Mapping Enterprise Governance of IT Models using Text Analyses

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Abstract

Enterprises are drawing upon the practical relevance of generally accepted good-practice models to implement EGIT. Despite the number of options for models available nowadays, when these models are used independently, they are not sufficiently wide-ranging to meet all the needs of an organization. No single model is sufficient to implement EGIT completely and efficiently. Therefore, organizations are concurrently implementing multiple models since most of these models only cover a specific aspect of IT. The ability to analyze large amounts of text reduces the need for skilled human resources. Therefore, a text analysis becomes a natural solution to compares core concepts of PAMs of EGIT models. The main goal of this thesis is to propose an artifact that enables the auditors and other stakeholders in an organization to perform quantitative and automatic pre-assessment about the conformance of an organization's processes compared to EGIT models with efficient human resource utilization. A Design Science Research Methodology was used to conduct this work. The research proposal was demonstrated and applied to COBIT 5 PAM and TIPA for ITIL PAM core concepts to highlight their similarities. To evaluate how this research helps reduce the complexity of simultaneous assessments, surveys and interviews with field experts were performed. We identified some relevant findings with positive results regarding the objective established.
Keywords: Enterprise Governance of Information Technology, Natural Language Processing, COBIT 5 PAM, TIPA for ITIL

1. Introduction

IT has become a success factor in achieving competitive advantage. It plays a crucial role in the sustainability and growth of organizations [14] [20]. Therefore, IT has become more than a commodity. Nowadays, IT is recognized as a strategic partner. It improves business by helping deliver faster and better products [30]. Given the importance and the advantages that come with IT, EGIT started to receive more attention in order to ensure efficiency, decrease costs and increase control of IT infrastructures [38] [32].

As a result, several questions arise when organizations decide to implement EGIT models. The increasing demand of industries force organizations to adopt multiple EGIT models. Thus, practitioners not only need to choose the appropriate models for their environment but also need to determine how to integrate them simultaneously [31] [7]. Each EGIT model has its own scope, definitions, and terminologies. This complicates the understanding of the overlap between different models [12]. Therefore, organizations struggle to assess and implement multi-models, leading to the research problem: there is no comprehensive approach to understand and identify the similarities between core process concepts of similar models. The goal is to provide a comprehensive approach that can help to perform a simultaneous assessment of different PAM of EGIT models by identifying the similarities between process core concepts.

To achieve the goal of this research, it is proposed an approach that through text analysis techniques compares the similarities between the core concepts of EGIT models. Most of the data used in EGIT models is textual data. The ability to analyze large amounts of text becomes crucial to the success of an organization. Therefore, a text analysis becomes a natural solution to reduce the need for skilled human resources.[42] [13]. To demonstrate the use of the proposal, the proposed artifact was applied to two of the most common EGIT models Process Assessment Models – the Control Objectives for Information and Related Technologies (COBIT) PAM and TIPA for ITIL PAM core concepts to highlight their overlap. This proposal is more scalable, flexible, and dynamic than manual efforts in aligning EGIT models.

To evaluate how this research helps reduce the complexity of simultaneous assessments two evaluations were performed: one with comparison with a specialists' mapping as a baseline, and another through surveys and interviews with field experts. We identified some relevant findings with positive results regarding the objective established.

To communicate the results to the scientific community, the results of this thesis were submitted and accepted in an international journal.

1.1. Research Methodology

The methodology chosen in this research work was the Design Science Research Methodology (DSRM). DSMR is a method used in Information Systems due to its ability to produce incremental solutions.

DSRM is an interactive methodology that aims at creating IT artifacts intended to solve an identified organizational problem [18]. The artifact developed should be based on existing theories with organizational acceptance. These artifacts can be constructs (vocabulary and symbols), models (abstractions and representations), methods (algorithms and practices) and instantiations (implemented and prototype systems) [18]. DSRM is composed of six defined activities:

1. **Problem identification and motivation:** describe a specific research problem and explain the importance of a solution.

2. **Define the objectives for a solution:** define the objectives of the solution. The objectives should be rationally inferred from the problem definition and the knowledge of what is possible and feasible.

3. **Design and development:** create the research artifact. In this phase, the desired functionality and its architecture should be determined.

4. **Demonstration:** shows that one or more instances of the problem can be solved with the use of the artifact.

5. **Evaluation:** observe and measure the artifact performance in the context of the problem. This evaluation involves the comparison of the objectives of the solution defined earlier were achieved with this artifact.

6. **Communication:** communicate the problem and the importance of the artifact, its utility, its novelty, and its effectiveness to researchers and other relevant audiences such as practicing professionals, when appropriate.

2. Research Problem

Enterprises are increasingly making tangible and intangible investments in their EGIT [15]. The number of EGIT models and their area of application have increased. Organizations can benefit from the various models since they can adopt models that best adapt to their needs [6]. Many organizations value the implementation of EGIT models. Not only has the number of organizations that implement EGIT models grown, but also the number of organizations that are implementing several models simultaneously [8].

The implementation of any of these models requires specific experience, knowledge, and resources, along with a high degree of effort and investment [6], in order to be successful. This means that it is not an easy task, and there is a significant risk of failure [1]. Although compelling in theory, these models can be challenging to implement in practice. Not only because of an increase in the number of models, and a widening of the area of application [21], but also because each EGIT model defines its own characteristics: scope, structure of process entities, definitions, terminology quality systems and approach, among other things [5].

Practitioners view these models as complementary rather than competitive [29] hence organizations can evaluate and adopt a combination of models that is more relevant to their business [4]. COBIT can help define what should be done by the organization and ITIL can provide the how for service management aspects. Also, COBIT can be used at the highest level, providing an overall practice based on an IT process model that should generically suit every organization. Specific models such as ITIL cover discrete areas and can be mapped to the COBIT model, thus providing a hierarchy of guidance materials.

Organizations are forced to adopt multiple EGIT models due to the increasing demands of the different industries coupled with compliance requirements [31]. This situation has increased the complexity of implementing models. This is because organizations struggle to understand how to adopt several models simultaneously. They also struggle with how to integrate them since these EGIT models often overlap [12]. The complexity of an organization increases with the implementation of multiple models. Lack of guidelines governing processes and different terminologies across different models are some of the challenges in integrating them. Implementing multiple models is often associated with higher effort, time, and cost than a conventional single model approach [7] [31] [6].

Besides its complexity, many benefits that result from integrating multiple EGIT models. Integrating models enable features that would not be available through the use of individual models, leading to a more comprehensive and efficient approach [8] [12] [37]. One of the opportunities identified in integrating multiple models is to optimize costs in audits and assessments [11]. NLP allows the analysis of large amount of text very fast. This is crucial to perform a mapping between process core concepts of different PAMs. Therefore, NLP becomes a natural solution to reduce the cost and time, and to optimize the use of human resources.

Several studies addressed the mapping or integration between different models [17] [33]. However, these studies usually involve specialists' interactions, so they are very time consuming and difficult to replicate.

Therefore, the research challenge addressed in this thesis is described as "there is no comprehensive approach to understand and identify the similarities between core process concepts of similar models, thus current approaches are ineffective and inefficient in multi-model environments".

3. Theoretical Background

In this section, we describe some theoretical background concepts about the relevant issues in the context of this thesis.

3.1. Enterprise Governance of IT

The way IT is used in business has experienced some transformations in the past decades. For many years, business executives considered IT a support area of the main business, so IT was not considered essential to be addressed at the board of directors.

Nowadays, IT is recognized as a powerful resource to achieve the enterprise objectives, to support business growth and process control since it is pervasive bringing myriad benefits, such as lower costs, better performance, efficiency, risk control and effectiveness [38] [14] [22]. The use of IT has become a crucial part of the support, sustainability, and growth of an organization [39].

As IT has become more crucial to business and in order to create value from the investments, it was necessary to manage IT as an asset instead of managing IT as a cost. This led to a shift in the definition of IT governance, focusing on the business involvements, toward "Enterprise Governance of IT" [14].

EGIT can be defined as "an integral part of corporate governance and addresses the definition and implementation of processes, structures and relational mechanisms in the organization that enable both business and IT people to execute their responsibilities in support of business IT alignment and the creation of business value from IT-enabled business investments" [14]. Therefore, EGIT is the responsibility of the board and business executives.

According to the IT Governance Institute [21], EGIT aims to elevate the strategic importance of IT, enabling an enterprise to sustain its operations and extend activities into the future while mitigating associated risks.

3.2. COBIT 5 PAM

COBIT 5 provides a process assessment model (PAM) for its 37 enabling processes that is based on ISO/IEC 15504. The COBIT 5 PAM [24] is composed of a set of indicators of process performance and process capability. The indicators are used as a basis for collecting objective evidence that enables an assessor to assign ratings.

3.3. TIPA for ITIL

Tudor's IT Process Assessment (TIPA) began in 2002. TIPA is a robust and internationally recognized model that results from the work of more than ten years of research, including experimentation on how to combine ITIL with the ISO/IEC 15504 [3].

The overall TIPA model is composed of a set of artifacts including process models, namely a PRM and a PAM, result of the transformation of the set of requirements and practices respectively included in the ISO/IEC 15504 standard and the ITIL de facto standard, into the TIPA for ITIL PAM.

3.4. Natural Language Processing

According to various authors, Natural Language Processing (NLP) can be defined as the area of research and application that explores how computers can process and analyze natural language. The main goal of the NLP field is to get computers to extract results from tasks involving human language, tasks like enabling human-machine communication, improving human-human communication, or merely doing useful processing of text or speech [25].

NLP can be viewed as a pipeline of various stages used to extract knowledge from unstructured text. These steps are needed to transform the raw text into a machine readable format. Also, it is important to clean the data since usually it is inconsistent, or contains an error. Below, there is an explanation of three less intuitive pre-processing techniques performed:

- **Tokenization:** Given a character sequence, tokenization is the task of chopping the sequence into pieces (usually words), called tokens perhaps at the same time throwing away certain characters, such as punctuation. NLTK Library has word_tokenize and sent_tokenize to easily break a stream of text into a list of words or sentences, respectively.

- **Stop words:** These words add little meaning to a text but that are very frequently used (such as 'the', 'a', 'an', etc.). Usually, these words are removed.

- **Lemmatization:** Reduces the number of inflectional forms of each word into its root. Normally, it removes inflectional endings in order to transform into a dictionary form of a word, also known as lemma.

3.5. Text Representation for Computational Analysis

Since computers can't understand text as humans, it is important to convert documents into a numerical representation. One of the most common ways to represent documents is Vector Space Model (VSM) [34] [36]. In this approach, documents are represented as vectors where each dimension corresponds to a separate term from the vocabulary. If a term occurs in the document, then the value is mapped to a numeric value different than zero [36]. There are many different weighting techniques to compute this value, which have the target to differentiate between the terms that are more important for a document [26].

A common weighting technique is the TF-IDF approach [28]. This measure calculates how important a word is in a document from a document collection [35]. This approach combines two methods: Term Frequency (TF) and Inverse Document Frequency (IDF). TF can be a simple count in which $tf_{i,j}$ is defined as the number of occurrences of a word t in a document d divided by the total number of words in the document. TF can be calculated as follows:

$$tf_{t,d} = 1 + \frac{n_{t,d}}{\sum_k = n_{t,d}} \tag{1}$$

IDF is used to attenuate the effect of words that occur too often, also known as stop words, like "the", "is", etc. Document frequency df_t is the number of documents that contain the term t. The IDF can be defined as follows:

$$idf(w) = \log(\frac{N}{df_t}) \tag{2}$$

The parameter N is the total number of documents divided by $\frac{N}{df_t}$, the number of documents that contain the word w.

Finally, the TF-IDF is simply the multiplication of TF by IDF:

$$idf(w) = tf_{t,d} \times \log(\frac{N}{df_t}) \tag{3}$$

Therefore, TF-IDF is a statistic that measures the relevance of a word in a particular document. The higher frequency terms are more important for representing the meaning than lower frequency terms.

The simple TF-IDF model works well and gives importance to the uncommon words rather than treating all the words as equal in the case of binary bag of words model. However, this approach fails to perform accurately when it encounters any sentence containing negations [10]. TF-IDF is an example of a traditional and very popular representation to compare texts [28] [2], and to classify text documents - both short and long [40] [41].

Other weighting methods can be used like Information Gain (IG), Chi-square, Mutual Information, etc. TF-IDF considers two documents as similar if they share rare, but informative, words [9].

3.6. Text Similarity Metrics

Similarity measures computes the distance or similarity between the description of two documents into a single numeric value. This value depends on two factors — the properties of the two documents and the measure itself. It is important to bear in mind that there is no universal measure best measure since their performance is depended on the data or the context of the problem.

3.6.1 Euclidean Distance

Euclidean Distance measures the distance between two points in the space. Euclidean distance is widely used in clustering problems, including clustering text. To measure the distance between two documents, represented by the vectors $\vec{t_a}$ and $\vec{t_b}$ respectively, the Euclidean distance can be defined as [19]:

$$D_E(\vec{t_a}, \vec{t_b}) = (\sum_{t=1}^{m} |w_{t,a} - w_{b,t}|^2)^{\frac{1}{2}} \tag{4}$$

Where the vocabulary is $T = \{t1, ..., tm\}$. TF-IDF can be used to compute the weights of the terms $w_{t,a}$.

3.6.2 Jaccard Coefficient

The Jaccard coefficient measures similarity as the intersection divided by the union. In the context of textual similarity, the coefficient divides the sum weight of common words in both documents with the sum weight of words that are present in either two documents. Jaccard Coefficient can be defined as follows:

$$SIM_J(\vec{t_a}\vec{t_b}) = (\frac{\vec{t_a} \cdot \vec{t_b}}{|\vec{t_a}|^2 + |\vec{t_b}|^2 - \vec{t_a} \cdot \vec{t_b}} \tag{5}$$

3.7. Cosine Similarity

Cosine similarity measures the similarity between two vectors. When documents are represented as vectors, the similarity between the documents is measured by the cosine of the angle between two vectors and. Cosine similarity is one of the most popular similarity measures applied to text documents, such as in in-formation retrieval applications and clustering [27].

Having cosine similarity as a measure, we have:

$$SIM_C(\vec{t_a}\vec{t_b}) = \frac{\vec{t_a} \cdot \vec{t_b}}{|\vec{t_a}| \times |\vec{t_b}|} \tag{6}$$

where $\vec{t_a}$ and $\vec{t_b}$ are dimensional vectors over the terms of the vocabulary $T = \{t1, ..., tm\}$. A cosine value of zero means that the two vectors are at 90 degrees to each other (orthogonal) therefore, there is no match between them. Contrariwise, a cosine value of one corresponds to the smaller angle thus a greater match between vectors [16].

Cosine similarity is a standard TF-IDF similarity and is a measure widely used in information retrieval [19]. It is also used to measure how similar documents are irrespective of their size.

4. Proposal

The main objective of this research is to provide a comprehensive approach that can help to perform a simultaneous assessment of different EGIT models by identifying the similarities between process core concepts.

4.1. Proposal

The primary purpose of this thesis is to promote the integration of different PAMs through the use of NLP similarity techniques. A joint approach of the PAMs of different EGIT models can contribute to a consistent focus on different but complementary domains, promote synergy and minimize duplication of the resources needed to perform process assessments.

The proposal is divided into three main activities, namely Data Collection, Pre-processing, and Vectorizing, which are summarized in figure 1.

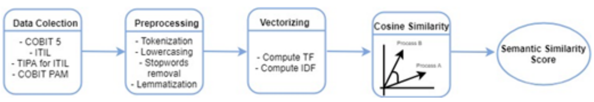

Figure 1: Main steps of the pipeline

4.2. Data Collection

The Data Collection step consists of collecting data from a specific domain. In our case, the domain is the EGIT field, mainly the EGIT models that have been proposed to improve EGIT in the organizations. From the raw data presented in the different publications that introduce and describe these EGIT models, we created a pipeline to extract the description from each process assessment core concepts (namely the Process Description of Outcomes (Os), Base Practices (BPs), and Work Products (WPs).

4.3. Pre-processing

Pre-processing is one of the most important steps when dealing with text. This step is used to clean and prepare the text for subsequent classification. Properly pre-processing text facilitates the extraction of the most important information presented in unstructured text and reduces the number of variant words in a sentence. By reducing the size of the dataset, there will be an increase in the effectiveness of the classification process.

The techniques used to pre-process the text can vary according to the problem statement. In our case, we applied a few simple pre-processing techniques such as Sentence Splitting and Tokenization, Removal of Stop words, Lemmatization, and Lowercased tokens. These techniques were applied in order to reduce the sparsity and vocabulary size of the data previously collected.

We started the pre-processing by breaking the generic dataset into words (tokens), a process also known as tokenization. Then, each token was converted to lowercase. All the punctuation from our dataset was then removed since they are just symbols that usually do not add any useful information. Then we removed several stop words. There is not a unique list of stop words, and so, in this research, a list of 179 stop words (like “the”, “is”, etc.) was used. Finally, the lemmatization technique was applied to the dataset.

4.4. Vectorizing

We derive a vector using Term Frequency-Inverse Document Frequency (TF-IDF) scores to represent each process description. After pre-processing the raw text, we compute the TF scores. TF measures the number of times a word occurs in a description. Next, we compute the IDF scores to compute the total number of descriptions and the number of descriptions that contain the word.

As mentioned earlier, this step weighs down words that occur too frequently. Then, we compute the TF-IDF that returns a vector per word per process based on the frequency of that word in that process and the collection of all processes. The vector will be a list of frequencies for each unique word in the dataset - the TF-IDF value if the word is in the process, or 0 otherwise.

4.5. Score calculation

To understand the matches between two processes, we made a pairwise comparison between all the concepts (we just compared similar concepts: Outcomes with Outcomes, Base Practices with Base Practices; and Work Products with Work Products). An example of a pairwise comparison is presented in figure 2. Two processes are more similar if they have a common set of Base Practices, Outcomes, and Work Products.

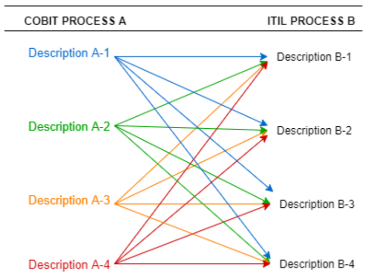

Figure 2: Pairwise comparison

Each core concept score is calculated by the average of each core concept description of one process with all the core concept description of the other process. Then, the highest average value is chosen to be the similarity core concept score between two processes.

The overall similarity score of two processes is obtained by the average similarity score of the three concepts:

$$PS = \frac{BPS + OS + WPS}{3} \tag{7}$$

The main goal of this step is to represent every set of descriptions from each concept as a vector whose length is equal to the vocabulary size of the dataset.

4.6. Demonstration

Without loss of generality, we demonstrate our proposal using the COBIT 5 PAM and the TIPA for ITIL PAM.

However, it is important to point out that the proposal is generic and can be applied to all the EGIT models that have a similar process structure. Although the generalization to other models and domains should be made with caution.

We start by cleaning the data by pre-processing it. Every process description was tokenized. Then, we calculate the TF-IDF score for each word in the description to accentuate the words that are relevant to the specific description. This process is exemplified in figure 3.

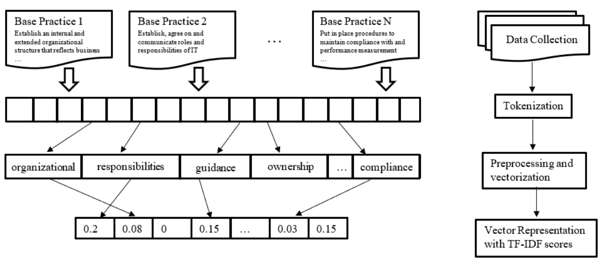

Figure 3: Vector Representation Diagram

As mentioned earlier, three core concepts of COBIT 5 PAM and TIPA for ITIL PAM were considered. After the calculation of the different scores of each core concept, we realized that the results for the Work Product concept were very high or very low. This is normal since, usually, the Work Product instances are just described using two or three words, so the words are rather similar or different. The Expected Results/Outcomes instances also are short descriptions, but not as short as the Work Products one. So the similarity results were not as extremes as the results of the Work Products. This can be justified by the fact that the description of the Outcomes is longer than the description of the Work Products.

Therefore, to calculate the process similarity score, we decided to use just the similarity between the Base Practices and Outcomes, using the following formula:

$$PS = BPs \times \frac{7}{10} + Os \times \frac{3}{10} \tag{8}$$

Similarity measures are likely to perform poorly given if the number of words to compare with is small. Thus, it was assigned different weights to each core concept considered. The Base Practices' core concepts have a higher weight since they are composed of long descriptions.

In this step, the performance of different similarity and distance metrics were evaluated. The weighting metric used was TF-IDF. Then it was tested the best average performance between different text similarity metrics. However, the best accuracy results were achieved using cosine similarity. This methodology not only had the best overall average efficiency but each process pair resulted in a similarity value closest to the reference mapping study presented in [23].

5. Evaluation

In this specific research, the authors compared the results obtained in this research with a benchmark proposed in [23]. It is important to remark that the benchmark was performed for an overall process comparison so, it did not go into the details of the respective PAMs. Nevertheless, it is a relevant mapping that contributes to a broader discussion of the similarities between COBIT 5 and ITIL processes.

Similarity is a complex concept that has been widely discussed in the linguistic, philosophical, and information theory communities. For the current task, the similarity between two text units is defined as a sense share, i.e., both text units share concepts above a predefined threshold. In this case, and based on the rating scale of both the COBIT 5 PAM and the TIPA for ITL PAM, we defined the following thresholds: 0%-15% - Not similar, 16%-50% - Partially similar, 51%-85% - Largely similar, 86%-100% - Fully similar.

We are only presenting the COBIT 5 processes that have more than a 50% similarity score with at least one ITIL process. This decision is based on the fact that higher results give us a high level of confidence regarding the semantic similarity between different processes.

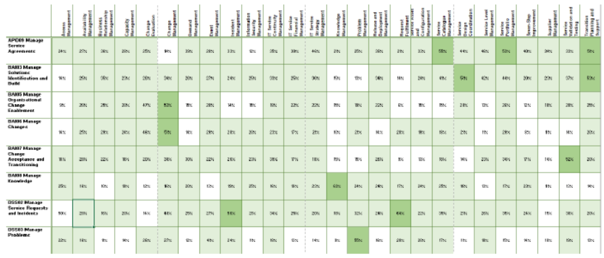

Figure 4: Result of text similarity between process of COBIT and ITIL

Some remarks regarding figure 4 should be highlighted:

- We just present the 8 COBIT 5 processes that have a semantic similarity score higher than 50% with at least one ITIL process. This means that, in principle, these are the COBIT 5 processes that are largely or fully similar to the ITIL processes.

- It is possible to conclude that the vast majority of the processes (7 out of 8) belong to the sometimes called primary processes (BAI and DSS domains)

- The processes with the highest degree of similarity are the DSS02 - Manage Service Requests and Request Fulfilment processes with a score of 64%

- From these 12 processes with results above 50%, 8 are in agreement with the benchmark

- There are some false positives regarding the following processes: APO09 Manage Service Agreements, BAI03 Manage Solutions Identification and Build, BAI05 Manage Organisational Change Enablement. The similarity score is higher than it should have been according to the specialists' mapping. According to the specialists, these processes do not have any related ITIL process, and so, a lower result was expected

- On the other hand, the processes APO09 Manage Service Agreements, BAI03 Manage Solutions Identification and Build, BAI05 Manage Organisational Change Enablement, BAI06 Manage Changes, and BAI07 Manage Change Acceptance and Transitioning are a false negative. This means that some results are below expected. For example, BAI07 Manage Change Acceptance and Transitioning corresponds to 5 ITIL processes, accordingly to the experts' mapping. Meanwhile, our solution only had a high result for one ITIL process.

- Most of the presented processes belong to and based on the specialists' mapping, our approach allows us to conclude that the more operational processes have higher results. This is normal, since ITIL is a more operational model than COBIT 5, and so, the overlap in these domains is higher. Therefore, we can argue that the interoperability between COBIT PAM and TIPA for ITIL is higher in this kind of processes

Overall, the results are in line with the specialists' opinion presented. However, the specialists' mappings are just a binary scale (0 or 1). So the level of granularity is not equivalent to our proposal.

5.1. Interview with experts

To evaluate our proposal, we gathered data through an online survey that was sent to 8 COBIT and ITIL experts. Due to time limitations, we are not able to inquire about all the COBIT and ITIL processes. So, we chose the COBIT 5 DSS domain. This choice is based on the fact that initial focus on any process assessment would be the core (sometimes called primary) processes, which are primarily part of the DSS domain.

To design the survey, we started by making a table with processes that belong to the DSS domain of COBIT 5 and the Service Operation domain of ITIL. The main idea was to evaluate the similarity between the processes in a 4-point rating scale.

We decided to use this scale since it is similar to a process assessment scale, and therefore is easier to grasp. It is important to note that similarity is a very broad and ambiguous concept. There may be some variance in the results. This survey allowed us to gather quantitative data about the experts' opinions regarding the similarity between processes. This survey was written and administered using Google Sheets.

Below, in figure 5, we present the similarity scores for all the processes belonging to the Deliver, Service, and Support (DSS) domain of COBIT 5, which are compared with the ITIL processes that belong to the service operation domain.

Figure 6 presents the average rating regarding the similarity of each process that results from the experts' survey. The practitioners' answers vary a lot form one another. This is a relevant mapping that contributes to a broader discussion of the sim-

	Event Management	Incident Management	Request Fulfillment	Problem Management	Access Management
DSS01 – Manage Operations	20%	23%	9%	14%	8%
DSS02 – Manage Service Requests and Incidents	27%	56%	64%	32%	50%
DSS03 – Manage Problems	41%	24%	20%	55%	22%
DSS04 – Manage Continuity	13%	31%	13%	19%	24%
DSS05 – Manage Security Services	43%	14%	18%	11%	45%
DSS06 – Manage Business Process Controls	23%	18%	18%	27%	20%

Figure 5: Process Similarity Scores

ilarities between COBIT 5 and ITIL processes. The green cells signify the experts confirm our results. On contrary, the red ones contradicted our results.

	Event Management	Incident Management	Request Fulfillment	Problem Management	Access Management
DSS01 – Manage Operations	2	2	2	2	2
DSS02 – Manage Service Requests and Incidents	2	3	3	2	1
DSS03 – Manage Problems	2	2	1	4	1
DSS04 – Manage Continuity	2	1	1	2	1
DSS05 – Manage Security Services	2	2	1	1	2
DSS06 – Manage Business Process Controls	2	2	2	2	2

Figure 6: Average similarity score from the surveys

Some remarks regarding the obtained results are presented below:

- The processes that were considered by the respondents largely similar or fully similar were the ones with higher results in the automatic similarity analysis
- From the presented processes, 18 out of 30 fell into the same similarity level
- The processes with the highest similarity is the pair DSS02 Manage Service Requests and Incidents Request Fulfilment with a score of 62% (largely similar). This result is consistent with the experts' opinions. Also, the COBIT process is divided into 2 ITIL processes, which were the ones that obtained the highest similarity scores
- Although the similarity between DSS03 – Manage Problems and Problem Management is high (41%), experts considered that these two processes are fully similar, assigning it a similarity level of 4.

Following the preliminary survey, we conducted a face-to-face interview with 2 experts, one from Portugal and one from Brazil. Figure 7 shows some information regarding the two practitioners. The interview allowed us to understand some of the reasoning behind their answers to the survey. Both experts mentioned that the similarity scores

ID	Country	Experience	Certifications	Industry
1	Portugal	30	Cobit Foundation, CRISC, CISA CGEIT, ISO 27000	IT consulting Regulation
2	Brazil	+30	COBIT 2019, ITIL, PMI, CISA, CRISC CGEIT, ISO 27000	Education IT consulting

Figure 7: Respondants Profile

are influenced by each expert's background and knowledge (for example, if they came from the ITIL 'world' or the COBIT 'world').

Both respondents highlighted that COBIT is a broader model that combines several areas, while ITIL is focused on IT service management. This means that not every process will have a match or will have a high similarity at a low-level spectrum, in spite of being similar at a high-level spectrum.

6. Conclusions

To conduct this research, we followed the DSRM process that consists of 6 phases of development.

Organizations needing to comply with multiple regulations are struggling to meet audits each year with a large number of business/IT resources being spent specifically to demonstrate the organization's compliance against well-known EGIT models. The problem this research targets is the lack of a comprehensive approach to understanding and identifying the similarities between core process concepts of similar models, thus current approaches are ineffective and inefficient in multi-model environments.

Following this, the proposal presents a new methodology that combines text analysis and data mining in order to automatically identify the similarities between EGIT models. The models were converted into computer readable objects. Then, the similarity results were automatically calculated using different measures. The most efficient measure was the cosine similarity to calculate the similarity score.

To assess the proposed artifact, two evaluations were made. In the first, we compared our results with a benchmark mapping provided by specialists [23]. In the second, we conducted an online survey to ITIL and COBIT experts. Then, we compared our results with the experts' opinions. From the evaluations, it becomes clear that our approach had positive results, especially for the more operational processes.

Therefore, we can state that NLP similarity techniques can have a high impact when addressing more operational processes i.e., these techniques can facilitate a simultaneous assessment. We believe that this is an important conclusion since operational processes are the most valuable and most frequently used processes in any organization.

The developed artifact and the results were communicated to proper audiences through the presentation and submission of a paper in the International Journal of Human Capital and Information Technology Professionals.

However, it is important to mention that our intention is not to automate all tasks and activities involved in an assessment. The main intention is to help auditors and stakeholders automate the more cumbersome and tedious steps in order to assess an organization's processes when multi-models are present.

6.1. Future Work

Regarding the results of this thesis, there are several opportunities that can be addressed for future work:

- Improving the proposed artifact by trying different weighting techniques such as Chi-square or Information Gain weighting metric instead of TF-IDF.
- Demonstrating and evaluating the proposed artifact for mapping different IT governance models (ex: CMMI, ASPICE, etc.).
- Creating a specific dictionary with terms used in these models. The idea behind this is to apply different weights to more important terms. Additionally, it is also possible to replace terms by its meaning. That way, if different terms have the same meaning, this would increase the similarity score.
- Integrate fuzzy logic to the proposal. This logic is the science that makes a computer understand and think the way humans do. That would help the computer to better understand the meaning of each process.
- Developing algorithms that let us improve and extend the capability of the assessment process through automation.

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