts and taxonomic relations number, semantic relations output and concepts input-output, revealed that simple concepts include more semantic relations in comparison with complex ones. Additionally, the cumulative results of semantic relations (i.e., concept input-output) demonstrated that simple concepts send and receive semantic relations, approximately twice that of the mean of complex concepts. In contrast, there is a balance between the means of non-taxonomic relations and semantic relations input with regard to simple and complex structure. In conclusion, the comparison between the means of semantic relations and concept structure clearly revealed that when the structure of concept was simple, the means of semantic relations increased. This idea was especially confirmed by the comprehensive results of concepts input-output. The exceptions are the findings of the means of non-taxonomic number and semantic input for verifying the mentioned idea. In general, movement from complexity to simplicity in concept structure is a major reason for generation of more semantic relations.

Inductive Approach

The inductive findings supported and approved the results of the deductive analysis in the previous sections. The discussions based on the inductive approach will start from the clarification of structural domains using descriptive statistics and continues to present arguments on the findings of the main hypotheses to generate the theoretical argument on structural analyses in ontologies through the following sections:

The first: Descriptive Analysis on the Frequency of the Usage of Simple and Complex Concepts

The findings of descriptive statistics exposed the higher usage frequency of simple concepts as compared with complex concepts. Moreover, valid percentage of the usage frequency confirmed that slightly more than half of concepts in VocBench belong to simple concepts. This finding, which is derived from SPSS frequency analysis, approved the results of the first research objective in determining the simplicity domain. Furthermore, a decrease in the number of compound terms result in increasing recall and precision (Pohlmann & Kraaij, 1997; Airio, 2006; Lazarinis et al., 2009; Leveling et al., 2011) and is an effective factor in improving IR performance (Airio, 2006). Therefore, the dominant domain of simple concepts can play a remarkable function in improving IR in terms of increasing recall and precision.

The second: Correlation Analysis between Concept Structure and Semantic Relations

The main hypothesis is to examine the correlation between simple structures of concepts and the amount of semantic relations. In this manner, semantic relations are the research factor and the structure of concepts play a function as casual factor. The factors include six groups which are taxonomic input, taxonomic output, non-taxonomic input, non-taxonomic output, taxonomic number and non-taxonomic number.

Results of the correlation between concept structure and semantic relations such as taxonomic output, non-taxonomic output, taxonomic number and non-taxonomic number reveals that concept structure has a negatively significant correlation with the amount of these semantic relations. This means that increasing of these semantic relations is caused by an increase in simple concepts and a decrease in the complex ones. The results of the correlations regarding taxonomic and non-taxonomic number play a tremendous role in analyzing the negative correlation between concept structure and semantic relations. This is due to the fact that taxonomic and non-taxonomic numbers include the total number of taxonomic and non-taxonomic input and output, or in other words the total numbers of semantic relations. In contrast, the correlation between concept structure and taxonomic input exposed a positive correlation between the simple and complex structure of concepts with these semantic relations. This means that an increase in the number of non-taxonomic output is caused by the increase in complex concepts. Greater levels of combination in concepts structure might result in positive correlation between concept structure and these semantic relations. This is because when the components of concepts increase, concepts might receive some semantic links from the related generic or the associative concepts. For example, the specific concept “Palm Oil Industry” may receive some taxonomic input from generic concepts such as “Palm”, “Oil” and “Nutrition Industries”. On the other hand, the findings in this section made evident that there is no relation between concept structure and non-taxonomic input.

In conclusion, the findings firstly indicated that there are correlations between concepts structure and semantic relations with the exception of non-taxonomic input. Secondly, our expectation of a negative significant correlation was approved by four out of six kinds of semantic relations which are taxonomic output, non-taxonomic output, taxonomic number and non-taxonomic number. This elaborates that simple concepts result in the increasing of the semantic relations. Thirdly, one semantic relation (i.e., taxonomic input) comprised of a positive correlation exists in the relation between concepts structure and semantic relations while there is no correlation between concept structure and non-taxonomic input. Fourthly, taxonomic and non-taxonomic numbers prepared comprehensive results with regard to hierarchical and associative relations in an ontology. Fifthly, the result of the inductive or the main hypothesis has approved the results of our scientific guess in the deductive or general hypothesis about the relation between concept structure and semantic relations. Moreover, we expected that the casual factor (i.e., concept structure) has a negatively significant correlation with the number of semantic relations or factors. In this case, the general findings of these sections have completely approved our expectation. Subsequently, there showed to be are relations between concepts structure and semantic relations. Furthermore, simplicity in the structure of concepts reasons from an increase in the semantic relations in VocBench.

Conclusion

The accumulated and synthesized results in this section discuses concepts structure and relates the deductive and inductive approach. The related information revealed that the domain of simple concepts is more than complex ones, which ultimately result in increasing the performance of IR in VocBench. This finding has been approved by the descriptive analysis based on the inductive approach (i.e., frequency analysis). The information derived from deductive and inductive approaches implied that complex concepts should be factored into their components in order to increase simplicity in concepts structure and to conclusively improve IR performance in VocBench. Therefore, the amount of complex concepts is an effective factor for decreasing the simplicity results in concept structure. In other words, the increase of simplicity in VocBench depends on decreasing the amount of complex concepts.

The casual arguments revealed the roles of the inductive hypothesis in supporting the deductive hypothesis via preparing precise information to achieve cognitive results. The arguments of the deductive hypothesis confirmed the relation between the means of concepts structure and semantic relations. The arguments clearly clarified that simple concepts, in general, cover more semantic relations. This means that an increase in semantic relations depended on the move towards simplicity in the structure of concepts. As stated previously, the inductive hypothesis complements the scientific guesses for a better clarification of the arguments of the deductive hypothesis. Furthermore, by supporting each other, the deductive and inductive hypotheses prepare in-depth information regarding the relation between concepts' structure and semantic relations. The arguments of the inductive hypothesis approved the fact that there are significant correlations between concepts structure and semantic relations. Hence, the decrease in the number of words in a concept's structure reasons for the increasing of its semantic relations. Subsequently, the combination of arguments on the deductive and inductive results implied that the number of semantic relation will increase as the amount of complex concepts decrease and the number of simpler concepts increase. This could be regarded as an effective casual factor to develop our knowledge on structural analysis, move toward simplicity in structural analysis and generate theoretical argument in ontologies.

This research is neither purely deductive nor inductive, but has relied on a mixed method of logical reasoning. This research started from structural analyses based on a deductive approach and ended up relying on an inductive approach to generate theoretical arguments on a novel idea on the relation between concepts and semantic relations. The unified arguments conveyed that there is a relation between simplicity in concepts structure and the rise in the number of semantic relations. Hence, our generated theory derived from the research argument, especially from the inductive approach is that "*Simplicity in concepts structure causes an increase in the number of semantic relations in structural analysis of ontologies*". In other words, an increase in the amount of semantic relations is caused by the increasing of simplicity in concept structure and decreasing the amount of complex concepts. Moreover, the simple structure of concepts reasons for increasing recall and precision in the process of IR performance. Consequently, the generated theory states that "*Simplicity in concept structure causes the increase of semantic relations*" which achieves the highest level of cognition in the structural analysis of ontologies to improve IR performance.

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