Knowledge Management Metamodel from Social Analysis of Lessons Learnt Registered in the Cloud

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Abstract. This article describes the development of a functional architecture for Personal Knowledge Management, defined from the lessons-learnt concept registered in a mass-use social network. This functional architecture applies, in practical manner, the implementation of a registry system of the personal lessons learnt in the cloud through a Facebook social network. The process starts by acquiring data from the connection to a non-relational database (NoSql) in Amazon's SimpleDB and to which a complementary analysis algorithm has been configured for the semantic analysis of the information registered from lessons learnt and, thus, study the generation of Organizational Knowledge Management from Personal Knowledge Management. The final result is the design of a functional architecture that permits integrating the Web 2.0 Application and a semantic analysis algorithm from unstructured information by applying machine learning techniques.

Keywords: Knowledge management · Tacit knowledge · Knowledge model · Organizational learning

1 Introduction

One of the trends in the study of Knowledge Management (KM) that has gained notoriety in recent years is Personal Knowledge Management (PKM), which is held as a process prior to Organizational Knowledge Management (OKM). This work focuses on the design and implementation of a functional architecture for Knowledge Management as a basic tool to integrate systems supported on cloud computing through social networks. The work seeks to show the possibility of a KM metamodel evidenced in a prototype of an application implemented in the Facebook social network, which demonstrates the possibility of doing OKM from PKM; the latter is developed from the base concept of the lessons learnt by individuals.

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The work was carried out in phases, with the first phase being the development of the conceptual aspects that define its structure. It starts with the conceptualization of the aspects that define and comprise a metamodel [1] and the stages that must be considered for its construction. Thereafter, the definitions of KM and PKM are presented. Regarding PKM, the work delves into and shares the new research trend that stipulates that flexible scenarios are required to support the knowledge generated by each human being [2]. At the end of this conceptualization phase, social network aspects will be worked on along with their support for the generation and socialization of knowledge, closing with the detailed concept of the lessons learnt as the type of knowledge that will be worked on in the metamodel developed as the proposal in this work.

The second part focuses on describing in detail the design, implementation, and verification of the prototype for Facebook. This will be implemented in the cloud through a non-relational database that will support the real registry of an undefined and random number of lessons learnt, which – in turn – apply and evidence the concept of flexibility of scenarios for PKM.

The final phase presents the second component of the applied model, which is the ontological analysis system, as tool and big data technique that verifies the real possibility of conducting OKM from PKM.

2 State-of-the-Art

2.1 Knowledge Management

Tacit knowledge as the first state of knowledge [3] has peculiarities characterized to define the strategies of its management. This knowledge can be divided into knowledge yet to be formalized and knowledge that cannot be formalized [4]. Knowledge that can be formalized and described explicitly is particularly characterized as *"know how"*, also called "Tacit Cognitive" knowledge and when it is specified through some tangible means, it becomes "Explicit Knowledge". Stemming from this concept, KM theories focus on the mechanisms that permit keeping knowledge within organizations [5] and in said evolution different models have been proposed, which now lead us to prefer working on the PKM concept, as one of the last work trends in this area.

2.2 Personal Knowledge Management

According to Razmerita, Kirchner, and Sudzina (2009), Miller (2005) and Pauleen (2009), PKM is a trend that manages to complement and rethink the dynamics of research and formalization of KM at organizational levels. These authors have delved into its conceptualization, highlighting the importance of PKM, as base nucleus of any greater magnitude process of KM, concluding on the need to for more experimental research on it. The first versions of KM systems have been mainly concerned with establishing integrated organizational systems that have often overlooked the basic parameters for "*the person*", who is the center of the generation of knowledge, to register, organize, and collaborate with the generation of new knowledge.

Also, PKM is supported on web 2.0 through a set of tools that permit individuals to create, encode, organize, and share knowledge, as well as socialize, broaden personal networks, collaborate in its organization, and create new knowledge [6, 7]. These authors base the characteristics of a system for PKM from the use of web 2.0 resources to avail of on-line communication and socialization mechanisms. For example, [8] proposes evolving in models that visualize performance indicators and PKM as objects and processes toward models based on an ecological view, which starts from the principles of socialization networks.

The interaction between the tacit and explicit dimensions of knowledge defines its nature by studying the source from where it is generated. A creation perspective exists related to the Knowing entity [3], which defines collective knowledge as an aggregation of individual knowledge. This aggregation cannot be generalized linearly as a sum of elements, given that its evolution generates a synergy that establishes that collective knowledge be a more complex process that integrates structures, dynamics, and relationships [9].

2.3 Lessons Learnt

Social capital has emerged as an adequate framework to explain knowledge exchange and transference mechanisms in organizations [10]. One of those mechanisms is denominated lessons learnt, which are defined as a type of explicit knowledge that results specifically from two main opportunities: i. *Errors and/or strengths obtained during any process of knowledge application or generation, and, ii. And from the possibility of innovation of an objective sought to be reached* [11].

These can also be defined as a type of knowledge that results from experience through complex, systemic, asynchronous, and individual reflection processes [12]. For knowledge transference to satisfy the needs of organizations, lessons learnt must be presented at the moment and within the adequate context, thus, defining the principle of opportunity. Thereby, knowledge generated can be reused [13].

Additionally, the conclusions of related works recommend that any process of generation of lessons learnt be supported on information systems with databases that permit diversity of models and objects of knowledge [12]. This seeks to facilitate precise location and rapid consultation of information required for knowledge to be subsequently distributed and accessed in timely maner by all those involved or interested in the context or situation being worked on [14].

In complementary manner, the opportunity to use lessons learnt also depends on systemic aspects that integrate, manage, and support an actual and closer concept of KM. Among these aspects, the following may be described: i. interested personnel; ii. a theme requiring their generation and consultation; iii. related experts; and iv. a system that supports the interaction and flow of said management [15].

2.4 Analysis of Social Behavior for Knowledge Management

Analysis of social behavior by applying semantic techniques is considered a new paradigm in OKM. Recently, the use of data and information extraction stemming from structured sources like Web 2.0 applications is gaining terrain in the study of the social web [16]. Cases of interest and publications have been reported in the field of social networks integration and their analysis. This new semantic approach permits the dynamic change of the semantic social network and establishment of knowledge management models from and toward people in organizations.

Modern organizations had never before had new needs and opportunities to use their knowledge more rapidly and efficiently from the implementations of applications supported on semantic analysis. Construction of sophisticated knowledge bases, decision support systems, as well as other intelligent systems often takes time and considerable economic resources [17]. Studies like those by [18] have implemented diverse web mining techniques to extract the semantics of the social structure underlying people's behavior, preferences, and tendencies; although it is important to analyze existing on-line social networks, the data and information extraction process related to profiles of users in applications supported on social web from structured sources, inevitably provokes a loss of the real semantics of the social system.

3 Methodology

3.1 Architecture Proposed

The KM metamodel applied herein was derived from the metamodel developed by [19]. Its structure is described through six entities: people, processes, documents, themes, tacit knowledge, and explicit knowledge. It abstracts essential entities from a domain of interest and its interrelations with the concepts of metamodels applied to KM and to software development.

For its dynamic part advanced processing techniques are included for application through the 'big data' technique, denominated 'latent semantic indexing (LSI)'. Figure 1 shows the flow or relationship among elements or entities that make up the metamodel proposed: data-information-knowledge. The metamodel proposal integrates entities in the following manner:

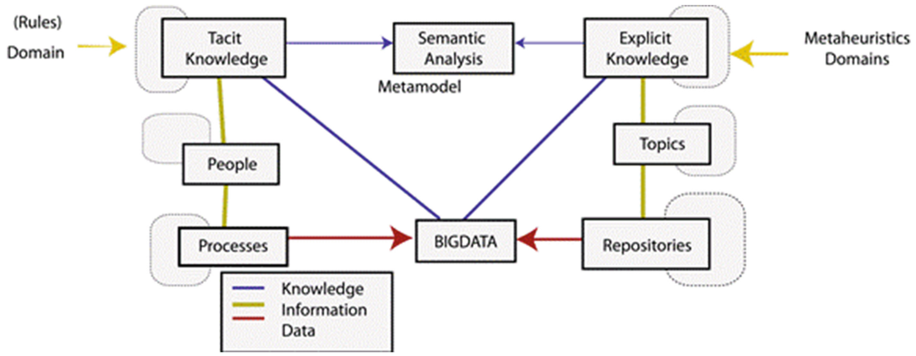

Fig. 1. Global architecture of the KM metamodel

The previous architecture is structured so that each of the components is interrelated for transmission within the chain of organizational data, information, and knowledge given through the following elements:

– *Processes:* The definition of necessary processes for the interaction of people and resources or platforms that comprise the system.
– *People:* The metamodel should be based on the interaction of tacit knowledge from the lessons learnt of each participant.
– *Repositories:* The opportunity to develop in the model and prototype the necessary documents and evidence of said lessons and of the model itself.
– *Topics (themes):* Represented in the possibility of defining categories and themes to generate knowledge from the different profiles of people who interact with the system.
– *Tacit knowledge:* Described and evidenced through the lessons learnt that exists in each human being.
– *Explicit Knowledge:* Reflected through the treatment of the lessons learnt in new forms of knowledge, using advanced processing techniques.
– *Semantic analysis*: The semantic analysis process is applied on an unstructured base, that is, sets of terms in a domain determined in text format. Each data analyzed behaves as taxonomy; the process is in charge of identifying key terms and classifies the terms the vocabulary contains within the database; this is to enable a simpler search for the system. The taxonomy gathers various terms around a set of concepts to then map and fraction these through the text mining flow implemented in Konstanz Information Miner (KNIME).

The metamodel uses the logical sequence of data, information, and knowledge. These three elements circulate through each of the entities of the model. The upper layer evidences the execution of a semantic analysis fed by sources of tacit and explicit knowledge. Tacit and explicit knowledge gather information from people and themes of interest, primarily. These, in turn, receive information from processes and repositories and, simultaneously, provide data to be processed by the Big Data LSI technique.

3.2 General Model - QIRISYA

The QIRISYA prototype, as the application will be identified ahead, was generated from the same conception of the model of lessons learnt within a social network environment. For its design, software has been developed to permit registering the lessons learnt by each user with a structure defined in three levels: Profile, Categories, and Subcategories. These can be established in personalized and flexible manner by each user. Given the vast amount of contributions expected, a non-relational database will be used to avoid the possibility of application saturation. The prototype can be seen in Fig. 2 with its explicit components: 1. User or knowing entity. 2. The application in the social network (Facebook). 3. The platform that supports the application: non-relational database; and 4. The semantic analysis system.

The user records the lessons learnt initially in the form of explicit knowledge, describing in text format the knowledge or experience acquired and recording it on the

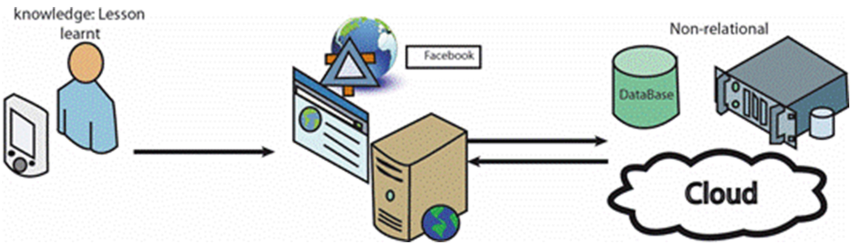

Fig. 2. General prototype diagram

profile, category and subcategory in which he/she seeks to relate it. These lessons do not have text limit, can be described as reflections, both simple on very punctual events and complex on the analysis on the participation in a project or on the reflection about another professional, personal, or educational activity.

To complement the prototype, a semantic analysis application was developed to permit precisely identifying and quantifying trends in the generation of knowledge, using key words and making the configuration for group analysis in the social network (Facebook). This facilitates the characterization of knowledge generation in work teams, *i.e.*, this last module permits bringing PKM in practical manner to an application of OKM.

To develop the functional application of lessons learnt, it was necessary to use different libraries that permit making structured connections and designs, these are: i. Facebook SDK PHP [20]: Used to make the communication of the external application with Facebook, defining the necessary permits and obtaining this platform's necessary data, like name, profile image, and identifying number of the user's account; ii. The FancyApps & Skarnelis [21] Used to manage the iframes on transparent backgrounds in the deployment of some of the notifications; iii. GoogChart [22]: Used to generate pie graphs and bar diagrams; iv. JQuery API [23]: It is a javascript framework used to give dynamism to html pages and it is used as base by different APIs; v. jsDatePick [24]: It is a javascript calendar that permits selection of dates upon defining the limits to generate graphics and vi. AWS SDK for PHP [25]: Used to establish communication between SimpleDB and the application, permitting manipulation of the necessary data through a development interface.

3.3 Design of the Functional Architecture and Semantic Analysis Algorithm

This section presents the development of the functional architecture that permits semantically analyzing lessons learnt from a data source defined and incorporated by each user onto the prototype (QIRISYA); crossing the structure of profile, categories, and subcategories defined by it. Semantic analysis on lessons learnt permits determining in an organization the current trends and behaviors that are a support for a foresight study of possible strategic planning goals, specifically in the management of human capital.

Given the large quantity of contributions expected, an unstructured data source is used that permits reducing the possibility of application saturation. Graphically, the architecture is shown in Fig. 3, where the flow is shown: data, information, knowledge through a logical sequence given among the application, the data source, and the segmentation of groups of people. The flow is guided from the social behavior of specific groups given by the social analysis process from the textual sources incorporated.

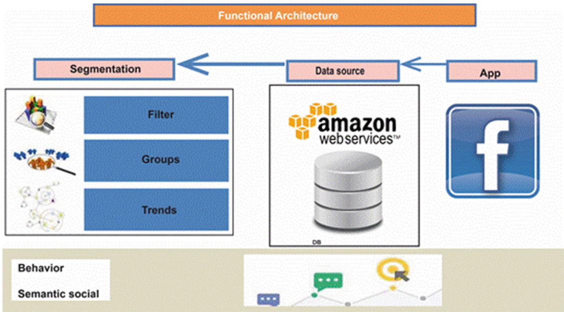

Fig. 3. General structure of the semantic analysis algorithm

The architecture proposes mechanisms for simple consultations seeking to facilitate support of decisions by connecting existing databases and corporate information systems through web services. The final result proposes the development of a comprehensive solution aimed at KM and whose objective is to establish the current state of the organization and its environment regarding the determination of work profiles and competencies. Implementation and use of this framework was conducted from several characterizations of users with different profiles and needs. Users selected followed the application's linking procedure and started to define their profiles and categories, permitting – in turn – to register lessons learnt in the application.

Figure 4 shows a chronological behavior of a user with his/her respective categories and profiles within the framework established by the application. Here, the system permits registering several lessons and, upon using the distinct options (like private and public records), information is managed from lesson-suppression operations, modification and visualization of statistics, and record of evidence of typifying the lessons learnt in the distinct profiles and categories.

Within the architecture proposed, the application of concepts requested by various authors is evident, when they state that further development is needed to facilitate PKM and which in this project has been visualized from the concept of the *"lessons-learnt typifying diagram"* through a social network (tacit knowledge → explicit knowledge), as shown in Fig. 1. Hence, it is permitted to profile each individual or groups of people, their generation of knowledge, showing the emphasis or progress of their lessons learnt in ranks or time periods defined by each user of the prototype. Finally, by applying an algorithm supported on textual analysis techniques at semantic level like LSI (Suarez & Salinas, 2009), we can inquire on trends and on the reality of the generation of

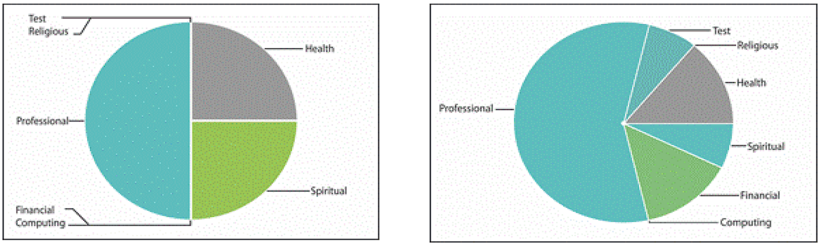

Fig. 4. Lessons-learnt typifying diagram

knowledge being carried out in work teams; thus, using the dissemination of lessons learnt from each of its members.

3.4 Semantic and Social Analysis Algorithm on Lessons Learnt in Web 2.0 Applications

Suppose the organization involves in its profiles three trends: (a) Project Management, (b) Knowledge Management, and (c) Management of Innovation and Technological Development. An analysis process of social behavior is of special interest for KM; especially, in dynamic environments where roles and profiles have to be analyzed by the members of an organizational unit. This is done to establish if a member has or does not have certain skills and/or knowledge; and, also, to analyze that other members should and can support other members of the organization in very particular or special roles. Thus, the question arises: how do you find the most suitable person for a given function, considering the social network? [26]. To answer said inquiry on the practical use of the prototype, a textual analysis algorithm is presented applied to the data source from the web 2.0 application. The algorithm is elaborated via a KNIME data environment that permits performing a predictive non-probabilistic social analysis from machine learning techniques to determine possible behaviors and social tendencies in lessons learnt in the QIRISYA web 2.0 application.

The algorithm elaborated through the KNIME flow permits determining, from machine learning techniques, a set of classifications, groups, and predictions on the current state of acquisition and KM on certain lessons learnt managed through the web service. Now, the data source correspond to nominal attributes and unstructured text sources that contain information about the classes, profiles, categories, descriptions, codes, dates of registry, and control, along with all the terminology appertaining to a set of lessons learnt in KM.

The characteristics of the data source include that in their totality they can be considered sequential multivariate data on time line. In the data cleansing and filtering process information is converted from text chain type to nominal attributes that facilitate follow up and interpretation of results, filtering of columns considered not having relevant information during the analysis process and, finally, a data balancing process was applied from the nearest-neighbor technique to give an oversampling to the minority class to mitigate deviations due to data still lacking. Figure 5 shows the result

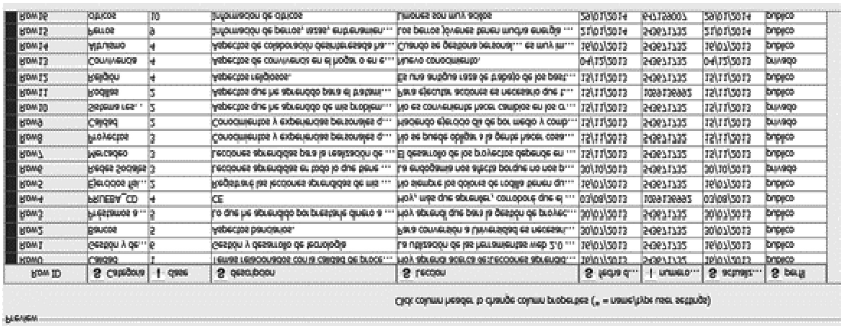

Fig. 5. Data set obtained

obtained of preliminary data cleansing and which will lead to the following data analysis phase.

The data source provided by the model comes specifically from a relational database embedded in a web service (Amazon web Services); this web service inter-operates with a web application (QIRISYA) aimed at management of web 2.0 lessons learnt.

During the information analysis process through machine learning, supervised analysis techniques were applied given that work was undertaken from a classification; for this the attribute *"profile class"* was determined as class; application of decision trees became a fundamental tool in the process. A type of gain ratio without pruning was implemented to the decision tree with 70 % training data and 30 % prediction data.

4 Results

As mentioned in previous sections, the repository analyzed corresponds to the information from the (QIRISYA) application database; the need to apply a cleaning and transformation process it was also determined to proceed to the analysis. The attributes analyzed correspond to information of lessons learnt within an organizational context in determined times, as observed in Table 1; the data stored in the database are finally categorized and synthesized, thus:

Table 1. Description of data-set attributes

Category	Class	Description	Lesson	Date of record	Record number	Profile update	Profile
Defines the category of lessons learnt	Identifies the profile classifier	Describes the type of profile	Determines the lesson learnt in a category	Indicates the date of in-corporation of the lesson	Record consecutive	Date of consolidation of lessons learnt	Public or private

The social analysis of the data source through the use of machine learning algorithms applies two experimental scenarios. The first scenario shows the correlation among the lessons learnt on a given theme and the profiles assigned to each category. In an exploratory scenario it can be noted how some skills are identified within the data set of lessons learnt; Fig. 6 permits graphically comparing the class behavior (profile) in distinct groups of lessons learnt; for example, for classes 2 to 5 we find the highest continuous concentration of lessons in a given time space. Within this context, an organization needs to use KM to guarantee successful implementation of change, as well as to maintain long-term competitive advantages from its intellectual capital.

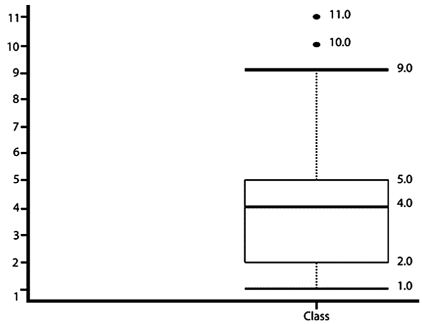

Fig. 6. Continuous distribution of the class attribute

The second scenario evidences the supervised classification criteria from decision trees that permit determining the tendencies and projections of the lessons learnt. The experimentation approached for the study of social behavior on lessons learnt in KM allows determining from a classifier (class) what the tendencies within a group in acquisition of knowledge from experience.

Observation of the results obtained for the sample of skills acquired from lessons learnt studied demonstrates that the model produces part of the lessons learnt and result in themes like *"health in the profession"* and *"experiences in the profession"*, originating a projection and tendency that can help to improve *"quality"*, *"professional skills"* and *"health conditions at work"*. Although, both *"health"* and *"profession or labor"* are different categories; semantically, the model determines that a direct relationship exists between the "labor activity" and "health" activities. Observing the decision tree in Fig. 7, which is generated in the machine learning process in the model developed, it can be identified that the initial node on the tree congregates nine of the 11 labor profiles controlled by the class attribute.

The decision tree provides an adequate structure to determine skills from the lessons learnt; it may be extrapolated as a multidisciplinary, dynamic, and non-probabilistic model to optimize performance, organizational learning, and organizational behavior, which are vital premises in the construction of KM systems. Herein, experiments are being conducted with a first multidisciplinary model of classical measures to unify

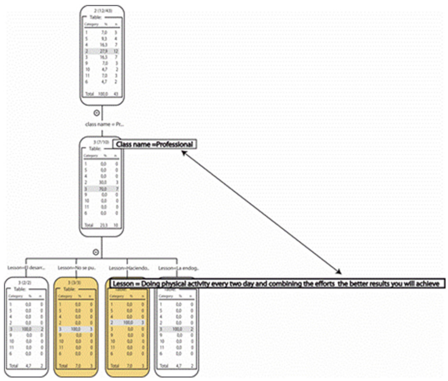

Fig. 7. Partial decision tree generated in the social analysis model

competencies, skills, and lessons learnt to bring them to the application of the analysis and engineering of knowledge, supported on machine learning techniques to provide and extract semantic relationships between concepts and propose as the following phase a meta predictive non-probabilistic model of broadened semantic social network analysis.

Also, three natural groupings emerge in the experimental study of the people who have relative knowledge and who provide different learning perspectives. A group is inclined to diminishing in uniform and weak manner its activity related to a knowledge domain, in the sense of applying lessons learnt in the *"pets"* and *"vehicles"* domain, while another natural group invites other profiles to consume significantly less knowledge to focalize on priority themes. It may be interpreted as a need of academic formation, or of a tutorial imparted by the individuals who already had the competency.

The third group, as shown by Fig. 8, represents a close social and semantic relationship among category, profiles, and lessons without regard to the time series, under three natural groups of profiles; in this scenario, the financial, religious, and labor profiles mark a mutual relationship with the health profile.

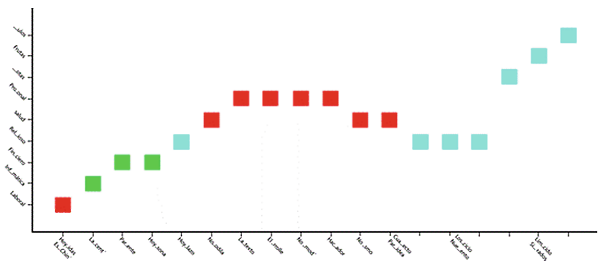

Fig. 8. Conformation of group profile (clusters)

5 Conclusions and Future Work

This work permits inferring that the development of empirical systems to apply PKM from algorithmic techniques supported by semantic social analysis are a latent, but real organizational alternative to manage knowledge and define improvement alternatives.

In particular, it is important to recognize that we successfully proposed an architecture that is applied and adapted to the world's most used social network and it is, likewise, supported on tools that facilitate their exponential growth, such as Amazon's Simple DB database.

This work has several extensions in its practical and research application, arising from each of its functional and structural modules, for example, from the functional point of view it would be important to continue delving into the systemic use of the application on knowledge generation routines for each person involved in the lessons learnt generation process. It may also be possible to delve into the dynamic generation of more lessons when including modules like early warnings in the use of the application. From the structural point of view, it would be necessary to verify the characterization in using the database to measure efficiency in its use, to reach a commercialization and massive-use process of the prototype at organizational levels.

In large volumes of data, a semantic analysis applied on a big data tool will permit asking a team or work group how their dynamic capacities are being generated for KM and what is the profile developed in it, from a systematic analysis of the individual or personal profiles of each of its members in a time line.

As stated by some authors referenced in this work, the work that needs to continue is the development of adequate and integral spaces where each person or individual feels comfortable and knowledge flow is facilitated that permits their self-recognition and, thus, generate the capacity to bring their tacit knowledge to explicit knowledge, which permits their collaboration with learning and development objectives within the contexts or environments in which they are developed. Finally, this model would be the first version to achieve a powerful version of a predictive non-probabilistic model of broadened semantic social networks analysis as basic component of the metamodel proposed in the functional architecture.

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