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Knowledge Management Systems based on Ontology Learning

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Darkness cannot drive out darkness; only light can do that.
Hate cannot drive out hate; only love can do that.

Martin Luther King Jr.

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RESUMEN

Para mantenerse competitivas en un mundo globalizado, las organizaciones modernas tienen que contar lo más actualizado posible, con el conocimiento asociado a sus propósitos y fines. Con la finalidad de aprovechar al máximo tales conocimientos, los principales procesos implementados en los modernos ***Sistemas para la gestión del conocimiento (KMS)*** deberían soportar lo mejor posible, el procesamiento y gestión de dichos conocimientos.

Por lo tanto, la calidad y los criterios del funcionamiento para el desarrollo apropiado de tales KMSs estará condicionado por: 1) los modelos usados de referencia para su diseño e implementación; 2) aquellas tecnologías útiles para ser incorporadas; y 3) los procesos de gestión eficaces y continuos para la ***Adquisición del conocimiento (KA).*** De hecho, recientemente, la ingeniería semántica ha facilitado la incorporación de las ontologías para soportar requerimientos de esta índole en sistemas como los KMSs. Particularmente, las ontologías se ha considerado gradualmente útiles para satisfacer varios requerimientos de gestión demandados por los diversos usuarios de este tipo de sistemas, a los cuales se les han denominado recientemente como "sistemas inteligentes".

Por otra parte, debido a que la información disponible en medios electrónicos y en la Internet aumenta constantemente, el conocimiento asociado a la misma, se ha vuelto cada vez más accesible a través de ***Recursos metodológicos (MRs)*** tales como nuevos métodos, técnicas y herramientas, usualmente creados para procesos de *Desarrollo* y ***Aprendizaje ontológico (OL).*** Asimismo, las ***Fuentes de conocimiento (KSOs)*** disponibles para recuperar y extraer tales conocimientos, han venido evolucionando también en término de sus propios MRs. Estos recursos, se han convertido paulatinamente en mecanismos útiles para simplificar el procesamiento de la información -asociada al conocimiento- de una forma semi-automatizada y sustentada cada vez más, por avances propios de la "Inteligencia Artificial".

En este trabajo, hemos considerado que las ***KSOs heterogéneas*** tales como las ontologías previamente desarrolladas, documentos, y bases de datos, favorecerían los procesos de OL. Asimismo, los procesos de KA asociados por la vía semántica a los KMS mejorarían la eficacia (eficiencia/efectividad) global y parcial de los ***procesos de gestión del conocimiento*** correspondientes y como consecuencia, favorecerían a su vez, la calidad esperada de los ***productos semánticos*** derivados (ontologías, agentes, las fuentes, etc.).

En ese mismo sentido, hemos validado que varios de los problemas asociados al desarrollo y uso de los KMSs basados en ontologías, se podrían afrontar con la aplicación de tecnología del ***Aprendizaje Ontológico (OL).***

De aquí que, nos hemos planteados los siguientes dos objetivos generales y sus correspondientes específicos:

1) ***Desarrollar bajo el enfoque de calidad sistémica un modelo de sistema de conocimiento (OLeKMS) basado en ontologías que pudiese satisfacer varios requerimientos de usuarios y de la calidad de éstos.*** Así, como objetivos específicos destacan: a) mantener continuamente actualizadas las base de conocimiento de los KMS a partir de mejorados procesos de gestión del conocimiento. b) Incorporar heterogéneos KSOs (ontologías, textos y base de datos) para mejorar los procesos del conocimiento de los KMS aplicando procesos de OL. c) Incrementar la participación de los usuarios de los KMS enfatizando en procesos de KA. d) Mejorar los servicios de comunicación para incrementar las relaciones requeridas entre los diversos procesos de gestión del conocimiento. e) Incrementar la eficacia de los procesos del conocimiento de los KMS a través de los MRs propios de OL. Y, f) Mejorar la calidad de los productos y servicios de los KMS, mediante la redefinición de las dimensiones aplicadas a los modelos usados (frameworks) para valorar el éxito de los KMS.

2) ***Desarrollar una metodología de OL que fuese útil para mejorar procesos del conocimiento de los KMSs***. Se contemplarían entre sus objetivos específicos: a) Identificar los principales problemas y fallas de las metodologías actuales para OL relacionadas con los citados KSOs. b) identificar los requerimientos de usabilidad de los usuarios y criterios de calidad a ser considerados en una metodología sistémica de OL que aprovechase mejor las diversas KSOs. c) Diseñar y probar experimentalmente las metodologías de OL a través de la aplicación a casos reales de estudio. Y, d) Evaluar diversos aspectos de usabilidad y funcionalidad de la metodología sugerida (SMOL) en comparación con otras recientes para OL.

De hecho, hemos abordado la complejidad de esta problemática y los objetivos planteados, usando el enfoque sistémico a través de una estrategia "push & pull". Es así que, hemos identificado primero los requerimientos (-pull) de los usuarios de los KMS y las necesidades (-pull) de calidad y éxito de tales sistemas. Y además, aparte de incorporar mecanismos mejorados (push-) para la gestión de las KSOs, también hemos identificado y validado las capacidades de los MRs asociados a tales fuentes (KSOs) para procesos de OL, a fin de incorporarlos (push-) a los procesos del conocimiento asociados a esos KMSs.

Por lo tanto, en esta tesis hemos sugerido un ***modelo de Aprendizaje Ontológico para los KMS (OLeKMS)*** especificando para ellos sus principales componentes (*Usuarios, Procesos, Fuentes de Conocimiento, Productos y la Comunicación*), bajo una perspectiva de calidad centrada en el usuario y basada en los procesos del conocimiento. Para cada uno de los componentes del modelo, se hizo una especificación detallada y ciertos detalles técnicos posibles, para su eventual implementación. A través de un caso de estudio universitario, se ilustra la aplicabilidad del modelo.

También y como parte de los objetivos de la tesis hemos desarrollado una ***Metodología Sistémica para el Aprendizaje Ontológico (SMOL)*** basada en KSOs heterogéneas. Se especificó el flujo de trabajo para la metodología propuesta así como las diversas fases involucradas en la construcción y/o reconstrucción del conocimiento asociado al dominio en cuestión. De hecho, para verificar las fases asociada a dicho flujo y las características de "usabilidad" por parte de los diversos usuarios involucrados, se ha aplicado SMOL a dos casos experimentales (del dominio académico y de fabricación). Además, se ha comprobado la flexibilidad de SMOL, así como sus capacidades para apoyar procesos parciales, interactivos, y recurrentes para que de una forma (semi-) automática, se puedan lograr procesos apropiados de KA. Los resultados más significativos (con sus correspondientes publicaciones anexas) se han sintetizado respectivamente en este trabajo.

Algunas de las conclusiones más importantes, producto del trabajo de investigación serían las siguientes:

La posibilidad de mantener las bases de conocimiento de los KMS ha sido incrementada debido a la re-definición y re-especificación, de procesos del conocimiento asociados a los KMSs basados en ontologías que han sido repotenciados a través de procesos de OL. Particularmente los (meta/sub) procesos asociados a KA (ej. *Extracting* and *Memorizing*).

Los MRs asociados a estos procesos de OL basados en diversas y complementarias KSOs como ontologías, textos y base de datos desarrolladas previamente (desde diferentes contextos organizacionales), así como la potencial mejora de los mecanismos de gestión (almacenamiento y recuperación) de dichos KSOs (*OLeKMS KSOs*) incrementan empiricamente la calidad de los procesos del conocimiento de los KMS (*OLeKMS Processes*) y por ende, la de sus productos derivados (*OLeKMS Products*).

Una nueva jerarquía de procesos del conocimiento para los KMS ha sido concebida considerando la perspectiva de sus usuarios. Particularmente hemos enfatizados en los procesos asociados a KA. A nivel de meta-procesos del conocimiento, se especificaron los de *Extracción, Memorización,* *Reúso* y el de *Compartir*. Y a nivel de sus correspondientes sub-procesos, se especificaron y mejoraron con recursos de OL los siguientes*: búsqueda, retención, transferencia y creación,*

Los servicios de comunicación requeridos para soportar los procesos del conocimiento han sido mejorados a través de diversas herramientas de información y tecnologías de comunicación (ITC) que se vienen incorporando a diversos MR útiles para procesos OL (ej. Web-Protégé).

Las medidas eficacia del rendimiento de los procesos del KMS (*OLeKMS Processes*) han sido incorporadas a los productos del modelo de KMS (*OLeKMS Products*) a través de dos vías: re-especificando la dimensión de utilidad del usuario (*User perceived usefulness*) y a través de las re-especificación de medidas de rendimiento en la dimensión de satisfacción del usuario (*User satisfaction*) de un marco de referencia de éxito (KMS success framework).

Las dimensiones de calidad/éxito asociadas a los marcos de referencia de éxito de los KMS (*success frameworks*) han sido re-especificados para incluir nuevas dimensiones de calidad sugeridas en la literatura (*Communication and Knowledge Processes*) y para re-ajustar aquellas (sub) dimensiones que se perfilan a favor de la percepción de los usuarios del KMS (*Perceived usefulness and User satisfaction*).

Asimismo, la nueva propuesta metodológica (*SMOL*) fue diseñada a partir de un análisis situacional previo de los procesos y productos de OL (SWOT technique). El mismo, reflejó la conveniencia de incorporar MRs para OL desde los nuevos y complementarios KSOs citados.

Un par de casos de estudios fueron útiles para probar *SMOL* en sendos dominios de aplicación como son el académico-universitario y el de manufactura. El primer caso, permitió verificar la funcionalidad de la metodología y además su aplicación al modelo de KMS (*OLeKMS model*) y el segundo, sirvió para ilustrar un proceso de desarrollo ontológico real, pero validado con las fases del flujo de trabajo propuestos en *SMOL*.

Finalmente, las cualidades y características de usabilidad y funcionalidad de *SMOL* han sido evaluadas usando métodos y técnicas de evaluación metodológica inspirada en métodos experimentales probados (DESMET), usualmente aplicada a metodologías de la Ingeniería de Software.

TABLE OF CONTENTS

LIST OF FIGURES

ABSTRACT

To keep competitive in the modern globalized world, current organizations have to count on the most updated knowledge associated with their purposes and ends. To make the most of the available knowledge, they have to support their main KM processes through the modern and specialized ***Knowledge Management Systems (KMSs).***

Consequently, the quality and performance criteria for a suitable KMS development mainly depend on appropriating model design considerations, some available and useful technologies, as well as by the possibility of obtaining the required knowledge under continuous and efficacious **knowledge acquisition (KA)** processes. In fact, semantic engineering has been recently incorporating the ontologies to support the modern KMS needs in a gradual fashion. Particularly, ontological technology has been considered useful to meet many users' knowledge-requirements associated with this type of recently denominated "intelligent systems".

On the other hand, although there is increasingly more information available, the associated knowledge has turned more accessible through the electronic media and even more simplified technological resources to support ontology development/management. Likewise, the available ***knowledge sources (KSOs)*** useful to recover and extract knowledge have been consolidating their associated ***methodological resources (MRs)*** useful to simplify the information processing through even more automatic ways, such as those in the Artificial Intelligence field.

In this sense, we have considered the complementarities of ***heterogeneous KSOs*** (such as previously developed ontologies, documents, and databases) as a very useful way to recover this demanded knowledge through ***Ontology Learning (OL)*** processes. Thus, to keep the organizational KMS knowledge-bases up-to-date and the efficaciousness of their associated KA processes, we have considered that under an appropriate OL application, it is possible to improve the global/partial efficaciousness of the corresponding organizational processes as well as the expected quality of their associated (semantic) products (ontologies, agents, KSOs, and so on).

In this regard, we have been examining in this work the relevant problems associated with the ***ontology-based KMSs*** which could be faced through the ***OL technology application.*** We have been dealing with this complex problematic under a sort of "push-pull strategy" supported by the systemic approach. On one hand, we have identified the main process-based KMS users' (pull-) requirement and the system quality/success (pull-) needs. On the other hand, apart from incorporating improved KSOs management (push-) mechanisms, we have also identified and validated the OL technological (push-) capabilities (based on the available MRs for each aforementioned KSO), to be incorporated into their associated KM processes.

Consequently, we suggest an integrated ***Ontology learning KMS (OLeKMS) model*** with the main constitutive components according to a process-based and user-centered quality/success vision. Complementarily, we have developed a ***Systemic methodology for OL (SMOL)*** that can cover our extended view of OL processes from heterogeneous KSOs. In fact, two experimental real cases (in the Academic and Manufacturing domains) have been applied to validate the SMOL usability characteristics to meet the main methodological users' needs as well as to evaluate the SMOL capabilities to support partial, interactive, and recurrent KA processes. The most significant results (with their corresponding publications attached) have been respectively synthesized in this work.

PART I. PHD DISSERTATION

1 INTRODUCTION

Organizations have to stay updated and competitive to deal with the modern world trend based on successful knowledge discovery, recovery, and management processes. The huge and increasing quantity of available information and knowledge has been pressing organizations to count on more strong and efficacious *Knowledge Management System (KMS)* implementations.

In fact, organizational managers are developing and improving their own knowledge-task and decision-making support systems related to owners, employees, clients, and users (Abdullah et al, 2008). Likewise, their corresponding organizations usually have much information accumulated and accessible in several structured, semi-structured, and unstructured formats associated with heterogeneous *Knowledge Sources (KSOs) such as databases, texts, and even ontologies.* This kind of sources has been increasingly used under semantic technologies for improving and updating their own KMSs (Bloehdorn et al, 2009).

Actually, some diverse technological resources based on Artificial Intelligence, Data and Text Mining, Semantic Web, and others, have been recently incorporated to the KMSs to turn them into more oriented knowledge acquisition and processing approaches. Besides, many of these recent KMS implementations are based on ontology resources for this development and support. According to previous reported experiences, the KMS implementations based on ontologies usually developed are Intelligent Decision Support Systems (IDSSs), Knowledge Support Systems (KSSs), Knowledge Based Systems (KBSs), and others.

On the other hand, some semantic-oriented Methodological Resources (MRs) such as tools, methods, and techniques have gradually become more elaborated and mature in the framework of Knowledge Engineering. Particularly, in the Ontology Learning (OL) field, these MRs are usually related to a specific KSO (usually as texts), but without any relation with the other useful aforementioned KSOs (databases and prior ontologies). Therefore, reaching an adequate and dynamic methodology for the integration of these three KSOs and their associated MRs would be useful for ontology-based KMS developers and users to increase the performance of their Knowledge Management (KM) processes.

Finally, the KMS quality is an important feature to be considered. In fact, some prior works about the KMS success framework have been revisited as a useful resource to evaluate or validate the qualities of KMS applications. From these KMS success framework proposals as well as an Organizational learning models (Argote and Miron-Spektor, 2011), it is possible to suggest the users' success dimensions where some KM processes may be improved by the OL technology application.

1.1. The KMS Problems And Motivation

Under this preliminary contextual background, it is possible to identify some relevant KMS problems:

1. The current KMSs do not have continuous Knowledge Acquisition (KA) processes to keep their knowledge-bases up-to-date and to extend their life-cycle functionality.
2. The KMS users are only partially involved with the whole KA processes. Commonly, they have a limited vision of the integrated KM processes and their derived semantic products.
3. The KMS users' needs and components such as knowledge sources, processes, and products may be revisited and interrelated in favor of their appropriate efficacy.
4. The KMS are demanding more effectiveness of their involved knowledge processes based on complementary Knowledge Sources (KSOs) such as ontologies, texts, and databases.
5. The KMS product quality and its associated success dimensions have lagged behind regarding some current technological trends.

The possibility of incorporating into the modern KMSs the OL technology capabilities is a crucial purpose of this work. In addition, to find the best way to organize the methodological resources (MRs) into a methodology for OL from diverse KSOs is a complementary purpose to this effort.

1.1.1 Justification and Hypothesis

Our previous OL methodological situational analysis (Gil and Martin-Bautista, 2013a) has shown some pertinent OL strengths and opportunities useful to justify our central hypothesis.

1. There are diverse and available OL methodological resources (MRs) to adequately support the KMS processes. Some representative MRs useful to support OL from heterogeneous KSOs (ontologies, texts, and databases) can be identified and classified as useful to improve the associated KM process performance.
2. The KMS knowledge extracting and memorizing processes useful to efficaciously support KA tasks must consider the OL from diverse KSOs. Under our perspective, the KM processes are crucial for the KMS success, particularly, considering the users' perceived usefulness about them to support the most common users' knowledge-task.
3. Some OL methodological resources (MRs) useful to support knowledge (re) using and sharing processes from diverse KSOs can be incorporated in KMS applications and models. The OL technology is able to support KM processes through modern tools (e.g. Web-protégé, Neon-toolkit). In this work, the OL incorporation into KMSs may be useful to support interactive and iterative users' knowledge requirements expressed below as the associated knowledge sub-processes (searching, retaining, transferring, and creating).

4. The measurement of the KMS knowledge process performance must be evaluated, due to the application of some current OL methodological resources. Under the systemic/controls paradigm, the KMS success would be favorably impacted by the KM processes improved by OL technology.

Derived from the above mentioned KMS problems and the potential application of OL technology, the **hypothesis** has been formulated as follows:

> *"How well could make the **Knowledge Management Systems (KMSs)** the most of the user-oriented **Ontology Learning (OL) processes** to keep their knowledge-bases up-to-date from heterogeneous **knowledge sources (KSOs)"***

1.2. Framework and Background

The increasing diversity of KMSs in any kind of organizations and enterprises has been practically pushing their users' requirements to be progressively supported through a more flexible Web-semantic technology. Due to the fact that the KMS have incorporated ontologies as a solution, we consider that current KMS developers have to include the OL technology application as an important KMS component (Knowledge processes) under a total-quality systemic approach. Below, we present a brief summary of the most remarkable concepts and antecedents that would support our work in that regard.

1.2.1 The Knowledge Management Systems

As a general KMS definition, "*the KMS objective is support the construction, sharing, and application of knowledge in the organizations*" (Alavi and Leidner, 2001). Likewise, there are increasing quantities of developed KMS with diverse purposes. The main IT applications associated to this KMS are oriented to: 1) the knowledge coding and sharing; 2) the creation of corporate directories; 3) flexible organizational task-workflows; and 4) the creation of knowledge networks.

On the other hand, we have classified specialized KMS (the KSSs) according to the main technology used as follows: a) *Traditional Systems*: they employ some conventional technology such as databases, discussion boards, spreadsheets, and e-mails; and b) *Intelligent systems:* they employ some MRs of Artificial intelligence related to web semantics, ontologies, user profiles, data- and text-mining, and so on. Our central purpose is oriented to consider the diverse KMS types which belong to the second aforementioned classification.

An extended summary of the specialized KMS profiles according to their main applications can be found in (Gil and Martin-Bautista, 2012).

1.2.1.1. The Gaines' KSS Model

The KMS users' requirements turn out to be one of the most important features to be considered in the proposal of a KMS model. The KSS model suggested by Gaines (1990) as a specialized KMS specification has been selected from the literature as the central reference to design our suggested KMS model. In addition, to summarize many of the central KMS users' requirements, this model explains the knowledge interchange relationships among communities of users (end-users and expert-users) as well as the required potential and useful KSOs to support the "knowledge creation" processes.

Some operational KMS conditions can be deduced from the Gaines proposal (1990): to be portable and flexible, to be able to explain its decisions and recommendations to users, and to provide automatic learning of new information.

Some KMS components and requirements are not explicitly described by Gaines (1990) in this suggested KSS model. We have included later in our *OLeKMS* model some of the most relevant ones related to the quality of the KM processes, the required KSOs management efficaciousness, and the enhanced communication services.

1.2.1.2. The Knowledge Management Processes

A key conceptual component of our proposal is related to the possibility of improving the quality and performance of the KM processes. Despite the fact that there are different KM process perspectives, we have considered some of them correlated with the main *knowledge cycle phases* summarized in (Mora et al, 2010). Particularly, we have selected as reference the knowledge processes associated with the organizational learning model suggested by Argote and Miron-Spektor (2011), hereafter named the A&M model. Aligned with this proposal, we have identified some *knowledge (sub) processes* as well as the possible and the organizational contexts to obtain the expected KSOs (ontologies, texts, and databases). We have updated the original A&M model to illustrate the KMS knowledge processes to be improved by OL technologies as well as the selected KSOs under organizational learning contexts.

On the other hand, aligned with the literature of the main KM processes centered in a user's perspective (Markus, 2001) (Kulkarni et al, 2007), we have expanded the traditional knowledge processes usually focused on *knowledge reusing* and *sharing* towards a more expressive and extended view. In fact, we have incorporated in our suggested KMS model two additional knowledge tasks denominated *Extracting* and *Memorizing* processes (Subsubsection 2.1.2.4). Through this incorporation, we have intended to support the ever more demanded KA requirements through enriched KM processes using OL technology. To deal with the systemic -holistic- specification of both groups of suggested knowledge meta/sub processes, we have also considered their possible and hierarchical interrelationships under the KMS success framework.

1.2.1.3. The KMS Success Framework

The fact that the KMSs have adequate qualities to reach the expected success is another important feature of our proposal. Indeed, the KMS quality requirements as well as including the possibility of measuring the success through quality indicators can help to suggest a better and consistent KMS model.

In this sense, we have reviewed the previous KMS success framework intending to include some new trends (quality dimensions) and to cover through an improved knowledge process (user-centered view) the requirements of our suggested KMS model *OLeKMS*. According to our interpretation, they have been originally conceived in a structural, static, and systematic fashion as a taxonomy of dimensions and relationships. In fact, the most relevant pioneer approaches introduced by Delone and Mclean (2002) have marked the schematic style of the dimensions (independent and dependent variables) used to explain or specify the quality components. Some other relevant and successive IS/KMS success framework proposals have been influenced by this structural approach in the expert-side, despite their important recommendations, justified changes, and impacting model improvements, Kulkarni et al (2007), Petter and McLean (2009), Jennex and Olfman (2006), Urbach and Müller (2012).

On the other hand, some recent KMS success frameworks consider various pertinent perspectives and dimensions, according to a more modern user knowledge requirement views. Indeed, they have incorporated the knowledge process view, some aligned dimensional arrangements, and re-specifications which consider the users' dimensions in accordance with their associated knowledge processes (Jennex and Olfman 2006) (Urbach et al., 2012).

In fact, this type of recent proposals of IS/KMS success models have turned out to be more flexible, process-centered, and subject to a systemic approach. In the same vein, our proposal of an extended process-based KMS success framework which can favorably impact the product quality has been suggested in Subsection 2.1.3.4. We have denominated this approach the user-centered view.

1.2.1.4. The Systemic KMS Qualities

Apart from the aforementioned KMS characteristics to be considered in the suggested *OLeKMS* model, the global KMS qualities have to be measured as well. Because there are many features and components involved in the system design process, we have selected as a reference the total quality systemic matrix proposal suggested by Callaos and Callaos (1994).

As a required systemic background, have introduced relevant concepts about the systemic and control paradigm useful to support the KMS antecedents described below. Specifically, we have considered the identification of some basic KMS components (users, processes, and products) and their essential relations under the systemic and control paradigms (Bunge, 1997) (Wand and Weber, 1995).

In the same vein, the required KMS qualities have to consider the process and product performance measures (efficacy, efficiency, and effectiveness) and the optimization purpose (control paradigm) to explain the relationships among the corresponding KMS means with ends.

Finally, the quality matrix suggested by Callaos and Callaos (1994) helps to consider the measures of references about the systemic products and processes under the OL domain. Concretely, the following relationships among them have been considered: 1) *Product efficiency*: maximize Product efficiency subject to Product effectiveness; 2) *Product effectiveness*: maximize Product effectiveness subject to Product efficiency; 3 *Process efficiency:* maximize Process efficiency subject to Process effectiveness; and 4) *Process effectiveness:* maximize Process effectiveness subject to external restrictions to the process. Likewise, the client and/or user interrelationships with Processes and/or Products have been also revisited in our suggested KMS model.

1.2.2 The Ontology Learning Technology

1.2.2.1 Ontology Learning

Ontology Learning (OL) was originally coined by Maedche and Stabb (2001). It can be described as an acquisition of a domain model from the data, so the OL is usually classified as a subtask of an information extraction field. Particularly, this interpretation has a relevant meaning when this extracting task is applied to obtain knowledge/information from electronic documents. In our work, we have considered a wide interpretation of OL by extending the OL scope to cover additional KSOs such as databases and previously developed ontologies.

A preliminary OL classification according to each KSO used to extract knowledge is introduced as follows:

- ***OL from texts:*** *it is the process of extracting ontology terms and concepts from plain texts using diverse methods/tools for terminology extraction* (Buitelaar et al, 2009) (Wong et al, 2012).
- ***OL from ontologies:*** *it is the process of acquiring knowledge from previously developed ontologies using methods/tools such as ontology matching, mapping, and alignment* (Pavel and Euzenat, 2013).
- ***OL from databases:*** *it is the process of extracting ontology components such as concepts, relations, and instances from the database schemas and from the contents of their records* (Cerbah, 2010) (Santoso et al, 2011).

1.2.2.2 The Ontology Learning Methodological Resources

There are some definitions regarding *Methodological resources (MRs)* that allow us to understand the concepts associated with MRs and to avoid confusions that sometimes happen in technical literature. The following definitions have been considered (Callaos, 1992) in our work, as the main set of MRs. A definition of each MR in the OL context, some examples for each KSO (ontologies, texts, and databases) and the performance quality measure are described as follows: 1) *Technique: "Subjective capabilities to handle a tool by users*"; the corresponding KSOs examples: Statistic analysis, NLP, and Clustering techniques; and the efficiency (ratio: input/output) as the quality measure.

2) *Tool: "Objective capabilities to apply techniques*"; the associated KSOs examples: Protégé-Prompt, GATE, and RDBToOnto; and the efficiency (ratio: input/output) as the quality measure.
3) *Method: "A way of thinking/acting to achieve an objective*"; the corresponding KSOs examples: Alignment, Linguistic, and Attributes; and with the effectiveness (ratio: output/objectives) as the quality measure.
4) *Methodologies: "Set of techniques, methods and tools*"; the related KSOs examples: FOAM, BOEMIE, and RTAXON; and the efficacy (ratio: efficiency/effectiveness) as the quality measure.

Regardless the KSO studied in the technical literature, several MRs have been proposed to support the users' needs in OL processes. These MRs for OL have been considered in this work to be convenient and useful as KM process enhancers. In fact, those MRs from diverse KSOs turned into a focal point in our previous associated works (Gil and Martin-Bautista, 2011, 2012, 2013a, 2013b).

1.2.2.3 The Ontology Learning Methodologies

Some methodological features are considered to be relevant in the design of an optional OL methodology which could be useful to empower the KMSs capabilities. Therefore, as a preliminary requirement to understand the OL methodologies, we have to identify some characteristics associated to OL methodologies which could be useful to make the most of many of their involved MRs.

Although there have been important technical advances about OL technology according to each KSO, some works with emphasis on methodological features have reported a high dispersion and little integration among those MRs to obtain some OL results from different KSOs (Shamsfard and Abdolahzadef, 2003), (Gomez-Perez and Manzano-Macho, 2004), (Petasi et al 2011), (Wong et al 2012).

In addition to the aforementioned MRs useful for OL from diverse KSOs, the OL methodologies have some particular characteristics that can help to classify them according to their most highlighting properties. In this sense, we have grouped them in a couple of methodology types (Callaos, 1992): *Systematic methodologies* are oriented to the efficiency, with a predetermined behavior, strict and closed, e.g., Structured Life Cycle; and *Systemic methodologies* are oriented to the effectiveness, with a non-predetermined behavior, flexible and open, e.g., Agile Process/Methods (Larman and Basili, 2004) (Boehm and Turner, 2004).

The OL methodologies documented in the literature and the current trends have been considered in this work as a reference and for comparison purposes. In this sense, some of the most relevant OL methodologies identified and selected such as the Simperl et al (2008) proposal, BOEMIE (Castano et al, 2007, 2009), DINO (Novaceck et al, 2008), or OntoCmaps (Zouaq et al 2011) have been considered to design our suggested OL methodology (SMOL) and to comparatively evaluate several distinctive features among them (in Subsubsection 2.2.6).

1.2.2.4 Ontology Development (OD) and Methodologies

Ontology Development (OD) has recently reached an important evolution in the semantic Web and Ontology engineering fields. The theoretical advances and the derived technological resources for OD have increased in the last two decades.

Some highlighted OD methodologies such as CyC, KACTUS, SENSUS Methontology (Gomez-Perez et al, 2003), and On-To-Knowledge Methodology (Sure and Studer, 2004) have been elaborated and proven as bases for “the creative” cycles of interaction that allow users to generate partial ontology versions until completing an operative version.

To illustrate a representative workflow OD process, we have enumerated the Methontology phases (life-cycle) as follows: 1) Specification, 2) Conceptualization, 3) Formalization, 4) Implementation, and 5) Maintenance (Gómez-Pérez et al, 2004, pg. 127). Likewise, other more recent OD proposals such as UPON (De-Nicola et al 2009) or the NeON methodology (Suarez-Figueroa et al, 2012) have considered several MRs for OD using previous KSOs (e.g. prior ontologies, text, and others). The main purpose of these methodologies is to support the OD process.

Finally, there are some essential features associated with the characteristic of usability of different OD methodologies reviewed recently in (Dahlem et al, 2009) which we have considered useful and essential for designing and evaluating our suggested OL methodology (in Subsection 2.2.6).

1.3. Objectives

According to the central purpose of this research, the main ***objectives*** are described as follows:

Objective 1: To develop under systemic quality criteria an ontology-based Knowledge Management System model (OLeKMS).

1.1. To keep the KMS knowledge-bases continuously updated improving their KM process quality based on the KSO task-management efficacy.

Under the premise that the KMS knowledge-bases have to be kept continuously up-to-date, the efficacy of the associated KM processes must be conditioned by the appropriate performance for reusing and sharing previously stored KSOs. Every time an OL process has to be (re-) applied, it is possible that some previously processed KSOs have to be reused. Our goal is to suggest appropriate KM processes which can make the best of the storage management mechanisms (Organizational memory systems) to obtain an increase on the partial and global performance.

1.2. To incorporate complementary Knowledge Sources to reach OL processes from previously developed ontologies, texts, and databases.

The huge information accessible -internal and external to the organization- through electronic ways (e.g. the Internet and others) which is available as KSOs under diverse (un)structured formats such as previously developed ontologies, documents, and databases, may be gradually more accessible using modern MRs, including OL tools. Our goal is to incorporate some MRs for OL from each of these KSOs within the main suggested KMS **knowledge sub-processes** (searching, retention, transfer, and creation) intending to improve their performance and, consequently, enhancing the derived KMS products.

1.3. To increase the KMS user participation with the diverse KMS knowledge processes emphasizing the Knowledge Acquisition tasks.

The users' participation has been usually conditioned by MRs for OL without any relationship with the main KM processes. Particularly, we are interested in some of them which have been recently used to support the knowledge discovery and recovery processes. Our goal is to combine diverse MRs with these OL capabilities to support the main KM processes of a KMS. Our ontology-based KMS model proposal emphasizes five crucial systemic components (*Users, KSOs, Processes, Products, and Communications*) empowered by the OL technology.

1.4. To enhance the Communication services increasing the relationships among the knowledge processes to support the KMS users' needs.

The diverse KMS users (End-users, Expert-users, and Knowledge engineers) are requiring efficacious communication facilities and services to appropriately support their interrelated knowledge tasks. The knowledge-task success among those users is progressively depending on the efficaciousness of the KM process interaction. The appropriate relationships among KM processes would favorably impact the KMS process performance. Our purpose is to model the required improved communication service among the diverse users and among their associated knowledge meta/sub processes.

1.5. To improve the associated KMS knowledge process performance efficacy based on the application of OL technology.

The importance of the KMS quality and success has to be considered in this research through the efficiency and effectiveness of the OL process measures. Our aim is to consider some previous KMS success framework dimensions to incorporate within them the convenient control mechanism required to enhance their performance.

1.6. To assure the KMS product quality through an integral and updated version of their required success framework dimensions.

The previous KMS success framework used as reference to validate and evaluate KMS designs and/or implementations would be revisited to consider the modern requirements of ontology-based KMSs. Our aim is to re-specify the quality dimensions and the user dimensions to be aligned with the integrated model of our systemic KMS proposal.

Objective 2: To develop an integrated Ontology Learning Methodology useful to improve the KMS Knowledge Processes.

2.1. To identify under a user's view the main OL problems and flaws on Processes and Products of the current OL methodologies.

Despite the continuous improvement in the MRs for OL, there are diverse features which could be revised to improve the associated KM processes which could affect the derived KMS products. Our goal is to identify the main OL associated strengths, opportunities, threats, and weakness (SWOT Analysis) according to each of these systemic features (Processes and Products) as a starting point to be considered within the suggested OL methodology as a whole.

2.2. To specify the users' requirements and usability criteria to be included in an OL methodology which makes the best of the heterogeneous KSOs (user-oriented).

Diverse users' requirements have to be considered to design an integrated OL methodology. Some of the most important ones could be the following: the involved knowledge processes to be supported, the opportunity to obtain knowledge from diverse contexts and complementary KSOs, some usability qualities, a diversity of MRs for each of these KSOs; some ontology quality evaluation issues, and so on. Our main purpose is to include under a multi user-oriented approach many of those requirements in the design of an optional OL methodology.

2.3. To design and experimentally test the suggested OL methodology through this development and to apply it in a couple of real case studies.

The designed OL methodology has to be validated through the experimental application in real case studies. The central purpose of the OL methodology application is corroborating the KM process functionality and its expected performance improvement. Collaterally, we intend to incorporate the OL methodology adjustment and fine-tuning derived of the corresponding lessons learned during both case study applications.

2.4. To evaluate some methodological usability features and OL comparative subjects through some methods for the evaluation of methodologies.

The designed OL methodology has to be evaluated considering some proven evaluation methods. Our goal is to check the qualities and properties incorporated into this systemic OL methodology as well as to compare some of their distinctive features with those of other documented OL methodologies.

1.4. Document Organization

This dissertation is organized in two parts. The first part (PhD Dissertation) introduces the KMS problematic, the motivations, and the relevant objectives of this research, as well as a short summary of the most significant obtained results whereas the second part (Publications) presents the associated publications which support our contributions. More details about these contents have been described subsequently.

Part I. PhD Dissertation

Part I introduces the basic concepts and antecedents about the subject of this work. We have focused on some relevant works associated with the KMS models and the OL application fields. In addition, we have summarized the work proposed in this dissertation, which is supported by the publications incorporated in Part II.

The KMS problematic, the motivations, and the general and specific objectives are introduced in Section 1. In fact, we have considered as framework and background some previous models about KSS, Organizational Learning, and Systemic total quality useful as a reference to outline our KMS model. On the other hand, we have also considered the MRs of OL as useful to establish the bridge between their potential capabilities to empower the associated KMS knowledge processes.

All work performed in this thesis is summarized in Section 2. We have grouped the results in two groups. The foremost results associated with our suggested KMS model (*OLeKMS*) and its systemic components have been detailed in Subsection 2.1. These *OLeKMS* model components incorporate many of the required OL resources to enhance their knowledge meta/sub process performance according to a hierarchical vision of the KM processes based on the user-centered perspective. On the other hand, the most relevant results associated with the SMOL methodology proposal have been summarized in Subsection 2.2. In this sense, the key relevant aspects about the SMOL development, a couple of case study applications, and the experimental evaluation have been described in the subsumed subsections.

Intending to increase the OL process quality (associated with the SMOL design), the research stay at the University of York (UK) helped us to consider and revisit some quality features regarding the semantics of the terms in the derived ontologies updated through OL processes. Specifically, the possibility of applying some NLP technologies (such as WSI and WSD) to validate the quality of the obtained ontologies was experimental and partially tested (UoY, 2011).

To end up Part I, Section 3 remarks the main conclusions obtained during this thesis period and Section 4 suggests some novel research lines to continue with the work performed in this dissertation.

Part II. Publications

During the PhD research work, different types of results and contributions have been partially consolidated and published on accredited journals and conferences. The most recent ones which are aligned with the purpose of this research have been respectively grouped regarding the KMS modeling and the OL methodology development.

Regarding the suggested KMS model, we have included an article that describes the suggested model fundamentals and their KMS constitutive components (Gil and Martin-Bautista, 2012) and another article containing a process-based KMS success framework proposal supported by OL technology, that (re) specified some (quality/users) dimensions associated with the quality requirement demanded by this rising type of ontology-based KMS (Gil and Bautista, 2013b, Submitted Dec/13).

As for our proposal of a novel OL methodology (SMOL), up to three papers have been included. The first one describes the application of the SMOL methodology to validate an OD real case in a manufacturing domain (Ramos et al, 2014). The second one deals with the specific details about the SMOL designing, applications, and evaluation considering the heterogeneous KSOs selected (Gil and Martin-Bautista, 2013a). The last one includes some details about the methodology strategy selection according to the available resources (KSOs and MRs) applying SMOL from databases (Gil et al, 2010).

2. JOINT DISCUSSION OF RESULTS

The most relevant results of our work may be grouped around the two central objectives of this dissertation. A novel model of an ontology-based KMS, the *OLeKMS* model, has been conceived to cover the overall KMS user's requirements related to their efficacious development and implementation needs. In addition, an integrated OL methodology also to satisfy the user's knowledge-task requirement, SMOL, has been conceived and tested as a way to build the expected bridge between all elements, means, and ends. We detail both related results in the following subsections.

2.1. The OLeKMS Model

Our proposal of the *Ontology Learning KMS (OLeKMS)* model is designed and described below considering some theoretical antecedents as follows: a) the KMS users' requirements (Gaines model), the organizational KM processes (A&M model), some KMS success framework tendencies (e.g. Jennex and Olfman framework, 2006), and some systemic quality considerations (Callaos' matrix).

Likewise, aligned with the convenience to reach efficacious KM Processes, an optional *Systemic Methodology for Ontology Learning (SMOL)* has been complimentarily developed in this work considering the aforementioned OL basic concepts and antecedents. Thus, the main results associated with this optional OL methodology have been detailed in Section 2.2.

2.1.1 An OLeKMS Model for Continuous Knowledge Updating

For the KMS modeling design purpose, we have considered some general and particular KMSs. In fact, our essential premise is that new knowledge is required for the continuous process of KMS updating in order to keep organizations/enterprises updated and competitive, and this associated knowledge is even more represented as ontologies in this new trend of KMSs.

However, diverse KSOs are overlooked as key features for the updating of the KMSs. We suggest an OL process for KA as a useful option to extend the life-cycle of these ontology-based KMSs. OL processes, from different KSOs (ontologies, texts, and databases), can improve KMSs through the growth of the knowledge, and through processes of comparison and restructuring of the knowledge structures in their knowledge-bases. In particular, we propose an appropriate ontology based KMS architecture that is designed to meet the users' requirements, related to their KM processes regarding their knowledge-based updating.

It is important to stress that one of the contributions of our *OLeKMS* model is the help it provides to users by extending the KMS life-cycle for the updating of their static- and dynamic- knowledge (taxonomic and rules) through efficient and effective OL processes from diverse and complementary KSOs. The KMS learning capability can be explicitly assumed (using MR for OL) to be an essential component of these types of systems (Gil and Martin-Bautista, 2011).

2.1.2 General OLeKMS Requirements and Design Criteria

This suggested ***OLeKMS*** model must be considered as a generalization of our previous (OLe-)KSS model proposal in (Gil and Martin-Bautista 2012). Even so, the former model has been gradually refined and extended including some additional enhancements regarding its constitutive components. Particularly, the KM process (re) specification and the product quality considerations have been motivated by the lack of a similar approach and suitable ontology-based KMS models useful for comparison purposes (see Subsection 2.1.5). Distinctively, the most relevant ***OLeKMS*** requirements have been summarized as follows:

- The most relevant KMS components/subsystems under the systemic and control paradigm have to be incorporated among them.
- The specifications of the main KM processes (user-centered view) improved by the OL technology under a bottom-up hierarchy have to be integrated in the model. Particularly, we have to emphasize the KM processes which are useful to improve the KA users' tasks. Some KM processes suggested in the literature to support the *knowledge cycle phases* have been used as a

reference (Mora et al, 2010) and, mainly, the functional ones in (Argot and Miron-Specktor, 2011).

- The increasing requirements for a more effective and efficient KA process have to be reinforced through the improved KSOs management (diversity, reuse, and accessibility) as well as the enhancement of the mechanisms to support the external/internal KMS relationships (facilities/service).
- Some recent KMS success framework and performance quality tendencies have been partially and globally incorporated within the corresponding *OLeKMS* components.

The main general system design considerations for the suggested model components are the following:

- All the *OLeKMS model* components have to keep some relevant/stable relationships among their main internal elements (cohesion criteria);
- All the *OLeKMS* components have to maintain some relevant/flexible interaction with the other model components (coupling criteria); and
- The OL technology applications (used MRs according to the involved KSOs) within the *OLeKMS* components have shown empirical evidence of enhancing the *OLeKMS* process performance.

2.1.3 The OLeKMS Components

The design considerations to formulate our *OLeKMS model* proposal are associated with a total quality systemic view of the main suggested components. Consequently, the five constitutive *OLeKMS model* components are the following: the *OLeKMS users,* the *OLeKMS Knowledge Sources (KSOs),* the *OLeKMS Processes,* the *OLeKMS Products,* and the *OLeKMS Communications.* A representation of the *OLeKMS* model components is shown in Figure 1.

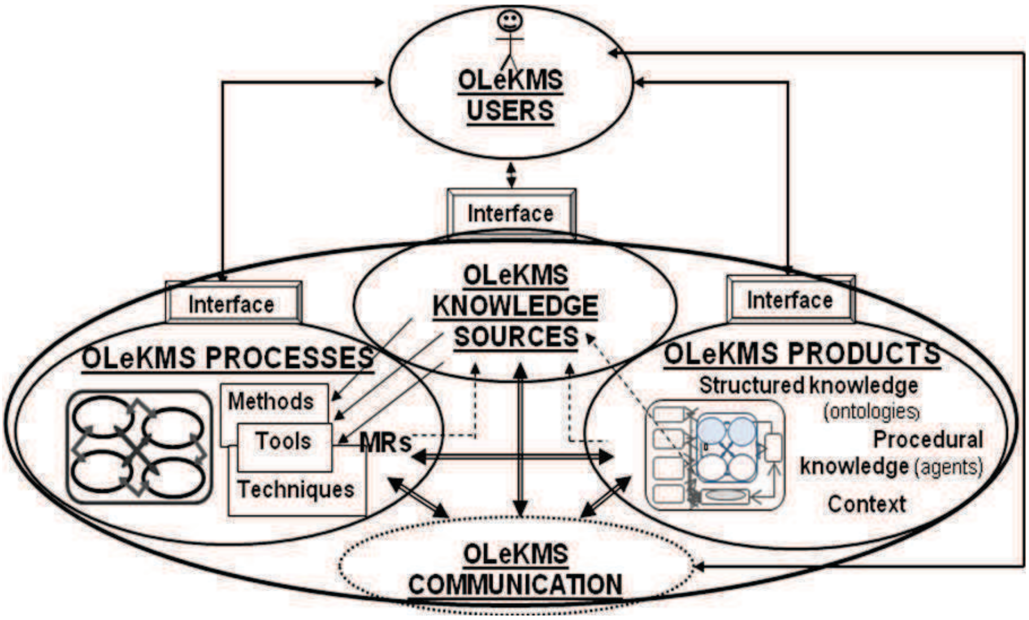


Figure 1. The *Ontology Learning KMS model (OLeKMS)*

The main *OLeKMS* components are specified as subsystems as follows:

2.1.3.1 The OLeKMS USERS

> ***OLeKMS Users*** *obtain added value from OLeKMS Processes. They make tasks/decisions about the knowledge domain that they already have or that they are constructing from possible OLeKMS Knowledge Sources. Graphic user interfaces may include the necessary and ergonomic operational options that can simplify knowledge processing and visualization. These processes should include efficient options to allow for recovery and for updating of related OLeKMS Products.*

OLeKMS Users are grouped according to their information and knowledge needs: (a) end-users – information and knowledge task-workers related to a specific domain such as the application of ontologies; (b) expert-users – designers of knowledge structures (ontologies and others) and guarantors to update them; (c) knowledge engineers – technical support managers responsible for the development and updating of processes through the appropriate means (MR), using the adequate technology.

2.1.3.2 The OLeKMS KNOWLEDGE SOURCES

> ***OLeKMS Knowledge Sources*** *are differently structured or unstructured sources that provide qualified knowledge to sustain the sub-processes involved in the OLeKMS Processes. These sources may be useful for OLeKMS Users to gain easy (explicit and implicit) knowledge access and processing mechanisms to storage in a kind of catalogs and/or repositories. This mechanism can support efficient quality cycles about the users' versions and their corresponding updating and revision during OLeKMS Processes.*

Our suggested *OLeKMS Knowledge Sources (KSOs)* have been considered useful to support KM/OL processes. A required KSOs management conception has been motivated from a couple of cited models in Gaines (1990) and the knowledge sub-processes from the A&M model. This conception intends to reinforce the KM process performance, because it must impact on the effectiveness of the diversity of the involved KSOs and the efficiency of reusing/sharing partial stored KSOs. The relevance of the texts, ontologies (models), and databases as the main *KSOs* used/managed in our *OLeKMS* model proposal is illustrated in Figure 2 (into the database-symbol on the left-side).

On the other hand, the different knowledge stored in this *OLeKMS* model component has been integrated into different organizational memory systems (Walsh and Ungson, 1991) that are suggested (as KRS/TMS) to appropriately manage these *OLeKMS* Knowledge Sources.

(1) *KSO repositories:* storage structures designed according to the formats adapted for documents (corpus), RDB-schemes, and the ontologies;

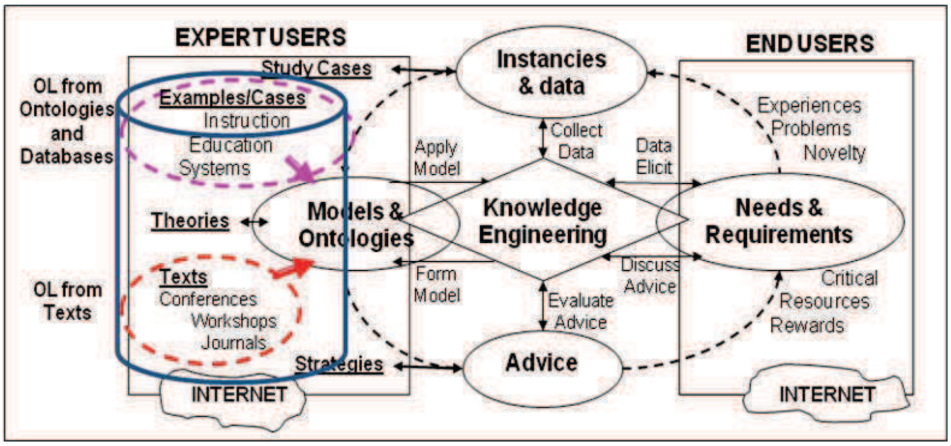


Figure 2. The *OLeKMS Knowledge Sources*: The KSOs useful to support KM processes

(2) *Agent repositories:* storage related to the agents that can process operate the dynamic knowledge according to the user' s demands or requirements;

(3) *MR repositories: storage structures for all the usable methodological resources (methods, techniques, and tools) in functional or adaptable terms (routines or automatic processes) to the associated KMS;*

(4) *User profiles and task profiles: storage structures to define and update users' preferences and tasks developed during knowledge processing.*

The first three aforementioned numerals (1 to 3) have been based on *Knowledge Repositories Systems* (KRSs) according to the technological characteristics required to appropriately manage these kinds of KSOs (Brandt et al, 2006). Likewise, numeral (4) as a complementary KSO resource (including the other associated knowledge representation such as mental maps, user directory, and log tracking) has been suggested to be managed by *Transactive Memory Systems* (TMSs) (Ammari et al, 2011). Introductory Organizational memory systems (KRS/TMS) are suggested in (Gallup, 2000).

These suggested Organizational memory systems are represented in Figure 3 (the storage icons inside the oval). Besides, due to this intended systemic solution, the main named knowledge sub- processes (explained in detail in the next Subsubsection) which could be supported by these memory systems (KRS/TMS) have been shown as well.

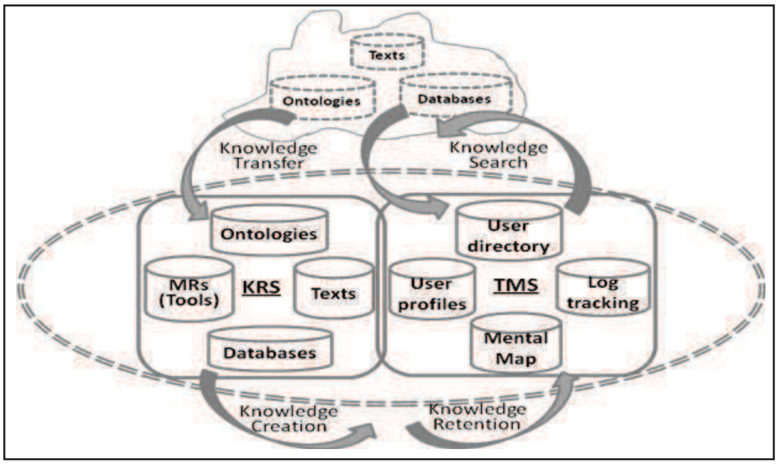


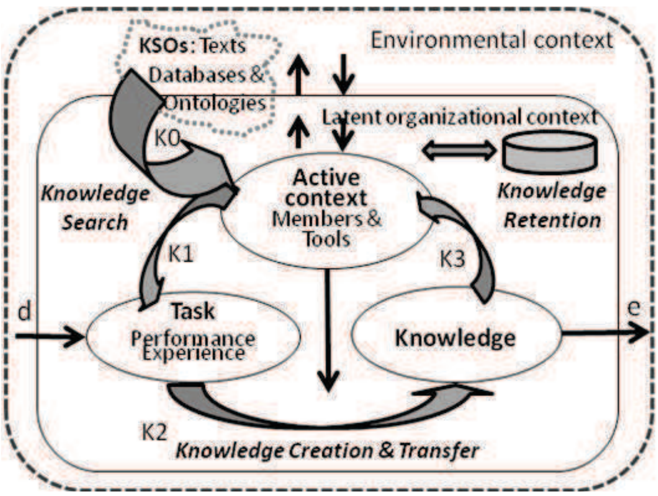
Figure 3. The *OLeKMS Knowledge Sources:* An organizational memory system

2.1.3.3 The OLeKMS PROCESSES

> ***OLeKMS Processes** are defined as the main knowledge (meta/sub) processes identified as useful to support the OleKMS Users' needs under some performance criteria. These (meta/sub) processes may enrich and adapt the existing knowledge in a (semi) automatic way through the application of OL technology (e.g. OL methodologies), using and distributing information from heterogeneous OLeKMS Knowledge Sources. Thus, the efforts/resources needed during the updating/development time-period are reduced.*

The MRs for OL are specifically presented as the main components of *OLeKMS* Processes. In fact, they can be useful to support partial KM processes during the updating and the enrichment of the KMS knowledge-bases. Thus, this model specification considers a sort of knowledge (meta/sub) processes involved with the general KMS user's requirements. Likewise, these KM processes would support some *knowledge cycles phases* and their equivalent ones analyzed and suggested in (Mora et al, 2010) such as the *Knowledge Preservation, Storage/Processing, Distribution, and Application* phases.

On one hand, to re-specify the *knowledge sub-processes*, we have updated the original version of the A&M model essentially highlighting the following three key features: 1) showing our suggested KSOs as available in the three organizational contexts (*Active, Latent,* and *Environmental*) of this A&M model; 2) extending the knowledge search scope (including the arrow identified as K0) to show the possibility of convenient KA processes through these KSOs; and 3) reinforcing the knowledge retention processes through the *OLeKMS Knowledge Sources* (shown by the store icon). The updated A&M model version has been represented in Figure 4.



Model considerations:

- An organizational learning model
- An extended knowledge search process
- Some organizational contexts (KSOs)

Identified Knowledge Sub-processes:

- Knowledge Search (K0 & K1)
- Knowledge Retention (K3)

Figure 4. The *OLeKMS Processes:* An organizational learning model as reference

In this same vein, according to the selected A&M model, the four knowledge sub-processes are *Search, Retention, Transfer,* and *Creation.* A short definition of these sub-processes is shown in Table

1 (first column), together with their potential improvement capability through the O
the *OLeKMS Knowledge source* management (second column).

Table 1. A summary of Knowledge sub-processes which may be improved within the *O.*

Sub-process	Definition	Subject to be Improved
Knowledge Search	It is a looking-for process for novel or known experiences from local or distant areas	• Different experiences can be found from exte • (Semi) automatic process/tool support extern • Structured and unstructured KSOs can be pro
Knowledge Retention	The flow and stock of knowledge in the organization's memory	• Knowledge "reuse" and whether the knowled • The knowledge decay and depreciation at dif • Characterization of the different types of org • Identification of routine aims to understand p
Knowledge Transfer	Learning indirectly from the experience of others as well as from their own experience.	• The absorptive capacity of the unit involved • Location and boundaries of the source of exp • Technological- and social- network mechani
Knowledge Creation	When a unit generates knowledge that is new to it.	• Diverse experience bases contribute to creati • Recording the successful experiences, routin • Online communities and social networks

On the other hand, under our systemic view, the *knowledge meta-process* has be hierarchical bottom-up extension -more aligned with the KMS user perspective- u set of meta-processes. These processes have been denominated *Extracting, Memoriz Sharing* processes. This set of meta-processes has been integrated with the p knowledge sub-processes according to the partial processing capability of the latter Bautista, 2013b). A representation of all of them is shown in Figure 5.

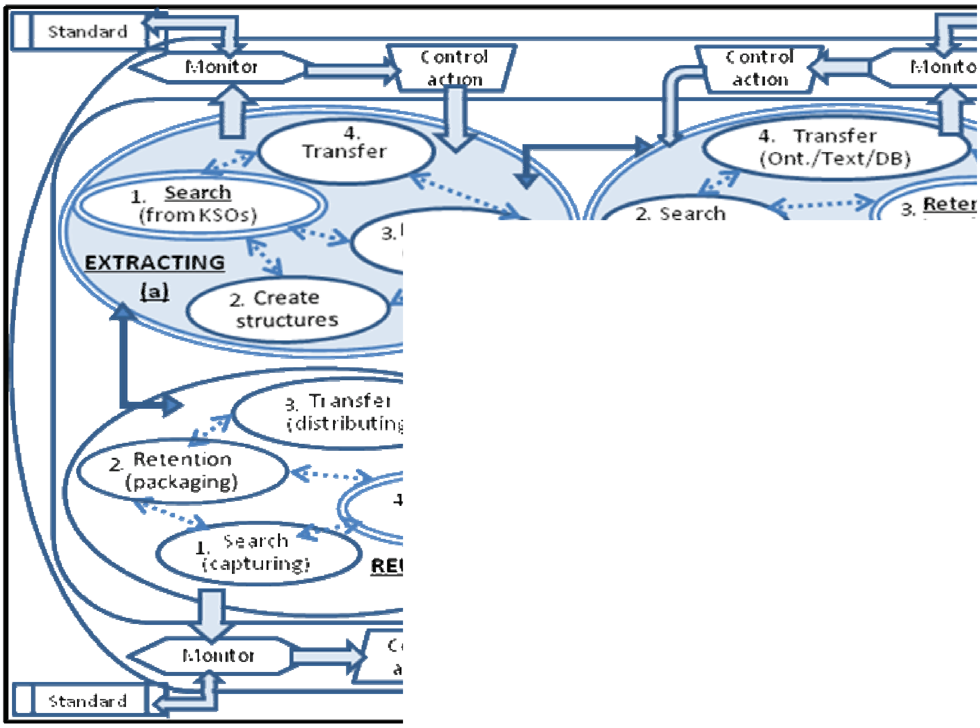


Figure 5. The *OLeKMS Processes:* The main knowledge meta/sub processes

A short definition of these meta-processes is included in Table 2 (first column). Like possibility of these meta-processes may be improved through the OL methodol (tested by the case study) under this *OLeKMS* model and these possible improvements are shown in the same Table 2 (last column).

Table 2. A summary of Knowledge Meta-processes which may be improved within the OLeKMS model

Meta-process	Definition	Subject to be Improved
Knowledge Extracting	Methods/tools for knowledge identification, recovery, and creation from structured/ unstructured KSOs	• The internal/external sources (KSOs) • The new methods/tools • The involved contexts (Local, Organizational & Environmental)
Knowledge Memorizing	Resources/means used to gather /updated knowledge /information continuously, offering proactive assistance to knowledge workers.	• Storage of the most relevant kind of knowledge required • The most relevant sub-processes and storage types (KRS/TMS) • Storage mechanisms suitable for each kind of KSOs
Knowledge Reusing	Mechanisms through which users can incorporate knowledge (from KSOs or stored contents) in their regular knowledge-tasks	• The regular knowledge-tasks which require improvement. • The heterogeneous KSOs and contexts (locations) • Explicit/tacit Knowledge comparing • Knowledge growing and restructuring
Knowledge Sharing	Explicit/tacit knowledge exchanges among people, friends, groups, a community, or an organization.	• Previous Case-study gathering • The involved users and their communication tools • Efficacious access to KSOs and the organizational TRM/TMS

It is important to point out that the two knowledge meta-processes identified as *Extracting* and *Memorizing* in our proposal (Figure 5, shadowed in gray), have never been referred under these names in the reviewed literature, as far as we know, at least, using these intended terminologies. We have selected these corresponding terms trying to highlight the increasing need to meet the KMS users' requirements for more useful and efficacious KA processes. Our complementary OL methodological proposal also goes in that direction.

Finally, the OL methodologies that combine a variety of MRs for OL from a user-centered perspective can be useful to support these identified *OLeKMS Processes.* As previously mentioned, any proposed OL methodology (non life-cycle based) of the above mentioned ones (in Subsubsection 1.2.2.3) can be used as a useful resource to empower the *OLeKMS Processes*. Due to this flexibility capabilities, we have suggested and applied SMOL (Subsubsection 2.1.4 and 2.2.5) as an optional OL methodology among other similar analyzed OL methodologies (in Subsubsection 2.2.6.2) to keep this kind of KMS updated.

2.1.3.4 The OLeKMS PRODUCTS

> ***OLeKMS Products*** *are defined based on partial results obtained during the OLeKMS Processes as well as on the structured or unstructured knowledge acquired previously (e.g., ontologies or profiles). Some particular results, such as KMS subsystems of reusable agents (Garruzzo et al, 2007) are also considered as partial OLeKMS Products. Consequently, these partial results remain accessible and updated as OLeKMS Knowledge Sources for re-use for any other OL purpose. The expected product qualities useful to validate the global KMS success have been integrated in this model component from the previous KMS Success frameworks.*

The *OLeKMS Products* have been specified according to the relevant knowledge structures to be managed and according to the quality and performance levels to be reached by their *OLeKMS Processes* based on some (re) specified KMS success dimensions.

The most detailed specifications associated with the suggested process-based KMS success framework have been essentially incorporated in this *OLeKMS* model component. The main relationships between the suggested KMS quality dimensions (*System, Products, Process,* and *Communication*), the user`s dimensions (*Perceived Usefulness* and *Satisfaction*), and the Net Benefit (*Individual, Organizational, Social*) have been depicted in Figure 6.

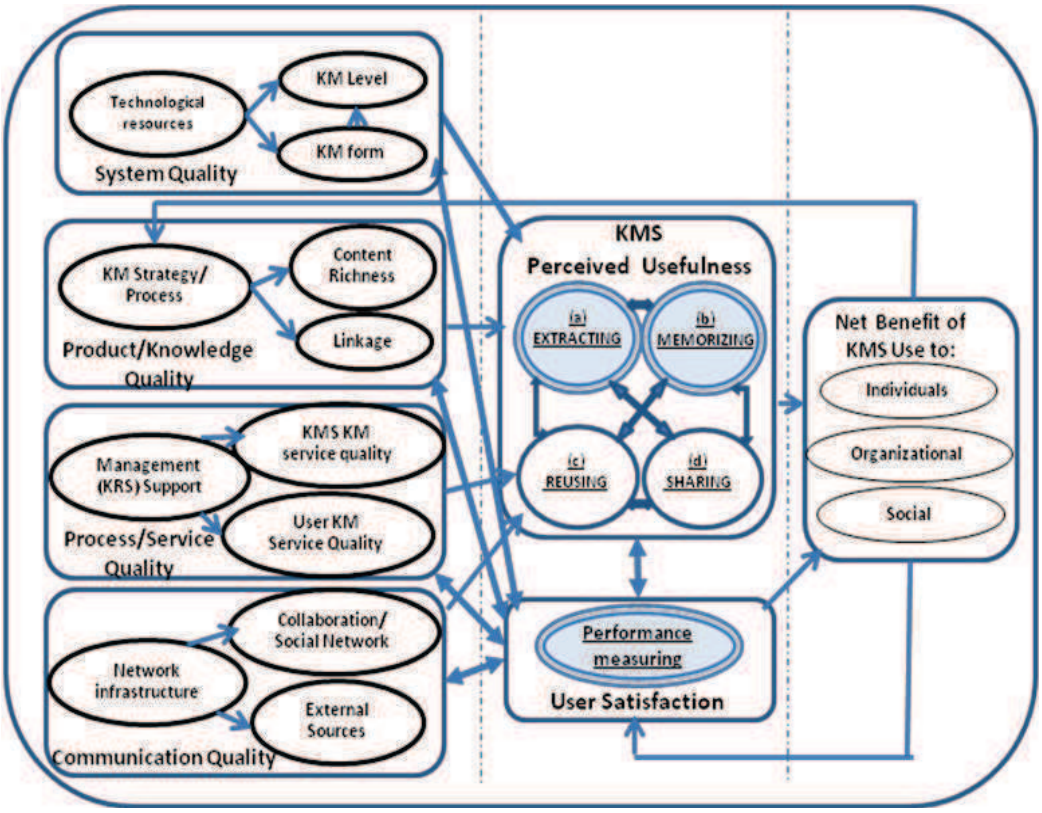


Figure 6. The *OleKMS Products*: The extended KMS success framework

It is important to point out that some of our suggested KMS success (sub) dimensions have been previously specified by other cited authors under justified reasons. Nevertheless, we have combined and re-specified some of them in our proposal focusing on a user-centered view emphasizing their main above mentioned knowledge (meta-) processes. So, the three (sub) dimensions re-specified as the most important contributions in our process-based KMS success view are associated with the following dimensions: *Communication quality, KMS perceived Usefulness, and User Satisfaction.*

To be consistent with this result summary, a short description of the main KMS success dimensions which have been included as *OLeKMS Products* of this extended model may be detailed as follows:

- *System Quality:* The technological skills as a key component to support the KM processes using high-end computational resources.

- *Product/ Knowledge Quality:* An infrastructure that integrates the KM processes into regular work practices. The user's knowledge-needs are supported according to users' levels.
- *Process/Service Quality:* Enterprise directives to ensure that adequate resources are allocated to the creation and maintenance of KM processes.
- *Communication Quality:* Technological resources for communication and improvement of information sharing and social networking tasks.
- *KMS Perceived Usefulness*: Subjective appraisal of the extent to which the user believes that this KMS contributes to use the knowledge capabilities.
- *User Satisfaction:* Some indicators about how the KMS contributes to the use of knowledge capabilities.
- *Net Benefit:* Net benefit as perceived by the different types of stakeholders.

A more detailed specification about our suggested KMS success framework components such as quality (sub-)dimensions and the re-specified user's dimensions (*perceived usefulness* and *satisfaction*) can be found in our research in advance (Gil and Martin-Bautista, 2013b).

2.1.3.5 The OLeKMS COMMUNICATIONS

OLeKMS Communication *supports internal and external communications among OLeKMS Users for sharing and transferring knowledge, in order to guarantee collaboration and coordination. Other connections needed to create and manage the OLeKMS Knowledge Sources of the knowledge networks of expert users are also considered.*

According to the Gaines model, some of the main knowledge user's needs for inter-exchange communication that would be supported by these *OLeKMS* components have to be considered (in Figure 1, the arrow symbols). These communication relationships have also to explain the convenience of communication service among the diverse user groups. Thus, the modern OL tools have considered some relevant needs of knowledge inter-exchanging among users (e.g. Web-Protégé) in addition to their improved GUI (e.g. ODEmapster).

In fact, the communication infrastructure and technologies (ICT) must support first the involved *OLeKMS Users* and their *OLeKMS* Processes (the arrow symbols in Figure 5) to increase the expecting *OLeKMS* efficacies. The Knowledge Acquisition, Refining, Organizing, and Sharing communication technologies (e.g. Web 2.0 tools), from the ICT perspective of "LA ROSA" proposal could be useful in this particular point (Ribiere and Bechina, 2010).

Finally, the *OLeKMS Communication* component intends to support our suggested *Knowledge Sharing meta-process* under the similar performance purpose of *knowledge transference* and *knowledge distribution* phases cited in (Mora et al, 2010) such as rapidity circulation and deployment.

2.1.4 The OLeKMS Application: University Case Study

A University Case Study was selected as the experimental academic domain to test the *OLeKMS* model with an OL methodological focus (Ramos and Gil, 2010).

The selected host-ontology for updating and enrichment purposes (called the DEA-ontology) is in a supervised evolutionary stage. For this Case Study, the *OLeKMS* components (*Users, Knowledge Sources, Processes, Products*, and *Communication*) are detailed along the following Subsections.

2.1.4.1 The OLeKMS Users in the Case

Some expert-users (specialized professors) and knowledge engineers were involved with the development of the DEA-ontology.

Thus, they also have the responsibility to keep this ontology updated under the quality conditions in this (OL) evolution stage. Sometimes, the associated *OLeKMS* Users have to learn about some of the KM tools to be used during the OL process.

2.1.4.2 The OLeKMS Knowledge Sources in the Case

During the SMOL application, some partial knowledge results were cataloged in repositories as *OLeKMS* Knowledge Sources, which were useful for the purpose of processing new and additional learning. Processed and obtained knowledge in diverse formats was identified as:

(a) *KSO repositories*: four ontologies associated with the academic domain were found and cataloged. The database and corpus used for OL were also recorded for future re-use. Likewise, some new subclasses during a data-mining process (in RDBToOnto) were developed from the database selected as KSO from another University. These subclasses, classified as knowledge structures (e.g., artifacts), were also included in KSO repositories;

(b) *Agent repositories:* an automatic agent for keyword identification during the OL from texts (WVTool plug-in for RapidMiner) was developed. This agent was cataloged because it can be useful for another OL process related to the corpus of documents already used, but it should be updated with additional complementary texts. Similarly, in other cases, for new corpora of different topics, this agent could be considered for this OL process or for any additional process;

(c) *MR repositories:* the various tools and methods used during the whole KA process for each KSO were cataloged as MR for possible re-use needs.

2.1.4.3 The OLeKMS Processes in the Case

Despite the fact that any other flexible and open methodology could have been used, SMOL was applied incrementally in the *OLeKMS Processes* for this Case study and this is summarized as follows:

Process 1: A host-ontology (DEA-ontology), which was taken from a previous project about a Decision Support System developed for a University specialized in Distance Education Administration (DEA) was selected to be updated (enriched/populated).

Process 2: Complementary knowledge was obtained by a comparison between the host-ontology (DEA) and another domain ontology located and recovered from the LUBM-ontology. During the OL process, the DEA-ontology of an academic management subdomain was updated by users through ontology matching methods.

Process 3: Important knowledge about the DEA domain was recovered and selected as a corpus of texts (480 files) from specialized journals related to this domain. A semi-supervised learning agent for text-mining was developed to enhance the OL. Then, some professors, as expert *OLeKMS* Users, used the tool GATE to update the host ontology (Gil et al, 2009).

Process 4: Relevant knowledge about the professors' profile sub-domains from a Relational Database (RDB) of another university was obtained .These were converted from RDB to a temporary ontology by inductive OL through data-mining techniques. A learned/matched process was applied between the RDB with the DEA-ontology by deductive OL (Gil et al, 2010).

The host-ontology was validated in every cited KA process using a reasoner tool named RacerPro to check the consistency of the quality. Some additional details of SMOL application for this Academic case are included in Subsubsection 2.2.5.1.

2.1.4.4 The OLeKMS Products in the Case

The partial results obtained as *OLeKMS Products* in each cited process of the SMOL application in the previous subsection are summarized below as follows:

Result 1: The four main classes and subclasses with the corresponding relationships and instances of the DEA-ontology for the original *OLeKMS* were used. The reviewed host-ontology's upper-classes are: Administration, Cognition, Economy, and Technology.

Result 2: Some professors' categories were defined and correlated with the Cognition-Dimension subclass in the host-ontology through OL from ontology, using an ontology recovered from the Internet (named LUBM). Students' profiles can be also affected by the professors' profiles, as was represented originally in the host-ontology.

Result 3: Some repetitive instances of locations and places where the professors obtained their degrees are identified as subclasses. Some specific instances of countries and cities (locations) for these subclasses are populated in the host-ontology by users during this OL process.

Result 4: Finally, a new and extended subclass was formed into the host-ontology through this OL process from a database of another University, considering the diverse instances of locations where the professors had obtained their University degrees (graduate/post-graduate). Additionally, some corresponding mapping with places (locations) between the RDB and the host-ontology were found by *OLeKMS* Users to test the validity and consistency of the ontology.

2.1.4.5 The OLeKMS Communications in the Case

For this Case Study, the *OLeKMS* Users were located in several University head offices across the country. Since they share similar interests, such as ‘‘trust partners’’ involved with the original KMS domain goals (advice/recommendations for students), their ‘‘social influences’’ are made easy and favorable. Consequently, the following ICTs to support KM processes for organizing, sharing, and creating knowledge have been used:

(1) the well-known Ontology Editor Collaborative Protégé helps users to reach agreements and to organize the new knowledge (enrich/populate) in the DEAontology;

(2) institutional emails have been used regularly to arrange meetings (face-to-face/media);

(3) some audio-conference meetings have been supported by the -VoIP- services of Skype;

(4) ‘‘MS-Messenger’’ has been used as instant-messaging tool to help users.

2.1.4.6 OLeKMS Case Study Results

The most relevant results of this Academic case study derived by the SMOL application have been grouped according to each *OLeKMS* component. Under our *OLeKMS* model proposal, it is easy to understand and explain the details of the users knowledge-tasks involved with an integrated KA process from diverse KSOs.

The associated users’ knowledge-tasks have been enhanced by automatic OL tools and other MRs which have simplified the users’ need for the *Knowledge Extracting* (e.g. Swoogle or RDBToOnto), *Memorizing* (Corpus in GATE), *Reusing* (e.g. Protégé-Prompt), and *Sharing* (Web-protégé) processes. The *OLeKMS* users’ tasks to support ontology enrichment and populating simplify the updating/including of diverse host-ontology classes (e.g. professor and student classes) and some class instances (e.g. study cities). Also, the case application has been useful to validate the consistency of the derived host-ontology (e.g. RacerPro tools) and the *Product quality dimension* to be measured (e.g. completeness and/or usability).

2.1.5 The OLeKMS Comparison among other KMS Models and Implementations

It was not possible to find any ontology-based KMS models for comparison purposes. It was possible just to find some architectures that were developed for DSSs, KBSs, and preliminary *Knowledge Management System* (KMS) models which can be useful to partially compare (qualities/scope) with our suggested *OLeKMS* model (Mora et al, 2010).

The most relevant features associated with these comparison results from the *OLeKMS* model proposal perspective are the following:

1. The reinforcement of the Knowledge processes (based on OL) intending an increase of their efficacious measures is a highlighted characteristic of our *OLeKMS* model proposal in comparison with other KMS models/implementations found in the literature (Holsapple, 2008) (Huang, 2009).
2. The extended version of OL using heterogeneous KSOs (e.g. databases) and the best management of these three mentioned KSOs intending to complement the effectiveness and the efficiency of the KM processes explicitly expressed in our *OLeKMS* model have some advantages over other more limited proposals in this sense (Huang, 2009) (Rajsiri et al, 2010) (Meier, 2007).
3. The convenience of an *OLeKMS* model which explicitly considers the importance of keeping their knowledge-bases and their functionalities based on ontologies continuously updated hasnot been considered by other KMS models/implementations (Huang, 2009) (Godoy, 2005) (Meier, 2007).
4. The *OLeKMS* model components have considered some explicit interrelations and quality dimensions (from the KMS success framework) overlooked in the other KMS models and/or implementations. Exceptionally, the proposal in (Mora et al, 2010) has considered the KMS also under a knowledge process view. In this sense, the *knowledge preservation* phase conceived by the authors has some similarities with our proposal for the *knowledge searching/extracting* processes, but we have specified additional details (KSOs and MRs) to include OL in those defined processes.

2.2. The SMOL Methodology

2.2.1 The SMOL Development

This suggested optional OL methodology (SMOL) has been conceived and designed from incremental and interactive experiences of some OL applications from complementary KSOs such as ontologies, texts, and databases ((Gil et al, 2008, 2009, 2010) (Gil and Martin-Bautista 2011, 2012, 2013a) (Ramos et al, 2014)).

2.2.1.1 The Ontology Learning Problematic

As a way to determine the main OL methodological requirements, it is convenient to review their associated MR problems according to the adopted systemic perspective. Therefore, to synthesize the general OL problems, a situational technical analysis, which is known as SWOT (Strengths, Weaknesses, Opportunities, and Threats), is used (Hill, T., and Westbrook, 1997). This technique simplifies the OL understanding from two broad perspectives. Firstly, it addresses the knowledge development and reconstruction as an OL process and, secondly, it studies the quality of the results from a semantic point of view.

In agreement with Gómez-Pérez, and Manzano-Macho, (2005), Shamsfard and Abdollahzadeh (2003); two conclusions taken from those studies about OL methodologies can be summarized as follows:

- Regarding OL Methods; a) there is not an established standard; b) the methods are not usually combined; and c) many methods are not associated with specific tools.
- With regard to OL Tools: a) all of them help to extract knowledge; b) a small group of them allows the retrieval of a complete taxonomy; c) only some tools support specific OL methods, and d) some of those tools are difficult to be evaluated.

It is also possible to infer that OL methodological options do not exist as a complete integration and dynamic way to face the OL problems for identifying and selecting "knowledge-objects" from different sources as ontologies, texts, and databases. Nevertheless, recent works show the incorporation image and videos as useful KSOs (Castano et al 2007) (Catsano et al, 2009). The OL methodologies must offer a wide and suitable support to users for the ontology updating purpose associated with their KMS.

The SWOT analysis applied in this work has been useful to overcome pertinent limitations present in previous OL methodologies. Some specific OL *weaknesses* and *threats* (dispersion of availability and non standard MRs as well as additional KSOs) and other OL *strengths* and *opportunities* (the reuse of available MRs and the systemic incorporation of emerging ones) can be useful to be incorporated below in our OL methodological proposal (SMOL).

2.2.1.2 Some Relevant OL Methodologies

Our SMOL proposal is more aligned with continuous KA processes (ontology enrichment and populating) in comparison with some of the most relevant OD methodology useful to develop/create ontologies. Some instances of the latter such as the Ontology-Guide-101 (Noy and McGuinness, 2001), ONIONS (Gangemi et al, 1999), Methontology (Gómez-Pérez et al 2004), UPON (De-Nicola et al, 2009), DILIGENT (Pinto et al, 2009), OntoClippy (Dahlem, 2011), and the NeON methodology (Suarez-Figueroa et al, 2012) have incorporated optional KSOs and MRs (e.g. tools) to build the "wanted ontologies". Thus, some above mentioned OD methodologies can be useful as a reference for evaluating below (by comparison) the most distinctive methodological characteristics of our proposal. However, our central interest for design and valuation purposes is based on the recent OL methodologies found in the literature.

Some of the most relevant OL methodologies which consider diverse MRs, KSOs, and/or (un) structured media found in the literature have been reviewed and used for comparison purposes. Specifically, they are the following: a) the Simperl et al in (Simperl et al, 2008); the BOEMIE (Castano et al, 2007,2009); c) the DINO (Nováček, 2008); and d) OntoCmaps (Zouaq, 2011).

The main characteristics/features of these selected OL methodologies (*main assumptions*, *methodological orientation profile*, workflow focal-point, ontology base of reference, and so on) have been used to evaluate our SMOL proposal by screening comparison (Gil and Martin-Bautista, 2013a). Additional details of the corresponding results can be found in Subsection 2.2.6.2 about the SMOL evaluation.

2.2.2 The SMOL Objectives

The main objectives of SMOL are:

- Taking the most potential knowledge changes to be expressed as *ontology-objects* (instances, classes, and relationships) for each specific KSO using diverse MRs.
- Customizing a cost/effective methodology-strategy (MR combination) to be applied according to the heterogeneous and available KSOs. Some costs would be associated with the tool acquisitions (non-open licenses) and the required user training.
- Clear identification of user-activities to be followed during each phase (Objectives /Input/MRs/Results).
- Improvement of the quality of updated ontologies by cyclical-control validation (Users' decision points).
- Reusing of knowledge based on cataloging/storing of partial inputs/results of declarative and implicit/procedural knowledge.

2.2.3 The SMOL Design Criteria

In this methodology design, we have considered some criteria based on previous studies:

- In the SMOL workflow design, we use the conceptual framework cited above (Yao et al, 2007). Some of these original Yao's process objectives were adapted and adjusted to our methodology as workflow. In this regard, the initial selection of strategy, the inclusion of cycles and decision points, as well as the details of the processes (tasks) have been introduced as improvements in comparison to Yao's framework. Let us remark that our proposal is user-centered, thus, the user's participation and the SMOL adaptation to the user are crucial points in comparison to Yao's proposal.
- The Methodology strategic selection phase has been designed considering that the users

of SMOL may adjust the MRs according to the information available in the KSO. The purpose is to select a suitable strategy (Top-Down, Bottom-Up, or Middle-Out) after estimating a sort of domain-complexity. This domain-complexity estimation could be obtained by Expert Users using a heuristic about the availability of KSOs or by assessing it according to their own domain expertise and background. This germinal idea was previously presented in Zhou (Zhou, 2007), where only texts are considered as a source. In our proposal, other sources (ontologies and databases) are also included.

- Knowledge Sources (KSOs) are configured as flexible, adaptive, and incrementally reusable sources. For instance, ontologies and OL corpora from texts could be also reused. For this reason, the storage mechanism for the efficacious management purpose of these sources becomes a key point in our design (KRS stated in Subsection 2.1.2).
- User/Task profiles are created and stored with the purpose of reusing them in recommending tasks. This process reinforces the intended user-centered aspect of our methodology (the above commented TMS in Subsubsection 2.1.2.2).

2.2.4 The SMOL Specification

The workflow of the Systemic Methodology for OL is proposed emphasizing the methods and techniques recommended to be used in each specific phase. This methodology workflow applied for OL from each KSO is shown in Figure 7 and summarized below:

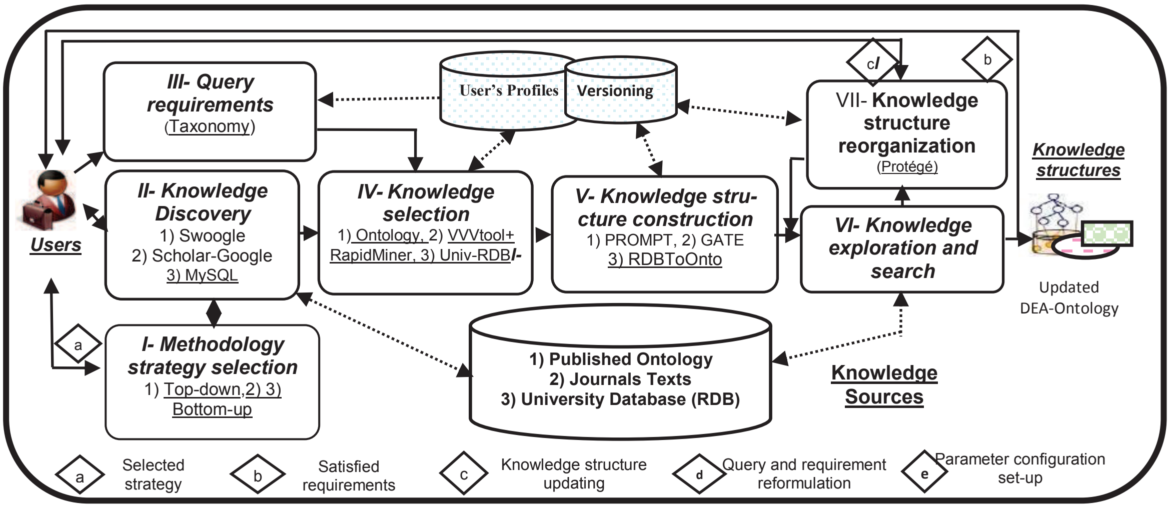


Figure 7. The *Systemic Methodology for Ontology Learning (SMOL)*

I. *Methodology strategy selection*. The complexity of the domain is evaluated based on the availability of: a) the thesauruses and dictionaries for that domain, b) other previously developed ontologies, c) knowledge updating frequency, and d) the disciplines that cover this domain. This methodology strategy is user-drafted through inductive/deductive OL processes and selected using a suitable arrangement of MRs for each related KSO. Query requirements. Different queries are formulated to the available KSO by browsers or other kind of applications. The queries are related to competence questions which the ontologies must support/meet.

II. *Knowledge selection.* A selection of the retrieved data from the formulated queries to the sources and repositories is performed. The associated meaning (semantics) and the consistency of the format of some potential *ontology-object* retrieved from each KSO are checked by Expert Users. Some MRs which can automatically check some ontology-object consistency are included.

III. *Knowledge structure construction.* Different structures such as ontologies and contexts can be interactively built with users' advice through MRs such as: ontology alignment, machine learning techniques, etc. The data-format conversions (automatic/manual) of the potential *ontology-objects* retrieved from each KSO are verified occasionally by Expert Users.

IV. *Knowledge exploration and search.* The knowledge structures are explored, verified, and validated and the search can be refined (automatic/manual according the available MRs).

V. *Knowledge structure reorganization.* OL Processes such as grouping of instances, ontology population, and other similar tasks are performed in this phase.

VI. *Knowledge system configuration.* Users set up the main modules/components of the KBS/KMS that have ontologies associated with the users' domain.

Throughout the SMOL workflow, up to five *Decision points* have been included supporting the user's participation to check the semantic quality during the OL process; the most relevant ones are the following: a) *Selected strategy:* validating the user satisfaction/agreement in relation to the methodology strategy selected*; b) Satisfied requirements:* verifying the satisfaction of the KMS users requirements; c) *Knowledge structure updating:* verifying ontology updating correctness for instance by an Ontology evaluation task; d) *Queries and requirement reformulation:* verifying ontology updating completeness; and e) *Configuration parameter certification:* validating the KMS operational parameters.

2.2.5 The SMOL Application: The Academic and the Manufacturing Domain

SMOL has been applied in two real case studies. The case studies are respectively associated with the Academic and the Manufacturing domains. The former has been partially introduced in the case of the *OLeKMS* model (Subsection 2.1.2).

These domain cases have been used to validate and test the SMOL application as regards its usability features during the KA process (Academic case) and for the quality validation during an OD process (Manufacturing case). This main objective of the former case is subdivided respectively into three partial sub-goals (steps) to reach a whole KA process from each KSO (ontologies, texts, and databases). On the other hand, the latter is subdivided in two partial sub-goals (steps) according to the available KSOs (prior ontologies and corpora).

2.2.5.1. The Academic Case Study

The three groups of SMOL workflow steps regarding each used KSO are detailed as follows:

1. OL by comparing/updating with another ontology domain located and recovered from the Internet. From this recovered ontology, the Academic management DEA-Ontology is updated by users through ontology-matching methods (FOAM) and tools (Protégé-Prompt).

2. OL from a selected set of texts from specialized Educational journals. Moreover, these users help the Knowledge engineers to evaluate the keywords obtained from the corpus using "unsupervised learning" under an automated agent developed for this case, helping as well as to validate the ontology updated in advance.

3. OL from a Relational Database (RDB) that belongs to another local University. It is converted from this RDB into a temporary ontology by inductive and deductive learning, using varied conversion-tools for turning RDB into ontologies.

A summary of the MRs used during the SMOL workflow application according to each of the involved KSOs is shown in Table 3.

Table 3. A summary of the main SMOL workflow steps for each KSO

	SMOL from Ontologies	SMOL from Texts	SMOL from Databases
1	The LUMB-ontology is found through the Internet and used to match with the host-ontology (OL from ontologies).	The corpus is developed from 1000 original academic texts and refined to finally select the 480 most relevant ones.	The other real database was found and used (RDB-IUTEPAS) as KSO for OL from the database.
2	The EuroWordnet tool is applied to translate DEA-ontology terms from English to Spanish.	A text learning agent was developed using text-mining tools (RapidMiner) to obtain relevant keywords of the corpus.	The RDBtoOnto and ODEMapster tools were used to update the host ontology from the database.
3	Expert-users validate the ontology term consistency to reach syntactic matching between both ontology terms to be matched.	Users validate the relevance of the previously identified keywords . They introduced them into the GATE tool to match them within the host ontology.	A deductive OL process (from the RDB-Scheme) was applied to update the host-ontology. The Protégé tool was used for term matching purposes.
4	The Protégé-Prompt tool is used for matching purposes, including support of a visual plug-in (CogZ) to help users.	The visual option on the GATE tool is used to validate the host-ontology updating process from these keywords.	Inductive OL processes (RDB data-mining) were applied to update the host-ontology (GUI of ODEMapster).
5	The Racer-Pro tool is applied to validate the host-ontology consistency.	The Racer-Pro tool is applied to validate the host-ontology consistency.	The Racer-Pro tool is applied to validate the host-ontology consistency.

In addition to suggesting a helpful and thorough SMOL workflow, some important OL technological contributions are obtained respectively as the results of this application from each KSO. The most highlighted contributions as partial and novel MRs are summarized as follows:

1) The visual user support for learning through ontology matching using the Protégé-Prompt with the CogZ plug-in. Thus, the reuse of domain ontologies which had been partially stored as KSOs (MR: a retention technique) can increase the efficacy of additional future OL processes.

2) The developed agent -using the RapidMiner tool- applied to identify relevant keywords from the corpus. Thus, the reuse of this agent (MR: an agent as a novel tool) in the same Academic case in

the corpus (using further texts) or in other cases (e.g. the manufacturing case in Subsubsection 2.2.5.3) can increase the efficacy of additional/new OL processes from texts;

3) The ontology option -in the GATE tool- used to validate the corresponding matching of these previously identified keywords with the terms of the host-ontology. The relevant keywords which are automatically identified (for instance, applying the developed agent) or included manually in the user's tool option (GATE Gazetteers) become a simplified way (MR: a new KA technique) to test some group/individual matching with the ontology-objects in the host-ontology

4) The two useful tools applied for OL from databases (RDBtoOnto and ODEMapster) to update the host-ontology through inductive (data-mining) and deductive (RDB-scheme) methods show an empirical evidence as a useful way (MR: a new method) to make the best for KA from databases.

2.2.5.2. Relevant Case Study Results from the Academic Case

Some results obtained as semantic-products in each mentioned OL process by the SMOL application in the previous subsection are summarized as follows: a) The four main classes and subclasses of the DEA-ontology were reviewed/updated; b) some professors' categories and student profiles were defined and correlated with the Cognition-Dimension subclass in the host-ontology through OL from the LUMB-ontology; c) some repetitive instances of locations and places where the professors obtained their degrees were identified as subclasses; d) a new and extended subclass was formed into the DEA-ontology through this OL process from a database of another University; e) some corresponding mapping with places between the RDB and the host-ontology were found by expert-users to test the validity and consistency of the result; and f) the analysis of the OntoQA metrics corresponds with the quality property of the DEA-ontology used to support a KMS application.

Finally, a derived multi-format KRS has been suggested also in SMOL to support future OL processes and knowledge reusing needs (in technical report (Ramos and Gil, 2011) such as: a) Some partial KSO repositories (corpus, group of ontologies, the RDB-IUPEPAS); b) Agent repositories (a relevant word identifier was developed as an agent in RapidMiner); and c) the MR repositories (instances of tools: Protégé-Prompt, GATE, RapidMiner, and so on).

2.2.5.3. The Manufacturing Case Study

The particular OD methodology adaptation applied in the manufacturing case study is shown in our work (Ramos et al, 2014). This particular OD process is derived from a customization/adaptation of the SMOL workflow. Specifically, it has applied OL processes from ontologies and from texts.

As the main result, the MOP-ontology has been developed (reusing three previously developed domain ontologies) and validated using the "keyword identification agent" developed in SMOL (RapidMiner of Rapid-I tool) for a matching validation process later (using the GATE tools previously developed for our Academic case study) (SMOL from texts, Gil et al, 2009).

The whole OD process to build the MOP-ontology has been summarized as follows:

1) The domain ontologies MASON, MTM, and MO have been (re) used as KSOs. The above mentioned methodological workflow oriented to support an interactive OD process has been followed to match those ontologies with their constitutive components (Ramos and Gil, 2011).

2) SMOL from text application. A corpus used as KSO has been built from 633 XML-texts. To validate the users' requirement satisfaction of the obtained MOP-ontology, some current Competence Questions (CQs) about the manufacturing domain were formulated. This CQ technique has been useful to compare the new developed MOP-ontology answers with the other obtained ones using the three previously developed ontologies.

2.2.5.4. Relevant Case Study Results from the Manufacturing Case

Some relevant results related to this case study, considering the SMOL viewpoint, are the following:

1. The domain complexity used as a reference to formulate a methodology strategy selection (as it is suggested in SMOL Phase 1) was a useful method/technique to deal with the domain complexity to define the best MRs useful to be applied according to this specific case. The final suggested strategy was the middle-out one (Ramos and Gil, 2011).

2. By analyzing the contents of the corpus, the obtained domain ontology (MOP-ontology) was validated. The analysis was carried out by matching ontology components with the relevant terms (keywords identified by the agents) in the developed corpus.

3. The combination of the keyword identification agent (developed in SMOL using the RapidMiner tool) with the GATE tool to support the Graphic Users Interface (GUI) needs during the matching process. In this sense, with the former, the difficulty of selecting the relevant keywords from the corpus (automatically) has been simplified and with the latter, a more adequate user visual matching among the texts-terms versus the ontological objects (visually supported) has been achieved.

2.2.6 The SMOL Evaluation

There are not so many alternatives for the evaluation of methodologies applied to the Ontology Development and Learning field. One of the most accredited methods and also, one of the most commonly referred ones in the Software Engineering area are the DESMET methods (Kitchenham, et al, 1997).

In this sense, we have used the combination of three methods suggested in DESMET to technically evaluate our integrated OL methodology proposal: 1) *Qualitative screening:* A feature-based evaluation executed by a single individual who not only determines the features to be assessed and their rating scale, but also carries out the assessment. For an initial screening, evaluations are usually based on the literature describing the software method/tools rather than the actual use of them; 2) *Qualitative experiment:* A feature-based evaluation implemented by a group of potential users who are expected to try out the methods/tools for typical tasks before delivering their evaluations; and 3) *Qualitative case study:* A feature-based evaluation performed by someone who has used the method/tool on a real project.

In this work, the *Qualitative screening* evaluation is divided into two: 1) using a previous study about the evaluation criteria of users' usability and suitability of OD methodologies cited in (Dahlem et al, 2009); and 2) using a comparison with other equivalent OL methodologies. Besides, other complementary methods for *ontological evaluation (OE)* suggested in (Sabou, and Fernandez, 2012) have been applied.

Consequently, some general features about the SMOL evaluation have been considered: a) *the Usability-feature analysis*: some relevant (OD) usability criteria such as *Adequate terminology, Descriptiveness, Error avoidance*, and *Consistency* can illustrate some individual qualities which have been incorporated into the SMOL methodology; b) *the characteristics of Ontology Development (OD) methodologies*: our OD comparison shows that SMOL has up to ten of the thirteen representative criteria for methodology usability/suitability used as reference; c) *the main features of the OL methodologies*: As a main result of this OL comparative analysis, we can state that SMOL has more elaborated MR options to support OL processes from complementary KSOs (domain-complexity, databases as KSOs, flexibility to incorporate new MRs, and so on; and d) *applying Ontology Evaluation (OE) methodologies*: we have incorporated/applied a couple of MRs (and tools) for ontology quality evaluations (e.g. OntoQA and RacerPro).

2.2.6.1. SMOL Evaluation: Discussion of Results

After completing the evaluation process using the three aforementioned DESMET methods, a summary of the main obtained results has been analyzed in this subsection.

Equally, consequently with the systemic quality perspective adopted, and for simplifying the discussion of the results, they are explained below according to each applied method. This explanation is given in terms of the favorable impact of some SMOL features assessed over the efficiencies and the effectiveness related to the KA Processes and their associated Products.

The *Qualitative screening* evaluation results (individually by OD characteristics and comparatively by OD/OL features) allow us to ponder the following elements:

- SMOL contains many of the relevant usability criteria (10 of 13) suggested by (Dahlem et al, 2009) just as happens with any other equivalent "open" methodology.

  Regarding the comparison of SMOL with other OD methodologies, SMOL contains, at least, the same criteria as any other similar one. Likewise, based on other more specific criteria related to this systemic methodology such as Descriptiveness, and Hiding formality, SMOL is better than several of them. Concerning the OD comparing approaches, SMOL has specifically improved the efficiency (including the *Satisfaction* criteria*)* and effectiveness of the KA Processes and the efficiency of the Products (by having the *Error-Handing* criteria).

- Complementarily, the SMOL methodological screening comparison to another four OL methodologies in Subsubsection 2.2.6.2 reveals some outstanding features about SMOL. Firstly, it considers MRs as customizable and reusable means according to users' objectives to dynamically select a methodological strategy to reach more effectiveness of the KA Processes.
- Secondly, KSOs such as database options have been included in SMOL as a key factor in the knowledge recovery about organizational facts (RDB-schemas) and some historical data trends (data mining). In this sense, none of the selected OD and OL methodologies for the comparison with SMOL takes into account (explicitly) the domain databases as another significant KSO. So, the importance of the customization of the MRs for the involved KSOs during the SMOL application is linked to the efficiency of the KA Processes;
- Some OE activities have been explicitly included into the SMOL workflow, such as *Decision point* for the phase tracking task developed by users, a workflow for OE control,; and a couple of tools for automatic ontological quality checking/measuring (Racer-pro/OntoQA). Specifically, all of them have been applied to this case.

On the other hand, under the evaluation of DESMET applying the Experimental and Academic case study, the most distinctive and prominent design properties about the SMOL qualities have been tested and validated. Some details about the SMOL assessing results are explained as follows:

- The MRs selection (associated with SMOL Phase I) was tested through the SMOL application. It was mainly useful to identify the ontology-objects required for enriching/populating the host-ontologies of both domains from each of the cited KSOs. This cited identification would favorably affect both Semantic-Product measures (efficiency and effectiveness).
- As another distinctive difference, the fact that SMOL users could combine diverse methodological strategies in relation to the selected MRs and KSOs or by reusing some of them which were previously cataloged has been tested and validated. Knowledge engineers can include some emerging/new MRs (e.g. tool). Thus, these flexibility features would impact on the efficiency and effectiveness of the KA processes.
- The users' recommendations and the ontology versioning considered as the SMOL design properties are tested and validated as useful resources to improve both KA Processes and Semantic-Product efficiencies.

- Some favorable survey results about the user's satisfaction experimentally tested and validated regarding the flexibility of SMOL related to the capability of the systemic MR integration and reusing are considered as an attribute that enhances the effectiveness of both KA Processes and Products.
- Regarding these DESMET methods, they reveal that SMOL could be considered as another tested and validated methodology for OL purposes under a systemic view. Moreover, SMOL presents additional high-quality ranked attributes to reach the best possible Semantic-Products through efficacious and integrated KA Processes.

After all, some of the most relevant advantages of SMOL as a novel methodology to support OL processes from heterogeneous and complementary KSOs in comparison with other previous approaches have been tested and/or inferred according to the real/potential effect over the OL Processes and OL Products obtained.

A summary of *most of the OL Process advantages* incorporated the SMOL methodology are the following: 1) making the most of knowledge availability from useful/qualified KSOs; 2) the incorporated database as another effective KSOs for OL; 3) the flexibility to start the OL process through any convenient KSO; 4) the flexibility to adopt MRs, including the emergent ones; 5) the fact that the MR's standardization is straightforward due to the systemic focus; 6) the standardized workflow-phases and quality OE means; and 7) the possibility of including some MR for OE due to this systemic view.

On the other hand, the *favorable impact over the semantic OL Products* through the SMOL applications can be summarized as follows: 1) partial Products/Processes can be stored (KRS) for reuse; 2) partial MRs/KSOs can be stored (KRS) for reuse; 3) users' logs / tracks can be stored (TMS) for sharing with other users; 4) another type of knowledge-representation can be included; 5) the GUI of the tools may be extended to manage stored MRs/KSOs; 6) some new kinds of MRs for OE can be included; and 7) some user's lessons learned can be replicated in other real cases.

3. CONCLUDING REMARKS

The following section shortly summarizes the obtained results and presents several conclusions.

- Consequently with our main *OLeKMS* model purpose, the possibilities to improve KM processes to guarantee the continuous updated state of the knowledge-base have been increased in this work, due to the fact that the KM process required for these purposes has been redefined and carefully specified (*OLeKMS Processes*). The MRs for OL incorporated in those associated KM processes must turn into more efficacious ones, because that can facilitate accessing internal/local knowledge (reusing *OLeKMS Knowledge Sources*) as well as the external KSOs using automatic agents/tools (e.g. Watson and/or Swoogle tools). Complementarily, with the improvement derived from the inclusion of external and internal KSOs, the efficiency of the management of the KSOs has been improved once the organizational memory system and its recovery mechanism (KRS and TMS) have been incorporated into the *OLeKMS Knowledge Sources*. In fact, these enhanced *OLeKMS KSOs* management mechanisms favorably impact the corresponding *Memorizing* and *retention* (meta/sub) processes related to KA tasks.

- The effectiveness of KA processes would be conditioned by the quality and quantity of KSOs available to update the *OLeKMS* knowledge-bases. A way to increase the quality of the associated KA processes was established through the incorporation of additional KSOs (ontologies, texts, and databases) from several organizational contexts (from the A&M model), particularly, the OL enhancement over the *OLeKMS Processes* which are susceptible to be improved using the modern MRs (e.g. automatic tools). The incorporation of additional KSOs (from external organizational contexts) has considered the impact over the efficacy through the (re)use of partial previously *used* and *memorized* KSOs (from internal/local contexts) for these ends.
- A novel hierarchy of knowledge (meta/sub) processes has been conceived considering the KMS user's perspective. The most relevant knowledge (meta/sub) processes associated with the KM tasks and, particularly, the KA processes, have been identified. Correspondingly, the knowledge meta-processes "*Extracting* and *Memorizing"* as well as the "*retention* and *search"* sub-processes have been primordially associated with KA tasks. Specifically, the latter has been derived from an updated version of the A&M model (see Figure 1) and improved by the OL technology (MRs for each KSO) to support some of the *OLeKMS Process* components. Some of these enhanced OL capabilities have been tested trough the SMOL application in both case studies.
- The associated Communication service required to support KM processes can be improved and supported through several recently developed ITC tools. The requirement by some users to support OD/OL processes has been enhanced through (interactive/iterative) primitive communication tools. Gradually, more of the new associated OL communication tools have incorporated some additional GUI capabilities, combining in a simplified way graphical knowledge representation from different KSOs (e.g. ontologies among them, databases versus ontologies, and/or texts versus ontologies). Those MRs increase the user's participation because they facilitate the communication required among the diverse involved users. Users can make the best of the Knowledge (meta-) processes such as *Reusing* and *Sharing* based on the application of some recent OD/OL tools (Web-Protégé, Protégé-Prompt, OntoCmaps, and so on).
- The KMS knowledge process performance efficaciousness has been incorporated in the *OLeKMS Products* component by twofold: on one hand, using a systemic bottom-up way associated to the (suggested KMS success) *user perceived usefulness dimension*, considering each knowledge sub-

process (*search, retention, transfer,* and *creation*) which could be improved by OL technology empowerment (favorably impacting the corresponding meta-processes: *Extracting, Memorizing, Reusing,* and *Sharing*); and on the other hand, the top-down way; specifying the performance measures to be reached through the application of those processes in the *User satisfaction dimension* (KMS success). Both User's dimensions and the induced relationships with the associated knowledge (meta-) processes have been synthesized (see Figure 6).

- The associated *OLeKMS* success dimensions have been re-specified to consider the new quality trends which are aligned with our original *OLeKMS model*. In this sense, the dimensions and sub-dimensions incorporated within the *OLeKMS Product* component have considered the best tradeoff among the technical required *quality dimensions* (e.g. *Communication* and *Knowledge processes*) and the knowledge performance improvement demanded by users in their corresponding *Perceived Usefulness* and *Satisfaction dimensions*. Our *OLeKMS* success framework proposal in advance has included the knowledge process measures as indicators to be used to check qualities and to make the required corrections using feedback and/or feed-forward control cycles.
- Due to the difficulty of identifying the main user requirement about a useful OL methodology, we have to incorporate an Analysis technique (SWOT in Subsection 2.2.1.1) to ponder the relevant features associated with the OL problematic under a systemic perspective (users/clients, the main processes, and their obtained products).
- In addition to the different features to be considered regarding the variety of KSOs included in an OL methodology (e.g. Contextual level, Process impact, MRs capabilities according to each KSO, and so on), the most relevant useful one to overcome weaknesses in OL methodological resources (by the SWOT analysis) as well as the new ones not considered previously in any other OD/OL methodology have been used to define the main users' requirement for designing the integrated OL methodology (analyzed in Subsection 2.2.6).
- An important aspect to verify and test the current results regarding the KMS and the SMOL applications has been performed through a couple of real case studies. So, the Academic case has been useful to experimentally test the straightforward SMOL workflow as well as the *OLeKMS model* applicability. On the other hand, the Manufacturing case has been useful to apply a dynamic methodological strategy selection as well as to consolidate the importance of reusing "procedural" knowledge which was previously developed as an agent ("keyword identification") for the Academic case**.** Throughout these case applications (considering the involved KSOs and both lessons learned), we have refined the SMOL workflow phases as well as derived some OL technological contributions (as MRs) associated to each KSO.

- SMOL has been validated and tested regarding the usability features among other OD methodologies using structured DESMET methods (from the software engineering field). Furthermore, by comparison with other OL methodologies, the most relevant OL features have been compared applying DESMET methods as well. Consequently with our SMOL evaluation results, the most relevant comparative advantages of SMOL against the other OL methodologies have been considered (and tested through the cases) useful to adequately support many of the KMS knowledge processes from heterogeneous KSOs. Particularly, this SMOL methodology application could be useful to stand out some relevant *OLeKMS* components (Processes, Products, and KSOs) as they were specified in the model.

4. FUTURE WORK

This PhD work presents an original ontology-based KMS model (*OLeKMS*) which could be (continuously) enriched and empowered by some updated OL methodological resources. Furthermore, an integrated OL methodology has been suggested (SMOL) to thoroughly incorporate the available heterogeneous KSOs as well as to include additional features not incorporated in previously revised OL methodologies. On the other hand, the diverse KMS quality requirements (the expert-view and the user-centered perspectives) have been (re)specified based on an integrated and extended total quality view (Users/Processes/Products/KSOs) and from some KMS success framework advances (in (sub)dimensions recommended in the literature). In fact, any relevant research field associated with 1) the KMS modeling (Mora et al, 2010); 2) the KMS success framework evolutions, and 3) the OL technology (MRs from each KSOs) is nowadays in continuous evolution and undergoing many changes. In this section, we present some research lines raised from the proposals presented in the memory.

The Ontology-Based KMS Modeling

Current KMS implementations are requiring appropriate references for a more adequate interrelation with the ontology technology (Cheng et al, 2009) (Alquiler et al, 2009). In fact, interesting theoretical approximations consider the ontologies as a potential resource for KMS development under quality standards (Mora et al, 2010). Besides, the system modeling activities have to consider the ontologies as a relevant resource because of their capability to meet many users' requirements (Nasir and Noor, 2010). On the other hand, recent works have introduced a performance comparison and/or combination of KMS with other technologies (databases or object oriented) as a way to show the ontological resources to improve the KMS capabilities (Chakrabortya et al, 2011). Furthermore, the complexity of integrating several inter-organizational ontologies in a convenient KMS network (based on ontology mediation) has been recently considered as well (Leung et al, 2013).

The KMS Success Frameworks

Our vision of a KMS framework proposal has considered the most recently published KMS success framework improvements. Consequently, our suggested organizations of the main associated KMS success (sub) dimensions have considered the quality and efficacy of the users' knowledge-task processes just as other authors have as well (Triche et al, 2012). Some important references about theoretical and experimental KMS success cases have been recently documented. The validation of the diverse KMS success (sub) dimension interactions which have been taken into account in the corresponding knowledge processes performance measures and indicators have also been recently considered in the literature (Jennex, 2013).

The OL Methodological Resources

Progressively, more MRs related to the different KSOs included in this thesis have been emerging. In the field of the OL from texts, new initiatives can be introduced once the machine learning algorithms and the NLP techniques have been gradually enhanced (Wong et al, 2012). About the OL from ontologies based on matching procedures, it has been improved during the last decade (Pavel and Euzenat, 2013). Thus, organizations such as OAEI intend to keep continuous open ontology matching workshops to evaluate new tools and software product initiatives (OAEI 2013). Finally, the OL from databases is another open research line which could be stimulated once the associated KMS users' requirements have demanded increasingly semantic association with the organizational data. Some innovative MRs for OL from databases (e.g. automatic tools) based on novel IA applications are up-and-coming recently (Chen et al, 2009) (Zhang et al 2010) (Santoso et al, 2011).

PART II. PUBLICATIONS

1. The OLeKMS modeling and refining
   1.1. *A novel integrated knowledge support system based on ontology learning: Model specification and a case study* (KNOSYS-2012).
   1.2. Toward A Process-Based KMS Success Framework Improved Through Ontology Learning Technology (Applied Ontology: Submitted Dec-2013)
2. The SMOL development and evaluation
   2.1. *Towards a Machine of a Process (MOP) ontology to facilitate e-commerce of industrial machinery* (COMIND-2014)
   2.2. *SMOL: A Systemic Methodology for Ontology Learning from Heterogeneous Sources* (JIIS-2014)
   2.3. Applying An Ontology Learning Methodology To A Relational Database: University Case Study (Conference: ICSC-IEEE-2010)

1. THE OLEKMS MODELING AND REFINING

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A novel integrated knowledge support system based on ontology learning: Model specification and a case study

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ABSTRACT

Semantic engineering is currently being adopted to support the knowledge-management processes needed by organizational users for decision-making and task-intensive knowledge activities. Such optional engineering strategies consider that some systems, such as the *Knowledge Support System (KSS)* fulfill the needs of the knowledge user, by providing the services and management qualities they require. Some key features of the KSS have been analyzed to identify their main characteristics or system components according to the most recent trends. Lately, some solutions have been proposed to develop this type of knowledge system based on the approaches, Ontology Development and *Ontology Learning (OL)*. In this paper, a novel model of an *Ontology-Learning Knowledge Support System (OLeKSS)* is proposed to keep these KSSs updated. The proposal applies concepts and methodologies of system modeling as well as a wide selection of OL processes from heterogeneous knowledge sources (ontologies, texts, and databases), in order to improve KSS's semantic product through a process of periodic knowledge updating. An application of a *Systemic Methodology for OL (SMOL)* in an academic Case Study illustrates the enhancement of the associated ontologies through process of population and enrichment.

1. Introduction

Some Knowledge Systems are oriented toward the support of users' requirements in organizational knowledge processing. These systems may be an alternate way of increasing the efficiency of Knowledge Management (KM) through semantic learning [1–3].

According to Venzin et al. [4], knowledge is important for the theoretical reality of strategic management, basically because knowledge simplifies sustainable, heterogeneous resource distribution, knowledge changes the nature of investment decisions, knowledge changes the nature of work and property and knowledge emphasizes the social context. This last point reinforces the twofold concept of KM systems as capable of managing individual and group knowledge, according to the following definition of KM given in [3].

"KM is a systematic method for managing individual, group, and organizational knowledge using the appropriate means and technology. At its root, it deals with managing people, what they know, their social interactions in performing tasks, their decision making, the way information flows, and the enterprise work culture."

For our proposal, we concentrate on the three most relevant aspects of KM:

(1) *the perspective of collectivist knowledge* -the social aspect of the interchange of knowledge (groups, communities, networks, and organization units) is considered, rather than the individualist aspect [5];
(2) *the reusability of the properties of knowledge* -the capability of knowledge to generate new information as a product of the intervention and processing carried out by users, the implicit and explicit quality features and the possibility of converting from the former to the later [6];
(3) *knowledge as a competitive resource from diverse knowledge sources (KSOs)*-an assessment for the support of decision/task/recommendation management, knowledge can be used as technical representation method (e.g., ontologies), and different KSOs can be recovered and discovered through diverse Methodological Resources (MRs) [7].

In the framework of KM, Decision Support Systems (DSS) are comprised of *Knowledge-based Systems (KBSs)* and the *Knowledge Support Systems (KSSs)* [8–10]. The KBS can be better qualified as software developed to satisfy specific user's needs, usually as an application for expert decision-making. They include expert systems, intelligent decision support systems or specialized data

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bases systems used to store experiences, lesson learned, know-how, and best practices, as well as technical solutions [11,12].

In KSS, they are oriented to help both knowledge activities, such as organizational practices and routines (e.g., document management), knowledge distribution (e.g., groupware), for the purpose of knowledge adoption (new products and new markets), and so on [13]. Keeping our work in a generic perspective, as proposed by Gaines [14], the term KSS "..*is used to encompass all systems (computer-based) whose primary function is to support knowledge processes in the society*". As the same author's state "..*the term is deliberately left unqualified -open- to encompass non-computer-based systems supporting knowledge processes*". Some details about this view of KSS are described in SubSection 2.1.

Our premise is that new knowledge is required for the continuous process of KSS updating in order to keep organizations updated, and this associated knowledge is usually represented as ontologies in the new trends of KSS. However, diverse KSOs are overlooked as key features for the updating of the KSSs. We suggest an OL process for Knowledge Acquisition (KA) as a useful option to extend the life-cycle of these KSSs. OL, from different KSOs, can improve KSS through the growth of the knowledge, and through processes of comparison and restructuring of the knowledge structures in their knowledge-bases.

To deal with this problem, we have focused on a systemic approach in order to include the necessary learning faculties of OL, considering it to be another KSS key component that can guarantee the continuous updating and enrichment of the organizational knowledge. In particular, we propose an appropriate ontology-based KSS architecture that is designed to meet the users' requirements, related to their KM-updating activities.

The principal focus of this work is:

(1) to study the characteristics of some KSSs, especially those with ontology-based mechanisms to meet diverse users' needs;
(2) to analyze the current characteristics and capabilities of OL methodology, in order to keep the ontology-based KSSs updated;
(3) to review the KSSs in a social perspective and to try to increase the available KSOs, in order to keep them as functional and updated as users require;
(4) to use some MRs for OL from diverse KSOs (such as ontologies, texts, and databases) for the processes of updating and enriching the knowledge processes of the KSS semantic structures (e.g., ontologies).

The main *contributions* in this work are:

(1) to provide a new perspective of KSS, based in OL, from diverse KSOs. The exchange social-relationships between knowledge generation communities (experts) and the communities of users have been considered [14];
(2) to identify the common characteristics of KSSs for functional systems in order to create general system architecture that can be a draft model and can be improved through ontological engineering;
(3) to present a systemic proposal for a KSS model based in OL (*OLeKSS*). A first model approximation can be found in [15];
(4) to apply a *Systemic Methodology for OL (SMOL)* in a specific case study to show how the associated knowledge of this KSS from diverse KSOs during a KA process can be enhanced. A first approach to this proposal for an OL methodology can be found in [16].

This article is structured as follows: a background review about the KSS and OL characteristics and approaches can be found in Section 2; a new view of KSS in a systemic OL perspective is given in Section 3; the novel *OLeKSS* model is described in Section 4; a real application in the form of a Case Study can be found in Section 5; a short discussion is included in Section 6; and finally, the conclusions and proposals for future research are presented in Section 7.

2. Background

The qualities and characteristics of some ontology-based KSSs and the essentials of OL in the methodological perspective are reviewed in this section.

2.1. Knowledge support systems

KSSs are usually qualified as "Knowledge-driven" DSS to support different users' needs for decision-making and task-intensive knowledge activities [17]. They must be specified in terms of their roles in the social knowledge process according to the perspective cited in Gaines [14]. This is in contrast to the practice of specifying them in technical terms or individual cognitive terms, as is currently the common trend. Gaines suggests some important requirements that a KSS must satisfy.

"(1) The social structure usually involves a professional community responsible for managing the processes of knowledge acquisition and dissemination and a client -users- community dependent on the knowledge for its activities. (2) A KSS will not contain all the knowledge relating to the processes in which it is involved, or provide all the facilities required. And, (3) Knowledge processes are intrinsically reflexive, applying to themselves."

Moreover, there are additional capabilities that the KSS must have, such as: being able to explain its decisions/recommendations to users; being portable and flexible; being an understandable representation of its knowledge; providing automatic learning of new information.

Currently, there are many specific KSSs oriented to medicine, KM, farming, industry, the economy, the environment, and so on. Commonly, these KSSs have been developed using technologies to support functionalities related to the sharing, distribution, capturing, codifying, and creating of knowledge [18].

According the technology used for system design and implementation, these KSSs can be classified as *Traditional Systems* and *Intelligent Systems*.

- *Traditional Systems* are comprised of KSSs that employ conventional technologies, such as databases, discussion boards, spreadsheets, and e-mails. Diverse KSSs have been implemented recently using this traditional approach, for example, DSS for cancer treatments [19]; KSS for medical emergency services [20]; DSS for costing job-orders [21]; and, KSS for strategic planning [22].
- *Intelligent Systems* are comprised of KSSs that also employ some MRs of artificial intelligence related to web semantics, ontologies, user-profiles, data- and text-mining, and so on. Because KSS implementation using ontologies is of crucial interest in this work, we have distinguished some KSSs by this criteria. The following non-ontology-based KSSs are illustrative of recent applications: KB-IDSS for diagnosis therapy [23]; KB-DSS for shipboard damage control [24]; KB-SS for sugar mill [25]; and, KB-SS for energy saving [26]. More details about ontology-based KSSs are provided in SubSection 2.2.

Specifically, we have oriented our model proposal with this type of ontology-based KSS. Using representative instances of this type of KSS, we have derived the main *OLeKSS* components in Subsection 2.2.1 through an inductive approach.

Finally, we have modeled ontology-based KSS according to the main KSS qualities (flexibility and learning), trends (OL and combined methods), and challenges (knowledge updating).

2.2. Ontology-based knowledge support systems

Ontologies and rules are the appropriate formalities to handle the static and dynamic behavior of knowledge for KSS. Ontology supports re-use of knowledge and knowledge bases (domain-knowledge) but lacks the expressivity power for problem-solving, while rules can deal with problem-solving and dynamic behavior (inferred and procedural -knowledge) better [27].

An increasing quantity of ontology-based KSS applications developed for different purposes can be found in the literature. This type of KSS attempts to satisfy a user's requirements, making the most of ontology frameworks to represent knowledge structures and associated rules. Some common representations are related to texts, users' profiles, task profiles and workflow, agents' coordination, and so on.

Recently, some ontology-based KSSs have been developed for knowledge-sharing, as well as task-based, collaborative and recommender purposes [28,29]. These are reviewed and grouped below in a summary of recent work for each type of KSS, in order to find common characteristics for use in a general, representative model of a KSS framework [14,30].

2.2.1. Common ontology-based KSS characteristics

Table 1 illustrates the characteristics of the KSSs, and their relevant components, such as: (a) links of *users* with their requirements; (b) *communications* and the sharing connections; (c) *processes* for knowledge discovering and restructuring; (d) the obtaining of knowledge*products*.

In this sense, these KSSs are developed to offer useful *knowledge to users*, according to their tasks and responsibilities, styles and preferences (contexts and profiles). The KSS must subsequently warrant the *dynamic communications* between the users' tasks and activities. Such task activities increase among users because they require specialized knowledge for effective decision-making, creation, acquisition and identification. These needs require new knowledge searching, recovery and discovery *processes* to acquire the structured knowledge as *semantic products* (e.g., ontology or context) while maintaining adequate performance.

These key elements, *Users, Communication, Processes*, and *Products* are important common characteristics to be included in this ontology-based KSS design. Nevertheless, the approaches found in the literature about the development of these KSS applications are distinguished by the following restrictions: (a) usually, the related KSS ontology development is obtained from scratch [2,31]; (b) only a few of them have included an explanation about how they can keep the associated knowledge-ontology updated [31–33]; (c) there is no evidence that the users/engineers can appreciate the importance of saving the learning to improve the associated ontology [29,30,34]; (d) knowledge updating strategies are not explained so the OL is not explicitly considered as a methodological option [31,34,35].

Our proposed model fulfills the KSS requirements cited by Gaines: KSS can be updated in a continuous, reflexive, portable, and flexible way, taking into consideration the KM activities of the users' communities, recommendation to users, understandable representation and automatic learning [14]. To achieve this, an *additional key element* can be included to support efficacious recovery and processing of knowledge. We suggest, as another model component, *Knowledge Sources* management to support efficient knowledge re-use from diverse sources (text, databases and ontologies). This would be used partially during OL processes to update the KSS. It is important to stress that one of the contributions of our *OLeKSS* model is the help it provides to users by extending the KSS life-cycle for the updating of their static- and dynamic- knowledge through efficacious OL processes from diverse and complementary KSOs. The KSS learning capability can be explicitly assumed to be an essential component for these types of systems.

All five KSS components allow this type of ontology-based KSS to be more efficient and effective in their support of the KM processes that relate to knowledge acquisition, storage, discovery, and distribution through OL methodologies.

Table 1
Some ontology-based KSS characteristics.

KSS's profile	Characteristics	Authors
Knowledge sharing (OntoShare System)	– Automatic Knowledge Sharing with aid of user's profiles (topics-concepts) – Ontological concepts according user's interest – Documents are represented as ontologies – The explicit knowledge is recovered by e-mail, keywords, and documents. Implicit knowledge may be shared through user's profiles	Davies et al. [32] Lee et al. [35]
Document recovery (MILK System)	– Distributed knowledge, located in different places should be integrated – Cross-fertilization and communication should be supported among users – Implicit organizational-members' knowledge should be accessible together with the explicit one – Documents should be presented to users where and when they may need them	Agostini et al. [78] Jung et al. [79]
Task and workflow (Liu and Wu)	– Collective task-based workplace simplifying the knowledge retrieval and sharing among peer-groups – Task profiles to support knowledge workers – Information retrieval and filtering techniques for text-processing, indexing, querying and profile tasks	Liu and Wu [28] Liu et al. [2]
Context-aware and processes-aware (KnowMore and FRODO-TaskMan systems).	– Heuristic ontology-based techniques to support task-workflow management – KnowMore was developed to extend support to knowledge-intensive tasks, considering three key elements such as: (1) information needs, (2) context-aware, and (3) ontologies (workflow- and domain-context) – Information space (system component): use ontologies meta-models and document indexed under task profiles – FRODO is conceived as an Agent Society based in ontologies	Holz et al. [80]
Problem-solving and Recommender Systems (RS)	– User profiling within RS is used to recommend on-line academic research papers – RS that allows to customize content to be suggested based on the user's browsing profile – One of them, developed a novel task-based knowledge RS – Ontology-based workflow according to the correlation among users, roles, and tasks	Middleton et al. [31] Zhen et al. [34]

Table 2
Methodological resources for ontology learning From each KSO

	Ontologies	Documents (Corpus)	Databases
Technique: Subjective capabilities to handle a tool	– String matching – Graph based – Statistic analysis	– Linguistic patterns – Semantic relativity – Data mining algorithms	– Rule-based (similarity) – Taxonomic structure analysis – Clustering techniques
Method: A way to think/doing to achieve an objective	– Alignment – Structured and merging – Matching	– Statistical – Linguistics – Machine learning	– Attributes – Instances and DB schemes – Synonyms and inclusions – Classes (or groups)
Tool: Objective capabilities to apply technique	Onion, PROMPT, FCA, Chimera, Glue, and OLA	ASIUM, Doddle II, Web-KB, GATE SVETLAN,Text2-Onto and OntoLearn	SemInt, DIKE, ARTEMIS, S-Match, DataMaster, RDBToOnto, ODEMapster
Methodologies: Set of techniques methods an tools	Approaches: – FOAM [41] – OD and OL (Prompt [65])	– Structured [46] – OL Framework [56] – DINO [45]	– Observer [81] – Garlic [82] – Rondo [83]

Table 3
SWOT Analysis applied to Ontology Learning Process and Products

	OL processes	OL products
S	There are: – Some stable OL methods, techniques and tools – Structured methodological proposals – Some integrated OL Development Tools (e.g. Protégé-Prompt, Text2Onto)	Main: – Structured knowledge is Ontology-based – Some standard languages (RDF, OWL) – Generalized ontology-approach uses – Users are learning about those resources
W	There are: – Very few GUI and App. interfaces – None methodological standard yet – Many unknown MR recently developed – Dispersion about different resources and KSO	There are: – GUI and App. are very inadequate – None customized store of partial products (as agents) for reuse purposes
O	May be…: – New OL methodological options may emerge – MRs could be standardized for integration and use purposes – MR could be developed by multi-disciplinary groups	May be: – A standard of quality of knowledge services is needed – Development of new products – Some previous developed partial knowledge products (reuse) may be included
T	May be: – OL technologies keep unconnected – Methodological resource dispersion tendencies can stay present – Keep technical-guided for the research line – New different knowledge structure may emerge	May be: – Users sometimes have the feeling that they are relegated by knowledge itself – System designs are not consider as reuse way – Scientific community could change the interest for ontologies a knowledge representation way

S = strengths, W = weaknesses, O = opportunities, and T = threats.

2.3. Ontology learning

Trying to simplify the general conception of OL related to our work, we found and selected the following three associated definitions: (1) "*The process of automatic or semi-automatic construction, enrichment, and adaptation of ontologies is known as Ontology Learning*" [7]. (2) "*Ontology enrichment is the task of extending an existing ontology with additional concepts and semantic relations and placing them at the correct position in the ontology*…." and, (3)"*Ontology population, on the other hand, is the task of adding new instances of concepts to the ontology" [36].*

The main technical advances and challenges of OL technology are to find and identify ontology objects, such as Classes, Instances, (non-) Taxonomic Relations, and Rules to be learned from KSOs (usually, only one source) as efficiently as possible. Commonly, these associated learning tasks can be based on semi-automatic approaches, such as NLP, Pattern Recognition, Clustering, Data Mining, and so on. Although several OL definitions related to methodologies are given in the technical literature [7,37], they usually deal with methods and techniques that are used to improve previously developed ontologies from a specific KSO. MRs for OL that is involved with texts or documents collected in a corpus are the most common KSOs referred to in the literature [38].

For our holistic point of view, we have extended this partial OL perspective (only one KSO) to a more general ontology-based KSS model, which may include dynamic and continuous learning processes as an essential component of the system, and takes into consideration diverse MRs from heterogeneous and complementary KSOs, including texts [39,40], ontologies [41,42], and databases [43,44]. We have also allow for the use (and re-use) of more than one of these KSOs in the same model. It is important to point out that we have not found many recent references that take up to two KSOs for specific KA processes into consideration [45,46].

Some MRs can be grouped according their OL purpose, which is to learn from: (a) other previously developed ontologies; (b) compendiums of documents; (c) database schemes and their data-values. Some possible instances of MRs by KSO are shown in Table 2.

Consequently, we consider that OL methodologies must combine all of the involved KSOs and MRs efficiently, according to availability, users' capabilities, and system-domain circumstances. The results of our study are analyzed in the following subsection, in order to better explain the methodological problem of OL, and also to consider the problem from a systemic perspective (Processes/Products/Sources).

2.4. The ontology learning methodological problematic

In the literature several authors have recently reported different point of view about how MRs can produce integrated OL results from different KSOs.

Therefore, to synthesize the general OL problems, a situational technical analysis, which is known as a SWOT (Strengths, Weaknesses, Opportunities, and Threats), was used [47]. This SWOT analysis has been made by applying two broad perspectives: OL Processes and OL Products (as is detailed in Table 3).

In this sense, in agreement with [37,48] and [49], it is also possible to infer that OL methodological options do not exist as a complete, integral, and dynamic method of facing the OL problem of knowledge recovery from different KSOs. Precisely, this wide variety of mechanisms and optional MRs makes it difficult to solve the OL problems without a systemic approach – a unified, standard, OL methodology.

There are some open OL methodologies (survey in [50]) which have been designed to overcome some of the restrictions associated with the cited OL problems. In this sense, any of them could be useful to support many of the OL tasks, prescribed in our model as *OLeKSS Processes* (Section 4).

The *SMOL* methodology was designed taking systemic premises into consideration, and includes the same criteria of flexibility and openness. It was introduced, applied and evaluated in *SMOL* and is used in the Case Study Subsection 5.2, [16] to explain the *OLeKSS Processes*, and is described briefly in the following subsection.

2.5. SMOL as an optional OL methodology

SMOL tries to conciliate the paradigms of system development based on total quality with user-centered services (adaptable and anticipative) in order to meet users' requirements [51]. Moreover, for our model, we extended the initial description of the paradigm made by Callaos with communications and the KSO elements. This essential conciliation is supported by *Systemic methodologies* instead of systematic ones [52]; *Systematic methodologies* are oriented to the efficiency, with a predetermined behavior, strict, and closed (e.g. Structured Life Cycle [53]). However, *Systemic methodologies* are oriented to effectiveness, with a non-predetermined behavior, and are flexible and open (e.g., the Agile Process [54]).

In this sense, *SMOL*'s users can exploit the main characteristics of *SMOL*, such as user-orientation, integration, flexibility, openness, and iterative capabilities. Likewise, this methodology combines some previously developed MRs according to the available KSO (users could draft flexible OL strategies).

For the phase-flow design of the *SMOL*, we adapted a knowledge-retrieval framework cited in [55]. To reach the users' systemic profiles, we included some decision points, new important phases (circumstantial-dependent), and feedback cycles for users' quality control of the updated ontology. A partial phase-flow representation of the *SMOL* is shown in Fig. 3 (adapted to this case study), and briefly described below.

I. Methodology strategy selection. The domain-complexity is evaluated according to [56] and used as the reference for selecting the most appropriate MRs and applying them for the particular domain-case. *II. Knowledge discovery*. The MRs from different KSOs and repositories are combined. *III. Query requirements*. Different queries are formulated for the knowledge sources available from browsers or other kinds of applications. *IV. Knowledge selection*. A selection is made of the retrieved information from the formulated queries to the KSOs and repositories. *V. Knowledge structure construction*. Different structures, such as ontologies and contexts can be built interactively with the users' advisory. *VI. Knowledge explore and search*. The knowledge structures are explored, verified, and validated. *VII. Knowledge structure reorganization*. Processes, such as grouping of instances, ontology population and other activities are similarly performed. *VIII. KSS Configuration*. Users set up modules of the KSS with associated and updated ontologies. More details about the application and evaluation of the *SMOL* can be found in [16].

Although any optional OL methodology may be used for an OL purpose, such as Dynamo, KACTUS, ONIONS, On-To-Knowledge, DINO, SENSUS, and Simper's et al. [45,46,50]. In our *OLeKSS* proposal, we have applied *SMOL* for the Case Study. Thus, we take some comparative advantages into consideration: the systemic perspective, the MRs' technical expertise, and the available KSOs. It is important to point out that there are no other open methodologies that have previously considered, in detail, the three cited KSO, as is done using *SMOL*. Further details of *SMOL*, applied to *OLeKSS Processes* can be found in SubSection 4.2.2.

3. Knowledge support systems under a systemic OL perspective

When conceiving a global solution for the systemic problems of creating a novel, user-centered Ontology-Learning KSS model, it is useful to adopt a holistic vision of KM users' requirements [51], using the established specifications for the KSS that were suggested by Gaines [14]. This systemic vision enhances not only the KSS systemic architectures, but also the delivery of OL processes and products as well. This core approach emphasizes the appropriate re-use of KSO and its management. In this sense, a new proposal should consider three systemic elements: (a) the diverse KSOs available as potential OL sources of a KSS social user's interchange perspective; (b) the convenient and appropriate relationships between an ontology-based KSS with the OL, in order to keep the knowledge continuously updated; (c) a novel *OLeKSS* model design to fulfill the expected systemic faculty (learning) and the quality requirement.

3.1. Social context of ontology-learning for KSS

In the Gaines' proposal, the KSS model works in a social context, representing and describing the relationship of knowledge exchange between professional communities (expert role) and the end-user communities [57].

These exchange mechanisms are related to the generation, transfer, assimilation, and re-conversion of knowledge in terms of the interchange relationship between the social communities

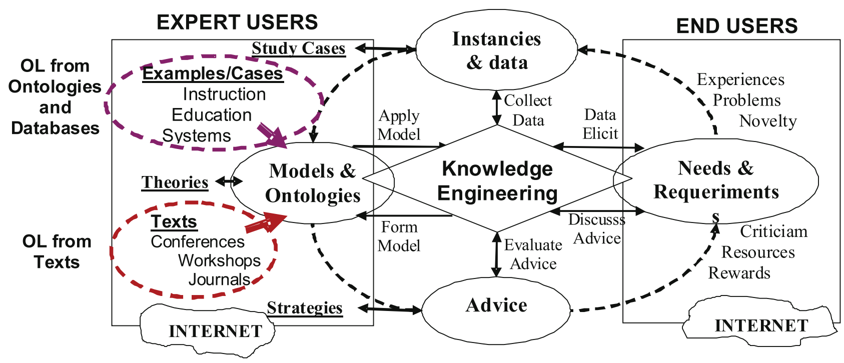

Fig. 1. The social context for ontology learning knowledge support process.

that manage the knowledge (the experts) and those who use it (the end-users) [14].

We propose a new social model (Fig. 1) in order to emphasize the OL potential for enhancing the *model* and the associated *ontologies* with the KSS, using the possible and diverse KSOs (represented in dash-ovals).

Through the OL processes, the available knowledge gathered on previous case studies and expressed as *published ontologies* (upper/domain) is useful to enhance the contextual-ontologies of KSS by comparing feed-forward.

Similarly, available knowledge from equivalent or contrasting information *system databases* (from the same organization or others) can be gathered by the OL to enhance the knowledge expressed in the ontologies associated with the intended KSS.

Some knowledge needed for intensive tasks that users are developing in their study or system domain require effective access to knowledge and processing from the *content in texts*. Through OL from texts, representative ontologies of this KSS can be updated if the recoverable knowledge can be learned from scientific texts (retrieved by the Internet) about conferences, workshops, and journals.

There are some recent proposals about the social side of users' knowledge, such as the Knowledge Collective Systems proposal, which unblock the Social Web 'Collective Intelligence' connections through new representation and reasoning techniques [58]. Likewise, an effective implementation of KM processes, such as knowledge-sharing and transferring over this kind of KSS requires adequate communication among users (experts, end-users, and knowledge engineers). For these processes to become most efficient, some "social influences" (identity, thrust and negotiation) should be considered as well [59].

To be precise, the appropriate identification of "subtle or soft" relationships among critical elements in a systemic perspective is always a latent problem. Thus, this KSS social context is introduced as the "integrator element", because both element-sides (KSS and OL) are able to be integrated using OL from diverse KSOs and can be supported by new inter-exchange web resources and technological trends.

3.2. Improved KSS by ontology learning

New knowledge is used and required for the continuous updating process of KSS (recovering/processing) and this knowledge is represented as ontologies; despite this, KSOs are overlooked as significant features or components of the KSSs. We propose an OL process for KA as a useful option. Indeed, KSOs, such as texts, ontologies, and databases that can be used for semantic learning purposes are usually not explicitly cited by authors as key elements integrated in the KSS's architectures reviewed above.

The reviewed KSSs (SubSection 2.2.1) illustrate how some ontology-based mechanisms have been applied to support the users' knowledge tasks (identification, registration, and recovery) and other work-flow requirements.

Therefore, any flexible and integral OL process that could positively impact the knowledge structures associated with these ontological resources must enhance the support provided to users by these types of KSS.

Ontologies developed for KSSs are used to represent and to describe the tasks and roles of organizational users. Others represent task-workflow and content-structure (documents). Also, there are ontologies to support user-profiles and the context of use, including knowledge about collaborative relationships that may emerge among diverse organizational members.

In summary, OL from different KSOs can improve KSS through the knowledge growth, restructuring and comparing processes related to: (a) knowledge-bases that belong to KBSs within those KSSs; (b) operational knowledge structures (e.g., profiles, contexts or workflow); (c) structured filtering of resources (e.g., rule-based or collaboration); (d) others (e.g., metadata or agents).

4. A novel ontology-learning KSS (OLeKSS): model specification

In this section, we present our proposed *Ontology-Learning KSS (OLeKSS)* model. To make the description of the model clearly understandable, we have used a hierarchical process-based scheme from the field of Systems Engineering [53]. Likewise, the quality system has been applied to present the essential components and relationships between them within the modeled *OLeKSS*'s architecture clearly [51].

4.1. Components of an ontology-learning knowledge support system

The main *OLeKSS* model components are: *Users, Processes, Products, Communications,* and *Knowledge Sources*. They are shown in Fig. 2 -as ovals- and described as follows:

- *OLeKSS Users* obtain added value from *OLeKSS Processes*. They make tasks/decisions about the knowledge domain that they already have or that they are constructing from possible *OLeKSS Knowledge Sources*. Graphic user interfaces may include the necessary and ergonomic operational options that can simplify knowledge processing and visualization. These processes should include efficient options to allow for recovery and for updating of related *OLeKSS Products;*
- *OLeKSS Processes* are applications of a set of MRs, such as methods, techniques, tools, and agents with the capability to construct or to update knowledge structures, such as ontologies and other representation types. These processes may enrich and adapt the existing knowledge in a (semi) automatic way, using and distributing information from heterogeneous *OLeKSS Knowledge Sources*. Thus, the efforts/resources needed during the development time-period are reduced;
- *OLeKSS Products* are defined based on partial results obtained during the *OLeKSS Processes* as well as on the structured or unstructured knowledge acquired previously (e.g., ontologies or profiles). Some particular results, such as KSS subsystems (e.g., reusable agents [60]) are also considered as partial *OLeKSS Products*. Consequently, these partial results remain accessible and updated as*OLeKSS Knowledge Sources* for re-use for any other OL purpose;
- *OLeKSS Communication* supports internal and external communications among *OLeKSS Users* for sharing and transferring knowledge, in order to guarantee collaboration and coordination. Other connections needed to create and manage the *OLeKSS Knowledge Sources* of the knowledge networks of expert users are also considered;
- *OLeKSS Knowledge Sources* are differently structured or unstructured sources that provide qualified knowledge to sustain the sub-processes involved in the *OLeKSS Processes.* These sources may be useful for *OLeKSS Users* to gain easy (explicit and implicit) knowledge access and processing mechanisms to storage catalogs or repositories. This mechanism can support efficient quality cycles about the users' versions and their corresponding updating and revision during *OLeKSS Processes.*

4.2. OLeKSS: a detailed specification

The main *OLeKSS* components and some interaction relationships are represented using UML class diagrams in Fig. 4. Some of the details of the subsystem are described below:

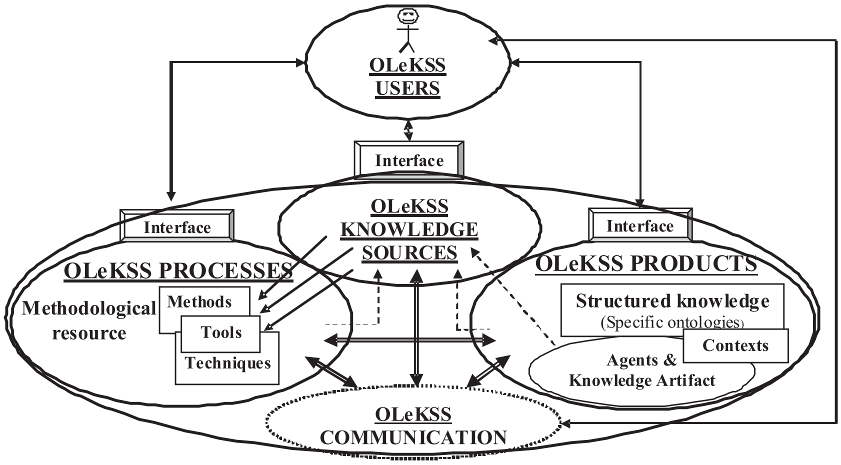

Fig. 2. *OLeKSS* model component specification.

4.2.1. OLeKSS users: relationships and interactions

OLeKSS Users are grouped according to their information and knowledge needs: (a) end-users – information and knowledge task-workers related to a specific domain such as the application of ontologies; (b) expert-users – designers of knowledge structures (ontologies and others) and guarantors to update them; (c) knowledge engineers – technical support managers responsible for the development and updating of processes through the appropriate means (MR), using the adequate technology.

There are many types of possible interchange relationships among different *OLeKSS Users*, according to the knowledge types (acquired and potential). Other emerging and necessary relationships may be considered, among them, before and during any specific process of interpretation and/or consensus during the learning process. Among the possible relationships of the users' interaction and interchange of knowledge, some management mechanisms are included that ensure communications among users of the same communities (intra) or those belonging to any of the other communities (inter).

The possible relationships among users can be: (1) queries and suggestions that allow us to obtain user's agreements and consensus regarding semantics (means/sense) of the ontology entities; (2) representation options to describe particular cases and instances about the specific case or domain study; (3) ubiquity in accessing and interchange mechanism to ensure better Internet communications among user's communities; (4) tool support including some existing or novel tools that simplify interchange between inter- and intra-user's communities (e.g., Collaborative Protégé [61]).

4.2.2. OLeKSS processes: methodological resources

The MRs for OL are specifically presented as the main components of *OLeKSS Processes*. They can be useful to support partial processes for KA and KM during the updating and enrichment of the KSS. Thus, the OL methodologies that combine a variety of MRs for OL from a user-centered perspective can be useful for the required *OLeKSS Processes.*

As mentioned previously, any proposed OL methodology (non-life-cycle based) of the technical literature can be used as an MR to empower *OLeKSS Processes*. We have suggested *SMOL* (Subsection 2.5) as a useful methodology to keep this kind of KSS updated, where users can make the most of additional KSO that is related to the system domain.

Specifically, *SMOL*'s users can start any domain-independent KA process, processing (and reusing) any of the cited KSOs through some of the MRs that are available and are compatible with the methodological strategy selected when *SMOL*'s Phase I is applied.

4.2.3. OLeKSS products: general specifications

In our model, various types of structures are suggested to store the knowledge types (acquired and potential) of explicit and implicit knowledge. The most relevant ones are detailed below:

(a) *structured knowledge:* ontology language formats (e.g., OWL) can be used to represent this type of knowledge, including some mechanisms for versioning;
(b) *contextual knowledge:* partial content knowledge about the specific domain and users may be registered. In other cases, this knowledge is referred to a thesaurus with complementary knowledge about terms and concepts regarding the domain;
(c) *procedures and intelligent agents:* this kind of application can be developed or obtained during *OLeKSS Processes* and stored as *OLeKSS Knowledge Sources* for the purpose of re-use. They might support specific *OLeKSS Products*, updating themselves through other, future *OLeKSS Processes*.

The quality of *OLeKSS Products* can be evaluated using various types of MR during the *OLeKSS Processes*, according to the consideration that the specific methodology selected has been included for these purposes. Particularly, the proposal for the *SMOL* methodology considers this quality-evaluation process of the user's decision-points and in two specific flow-phases (V and VII).

4.2.4. OLeKSS knowledge sources: storage structures

The knowledge stored in the model components above is integrated into different storage types that are suggested for *OLeKSS Knowledge Sources*:

(1) *KSO repositories:* storage structures designed according to the formats adapted for documents (corpus), RDB-schemes, and the ontologies;
(2) *agent repositories:* storage related to the agents that can process operate the dynamic knowledge according to the user's demands or requirements;
(3) *MR repositories:* storage structures for all the usable methodological resources (methods, techniques, and tools) in functional or adaptable terms (routines or automatic processes) to the associated KSS;
(4) *profiles of users and tasks profiles:* storage structures to define and update user's preferences and tasks developed during knowledge processing.

Table 4
OLeKSS Communication supported by ICT tools according to LA ROSA model

KM process	TOOLS	DESCRIPTION
Locate, create, discovery and map knowledge	Social network analysis	Mapping informal link among people
	Group decision support system	Developing new ideas and decision-making
Acquire and Capture	Content syndication tools	Distribution of content filtered from KSOs
	Forums and discussion groups	Capture discussion and problem solving shared
Refine, Validate and Maintain	On-line expert communities	To review/decide what is an useful knowledge
	Workflow systems	Accelerate validation/maintenance flows
Organize, store and protect	Ontologies/taxonomies (shared)	Being agree about domain/components/relations
	Folksonomies/tagging (Web 2.0 tools)	Describe/categorize content with their own words
Share and Transfer	On-line Community of Practice (CoP)	To share virtually texts, discuss issues, vote, etc.
	Groupware/collaborative tools/emails	To support/increase the team communication
	Knowledge portals/wikis/blogs	Access enterprise KAs, contents and experiences
	P2P tools/video and audio conferencing	Ways to share content/real-time comm. among users
Apply, Use, Adopt and Adapt	Help desk tools	Support users in case of diagnosing, planning,
	Workflow collaborative tools	Forecasting and decision-making process

Table 5
Case study summary: some involved *OLeKSS* components

Knowledge Source	*OLeKSS*-products:	*OLeKSS*-processes:	Enrich./populat. object	Data pre-processing
Ontologies (LUMB from Web)	– Ont. enrichment – Ont. comparison – LUMB as KSO	– Swoogle – Protégé-prompt – Racer-Pro	+Class: cognition\dimension\professor *Classes: person\student and administration\University	– WordNet/synset – Spanish to english dictionary.
Documents (480 texts of journals)	– Ont. population – Knowledge agent – Corpus as KSO	– Rapid-I – GATE (Ont.) – Racer-Pro	+Class: cognition\dimension\professor\UniversityCity +Instances: \\city	– Google-Scholar – WordNet/synset – GATE (Gazet)
Databases (RDB of IUTEPAS University)	– Ont. enrichment – Ont. population – RDB as KSO	– RDBToOnto – ODEMapster – Protégé – Racer-Pro	+Class: \\PostgradeTitle and \\gradeTitle #Class: \\UniversityCity by \\UniversityTitle and UniversityCity +Instances: \\University-Title and \\City	– FoxPro – MS-Excel – MS-Access – MySQL RDBMS

Ont. = ontology, object = +added, * reviewed, # changed

A fuzzy RDB-schema specification may be used as the structure where the content/records (e.g., ontologies or corpus) are stored for re-use.

4.2.5. OLeKSS communications: associated technologies

The communication infrastructure and technologies must support the involved *OLeKSS Users* and "user communities", such as Knowledge Acquisition, Refining, Organizing, and Sharing, (from the perspective of "LA ROSA" [62]).

Table 4 summarizes (but does not exclude) some Information and Communication Technologies (ICTs) useful for the support of several knowledge-tasks of users that require collaborative and coordinating activities among users (see Table 5).

Particularly, the emphasis on supporting the KM processes or "social influences" associated with knowledge sharing and transferring can also affect the effectiveness of the results of these knowledge-tasks [59].

4.3. Some relevant aspects of the OLeKSS systemic perspective

As shown above, our proposal considers that the OL from different KSOs could improve the KSSs through knowledge growth, restructuring, and comparing processes related to knowledge-bases within those KSSs, operational knowledge structures, and the structured filtering of resources.

As well as having characterized the more common KSS's profiles described in the literature, we have also summarized some of the advantages of this systemic approach as follows: (a) it is explicitly shown how these KSOs (ontologies, texts, and databases) can be associated with *OLeKSS* through OL mechanisms based on the e-society possibilities (Fig. 1); (b) the *OLeKSS* architecture (Fig. 2) represents profiles of KSS developed previously, but it also considers an important systemic component – the KSOs and the MRs involved, and expressed in OL methodologies; (c) the flexibility of our design shows how the knowledge associated with the *OLeKSS* can be recovered and updated from KSOs by applying any accredited OL methodology. *SMOL* was selected in this case.

As far as we know, there are no previous references about the design of KSS architecture that also consider the OL methodologies and KSOs as systemic components.

5. Academic case study

A University Case Study was selected as the experimental academic domain to test the *OLeKSS* model with a methodological focus [63].

The selected host-ontology for updating and enrichment purposes (called the DEA-ontology) is in a supervised evolution stage.

For this Case Study, the *OLeKSS* components (Users, Processes, Products Knowledge Source and Communication) are delineated into the following subsections.

5.1. Involved OLeKSS users

Some expert-users (specialized professors) and knowledge-engineers were involved with the development of the DEA-ontology. Thus, they also have the responsibility to keep this ontology updated under the quality conditions in this (OL) evolution stage. Sometimes, users have to learn about some of the KM tools to be used during the OL process.

5.2. OLeKSS processes

Although any other flexible and open methodology could have been used, as mentioned above (in Section 4.2.2), *SMOL* was ap-

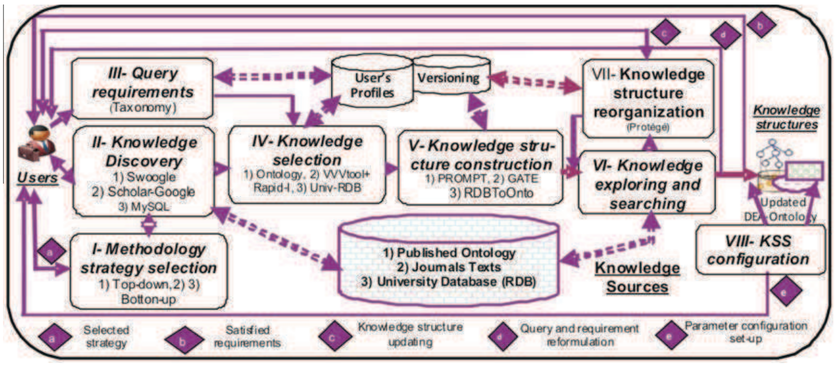

Fig. 3. Systemic Methodology for Ontology Learning (SMOL) phase-flow.

plied incrementally in the *OLeKSS Processes* for this Case Study (Fig. 3), and this is summarized in the following meta-processes.

Process 1: A host-ontology, which was taken from a previous project about a Decision Support System developed for a University specialized in Distance Education Administration (DEA) was selected to be updated.

Process 2: Complementary knowledge was obtained by a comparison between the host-ontology (DEA) and *another domain ontology* located and recovered from the Internet (LUBM-ontology [64]). During the OL process, the DEA-ontology of an academic management subdomain was updated by users through ontology-matching methods (the Protégé-Prompt-CogZ tool [65]) [66].

Process 3: Important knowledge about the DEA domain was recovered and selected as a *corpus of texts* (480 files) from specialized journals related to this domain. A semi-supervised learning agent for text-mining was developed (using the Rapid-i tool [67]) to enhance the OL. Then, some professors, as expert*OLeKSS Users*, used the tool GATE to update the host ontology [68,69].

Process 4: Relevant knowledge about the professors' profile subdomains from a *Relational Database* (RDB) of another university were obtained [70]. These were converted from RDB to a temporary ontology by inductive OL through data-mining techniques, using the RDBToOnto tool [71]. A learned/matched process was applied between the RDB with the DEA-ontology by deductive OL, using the ODEMapster tool [16,72].

The host-ontology was validated in every cited KA process using a reasoner tool named RacerPro to check the consistency of the quality [73].

5.3. OLeKSS products

The partial results obtained in each cited process of the *SMOL* application in the previous subsection are summarized below.

Result 1: The four main classes and subclasses with the corresponding relationships and instances of the DEA-ontology for the original *OLeKSS* were used. The reviewed host-ontology's upper-classes are: Administration, Cognition, Economy, and Technology. Part of the taxonomy representation of the DEA-ontology (a display-screen based in Protégé [61]) is shown in Fig. 5.

Result 2: Some professors' categories were defined and correlated with the Cognition-Dimension subclass in the host-ontology through OL from ontology, because source (LUBM). Students' profiles can be also affected by the professors' profiles, as was represented originally in the host-ontology.

Result 3: Some repetitive instances of locations and places where the professors obtained their degrees are identified as subclasses. Some specific instances of countries and cities (locations) for these subclasses are populated in the host-ontology by users during this OL process.

Result 4: Finally, a new and extended subclass was formed into the host-ontology through this OL process from a database of another University, considering the diverse instances of locations where the professors had obtained their University degrees (graduate/post-graduate). Additionally, some corresponding mapping with places (locations) between the RDB and the host-ontology were found by *OLeKSS Users* to test the validity and consistency of the result.

5.4. OLeKSS knowledge sources

During the *SMOL* application, some partial knowledge results were cataloged in repositories as *OLeKSS Knowledge Sources*, which were useful for the purpose of processing new and additional learning.

Processed and obtained knowledge in diverse formats was identified as:

(a) *KSO repositories:* four ontologies associated with the academic domain were found and cataloged. The database and corpus used for OL were also recorded for future re-use. Likewise, some new subclasses during a data-mining process (in RDBToOnto) were developed from the database selected as KSO from another University. These subclasses, classified as knowledge structures (e.g., artifacts), were also included in KSO repositories;

(b) agent repositories: an automatic agent for keyword identification during the OL from texts (WVTool plug-in for Rapid-i) was developed. This agent was cataloged because it can be useful for another OL process related to the corpus of documents already used, but should be updated with additional complementary texts. Similarly, in other cases, for new corpora of different topics, this agent could be considered for this OL process or for any additional process;

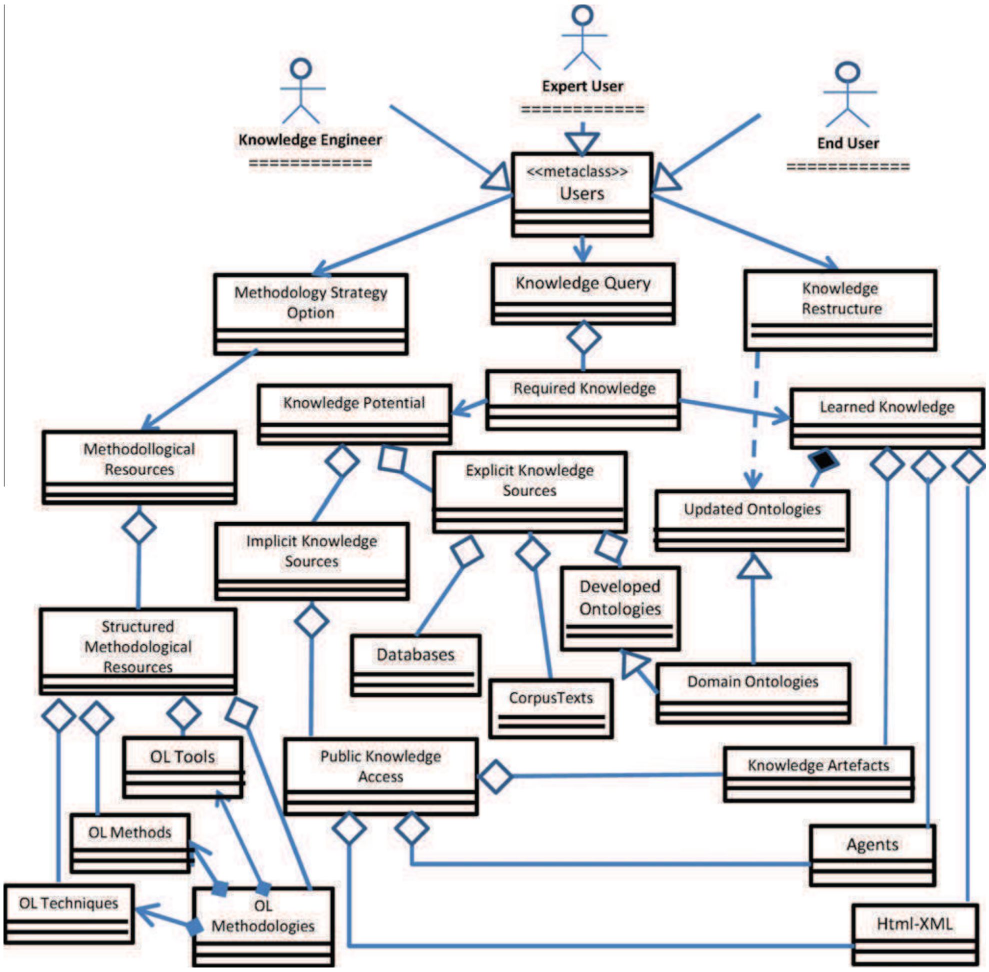

Fig. 4. *OLeKSS* model is represented in UML by class diagram.

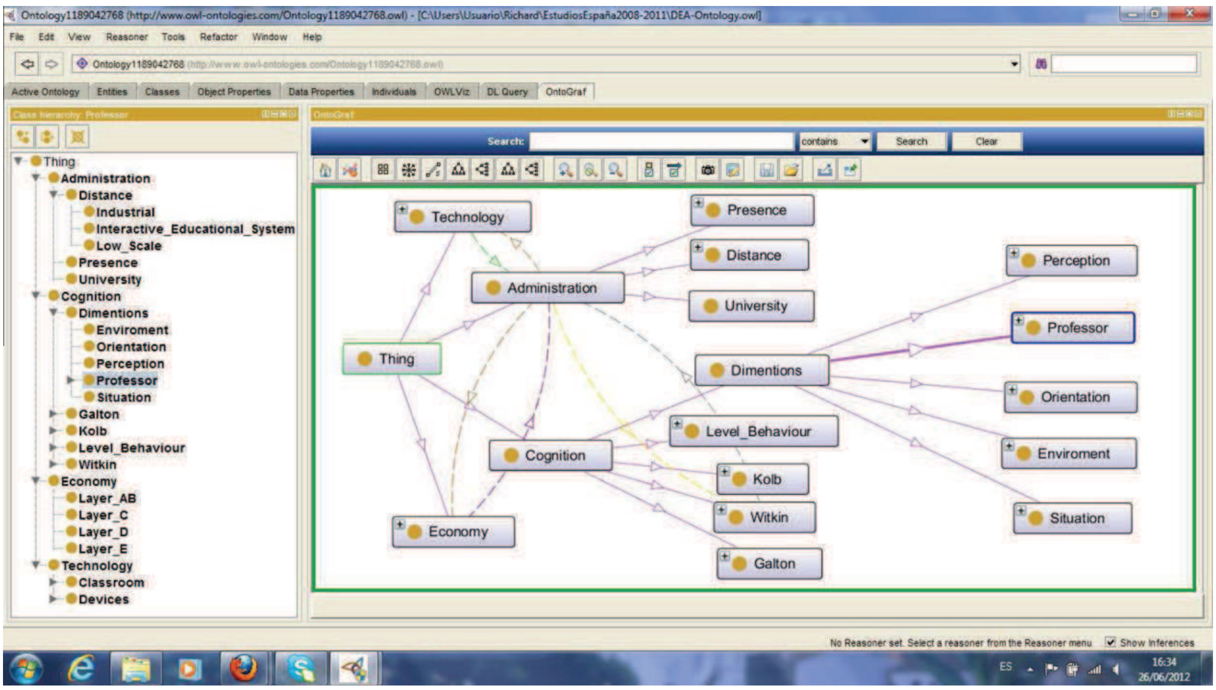

Fig. 5. DEA-ontology display: enriched and populated classes (Protégé 4.1).

(c) *MR repositories:* the various tools and methods used during the whole KA process for each KSO were cataloged as MR for possible re-use.

5.5. OLeKSS communications

For this Case Study, the *OLeKSS Users* were located in several University head offices across the country. Since they share similar interests, such as "trust partners" involved with the original KSS domain goals (advice/recommendations for students), their "social influences" are made easy and favorable. Consequently, the following ICTs to support KM processes for organizing, sharing and creating knowledge have been used: (1) the well-known Ontology Editor Collaborative Protégé helps users to reach agreements and to organize the new knowledge (enrich/populate) in the DEA-ontology; (2) institutional emails have been used regularly to arrange meetings (face-to-face/media); (3) some audio-conference meetings have been supported by the -VoIP- services of Skype; (4) "MS-Messenger" has been used as instant-messaging tool to help users.

5.6. Lessons learned

The following aspects are considered the most relevant "lessons learned" from the Case Study: (1) usefulness of the *OLeKSS* model; (2) advice for users about how they can overcome errors during *OLeKSS Processes*; (3) some foresight for integration, consistency, and content extraction; (4) scope of the mechanisms of communication.

(1) The flexibility of the *OLeKSS* model helped users in different activities related to the updating of the knowledge of the associated ontologies. The effectiveness of OL from diverse KSOs has been improved and it is possible to reach new knowledge through inductive and deductive automatic learning (by data, text-mining, or ontology-matching). The KSS capabilities associated with knowledge recovery and organization have being enabled, thus reducing the corresponding manual effort. Some important results (dynamic-knowledge) expressed as *OLeKSS Products* and *Knowledge Sources* (e.g., agent, selected KSOs, and MRs) can enhance the future efficiencies of additional *OLeKSS Processes* and help users to procure continuous updating of the *OLeKSS Products*.
(2) To avoid errors and mistakes associated with data and knowledge processing, the documentation related to each KSO is made available: (a) it is needed for the documentation associated with each potential KSO to correct/adjust incompatibilities (format/domain) with the host-ontology that is to be updated; (b) it is also used to track all the updating facts that must be recorded in log-files.
(3) Adequate integration of data-models, consistency of validation, and content extraction are recommended [74]: (a) ontology mapping is proposed (and used for each KSO) as the main data-model mechanism for the integration of OL from diverse KSOs; (b) consistency of the ontology can be reached by at least two ways, first by using rule-languages of highlevel for reasoning expressively (OWL-DL used in DEA-ontology) and second by applying a reasoner tool (Racer-pro) to repair inconsistencies; (c) users must be open to learn/apply new MRs to reach automatic OL extraction of relevant contents from each KSO.
(4) Appropriate communication mechanisms among the involved *OLeKSS Users* help to support user-expert's interactions with: (a) the end-users to gather their knowledge-task requirements; (b) the KSS specialists (System Engineers) to explain the (re)configurations of the subsystems required by OLeKSS once the host-ontologies have been updated.

6. Discussion

Validating our suggested KSS model by comparison with other similar models that are available in the literature would be useful and convenient. Although we have attempted to find other ontology-based KSS models (or referenced) for comparison purposes, we could not find any. However, we found some frameworks and architectures that were developed for DSSs, KBSs and Knowledge Management System (KMS) which can be useful to partially compare (qualities/scope), with our proposed *OLeKSS* model.

The *Basic Architecture for DSS* in [10] is essentially constituted by the following subsystems: (a) the language; (b) the presentation; (c) the knowledge; (d) the problem-processing. This architecture has up to three "subsystem equivalents" with the *OLeKSS* components (*Users, Communication*, and *Knowledge Sources*). Despite the pertinence of these elements and their systemic (inter-) relationships for our modeled KSS, all of them are insufficiently described or designed in this architecture. In our model, we have included some specific details, for design purposes, of all *OLeKSS* components (re-use/agents) in an effort to achieve efficacious *OLeKSS Processes*. Consequently, we consider that our systemic model is best aligned with Information Systems theories for Design and Action (for KMS and DSS) but that the other is only oriented to Information Systems theories for Analyzing and Explaining [75].

A *Knowledge-based System for Strategic Planning* designed in [22] is comprised of four main subsystems: the database management, the model base, the knowledge acquisition, and the dialog. Compared to our model, this implemented system does not include important components which we have considered in *OLeKSS*, such as *Communication* and diverse *Knowledge Sources*. In our proposal, the last is the key, reinforced component for restoring and re-use and support the best possible the efficiency of *OLeKSS Processes*.

The ontology-based *KBS for Collaborative Process Model* suggested in [76] represents the functionalities of the three main knowledge processes sequentially (gathering, representation/reasoning, and collaborating). The authors describe, in detail, some ontologies developed to support the collaborative KBS, as well as the set of deduction-rules applied. Regarding the difference with *OLeKSS*, as with previous cases, the relevant components of our model, such as Communication and KSOs, are not considered as key elements to support KA processes. Although, the authors of this model state in their conclusion that the main components of the ontologies (concepts, relationships and restrictions) and inference-rules can be enriched, they do not include in their KSS functionalities a way to apply this ontology enrichment process.

The *Opportunistic Reasoning Platform* in [27] is an ontology-based KBS model with a partial implementation. The main components of this platform are designed for reasoning from the web and oriented by the system needs (ontology toolkit, storage, query and reasoning systems). Although, it is possible to establish some correspondences of this KBS platform with three *OLeKSS* components (*Users, Products, Communication*), these authors do not include details about how the Knowledge Sources and Processes during KA processes can be used, which we have considered imperative in our model, in order to keep the associated ontologies updated. Even though these authors highlight the importance of keeping the ontologies/rules updated for this platform, they do not include details about how to do this.

Finally, the *Ontology-based of KMS Architecture* suggested in [77] has similarities with the components of our proposal (users/ knowledge engineers, knowledge sources, and services as processes). Compared with our model, users of this architecture cannot interact directly with each of the other system components as they would occasionally be required to do. Therefore, the interaction between the components of this architecture can only be reached through hierarchical layers, but in our model, they can interact directly. Despite the importance of a Communication component such as found in *OLeKSS*, this component is not considered appropriately in this architecture. Our premise of an emerging updating and enrichment process through OL from complementary KSOs (e.g., ontologies) is also not included.

7. Conclusions and future work

The analysis of KSSs features has shown that there are different types of KSSs, which can be classified according to the technology used for their specific implementation. Recently, the ontologies have been gradually incorporated to support KSS development as additional Artificial Intelligence MRs. The ontologies of these KSSs must be updated to respond to the continuous knowledge that users need, but until now, an explanation of how the updating process can be carried out has not been explicitly specified in the literature.

In this paper, a new framework for the social context of KSS knowledge and *OLeKSS* components has been proposed to support the improving development of KSS, based on its own learning capability. Indeed, OL is considered to be a useful way to enhance this competence by providing the required and convenient process of updating knowledge. In this sense, Gaines's KSS social view, updated in this study, is a more comprehensive one (as a systemic integrator) to satisfy the varied and continuous knowledge that users need, compared with the traditional approach to KBS.

Our novel *OLeKSS* model considers the general system components, identified as *Users, Process, Products, Communications,* and *Knowledge Sources*, simplifying the required process of updating knowledge. Thus, this proposed *OLeKSS* architecture can be useful as reference for any ontology-based KSS design and development.

SMOL was applied in this particular case as a systemic option for dealing with all the *OLeKSS* components. It enables *OLeKSS Users* to discover, recover, and manage the potential knowledge from diverse KSOs through OL, and to maintain the updating of corresponding *OLeKSS Products* (ontologies).

In addition, the knowledge acquired and recorded as *OLeKSS Knowledge Sources* during the *OLeKSS Processes* is useful for re-use during the processes of enrichment and population of the ontologies for the associated KSS.

In future work, we are going to deal with an additional subsystem specification related to the quality of the *OLeKSS Products,* such as ontologies, agents and system domains. In this sense, we are working in the specification of *wikis* to support the semantic meaning of the updated ontologies.

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References

[1] M. Abdullah, C. Kimble, I. Benest, R. Paige, Knowledge-based systems: a re-evaluation, Journal of Knowledge Management 10 (3) (2006) 127–142.
[2] D. Liu, I. Wu, K. Yang, Task-based k-support system: disseminating and sharing task-relevant knowledge, Expert System with Applications 29 (2005) 408–423.
[3] E. Sallis, G. Jones, Knowledge management in education: enhancing learning and education., Kogan Page Lim.UK & Stylus Publishing, USA, 2002.
[4] M. Venzin, G. Von-Krogh, J. Roos, Future Research into Knowledge Management, Knowing in firms: Understanding, managing and measuring knowledge, Sage Publications, London, 1999.
[5] G. Von-Krogh, Individualist and collectivist perspectives on knowledge in organizations: Implications for information systems research, Journal of Strategic Information Systems 18 (2009) 119–129.
[6] I. Nonaka, H. Takeuchi, The Knowledge Creating Company: How Japanese Companies Create the Dynamic of Innovation, Oxford Univ. Press, 1995.
[7] A. Maedche, S. Staab, Ontology learning, in: Handbook on Ontologies, Springer, 2004, pp. 173–189.
[8] M. Stankosky, Creating the discipline of knowledge management, Elsevier Inc., 2005.
[9] G. Phillips-Wren, M. Mora, G. Forgionne, J. Gupta, An integrative evaluation framework for intelligent decision support systems, European Journal of Operational Research 195 (2009) 642–652.
[10] C. Holsapple, Dss architecture and types, Handbook on Decision Support Systems, vol. 1, Springer, 2008, pp. 163–189.
[11] S. Antony, R. Santhanam, Could the use of a knowledge-based system lead to implicit learning?, Decision Support Systems 43 (2007) 141–151
[12] S. Staab, R. Studer, H. Schnurr, Y. Sure, Knowledge processes and ontologies, IEEE Intelligent Systems & Their Applications 16-1 (2001) 26–34.
[13] A. Aurum, F. Daneshgar, J. Ward, Investigating knowledge management practices in software development organisations – an australian experience, Information and Software Technology 50 (2008) 511–533.
[14] B. Gaines, Knowledge-support systems, Knowledge-Based Systems 3–4 (1990) 192–203.
[15] R. Gil, M.J. Martin-Bautista, An ontology-learning knowledge support system to keep e-organizations knowledge up-to-date: a university case study, LNCS, vol. 6866, Springer, 2011. pp. 249–263.
[16] R. Gil, L. Contreras, M.J. Martin-Bautista, A systemic methodology for ontology learning: an academic case study and evaluation, IC3K, KEOD-2010, October 25–28, Valencia-Spain, vol. 1, 2010, pp. 206–212.
[17] D. Power, Decision support systems: a historical overview, in: Handbook on Decision Support Systems, International Handbooks on Information Systems, vol. 1, Springer, Berlin, Heidelberg, 2008, pp. 121–140.
[18] A. Abecker, L. Elst, Ontologies for knowledge management, in: Staab, Studer (Eds.), Handbook on Ontologies, International Handbooks on Information Systems, Springer, Berlin, Heidelberg, 2009, pp. 713–734.
[19] R. Sinha, M. Manohara, M. Vidyasagar, A novel knowledge base decision support system model for breast cancer treatment, Sri Lanka Journal of Bio-Medical Informatics 1 (2) (2010) 97–103.
[20] L. Chittaro, R. Ranon, E. Carchietti, A. Zampa, E. Biasutti, L. De-Marco, A. Senerchia, A knowledge-based system to support emergency medical services for disabled patients, in: Artificial Intelligence in Medicine, LNCS, vol. 5651, Springer, Berlin, Heidelberg, 2009, pp. 176–180.
[21] L. Talluru, A. Deshmukh, A knowledge-based decision support system for costing job orders, The Review of Business and Information Systems 7 (3) (2003) 1–11.
[22] H. Huang, Designing a knowledge-based system for strategic planning: a balanced scorecard perspective, Expert Systems with Applications 36 (2009) 209–218.
[23] T. Padma, P. Balasubramanie, Domain experts knowledge-based intelligent decision support system in occupational shoulder and neck pain therapy, Applied Soft Computing 11 (2) (2011) 1762–1769.
[24] F. Calabrese, A. Corallo, A. Margherita, A. Zizzari, A knowledge-based decision support system for shipboard damage control, Expert Systems with Applications 39 (9) (2012) 8204–8211.
[25] R. Dodd, A knowledge based supervisory support system for pan stage operations in a sugar mill, Ph.D. thesis, PhD dissertation Royal Melbourne Institute of Technology University,Melbourne, Victoria, Australia, 2009.
[26] H. Shigeyoshi, S. Inoue, K. Tamanoi, S. Aoki, H. Tsuji, T. Ueno, Knowledge and transaction based domestic energy saving support system, LNCS, vol. 6884, Springer, Berlin, Heidelberg, 2011. pp. 242–251.
[27] C.P. Godoy, Knowledge-based reasoning over the web, Ph.D. thesis, Departamento de Lenguajes y Sistemas Informáticos de la Universidad del País Vasco, Spain, 2005.
[28] D. Liu, I. Wu, Collaborative relevance assessment for task-based knowledge support, Decision Support Systems 44 (2008) 524–543.
[29] N. Sánchez-Pi, J. Carbó, J. Molina, Kbs in context aware applications: commercial tools, IWINAC 2009, Part I, LNCS 5601, 2009, pp. 415–425.
[30] D. Feldkamp, K. Hinkelmann, B. Thonssen, The Modelling of Knowledge-Intensive Processes Using Semantics, Springer-Verlag, 2010.
[31] S. Middleton, NR. Shadbolt, D. De-Roure, Ontological user profiling in recommender systems, ACM Transactions on Information Systems 21 (2004) 54–88.
[32] J. Davies, A. Duke, Y. Sure, Ontoshare: an ontology-based knowledge sharing system for virtual communities of practice, Journal of Universal Computer Science 10 (3) (2004) 262–283.
[33] R. Boselli, F. De-Paoli, Semantic navigation through multiple topic ontologies, in: Proceedings of SWAP 2005, 2005, pp. 14–16.
[34] L. Zhen, Q. Huang, Z. Jiang, Recommender system based on workflow, Decision Support Systems 48 (2009) 237–245.
[35] H. Lee, J. Kim, J. Koh, A contingent approach on knowledge portal design for rd teams: relative importance of knowledge portal functionalities, Expert Systems with Applications 36 (2009) 3662–3670.
[36] G. Petasis, V. Karkaletsis, G. Paliouras, A. Krithara, E. Zavitsanos, Ontology population and enrichment: state of the art, in: Paliouras et al. (Eds.), Multimedia Information Extraction (LNAI) 6050, 2011, pp. 134–166.

[37] A. Gómez-Pérez, D. Manzano-Macho, An overview of methods and tools for ontology learning from text, Knowledge Engineering Review 19 (2005) 187–212.
[38] P. Buitelaar, P. Cimiano, B. Magnini, Ontology Learning from Text: An Overview: From the Book Ontology Learning from Text: Methods, Evaluation and Applications, IOS Press, 2005.
[39] P. Buitelaar, P. Cimiano, Ontology Learning and Population: Bridging the Gap Between Text And Knowledge, IOS Press, Netherland, 2008.
[40] P. Cimiano, Ontology Learning and Population from Text: Algorithms, Evaluation and Applications, Springer-Verlag, New York, LLC, 2006.
[41] M. Ehrig, Ontology Alignment: Bridging the Semantic Gap, Springer-Verlag, 2007.
[42] J. Euzenat, A. Mocan, F. Sharffe, Ontology Management, Ontology Alignments: An Ontology Management Perspective, Springer, 2007.
[43] I. Astrova, N. Korda, A. Kalja, Rule-based transformation of sql relational databases to owl ontologies, in: Proceedings of MTSR, 2007, pp. 1–16.
[44] F. Cerbah, Mining the content of relational databases to learn ontologies with deeper taxonomies, in: IEEE/WIC/ACM 1, 2008, pp. 553–557.
[45] V. Novacek, L. Laera, S.Handschuh, Semi-automatic integration of learned ontologies into a collaborative framework, in: IWOD/ESWC, 2007.
[46] E. Simperl, C. Tempich, D. Vrandecic, A Methodology for Ontology Learning, Chapter of Book Ontology Learning and Population, IOS Press, 2008.
[47] T. Hill, R. Westbrook, Swot analysis: it's time for a product recall, Long Range Planning 30 (1997) 46–52.
[48] N. Shamsfard, A. Abdollahzadeh, The state of the art in ontology learning: a framework for comparison, The Knowledge Engineering Review 18 (4) (2003) 293–316.
[49] H. Zargayouna, A. Nazarenko, Evaluation of textual knowledge acquisition tools: a challenging task, Lenguage Resources Evaluation Conferences 1 (2010) 435–440.
[50] N. Dahlem, A. Hahn, User-friendly ontology creation methodologies-a survey, in: 15th Amer. Conf. on Information Systems, California-USA, 2009, pp. 1–9.
[51] N. Callaos, B. Callaos, Designing with a system total quality, in: Educational Technology, 1994, pp. 29–36.
[52] N. Callaos, B. Callaos, Toward a practical general system methodological theory, Journal of Systemics, Cybernetics and Informatics (2003) 114–120.
[53] J. Whitten, L. Bentley, System Analysis and Design Methods, Mc Graw-Hill, 2005.
[54] G. Miller, The characteristics of agile software processes, in: Proceeding of the 39th Int'l Conf. and Exhibition on TOOLS'01 IEEE, 2001.
[55] Y. Yao, Y. Zeng, N. Zhong, X. Huang, Knowledge retrieval, in: Proceedings IEEE/WIC/ACM Int. Conf. on Web Intelligence, 2007, pp. 729–735.
[56] L. Zhou, Ontology learning: state of the art and open issues, Information Technology and Management 8 (3) (2007) 241–252.
[57] B. Gaines, M. Shaw, Knowledge acquisition, modeling and inference through the world wide web, International Journal of Human–Computer Studies 46 (1997) 729–759.
[58] T. Gruber, Colective knowledge systems: where the social web meets the semantic web, On WWW, 2007, pp. 1–19.
[59] G. Franco, P. Maresca, G. Nota, Modeling social influences in a knowledge management network, International Journal of Distance Education Technologies 8 (1) (2010) 1–16.
[60] S. Garruzzo, D. Rosaci, G. Sarné, Mars: an agent-based recommender system for the semantic web, LNCS, vol. 4531, Springer, 2007. pp. 181–194.
[61] Protege, Protege stanford university, 2008. <http://protege.stanford.edu/>.
[62] V. Ribière, A. Bechina, Knowledge management Technologies Chapter 12 In Search of Knowledge Management: Pursuing Primary Principles, Emerald Group Publishing Ltd., 2010.
[63] L. Ramos, R. Gil, Information system to support the management of the distance education (Spanish), Télématique, Venezuela, 9 (2010) 98–119.
[64] Swat-Project, Lehigh university benchmark (lubm), March 2009. <http://swat.cse.lehigh.edu/projects/lubm/>.
[65] Protege-Prompt, Tool manage multiple ontologies in protege, March 2009. <http://protege.cim3.net/cgi-bin/wiki.pl?Prompt>.
[66] R. Gil, A. Borges, L. Ramos, L. Contreras, Ontologies integration for university institutions: approach to an alignment evaluation, in: 19th Australian Conference on Software Engineering, ASWEC'08, 2008, pp. 570–578.
[67] Rapid-I, Predictive analytics, data mining, and text mining, March 2009. <http://rapid-i.com/>.
[68] GATE, General architecture for text engineering, March 2009. <http://gate.ac.uk/support.html>.
[69] R. Gil, A. Borges, L. Ramos, L. Contreras, M.J. Martin-Bautista, Improving ontologies through ontology learning: a university case, in: World Congress CSIE'09, IEEE Computer Society, Los Angeles-USA, March–April 2009.
[70] IUTEPAS, Instituto Universitario de Tecnología Pascal, IUTEPAS, Acta Constitutiva, 1996. <http://www.iutepas.8k.com/>.
[71] F. Cerbah, Learning highly structured semantic repositories from relational databases: the rdbtoonto tool, LNCS, vol. 5021, Springer, 2008. pp. 777–781.
[72] Neon-Project, NeOn ToolKit, NeOn-toolkit.org, 2010.
[73] RacerSystem, March 2009. <http://www.racer-systems.com/>.
[74] S. Bloehdorn, P. Haase, Z. Huang, Y. Sure, J. Völker, F. van Harmelen, R. Studer, Ontology management chapter 2, in: Semantic Knowledge Management, Springer-Verlag, Berlin, Heidelberg, 2009.
[75] S. Gregor, The nature of theory in information systems, MIS Quarterly 30 (2006) 611–642.
[76] V. Rajsiri, J. Lorre, F. Benaben, H. Pingaud, Knowledge-based system for collaborative process specification, Computers in Industry 61 (2010) 161–175.
[77] R. Meier, Knowledge Management Systems: Information and Communication Technologies for Knowledge Management, Springer, 2007.
[78] A. Agostini, R. Bosellim, F. De-Paoli, R. Dondi, Situation-based knowledge presentation for mobile workers, in: Proced. World Academy of Science, Engineering and Technology, vol. 3, January 2005.
[79] S. Jung, J. Kim, J. Herlocker, Applying collaborative filtering for efficient document search, in: IEEE/WIC/ACM Int. Conf. on Web Intelligence, 2004.
[80] H. Holz, O. Rostanin, A. Dengel, T. Suzuki, K. Maeda, K. Kanasaki, Task-based process know-how reuse and proactive information delivery in tasknavigator, in: CIKM'06, USA, vol. 1, 2006, pp. 522–531.
[81] E. Mena, A. Illarramendi, V. Kashyap, A. Sheth, OBSERVER: An Approach for Query Processing in Global Information Systems Based on Interoperation Across Pre-Existing Ontologies, In Distributed and Parallel Databases 8 (2) (2000) 223–271.
[82] Carey, M.J. Towards heterogeneous multimedia information systems: the Garlic approach, in Research Issues in Data Engineering, 1995: Distributed Object Management, Proceedings. RIDE-DOM '95. Fifth International. Workshop on IBM Almaden Res. Center, San Jose, CA, (1995), pp. 124–131.
[83] S. Melnik, E. Rahm, P. Bernstein Rondo: a programming platform for generic model management in Proceeding SIGMOD '03 Proceedings of the ACM SIGMOD New York, NY, USA (2003), pp. 193–204.

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A PROCESS-BASED KMS SUCCESS FRAMEWORK

EMPOWERED BY ONTOLOGY LEARNING TECHNOLOGY

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A PROCESS-BASED KMS SUCCESS FRAMEWORK

EMPOWERED BY ONTOLOGY LEARNING TECHNOLOGY

ABSTRACT

Organizations require empowered Information Systems (IS) and *Knowledge Management Systems* (KMS) to support several user's knowledge-tasks and decision-making responsibilities. Gradually, some KMS applications founded on Artificial Intelligence and semantic technology (ontology-based) have emerged to accomplish more suitable KMS under appropriate quality levels. In parallel, the previous IS/KMS success frameworks commonly used to evaluate the demanded quality levels are just based on taxonomy of quality dimensions. Based on a recent *KMS Success Framework* that includes the *knowledge-process performance* to complement the previous traditional tendencies (dimensional view), we improve the efficacy of the ontology-based KMS assessment through these knowledge-process framework. We propose the use of *Ontology Learning (OL)* technology to enhance the associated process performance of this kind of KMS. A case study has been included to illustrate the systemic enhancement and the results. The methodological resources used to introduce changes and to reach an empowered KMS implementation have been completed by applying an Ontology Learning methodology.

Keywords: *Knowledge Management System (KMS), KMS Success frameworks, Knowledge Processes Performance, Ontology Learning (OL), Case Study*

1. INTRODUCTION

Organizations have to stay updated and competitive to deal with the modern world trend based on successful knowledge discovery, recovery, and management processes. The huge and increasing quantity of available information and knowledge has been pressing organizations to count on more strong and efficacious Information Systems (IS) and *Knowledge Management Systems (KMS)* implementations.

In fact, some diverse technological resources based on Artificial Intelligence, Data and Text Mining, Semantic Web, and others, have been recently incorporated to the ISs and KMSs to turn them into more oriented knowledge acquisition and processing approaches. According to previous reported experiences, the KMS implementations based on ontologies usually developed are Intelligent Decision Support Systems (IDSSs), Knowledge Support Systems (KSSs), Knowledge Based Systems (KBSs), and others (Lee et al., 2009) (Shigeyoshi et al., 2011) (Padma and Balasubramanie, 2012). Moreover, the quality and efficacy of these developed KMSs are important features to be considered (Stankosky, 2005) (Power, 2008) (Ribiere and Bechina, 2010).

In this same vein, our central premise is related to the *Ontology Learning* (OL) technology capability to empower modern *Ontology-based KMS* under a context of an extended KMS success framework (Mora et al, 2010. Gil and Martin-Bautista, 2012, 2013).

In this sense, the most relevant IS/KMS success frameworks and their derived versions have arisen during the last two decades. Two significant proposals suggested by (DeLone and McLean, 1992), and updated in (DeLone and McLean, 2002) have become the main breakthrough of the literature, essentially due to the fact that they consider a taxonomy of quality dimensions (independent variables), and the user's dimensions impacted or favoured (the dependent variables) by the previous ones. Despite the fact that other new proposals and variants developed by other important authors have emerged during the last decade, most of them consider these two cited frameworks as their main reference (Seddon, 1997) (Rai et al., 2002) (Petter et al., 2008) (Petter and McLean, 2009) (Urbach and Müller, 2012).

One of the first proposals considering the knowledge processes as a referent to include dynamic behaviour in the KMS success model can be found in (Jennex and Olfman, 2006, 2011). To contextualize, we have emphasised the KM processes of our proposal in two user's dimensions of prior KMS success frameworks (Jennex and Olfman, 2011) and (Kulkarni et al., 2007). Following these preceding introductory steps, we have extended this process-based perspective in our framework, including the convenience to measure the performance of these knowledge processes empowered by the OL technology. An illustrated example of the application of this proposal of a process-based KMS success framework improvement based on OL technology has been included in this paper as a case study.

Likewise, in this paper, we have outlined in detail how the knowledge (meta/sub) processes are the mechanism of interaction among the diverse dimensions of this KMS success approach. Indeed, a group of four meta-processes (*Extracting, Memorizing, Reusing,* and *Sharing),* as well as the performance measuring of their efficacy, can be used to explain essentially the user's dimensions of this novel approach.

The main focus of this work is:

- To describe an extended KMS success framework based on a hierarchy of *Knowledge process* under an user-centred view
- To identify the *Knowledge (meta/sub) processes* feature susceptible to be improved through OL technology;
- To determine how the *performance measures* of the associated *knowledge (meta/sub) processes* are affected by the OL improvements;
- To apply OL changes and improvements to the KM processes for a specific KMS Case study.

On the other hand, most of the KMS implementations have to deal with *knowledge management* (KM) acquisition and processing problems. Besides, many of these KMS implementations are based on ontology resources for this development and support. In this sense, a few optional experiences have been recently found in the literature where the OL technologies could be useful to face problems associated with the Knowledge Acquisition (KA) processes and keep this kind of KMSs updated (Gil and Martin-Bautista, 2011, 2012).

Specifically, the essential problem to face in this work is associated with the opportunity to improve the KMS performance efficacy (*User Satisfaction dimension*) of these involved knowledge process layers (*KMS Perceived Usefulness dimension*) through the application of a Systemic Methodology for OL (SMOL). The validation of the general OL improvement proposal is supported by the SMOL application in a real ontology-based KMS Case study.

Likewise, the main contributions of this work are the following:

- To suggest an optional KMS success framework (re) specifying the users' dimension according to their associated knowledge meta/sub processes;
- To explain how to incorporate OL technology to the defined knowledge processes to reach the associated KMS success performance improvement;
- To validate through a Case study application how the processes-based KMS success framework can be improved by the OL technology;
- To suggest some derived considerations/recommendations to face other similar KMS case studies assessment under the context of these extended KMS success frameworks.

As a summary, in this work we have suggested an extension of a KMS success framework based essentially on the knowledge process performance. Additionally we have shown (using a real case study) how those identified knowledge processes can be improved by OL technology in the case of ontology-based KMSs.

To conclude this Section, this article has been structured as follows: the diverse backgrounds about the evolution of IS/KMS success frameworks and the OL technologies have been introduced in Section 2; a summary about the two knowledge processes layers of the selected KMS success frameworks related to the user's dimensions is explained in Section 3; the specification of the improvement of the knowledge processes through OL is detailed in Section 4; the KMS University Case study is illustrated in Section 5; and finally, the conclusions and future works are given in Section 6.

2. BACKGROUND

The progress of IS/KMS quality models and the technological evolution based on ontology development and Ontology Learning (OL) are introduced in this Section. Specifically, a short summary about the IS/KMS success frameworks evolution is introduced in Subsection 2.1; the KMS implementations based on ontologies and the OL as a mechanism to keep updated is pointed out in Subsection 2.2; and the OL as a KMS empowering resource in Subsection 2.3.

2.1 The IS/KMS Success Framework Evolution

An interesting evolving process has characterized the IS/KMS Success models identified in the related literature. According to our interpretation, they have been originally conceived in a structural, static, and systematic fashion (as taxonomy of dimensions and relationships), that we have identified by the expert-side view.

In this sense, the most relevant pioneer works introduced by (Delone and Mclean, 1992) have marked the schematic style of the dimensions (independent and dependent variables) used to explain or specify the quality components. Some other relevant and successive IS/KMS success models/frameworks proposals have been influenced by this structural approach (expert-side) despite their important recommendations, justified changes, and their impacting model improvements (Delone and Mclean, 2002) (Kulkarni, 2007) (Petter, 2009) (Jennex and Olfman, 2006, 2011) (Urbach and Müller, 2012).

On the other hand, some recent KMS success frameworks consider various pertinent perspectives and dimensions, according to a more modern user knowledge requirement views (user-centred). Indeed, they have incorporated the knowledge process view, some aligned dimensional arrangements, and re-specifications which consider the users' dimensions in accordance with their associated knowledge processes (Jennex and Olfman 2006, 2011), (Urbach et al., 2012).

However, this few recent proposals of IS/KMS success models have turned out to be more flexible, process-centred, and systemic styles. In our proposal of process-based KMS success model, we have denominated this approach the *user-centred view*. Focused on this novel knowledge processes trend, we intend to trace out how the KMS associated ontology-based KMS (meta/sub) processes and their consequent performance can be improved through OL.

2.2. Ontology-based KMS Implementations

Diverse implementations of KMS have been oriented to support knowledge users' requirements. In the recent literature, we have found some of them oriented to support knowledge and decision-making tasks regarding organizational knowledge users' needs. Some common KMS implementations are related to profiles oriented to: Workflow, Problemawareness, Knowledge sharing, Document recovery, and so on (Lee et al., 2009) (Shigeyoshi et al., 2011) (Padma and Balasubramanie, 2012).

A particular specialization of this kind of KMS has been identified in the literature as *Knowledge Support System (KSS)* and Decision Support System (DSS) instances (Gaines, 1990). Besides, the perspective of KSS as a variant of "Knowledge-driven" DSS has been also considered in (Power, 2008). In this same vein, some other authors have identified the DSS as a category of KMS specializations in (Stankosky, 2005) (Ribiere and Bechina, 2010).

Precisely, an updated characterization and classification of the main KSS's profiles as KMS implementations can be found in our previous work in (Gil and Martin-Bautista, 2012). This cited classification considers KSS applications such as *Traditional systems* and *Intelligent Systems.* We have focused on the latter, because this type of KSS is primordially ontology-based implemented, and consequently, they are able to be improved through the pertinent MRs of the OL technology as they are summarized in the prior Subsection 2.2.

In this work, the ontology-based KMSs are our central point of interest because they are able to be updated using heterogeneous KSOs through OL technologies according to the *Methodological resources (MR)* associated with each one of these sources (Mora et al, 2010). A vision of the main MRs is detailed in the subsection below.

2.3. OL Technology used as a KMS Empowering Resource

The OL technology usually associated with the Semantic Web movement has been considered primordially to suggest the extended KMS success framework view. Essentially, in this work, we intend to show how the incorporated OL mechanisms in the *knowledge processes* can improve the *performance measure* of their associated user dimensions (*Usefulness* and *Satisfaction*).

To simplify this purpose, we have selected the OL definition in (Petasis et al., 2011) "*as the process of automatic or semi-automatic construction, enrichment, and adaptation of ontologies*" Besides, "*the ontology enrichment and populating are defined as a couple of (semi) automatic tasks".* The former has been selected to extend an existing ontology with additional concepts and semantic relationships and to place them in the correct position and the latter is associated with tasks to add new instances of concepts in the ontology (Maedche and Staab, 2001).

In this sense, the specialized KMS's profiles in (Gil and Martin-Bautista, 2012) illustrate how some ontology-based mechanisms have been applied to support the users' knowledge tasks (identification, registration, and recovery) and other workflow requirements. Therefore, any flexible and integral OL process that could positively impact on the knowledge structures (taxonomic or non-taxonomic) and the continuous classes/instance updating (populating or enrichment) associated with these ontological resources must enhance the support provided to users by these types of specialized KMS.

Likewise, the *knowledge processes* enhanced by OL have been chosen as the foremost linker between this new dynamic proposal (systemic view) beside the static or structural (systematic view) of the preceding framework trends. In fact, the OL technology traditional view based on the unique *knowledge source (KSO)* such as text or documents is extended in these approaches to use other KSOs such as databases and other previously developed ontologies.

Consequently, some relevant and useful MRs for OL such as techniques, tools, methods, and/or methodologies, which may be used to improve the efficacy of the associated *knowledge processes*, have been summarized for each KSO in Table 1 (Callaos, 1992).

Table 1. Methodological Resources (MRs) for Ontology Learning from each KSO

Definition of MRs (Callaos 1992)	Ontologies	Texts (Corpus)	Databases	Measures
Technique: Subjective capabilities to handle a tool by users	- String matching - Graph based - Statistic analysis	- Linguistic patterns - Semantic relativity - Data mining algorithms	- Rule-based (similarity) -Taxonomic structure analysis - Clustering techniques	Efficiencies: Ratio Output/Input
Tool: Objective capabilities to apply techniques	- Alignment - Structured & merging - Matching	- Statistical - Linguistics - Machine learning	- Attributes, - Instances & DB schemas. - Synonyms & inclusions - Classes (RTAXON method)	Efficiencies: Ratio Output/Input
Method: A way to think/doing to achieve an objective	ASMOV. MapPSO Prompt, FCA-Merge & H-CONE	CRSTOL. ASIUM, GATE, OntoLearn Text2Onto	ARTEMIS, DIKE, DataMaster ODEMapster, RDB-ToOnto	Effectiveness: Ratio Objectives/Output
Methodologies: Set of techniques methods and tools	Approaches: - FOAM -OL: Protégé-Prompt	- OL Framework - Structured - BOEMIE - DINO	- Observer - Garlic - Rondo - RTAXON	Efficacy Ratio Objectives/Input

Finally, according to the efficacy *performance measuring* of these *knowledge processes*, some considerations based on existing indicators and measures of IS/KMS Success have been incorporated in this suggested process-based framework (Urbach and Müller, 2012) (Almutari and Subrananian, 2005).

3. AN EXTENDED PROCESS-BASED KMS SUCCESS FRAMEWORK

We have introduced the process-based KMS success framework considering a systemic vision constituted by a two KM process abstraction level. In this new framework, the traditional approach based on a dimensional arrangement under a hierarchical interrelationship scheme (system expert view) has been extended and detailed in our proposal to incorporate the perspective of the *knowledge process* performance (users-centred view). A representation of this novel extended KMS success model is shown in the Figure 1.

The most important KMS success model's dimensions about the qualities and users were updated on this cited work, considering some relevant versions of the previous IS/KMS success models (DeLone and McLean, 2002) (Kulkarni, 2007) (Jennex and Olfman, 2011) (Urbach and Müller, 2012).

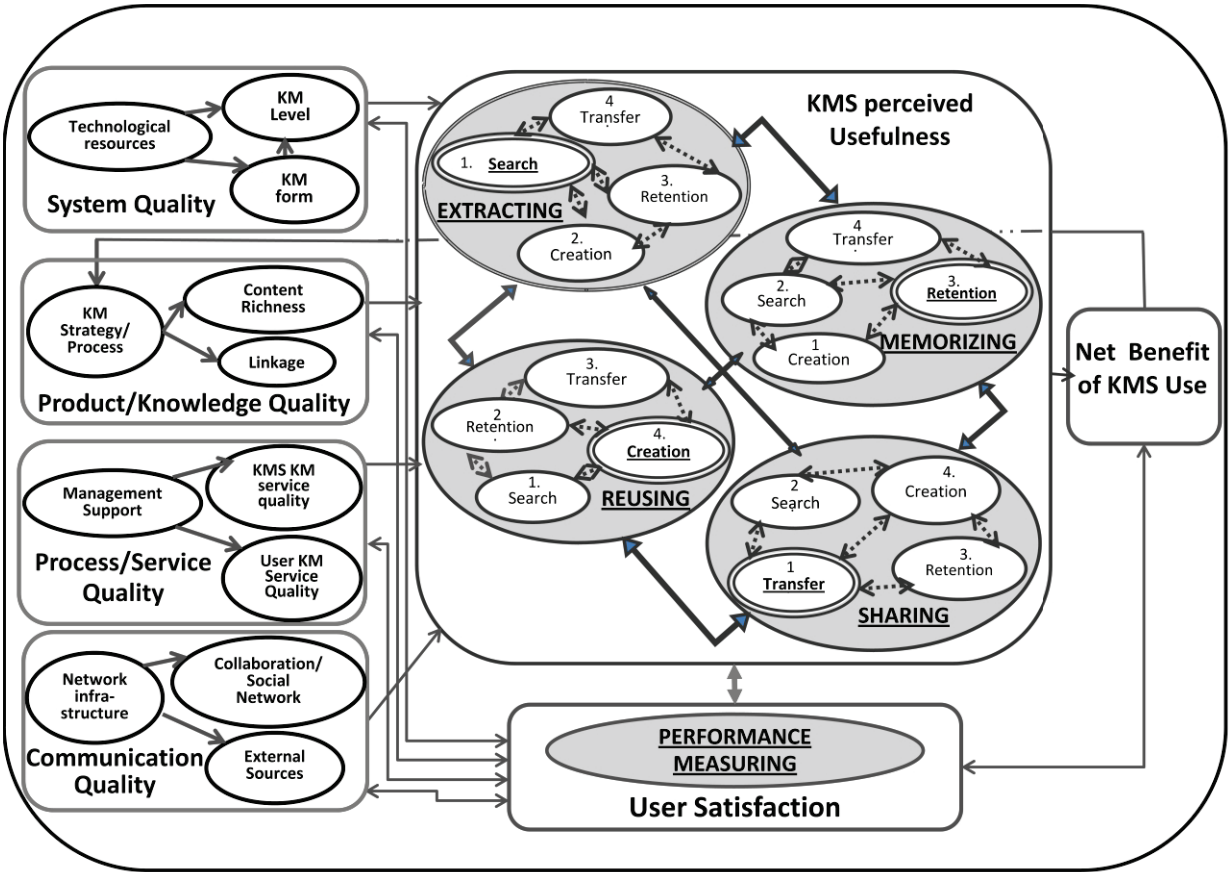

Fig. 1. Process-based KMS success framework model

In this sense, this novel model includes new trends about the KMS' four quality (sub-) dimensions (in left side of Figure 1). Particularly, the *Process/Service dimension* and the *Communication dimension* have been specially also considered. The main associated premise about to emphasise in those dimensions is related to the quality of the identified KM processes can be increased by the success of those two dimensions. Likewise, the four holistically interrelated *knowledge (meta/sub) processes* to conceive the new vision of the KMS *Perceived Usefulness dimension* have been also included. Finally, an associated control-evaluation meta-process called *Performance Measuring* has also been included in the model as a required expansion of the *User Satisfaction dimension*.

In short, we have chosen and updated the four independent quality dimensions and the three dependent dimensions of the suggested framework as follows (Figure 1):

1. *System Quality*. Including the following sub-dimensions; *Technological resources*, *KM level,* and *KM forms*;

2. *Product/Knowledge Quality.* Including the following sub-dimensions: *KM strategy process, Context richness, and Linkage;*

3. *Process/Service Quality.* Including the following sub-dimensions: *Management (OMs) support, KMS KM service Quality, and User KM Service Quality* (Jennex and Smolnik, 2011)*;*

4. *Communication Quality.* Including the suggested and re-specified sub-dimension*: Network infrastructure, Collaborations/social networks, and external sources* (Urbach et al, 2010);

5. *KMS Perceived Usefulness.* Including the novel introduced sub-dimensions*; Knowledge Extracting* and *Knowledge Memorizing,* in addition to the other sub-dimensions such as *Knowledge Reusing and Knowledge Sharing* cited in prior works (Velazquez et al., 2009).

6. *User Satisfaction.* Including the novel introduced sub-dimension; *Performance Measuring.*

7. *Net Benefit of KMS Use.* It corresponds with each involved stakeholder: *Individuals, Organization, and Social.*

So as to simplify the description of each of the involved dimensions of this process-based framework, a short summary of all of them is shown in Table 2. Likewise, a summary about the main associated sub-dimensions are described in Appendix A (Table A.1).

Table 2. Short description of the main Process-based KMS success dimensions

Dimension	Short Description
System Quality	The technological skills as a key component to support KM processes using high-end computational resources
Product/Knowledge Quality	An infrastructure that integrates KM processes into regular work practices. The user's knowledge-needs are according to users' levels
Process/Service Quality	Enterprise directives to ensure that adequate resources are allocated to the creation and maintenance of KM
Communication Quality	Technological resources for communication, and improvement of information sharing and social networking tasks
KMS Perceived Usefulness	Subjective appraisal of the extent to which the user believes that this KMS contributes to use the knowledge capabilities
User Satisfaction	Some indicators about how the KMS contributes to the use of knowledge capabilities
Net Benefit	Net benefit as perceived by the different types of stakeholders

Following this vein, the dimensional interrelationships (the arrows in Figure 1) have been projected in Table 3, under a similar way to the ones discussed in (Petter et al, 2008) and (Urbach and Müller, 2012).

Finally, the two processes-based empowered dimensions (Users Perceived Usefulness and User Satisfaction) which have respectively enclosed the knowledge (meta/sub) processes and the *measuring process* (highlighted as shadowed ovals in Figure 1) represent our main focus to support our OL improvement proposal.

Table 3. Dimension interrelations

Antecedent		Explained Construct	Projected Support
KMS Perceived Usefulness			
- System Quality	→	Knowledge Sourcing/Sharing	~ Mixed support
- Product/Knowledge Quality	→	Knowledge Sourcing/Sharing	~ Mixed support
- Processes/Service Quality	→	Knowledge Sourcing/Sharing	º Insufficient Data
- Communication Quality	→	Knowledge Sourcing/Sharing	+ Moderate
User Satisfaction			
- System Quality	→	User Satisfaction	++ Strong
- Product/Knowledge Quality	→	User Satisfaction	++ Strong
- Processes/Service Quality	→	User Satisfaction	+ Moderate
- Communication Quality	→	User Satisfaction	+ Moderate
Net Benefit of the KMS Use			
- System Quality	→	Net Benefit	+ Moderate
- Product/Knowledge Quality	→	Net Benefit	+ Moderate
- Processes/Service Quality	→	Net Benefit	+ Moderate
- Communication Quality	→	Net Benefit	+ Moderate

3.1. Users Dimensions: Two Levels of Knowledge Processes

Regarding our user-centred view, the result of the KMS success is recognized by users in the two related dimensions of the framework. Thus, the KM (meta/sub) processes are related primordially with the *KMS Perceived Usefulness* dimension and the KM processes performance within the *User Satisfaction dimension* (respectively in the top-centre and bottom-centre of Figure 1).

In this sense, the users' associated KM meta-processes have been mainly conceived from the theoretical proposals obtained in the related KM literature together with some experiences with systemic methodology application. In the literature, knowledge sharing and reusing are considered as the most developed KM activities associated with the users (Markus, 2001) (Kulkarni et al., 2007). Nevertheless, we have explicitly considered and incorporated into this extended KMS Success framework proposal two increasingly relevant organizational knowledge-tasks activities associated with the knowledge extraction and memorization, under a systemic upper abstraction-level.

So as to offer a bottom-up description of the involved meta/sub processes, we first introduce the lower abstraction-level sub processes and afterwards, those corresponding to the upper abstraction-level. Indeed, the sub-processes have been conveniently adapted by the authors from the Organizational learning domain of (Argot and Miron-Spektor, 2011) in the next subsection.

3.2. Knowledge Processes to Increase the Perceived Usefulness by the User

With the intention to incorporate the appropriated user's view supported by dynamic knowledge processes in an *Extended KMS Success Framework*, we have considered reviewing the KM and Organizational learning processes to enrich the traditional structured IS/KMS success view.

In this sense, we have reviewed some Organizational Learning frameworks suggested in the works by (Argyris and Schön, 1978) (Kim, 1993) (Nonaka and Takeuchi, 1995) (Nonaka and von Krough; 2009) (Argote and Miron-Spektor, 2011).

We have selected as a reference to be supported by our suggested knowledge (meta/sub) processes., the corresponding Knowledge cycle phases synthesized in (Mora et al, 2011). These phases are named by the cited authors as: *Knowledge Preservation, Storage/Processing, Distribution, and Application*. Likewise, we have chosen this latter work (hereafter the A&M model of Argote and Miron-Spektor (2011) as a significant model reference for drafting our process-based model proposal. An updated representation of the knowledge-sub processes based on this model can be found in Figure 2.

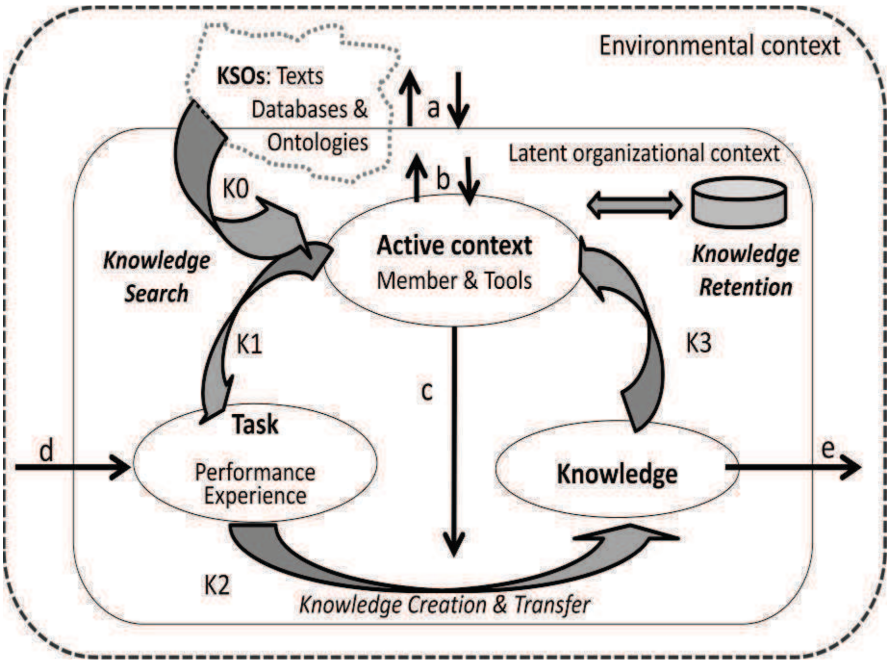

Fig. 2. Updated Organizational Learning Framework

This A&M model is based on an ongoing cyclical (sub) process that occurs over time through the task experiences. This *cyclical process* converts task-data into knowledge consistent with *the context.* The basic elements of organizations are *members, tools, and tasks*. These elements and their networks (e.g. Member-member, member-task, task-tools, and so on) are the primary mechanisms in organizations through which *Organizational Learning* occurs and the knowledge is *searched, created, retained, and transferred*. For our study, these later four *knowledge sub-processes* are essential to conceive the suggested extended framework.

Specifically, in the original A&M model, the *knowledge search sub-process* is represented only by the equivalent K1 arrow. In our updated proposal (Figure 2), we have incorporated the K0 arrow to illustrate how the knowledge can be (semi-) automatically discovered and recovered (*Knowledge Extracting activity*) from heterogeneous KSOs and diverse contexts. Likewise, the increasing proliferation of structured knowledge such as Ontologies, thesauruses, folksonomies, has led the organizations to perform knowledge extraction activities from this type of KSOs as well.

On the other hand, as regards the *knowledge meta-processes*, we have opted for a techno-centric KM perspective with a focus on semantic and communication technology in (Gil and Martin-Bautista, 2012). Ideally, the most appropriated ones have been applied to improve *Knowledge Sharing* and *Reusing* meta-processes. Under this perspective, we have extended the vision to the *knowledge meta-processes*, including the KM capability of *Knowledge Extracting* and *Memorizing* aligned with the highlighted user's dimensions identified in the previous Section 2.

A summary of these knowledge sub-processes with the corresponding aspects which could be improved through the OL technology is shown in Table 4.

Table 4. Summary of Knowledge Sub-processes

Sub-process	Definition	Subject to be Improved
Knowledge Search	It is a looking-for process for novel or known experiences from local or distant areas	• Different experience can be found from external sources (KSOs) • (Semi) automatic process/tool support external recovery • Structured and unstructured KSOs can be processed
Knowledge Retention	The flow and stock of knowledge in the organization's memory	• Knowledge "reuse" and whether the knowledge is "forgotten" • The knowledge decay and depreciate at different rates • Characterization of the different types of organizational memory • Identification of routines aims to understand patterns
Knowledge Transfer	Learning indirectly from the experience of others as well as from their own experience.	• The absorptive capacity of the unit involved • Location and boundaries of the source of experiences • Technological- and social- network mechanisms
Knowledge Creation	When a unit generates knowledge that is new to it.	• Diverse experience base contributes to creativity • Recording the successful experiences, routines and practices • Online communities and social networks

On the other hand, for the upper abstraction-level of our suggested framework, the four meta-processes considered are the following: a) Knowledge Extracting, b) Knowledge Memorizing, c) Knowledge Reusing, and d) Knowledge Sharing. Some details about these knowledge meta-processes and their potential aspects to be improved are summarized in Table 5. A more specific description of each knowledge meta-processes under a systemic interrelationship perspective with their four involved knowledge sub-processes have been included in Appendix B.

Additionally, to be consequent with the required knowledge process performance efficacious, an emerging standard-control process has been included in the KMS success framework (*User Satisfaction dimension*) named by the authors as *Performance Measuring.* This measuring process has been defined as a mechanism for measuring the input and output of the knowledge processes. Through this control mechanism, it is possible to adjust the main KMS objectives, scopes and resources according to some quality standard indicators, to increase the knowledge process/product efficacy in proportion to the partial reached efficiency and effectiveness performances.

Table 5. Summary of Knowledge Meta-processes

Meta-process	Definition	Subject to be Improved
Knowledge Extracting	Methods/tools for knowledge identification, recovery, and creation from structured/ unstructured KSOs	• The internal/external sources (KSOs) • The new methods/tools • The involved contexts (Local, Organizational & Environmental)
Knowledge Memorizing	Resources/means used to gather /actualize knowledge /information continuously, offering proactive assistance to knowledge workers.	• Storage of the most relevant kind of knowledge required • The most relevant sub-processes and storage types (KRS/TMS) • Storage mechanisms suitable for each kind of KSOs
Knowledge Reusing	Mechanisms through which the users can incorporate knowledge (from KSOs or stored contents) in their regular knowledge-tasks	• The regular knowledge-tasks which require improvement. • The heterogeneous KSOs and contexts (locations) • Explicit/tacit Knowledge comparing • Knowledge growing and restructuring
Knowledge Sharing	Explicit/tacit knowledge exchanges among people, friends, groups, a community, or an organization.	• Previous Case-studies gathering • The involved users and their communication tools • Efficacious access to KSOs and the organizational TRM/TMS

4. THE IMPROVED KMS KNOWLEDGE PROCESSES THROUGH OL

The use of OL technology to keep some intelligent systems such as ontology-based KSS implementations updated has been cited in some previous works (Abecker and Elst, 2009) (Fernandez-Lopez et al., 2012). Particularly, when the OL is applied from heterogeneous KSOs, its updating capability over some KMS implementations is pointed out as a useful and efficacious process during the required continuous KA task (e.g. Knowledge Extracting) (Gil and Martin-Bautista, 2010, 2012).

OL from different KSOs can improve some specialized KMS through the knowledge growth, restructuring and comparing processes related to: (a) knowledge-bases that belong to KBSs within those KMSs; (b) operational knowledge structures (e.g., profiles, contexts, or workflow); (c) structured filtering of resources (e.g., rule-based or collaboration); (d) others (e.g. agents).

Therefore, in the next Subsections, we have specified how the OL technology can be applied to the knowledge meta/sub processes of the corresponding users' associated dimensions (*Perceived Usefulness and Satisfaction*) to increase their performance efficacious. Specifically, the OL improvement of the *knowledge sub-processes* is shortly described in Subsection 4.1; the *knowledge meta-processes* improved by OL are described in Subsection 4.2; and, the performance measurements and efficacious outcomes are summarized in Subsection 4.3.

4.1. The OL Improved Knowledge Sub-processes

In this Subsection, we have analysed how the *OL* mechanisms can be incorporated (desirable and feasible changes) as enablers of these *knowledge sub-processes*. In fact, some relevant components based on these sub-processes have been considered in Figure 1 as well.

In fact, in order to enhance the knowledge sub-process with OL mechanisms, we have previously adapted these sub-processes and the context(s) interpretation of the preliminary process-based KMS success model suggested in (Jennex and Olfman, 2011) and our updated version of the A&M model. This adaptation can be found in the cited Figure 2.

All the *knowledge sub-processes* (*search, retention, transfer,* and *creation*) have been updated and enhanced with this OL technological view. Complementarily, the integrated specification of the *Knowledge Memorizing meta-process* mediated by ontology-based application (in Subsection 4.2.2), could also improve the systemic partial efficacy of these involved *knowledge sub-processes*.

Some of the most relevant effects over the *knowledge sub-process* by-product of OL enhancement and some memorizing resources are summarized in Table 6.

Table 6. Knowledge sub-processes Enhanced by OL and *Memorizing meta-process*

Sub-processes	Features to be considered	Technological OL purposes and potential goals
Knowledge Search	• Potential heterogeneous KSOs • Varied organizational contexts as sources • Tacit/implicit KA	• Effective OL MRs from complementary KSOs • Effective/efficient OL from diverse source links • Effective/efficient KM through the MRs of OL
Knowledge Retention	• Potential/partial diverse KSO databases • Links to potential/partial KSO locations • Tacit/implicit potential knowledge storage • Appropriate knowledge query mechanisms	• Continuous knowledge updating by automatic OL • Automatic search/updating through OL tools • OL from prior stored tacit/implicit knowledge • MR of OL aligned with the storage/query means
Knowledge Transfer	• Heterogeneous KSO sharing capabilities • Tacit/implicit knowledge sharing MRS • Expert and user interaction mediated MRs • Consensual/agreement KM mechanisms	• OL sharing MRs considering diverse KSOs • Tracking of the KSOs according to the applied OL • MRs of OL to support Experts/Users' interactions • MRs of OL to support Experts' consensual process
Knowledge Creation	• Heterogeneous KSO query mechanisms • Consensual/agreement KM mechanisms • Expert and user interaction mediated MRs • Semantic discovery and analytical tools	• MR of OL aligned with the query users' needs • MRs of OL to support Experts' consensual process • MRs of OL to support Experts/Users' interactions • OL based semantic data/text analysis tools

4.2 The OL Improved Knowledge Meta-Processes

In the next Subsections, we have developed a short description regarding some possible favourable impact (systemic or emerging properties) over the *knowledge meta-processes* once their particular involved OL sub-processes have been enhanced by OL technology.

4.2.1 The OL Improved Knowledge Extracting Meta-Process

Intending to reach a more efficacious (effective and efficient) *knowledge Extracting* meta-process based on OL mechanisms, some important aspects have characterized this re-specification. The most relevant ones are the following: 1) the most diverse organizational contexts (the three cited in Figure 2) useful to obtain complementary and heterogeneous KSOs; and 2) the most suitable MRs for automatic OL associated with each one of this potential KSOs.

Regards an extended contextual view, we have expanded the KSO scope to become more “active” up to the three *Contexts* suggested in the selected referential *A&M* model. Specifically, under this perspective, the required knowledge would be searched and recovered from diverse KSOs of these significant contexts: the *Local* one (in the same organizational unit), the Organisational one (all the enterprise units), and the *Environmental* one (external organizations/institutions).

Concerning the MRs available to apply OL from these heterogeneous KSOs, the efficacy of the automatic OL tools (e.g. CRSTOL, RDBToOnto, Watson, and so on) as another key focus of attention for the *Knowledge Extracting meta-process* specification has been considered.

In fact, some instances of Extracting meta-processes are supported for partial and previous retention sub-processes where some selected KSOs and/or MRs (e.g. automatic procedures) have been previously used for OL purposes and later *transferred* to the required *Memorizing meta-processes* as reusable resources. This kind of flexibility over instances of the *Extracting meta-processes* must enhance the efficiency of additional or new *Extracting/search meta/sub-processes*.

4.2.2 The OL Improved Knowledge Memorizing Meta-Process

In this Subsection, we have suggested an integrated *Memorizing meta-process* architecture (represented in Figure 3) that has to support the other important *knowledge (meta/sub) processes* previously highlighted in this work.

The *Knowledge Repository System* (KRS) and the *Transactive Memory System (TMS)* are the most common Organizational Memory (OM) subsystems cited in the relevant literature (Markus, 2001) (Wegner, 1995). Under this integrated *Knowledge Memorizing* architecture, we have considered and included some designing features about the most recent kind of memorizing subsystem implementations (Brandt et al., 2006, 2008) (Decker et al., 2005) (Ammari et al., 2011).

Regarding these OM subsystems, in this proposal, on one hand, the KRS can store KSOs and MRs useful for OL and user’s information/knowledge queries. On the other hand, the TMS can store the associated resources required for tracking the associated users’ activities about KMS knowledge changes. Both subsystems can support essential tasks of knowledge reusing and sharing. Some details about KRS/TMS subsystems have been included in Appendix B (letter B).

In the same vein, our suggested *Memorizing meta-process* architecture considers the following aspects: 1) it can *retain* (store) the most relevant kind of knowledge required to support the *knowledge (meta/sub) processes*; 2) the components (TMS/KRS) (delimited by rectangles in Figure 3) emphasize the *knowledge process* which they can support best and directly; 3) it includes all the KSOs considered in this work, particularly the previous developed Ontologies as another useful source to support *Knowledge Extracting processes;* and 4) it can also retain some possible MRs for OL such as specialized tools and derived procedures (agents) for potential *Knowledge Reusing* purposes.

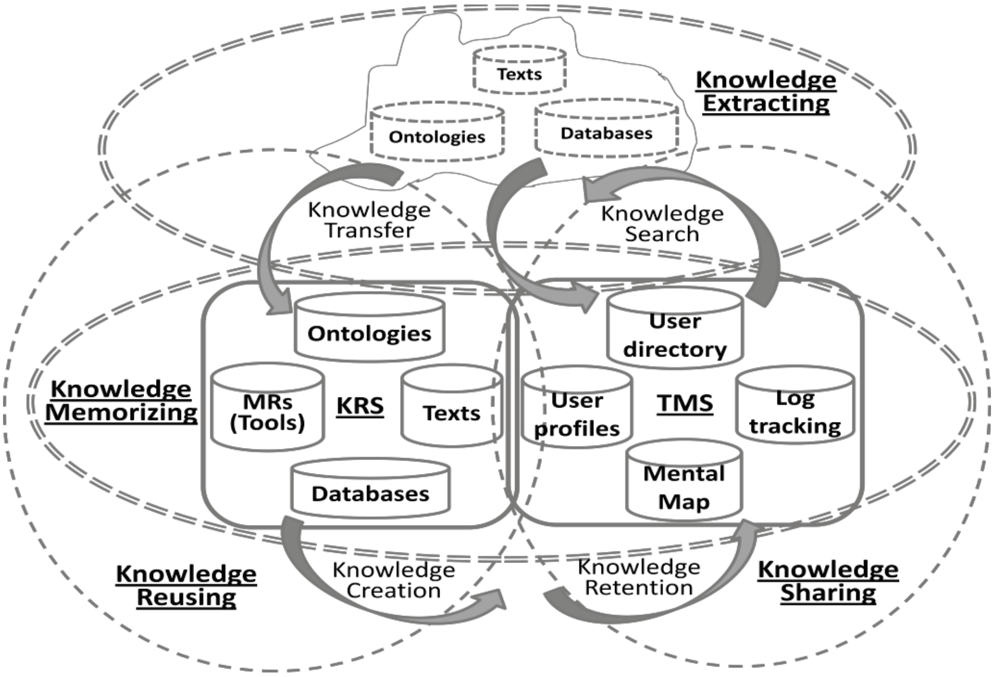

Fig. 3. Overview of improved *Memorizing meta-process*

4.2.3 The OL Improved Knowledge Reusing Meta-process

New knowledge is used and required for the continuous updating process of the KMS (*Extracting and Memorizing* processes) and this knowledge is increasingly represented as ontologies. Despite this, KSOs are usually overlooked as significant features or components of the KMSs.

According to the related literature (Markus, 2001) (Kulkarni et al., 2007), the *Knowledge Reuse*, has been associated with the knowledge obtained from documents (partial text contents) or other kinds of content objects (e.g. classes in ontologies, attributes of databases, and so on) to increase organizational-members' knowledge-tasks. In our proposal, the sources to facilitate the *Knowledge Reuse* requirements *(search and transfer sub-processes)* could be obtained through two different ways: 1) from the KSOs of the three cited organizational contexts and 2) from the KSOs previously stored in the KRS/TMS subsystems implemented in the *Knowledge Memorizing meta-process*.

In summary, some (semi-) automatic extracting processes for OL from complementary KSOs (through diverse contexts and/or previously stored through OM subsystems) could improve the effectiveness and efficiency of diverse *Knowledge Reusing meta-processes.*

4.2.4. The OL Improved Knowledge Sharing Meta-Process

To characterize the exchange-interaction between end-users requiring knowledge (e.g. queries and/or advises) by professionals (expert's knowledge generators) as a *Knowledge Sharing meta-process* mediated by a specialized KMS, we propose to use an updated version of a specialized KMS model (Gaines, 1990).

Particularly, this updated Gaines' model (in Figure 4) is useful to articulate the *Knowledge Sharing process* among the *Expert* community and the *End-user* community. The expert-users can directly support their knowledge task-activities based on the potential and complementary KSOs (ontologies, databases, and texts) necessary for the OL processes recovered from the three prior cited contexts.

Through the MR for OL, the available knowledge gathered on previous *Examples-Case*s (in Figure 4, top left-side) is usually expressed as previous *published ontologies* or *system database* format from the three cited contexts. These KSOs are useful to improve (update/enrich) the domain-ontologies of the associated KMSs. Indeed, both KSOs (ontologies/databases) can be searched by automatic MRs for OL to improve their ontological KMS domains (e.g. taxonomic changes/ontology population).

Finally, and not less important, some users' needs would require effective knowledge access and processing of the documents and text format. Through MR for OL from contents in texts, significant ontologies of this kind of KMS can be updated with scientific texts retrieved from the Internet of the Environmental context (e.g. conferences, workshops, and journals in Figure 4, bottom-left side), and/or from technical manuals or executive documents of the same Unit or Organisational contexts.

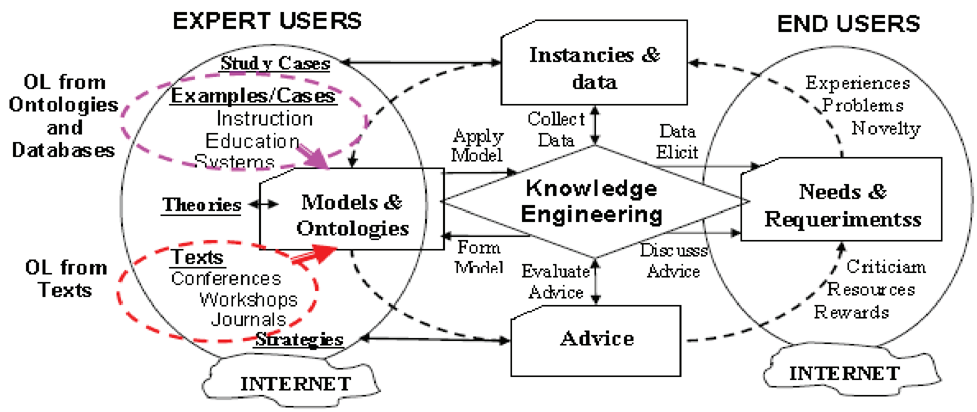

Fig. 4. The social context for the knowledge support process

4.3. The Efficacious Performance Improvement

The fundamental purpose behind measures is to improve performance. Precisely, each *knowledge meta-process* has to be measured to reach the expecting quality level demanded by the specific organizational cases. Some quality standard measures could be considered also in this process-based KMS success framework.

We have applied technological enablers (mainly based on OL mechanisms) to enhance each one of the four *knowledge sub-processes* of the suggested framework. These enhanced sub-processes could affect (locally and/or globally) the performance of the correlated *knowledge meta-processes* according to the quality dimensions (re) specified in the framework.

Particularly for this work, the *efficiency* is related to the capability to produce an output with minimum input (ratio input/output); *effectiveness* is associated with the ability to reach a desired result (ratio objective/output); and *efficacy* is the relationship between effectiveness and efficiency (ratio objective/input) (Callaos and Callaos, 1994) (Checkland, 2000). Indeed, the corresponding OL efficiency indicators are usually associated with the OL processes and the effectiveness measures are related to semantic OL products (enhanced ontologies). However, both types of measures have been considered by each involved KSO in the case study.

The efficacy of the associated MRs to the OL processes and obtained products is shown in the next Section. Particularly, the OL tools used in the case study help to illustrate how the partial OL processes have favourable effects on both types of efficacy performance measures.

5. AN ONTOLOGY-BASED KMS IMPLEMENTATION AS A CASE STUDY

In this section, we have specified how the architectural components of this suggested KMS Success Framework related to the associated users' knowledge processes can be improved through OL mechanisms to support KSS users' task knowledge requirements in a distance education University of Venezuela (Ramos and Gil, 2010).

In order to better explain the OL improvement by the application of MRs to the *knowledge processes*, we have used as referent a case study about an ontology-based KSS developed for an academic domain. This case has evolved from our previous works about a suggested OL methodology called SMOL developed and applied for this same case in (Gil et al., 2010) (Gil and Martin-Bautista, 2011, 2012).

Concretely, this University case study was selected as the experimental academic domain to test an ontology-based KSS developed under a methodological focus. The selected host-ontology associated with this KSS for updating and enrichment purposes (called the DEA-ontology) is in a supervised evolutionary stage. The main objective of this experimental case study implies the update and enrichment of the DEA-Ontology in an incremental and iterative way, with knowledge acquired from three KSOs such as another ontology, a set of documents, and a database.

This Section is structured as follows: some OL processes developed according to each cited KSO are explained in Subsection 5.1; the most relevant activities associated with the *Knowledge meta-processes* are described in Subsection 5.2; the associated KMS Success (sub) dimensions improvement through OL and their associated performance outcomes are summarized in Subsection 5.3; and finally, the main lessons learnt from the case are described in Subsection 5.4.

5.1. The OL Technology Application by each KSO

The OL technology application from each KSO (ontologies, texts, and databases) is described as follows:

1) OL by updating with other ontology domain located and recovered from the Internet (called LUMB-ontology). The DEA-Ontology is OL updated from the LUMB-ontology by users through ontology-matching methods (FOAM) and the tool (Protégé-Prompt);

2) OL from a selected set of texts (480) recovered from educational journals. The DEA-ontology under an automated data-mining agent developed for this case (in RapidMiner tool) has been OL updated (in GATE tool) through this "unsupervised learning" agent; and

3) OL from a Relational Database (RDB) that belongs to another University (IUTEPAS). This RDB is automatically converted into a temporary ontology by inductive (RDBtoOnto tool) and deductive learning (ODEMapster tools) for turning this RDB into ontologies. These derived ontologies have been used to update/enrich the host ontology (DEA-ontology).

Additionally, a summary of the OL processes from the three KSOs is shown in Table 7.

Table 7. Case study summary: some evidences of OL from each KSO

Knowledge Source	Structured Knowledge	SMOL tools applied	Enriched & Populated DEA-Ontology object	Data Pre-Processing
Ontologies (LUBM from Web)	- Ont. Enrichment - Ont. Comparison - LUBM as KSO	- Swoogle - Prompt - Racer-Pro	+Class: Cognition\Dimension\Professor *Classes: Person\Student& Administration\University	- WordNet/Synset - Spanish to English Dictionary.
Documents (480 texts of journals)	- Ont. Population - Knowledge agent - Corpus as KSO	- Rapid-I - GATE (Ont.) - Racer-Pro	+Class: Cognition\Dimension \Professor\UniversityCity +Instances: \\City	- Google-Scholar - WordNet/Synset - GATE-Gazetteers
Databases (RDB of IUTEPAS University)	- Ont. Enrichment - Ont. Population - RDB as KSO	- RDBToOnto - ODEMapster - Protégé - Racer-Pro	+Class: \\PostgradeTitle & \\gradeTitle #Class: \\UniversityCity by \\UniversityTitle&UniversityCity +Instances: \\UniversityTitle & \\City	- FoxPro - MS-Excel - MS-Access - MySQL
Ont.=Ontology, Ontology' Object= +Added, *Reviewed, #Changed				

5.2. Relevant Activities Associated with the Knowledge Meta-Processes

The academic/educational KM activities identified and used in the University of this case study have been directly related to the four *Knowledge meta-processes* associated with the *Perceived Usefulness dimension* of the KMS Success framework. Particularly, this KSS case study supports, respectively, Students'/ Advisors' knowledge tasks about their recommended/required optional courses/careers, educational technology, and/or specific learning styles according to the economic available resources.

To simplify and summarize the most KM r*elevant purposeful activities* associated with these *knowledge meta-processes* (*Extracting, Memorizing, Reusing, and Sharing*), a system analysis technique identified as CATWOE has been applied (Checkland, 2000). A summary of these purposeful activities applying this technique is shown in Table 8.

Likewise, each of the *knowledge meta-processes* of the *Perceived Usefulness dimension* for the case study are shortly described highlighting some (semi-) automatic MR and tools used for OL as follows:

Table 8. The CATWOE for the *Relevant purposeful activities*

	EXTRACTING	MEMORIZING	REUSING	SHARING
C	Experts, Know.Eng. & CoP professors	Experts & Know.Eng.	CoP professors, Staff, Students.	Experts, Know. Eng. & Students
A	Experts & Know.Eng.	Experts & CoP	Students, Office staff	CoP & Experts
T	Know. from diverse KSOs (Ont./Texts/DBs)	Store/update & Search: KRS/TMS	Career-decisions recommendations	Know.Exchange: staff/students/experts
W	(Semi) automatic tools to create Know. from KSOs	Storing/recovering mediated by ontologies	Support the programme academic decisions	Support Expert-Client Know. exchange
O	Educational & planning Offices (CoP/Experts)	Staff Educational & planning Offices	Local Student advice head office	Educational/Planning officers (CoP/Experts)
E	Distributed Experts & diverse KSOs available	Central KRS/Web Ontology-Editor	Distributed Univers. Head office users	Distributed university Staff, CoP & Experts
C=Client, A=Authors, T=Transformation, W=World-view, O=Owners, E=Environment, CoP=Community of Practice, Know.=Knowledge USERS roles: Experts=Advisors; Clients=Students; Know.Eng.=Knowledge Engineers				

1) Extracting meta-process:

This *Extracting meta-processes* have been applied from other previous developed ontologies (LUMB), a corpus of documents (480 texts of journals), and a database of another University (IUTEPAS) as the most representative KSOs. Likewise, different MRs (tools) for *Knowledge Extraction* can be applied to support OL (semi-) automatic processes from each of these KSOs. Specifically, the Protégé-Prompt tool for OL from ontologies; the GATE and RapidMiner tools for OL from texts; and the RDBToOnto and ODEMapster tools for OL from Databases.

2) Memorizing meta-process:

To support this *Memorizing meta-process*, we have grouped/stored knowledge/information in KRS and TMS systems for a possible knowledge reusing purpose. On one hand, the three types of KRS used have been the following: (a) KSO repositories: partial database, ontologies, and

Corpus. Likewise, some new ontology subclasses during a classification process were identified as knowledge structures; (b) Agent repositories: an automatic agent for keyword identification during the OL from texts was developed. This agent could be reused for other OL process for any additional process; and (c) MR repositories: the various tools and methods used during the KA process for each KSO were catalogued as MR. On the other hand, the main TMS used is based on the Web-Protégé tool, the institutional e-mails, and Skype as a video-conference mechanism.

3) Reusing meta-process:

This meta-process is related to the support of recurrent knowledge activities of the different user's needs. Particularly, Students make queries to the Advisors and KSS services to get some advice or recommendations about their optional course, study styles, and the most appropriate educational technologies according to their needs. The Advisors and the KSS services can support their queries over the knowledge base system developed through the DEA-ontology. The KRS and TMS (as interaction mechanisms) implemented for the *Memorizing* and *Sharing meta-processes* can support the queries which made by both Advisor and Student communities (Expert-users and End-users of Figure 3). The main semi- automatic OL tools involved are: the Protégé-Prompt (CogZ) tool for queries over the DEA-ontology; the RapidMiner and GATE tools for queries over texts/ontologies; and the Foxbase and ODEMapster tools for queries over databases/ontologies.

4) Sharing meta-process:

The whole *Sharing meta-process* (represented in Figure 4) could be summarized as follows: 1) the knowledge demanded by the Student-community as queries made to the Advisor-community; 2) the Advisors-experts need to review (search) previously recorded examples and cases, theories, and strategies; 3) the Advisors-experts needs to review the stored past events (KRS/TMS); 4) A creative process of recommendations/advices is followed by the Advisor-community (supported by the KSS) to answer (in) directly to the Student's queries. The main OL tool that we have used for *Knowledge Sharing* is the suite associated with Web-Protégé tool. Throughout this tool, the Advisors (Expert-users) have coordinated (as CoP) their *Knowledge Sharing meta-processes* (and *Knowledge Reusing* also) to keep the case domain ontology (DEA-ontology) updated through the MRs for OL from these KSOs. Likewise, institutional e-mails and video-conference based on Skype tools were also applied.

5.3. Dimensions of the KMS Success Framework Improved through OL

The associated user's dimensions impacted favourably by the OL processes are detailed according to each one of the corresponding sub-dimensions. Specifically, the knowledge meta-processes (*Extracting, Memorizing, Reusing, and Sharing)* are sub-classified by the KSOs involved (ontologies, texts, or databases) and usually, the main MRs (tools) are applied to reach a higher efficiency/effectiveness of the detailed OL improvement.

The OL technology applied to the *knowledge sub-processes* for each KSO (ontologies, texts, and databases) has derived in some knowledge sub-products obtained (such as the updated ontology). A summary of some case study outcomes which could be impacted by the improvement of performance measures of the knowledge sub-process according to each KSO are shown in Table 9.

Table 9. Enhanced sub-process impact over the efficacy measures

KSOs	Sub-processes (MR-tools)	Knowledge Products	Increased measure
Ontologies: (LUMB-ontology from Web)	– Know. Search (Swoogle) – Know. Creation (Protégé-Prompt) – Know. Retention (LUBM/DEA) – Know. Creation (Racer-pro)	– Ontol. enrichment – Ontol. comparison – LUMB as KSO for reuse – Know. Quality check	– Efficiency – Effectiveness – Efficiency – Effectiveness
Documents: (480 texts of journals)	– Know. Search (Google-Scholar) – Know. Creation (Rapid-I) – Know. Transfer (GATE-Ontol.) – Know. Retention (Corpus/DEA) – Know. Creation (Racer-pro)	– Ontol. population – MRs-tool as an agent – Restructured Know. – Corpus as KSO – Know. Quality check	– Efficiency – Efficiency/Effectiveness – Effectiveness – Efficiency – Effectiveness
Databases: (RDB of IUTEPAS University)	– Know. Creation (RDBToOnto) – Know. Transfer (ODEMapster) – Know. Transfer (Protégé) – Know. Retention (RDB/DEA) – Know. Creation (Racer-pro)	– Ontol. enrichment – Ontol. population – Ontol. mapping – RDB as KSO for reuse – Know. Quality check	– Efficiency – Efficiency/Effectiveness – Effectiveness – Efficiency – Effectiveness
Know.= Knowledge, Ontol. Ontology			

Likewise, each *knowledge meta-process* has been analysed according to the expected efficiency and effectiveness possibilities considering the (semi-) automatic and user friendly capabilities of the specific tools, used to support OL pre-processing. A summary of the main important potential improvements associated with these adapted tools about the performance measures are detailed in Table 10.

Additionally, some performance quality-dimensions indicators to be measured through the *Performance measuring* processes (*User Satisfaction dimension)* have been considered from the list of indicators identified in (Urbach and Müller, 2012) and (Almutairi and Subramanian, 2005). A graphical representation of some of them is shown in Figure 5.

Table 10. OL Improvement reached for each knowledge meta-process

Sub Dimension		Improvement & tools	
		Efficiency (Input/Result)	Effectiveness (Objective/Result)
Knowledge Extracting	On	Automatic On. Matching (Protégé-Prompt)	Visual object identification (CogZ plug-in)
	Tx	Automatic text search/processing (Rapid-i)	Relevant words/terms identifications (Wordtool plug-in)
	DB	Automatic instance conversion (RDB2Onto)	Conceptual models/instance contents (Protégé-OntoBase)
Knowledge Memorizing	On	KRS to store used ontologies (Protégé)	Selected Object's contents from On. (OWL-directory)
	Tx	TMS/KRS to store corpus (GATE)	Representative texts of/from contexts (GATE)
	DB	KRS to store RDB scheme/data (Foxbase)	Significant RDBs with related knowledge (Foxbase)
Knowledge Reusing	On	Reusing On. from KRS/Web (GATE/Swoogle)	Agent & Ontological-MR from KRS/TMS
	Tx	Reusing text/corpus from TMS/KRS (GATE)	Agent & Texts-MRs from KRS (Rapid-I agent)
	DB	Reusing database objects from KRS (Foxbase)	Database-MRs from KRS (Foxbase/SQLserver)
Knowledge Sharing	On	On. are updated by sharing tool (WebProtégé)	On. updating is documented/traced (WebProtégé)
	Tx	Text & Corpus management (GATE)	Corpus complemented with a thesaurus (WordNet)
	DB	Database browser by sharing tool (NEON-tool)	RDB tool integrated with ontology editor (ODEMapster)
On.=Ontologies; Tx=Texts; DB=Databases; MRs=Methodological resources			

Several of these indicators have been integrated as they were originally identified, and others have been adapted/adjusted according to the goal of the specific KMS success dimensions such as the case of *Process/Service Quality* and *Communication Quality dimensions*. For instance, the turnaround indicator in priors IS/KMS success frameworks has been interpreted as a *System Quality dimension*, but nowadays this indicator is considered as a measure of the computer-network capability instead. In fact, it is located in the Communication Quality dimension in our framework in Figure 5 (bottom-left side).

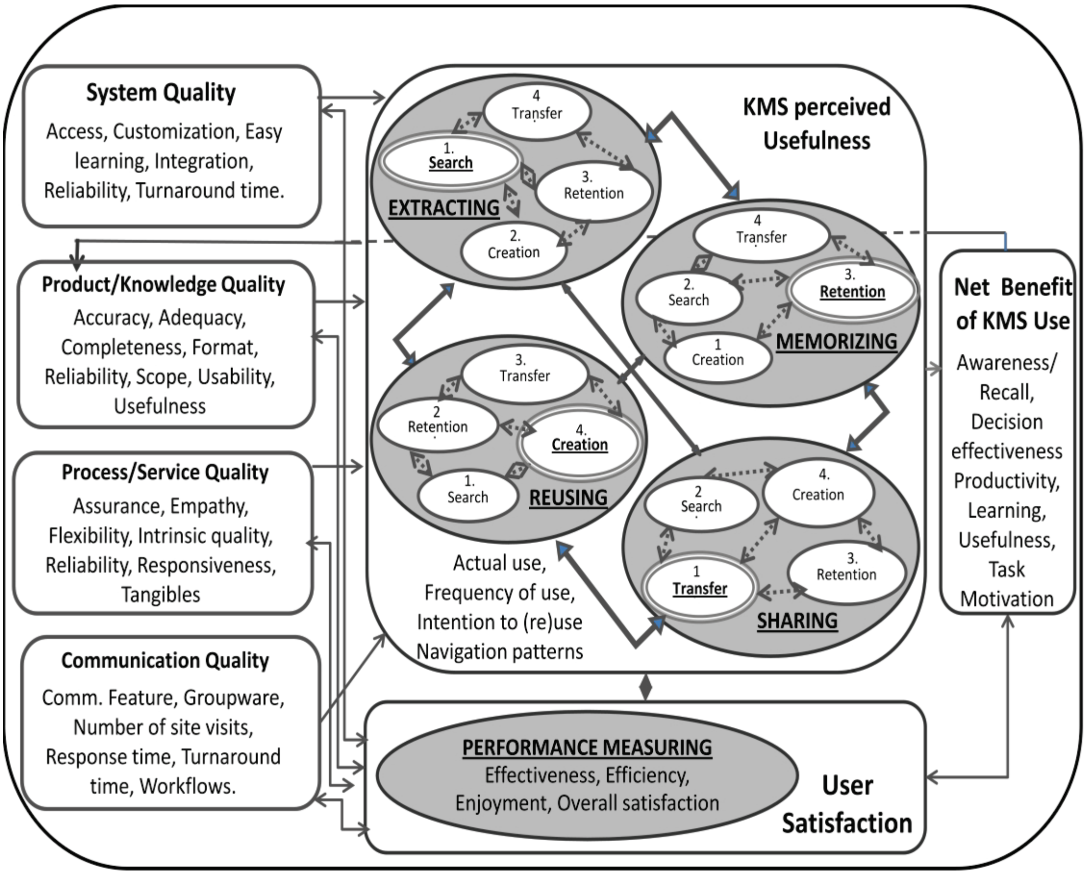

Fig. 5. Instances of dimensions items/indicators to be measured

5.4. Case Study Lessons Learned

Regarding the KMS success framework improved by the OL application, the most relevant "lessons learned" aspects considered are the following:

1. This hierarchical process-based KMS success approach could be easily understandable through the *knowledge processes* and their performance measures specified respectively in the *Perceived Usefulness* and the *User Satisfaction dimension*. The case study helps to describe thoroughly the *knowledge (meta/sub) processes* improved by OL. The OL improvements have been specified and confirmed for each *knowledge process* (partially and globally) according to some real and specific MRs and the three KSOs: ontologies, texts, and databases.

2. The four quality dimensions of this process-based KMS success framework can be easily associated with *knowledge (meta/sub) processes* which could be subject to improvement through OL technology. Through the case study, real MRs involved with the OL processes from diverse KSOs help to illustrate the consequence over the corresponding

KSS knowledge processes. As well, some associated knowledge-process performance measures/indicators have been considered.

3. The *Knowledge meta-processes* constructs suggested from the original process-based KMS success framework have been tested through the Case study application. Some important abstractions to conceive and specify the knowledge *Extraction, Memorizing, Reusing, and Sharing processes* have been reached in this work. This achievement has been possible, through an appropriate combination of specific and useful MRs for OL according to each KSO used during the Case study development.

4. Through the Case study, it has been possible to introduce indicators and items to be measured related to the knowledge process efficiency and effectiveness. For instance, new knowledge can be reached through deductive and inductive automatic OL using data-mining, text-mining, or ontology-matching processing (e.g. Extracting/ Memorizing); the knowledge processing manual effort can be reduced (e.g. Memorizing/ Reusing); and the continuous and efficacious knowledge updating can be automatically supported (e.g. Extracting/Sharing).

5. The cyclical feedback and the feed-forward mechanism to measure the process performance have been implemented and tested through the Case study. Carrying out the real case, diverse *Expert-users* (Advisors) have expressed their opinions/recommendations to the *End-users* (Students) about quality dimension correctives and changes to (re) adjust the (pre-) established quality standards (indicators).

7. CONCLUSIONS AND FUTURE WORK

A process-based KMS success framework has been introduced as an optional reference to validate and evaluate instances and implementation qualities of ontology-based KMS. Indeed, the involved and detailed KMS success dimensions (*User Perceived Usefulness and User Satisfaction)* have been used as a set to support the conceived *knowledge processes* re-specification based on progressively more common ontology-based KMS implementations. Due to the fact that many of these KMS developed recently have used ontologies as an essential implementation resource, it is possible to generalize the application of the OL technology as an enhancer to other similar KMS cases. Under this KMS success framework proposal we can illustrate how the OL technology can improve the associated knowledge process performance.

As a key point of this suggested framework, the *knowledge meta-processes* associated with the *User Perceived Usefulness* have been re-specified in this work Likewise, the process performance paradigm is another fundamental aspect considered to prescribe and model the optional OL mechanisms used/applied to improve the involved *knowledge processes*. Specifically, the *Performance measuring* process incorporated in the *User Satisfaction dimension* helps illustrate the potential performance supported by OL technology. This specified performance measuring can be useful to re-set and adjust the parameters and indicators of the four *Quality dimensions* in real cases of KMS implementations to reach more success.

Particularly, also the OL technology application over the KM process (according to MRs for diverse KSOs such as ontologies, texts, and databases) has been useful to explain the hierarchical interrelationships among these involved sub-processes (s*earch, retention, transfer, and creation*) with their corresponding *knowledge meta-processes (Extracting, Memorizing, Reusing, and Sharing)*. Some additional details in Appendix A.

In fact, the experimental possibility to update the indicator/measures to expand the KMS capability of receiving a feedback/feed-forward adjustment by-product of the *User Satisfaction* assessment (through *Performance measuring*) has been increased under this OL technological perspective. In this way, the possibility of overcoming limitations of the previous IS/KMS success frameworks for ontology-based KMS cases which consider the quality dimensions just as independent variables has been increased.

The experimental testing of the KMS success dimensions through the KSS Case study used as reference for OL improvement is another important outcome of this work. Indeed, some of the most relevant lessons learnt from this KMS case have been derived and explained.

Among the future work, it would be convenient to extend the application of this proposal (OL technology as KMS enhancer) to other KMS implementations. Likewise, any other additional performance indicators and measures associated with the knowledge processes and dimensional qualities can be incorporated according to the particular and derived cases study experiences.

APPENDIX A: THE KMS SUCCESS FRAMEWORK SUB-DIMENSION

TABLE A.1: KMS Success Framework: Short Sub-dimension description

Dimension	Sub-Dimension	Short Description
S-Q	*Technological Resource:*	It includes Hardware, Software, Network, Interface, and Database capabilities for KMS
	KSS form:	Knowledge accessibility (online/single interfaces). Two clusters are relevant: 1) some integrative functions and 2) some adaptive functions
	KSS level:	The strength of this sub-dimension is conditioned by the integration and computerization of the knowledge. The efficacy of the Knowledge Memorizing and Extracting processes is relevant
P/K-Q	*KSS Processes*	Identify the task, the members, and tools with requiring knowledge processing. Intending to support which knowledge to be searched, recorded, reused and shared
	Content /Richness:	Usually related to the codification strategy (explicit knowledge recorded). The reuse of codified knowledge from KSOs is good. Knowledge Extracting process is crucial
	Linkage:	Usually associated with the personification strategy to recover implicit knowledge from experts. *Knowledge Sharing* makes easier to support users' personal relationships
P/S-Q	*Management Support*	To support the satisfaction of the organization's needs through an adequate allocation of KMS resources for creating and maintaining KM activities
	KM Service quality	The support provided by the IS organization unit to the KSS users and the maintenance of their KM activities.
	User Service quality	The support with the routines, procedures, and manuals required by users to develop the KM activities.
C-Q	*Network management*	Supporting Organizational Communication unit to allocate network resources & keep the internal/external communication open/flexible to support Knowledge Extracting process from various contexts. The Security/Protection must be guaranteed
	Collaboration (social network)	An increasing trend for Knowledge Sharing among users and experts from different organizational contexts push the organization to encourage diverse ways to keep the social networks open and active
	KSO accessibility	The KSO accessibility throughout (semi) automatic Extraction meta-process is a key element to find novel and updated knowledge
P-U	*Knowledge Extracting*	Methods/tools for knowledge identification, recovery, and creation from structured/ unstructured KSOs
	Knowledge Memorizing	Resources/means used to gather /actualize knowledge /information continuously, offering proactive assistance to knowledge workers
	Knowledge Reusing	Mechanisms through which the users can incorporate knowledge (documents or other content) in the regular knowledge-tasks
	Knowledge Sharing	Explicit/tacit knowledge exchanges among people, friends, groups, a community, or an organization
U-S	*Performance measuring*	The mechanisms for measuring the knowledge processes input/output in order to adjust their goals according to some quality standards. Increasing the knowledge process/product efficacy in proportion to their partial reached efficacy performances
N-B	*Individual Benefit*	Some indicators for the Individual level could be: learning, productivity, job performance, task innovation / performance, and so on
	Organizations Benefit	Some measures could be: cost reduction, coordination/collaboration enhancement, improved outcomes decision-making, overall productivity
	Society Benefit	Some indicators for the Social benefit could be consumer welfare, creation of jobs, and economic development
Q: Quality; S: System; P/K: Product/Knowledge; P/S: Process/Service; C: Communication, P-U: Perceived Usefulness; U-S: User . Satisfaction; N-B:Net Benefit		

APPENDIX B: DESCRIPTION OF THE KNOWLEDGE META-PROCESSES

The four *knowledge meta-processes* identified in this work as part of the *Extended KMS Perceived Usefulness* (*Extracting, Memorizing, Reusing,* and *Sharing*) may be explained as a result of the emergent properties (systemic ones). They derive from the interrelationships among the customized *knowledge sub-processes*. A general systemic representation of these *Knowledge meta-processes* is shown in Figure 6.

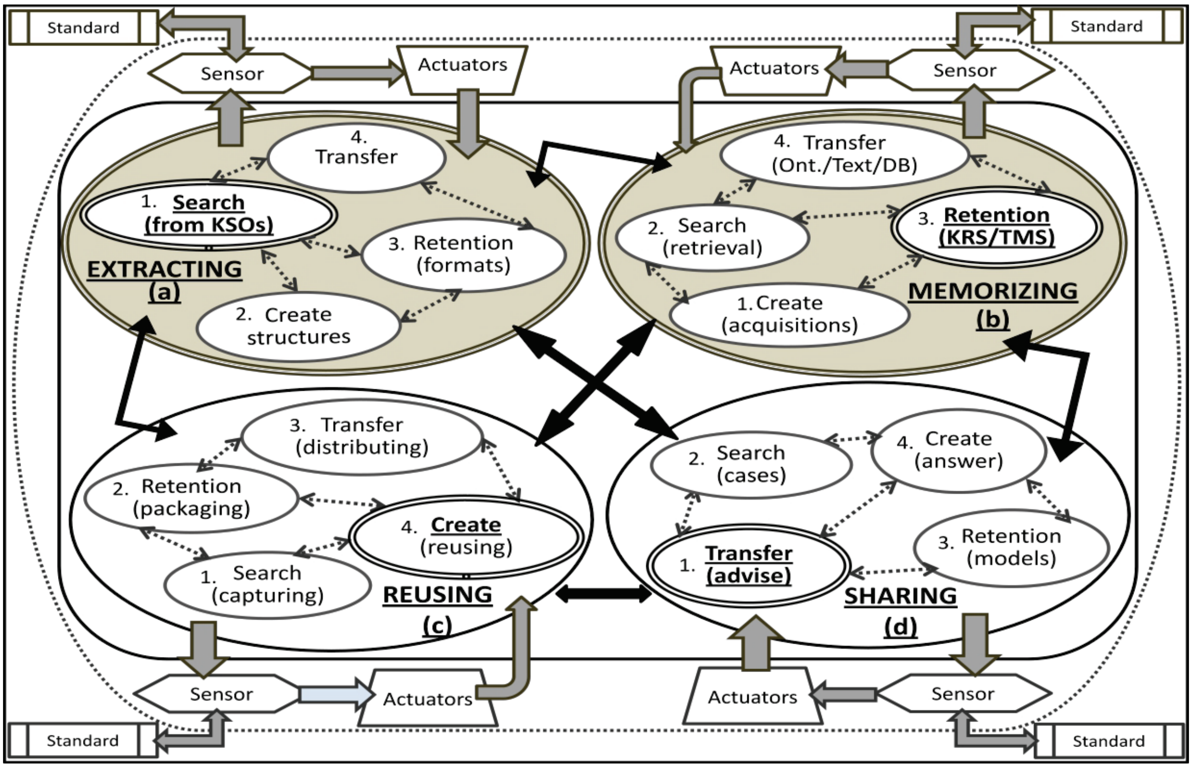

Fig. 6. The *knowledge (meta/sub) processes* and the performance measuring

In the next Subsections identified of this Appendix B identified with literals (A to D), we describe each one of these *knowledge meta-processes* based on the customization of the *knowledge sub-processes* used as reference. According to the purpose of each meta-process, these sub-processes have been reordered and numerated.

It is important to point out that an emerging *Performance Measuring* meta-process has been represented in the same Figure 6 (attached to each meta-process oval) using the closed-loop control as a feedback mechanism. This control mechanism has been depicted by the sensor, the actuators, and the standard as the key components of this mechanism in (Ramaprasad, 1983), (Astrom and Murray, 2008).

The next specified *knowledge meta-processes* will be associated with the dependent dimension of *User Perceived* in our suggested framework (in Section 5). However, the *Performance Measuring* will be coupled to the dependent dimension *User Satisfaction*.

A. – The Knowledge Extracting Meta-process

The main activities of the *Knowledge Extracting* m*eta-process* are primordially based on the cited *knowledge sub-processes*. The arrangement of these sub-processes is aligned according to the knowledge extraction procedure suggested in (Villazón-Terrazas and Gómez-Pérez, 2012).

Concretely, the steps of this cited procedure may be re-defined as follows: 1) the *knowledge searching* for accessing the KSOs, useful to calculate precision and coverage and to make some evaluations based on consensus and quality; 2) the *knowledge* c*reating* for drafting an assessment table; 3) the *knowledge retention* from the most appropriated KSOs selected; and 4) the *knowledge transferring* (toward *Memorizing meta-process*) for eventual *Knowledge Reusing* of the selected KSOs.

B. – The Knowledge Memorizing Meta-process

We have specified this *Memorizing meta-process* according to the cited OM stages suggested in (Walsh and Ungson, 1991), As regards the main *knowledge sub-processes* used to specify this *meta-process*, the *Knowledge retention sub-process* is the most pertinent one involved.

Specifically, the *Knowledge Memorizing meta-process* specification keeps a logical correspondence between three OM stages with the three *knowledge sub-processes.* Respectively, the correspondences are described as follows: 1) the *Knowledge creation* with the *Acquisition-stage* as a consequence of the created structured partial knowledge based on decisions-made and decisions-evaluation tasks; 2) the *knowledge search* with the *Retrieval-stage* through controlled (ad-hoc) or automatic (task-routines) ways to access memorized knowledge; 3) the *knowledge retention* with *Retention-stage* due to the different types of past experiences to be recorded in different kinds of repositories. On the other hand, we have projected the *knowledge transfer sub-process* based on the user's requirement of memorized knowledge interchange throughout other *knowledge meta/sub processes* (e.g. *Reusing*).

An integrated vision of a *Knowledge Memorizing meta-process* aims to show how to support the (meta) requirements of the *Knowledge Reusing* and *Knowledge Sharing* relevant for the *KMS perceived Usefulness dimension* in the extended framework of our proposal.

Therefore, the key elements of an eventual implementation of this *Memorizing meta-process* in a KMS application should consider the flexibility of the ontology-based schema introduced in some recent OM works. In this sense, we have reviewed some KRS and TMS ontology-based implementations, in (Abecker et al, 1998) (Brandt et al., 2006, 2008) (Decker et al, 2005) (Ammari et al., 2011), respectively. A general description of both supporting *Memorizing meta-process* through the KRSs and TMSs implementations can be summarized as follows:

Knowledge Repositories System (KRS): It is a computerized system that captures, organizes, and categorizes an organization's knowledge systematically. The repository can be searched and data can be quickly retrieved. The nature of the repository only changes to contain / manage the type of knowledge it holds. A KR can take many forms to "contain" the knowledge it holds. For instance, a community of experts is a tacit knowledge or experience KR. Likewise; the effective KR includes conceptual, procedural, and meta-cognitive techniques.

Transactive Memory System (TMS): According to Wegner (Wegner, 1995), a TMS consists of the knowledge stored in each individual's memory combined with meta-memory containing information regarding the different teammate's domains of expertise. Group members learn who knowledge experts are and how to access prior know-how during the communicative processes. The basic components of TMS have to cover the following: 1) specialization; 2) coordination; and 3) credibility (Ilgen et al., 2005). On the other hand, a well-developed TMS should achieve three essential goals: Efficiency, Scope, and Flexibility in (Argote and Ren, 2012).

C. - The Knowledge Reusing Meta-process

According to the Markus's position (Markus, 2001) about the Knowledge Reuse, we have projected their suggested four stages (*capturing, packaging, distributing,* and *reusing*) using our referential four *knowledge sub-processes*. These cited four stages are described under our recommended arrangement of the *knowledge sub-processes* as follows: 1) *knowledge searching,* by capturing or documenting knowledge such as passive by-product of knowledge work, technological support, and other strategies for recording; 2) *knowledge retention,* by packaging knowledge through index processing, polishing, and cleaning; 3) *knowledge transfer,* by distributing knowledge support to recall or push knowledge from/to users; and finally, 4) *knowledge creation,* by the recall or recognition of significant knowledge.

Any of these stage/sub-process interaction within this *Knowledge Reusing meta-process* implies also some other systemic relationships -outer- with the other three meta-processes according to their expected outcomes, goals, and/or specific purposes. This interrelated meta-process behavior is common and easy to identify among the other *knowledge meta-processes* of the Architecture model suggested in Figure 3.

D. - The Knowledge Sharing Meta-process

We have firstly considered the cited Gaines' model in (Gaines, 1990) because it is possible to elucidate the social knowledge exchange mechanisms. Specifically, an updated version of this Gaines's model (in Figure 4) may explain some interchange relationships between the social communities that manage or create the knowledge (*Experts-users*) and those clients who use it (*End-users*). Additionally, we have considered the A&M model because it may easily explain how the *Knowledge sub-processes* may get involved with the knowledge exchange processes suggested by

Gaines. Particularly, we have stressed how the *knowledge search* process from diverse KSOs of different *Context levels* in the A&M model can be straightforwardly explained.

In this sense, according to Gaines's model, both communities (expert and users) share the knowledge needs and possible answers (reuse) under a cyclical interaction based on analogies with the *knowledge sub-processes* of the A&M model.

Concretely, the Gaines' model interactive/iterative cycle (in Figure 5) could be summarized as follows: 1) the *knowledge transfer* expressed as the knowledge required for the user-community (in the form of instance and data) that is demanded by queries to the expert-community, according to their related study cases; 2) the *knowledge search* expressed by the experts needs to review previous examples and cases, theories, and strategies; 3) the *knowledge retention* to meet the experts needs (in number 2) which was stored in the past events as abstract models or interrelated information; 4) the *knowledge creation* explained through the creative processes followed by the expert-community to answer the user's questions/queries as recommendations/ advices; and 5) the *knowledge transfer* (again in sub-process number 1) of these created or developed recommendations to be exchanged with the user-community.

REFERENCES

Abecker, A., Bernardi, A., Hinkelmann, K., Kuhn, O., & Sintek, M. (1998). Toward a technology for organizational memories. Intelligent Systems and Their Applications, IEEE, 13 (3), pp. 40-48.

Abecker A., Elst, L. (2009). Ontologies for knowledge management, in: Staab, Studer (Eds.), Handbook on Ontologies, International Handbooks on Information Systems, Springer, pp. 713–734.

Almutairi, H. & Subramanian, G. H. (2005). An empirical application of the DeLone and McLean model in the Kuwaiti private sector. The Journal of Computer Information Systems, 45(3), 113+.

Ammari, A., Dimitrova, V., Lau, L. M. S., Tzagarakis, M., & Karacapilidis, N. (2011). Augmented Collaborative Spaces for Collective Sense Making: The Dicode Approach. In The International Workshop on Adaptive Support for Team Collaboration 2011, held in conjunction with the International Conference on User Modeling, Adaptation, and Personalization (UMAP2011), Girona, Spain, July 15, 2011 (Vol. 743, pp. 3-13). CEUR.

Argote L., & Miron-Spektor E. (2011). Organizational Learning: From Experience to Knowledge, Organization Science, September/October 2011 22:1123-1137.

Argote, L. & Ren Y. (2012) Transactive Memory Systems: A Microfoundation of Dynamic Capabilities. Journal of Management Studies, pp.1467-6486

Argyris, C. & Schön, D. A. (1997). Organizational learning: a theory of action perspective. Reis, (77/78), pp. 345-348.

Astrom, K. J. & Murray, R. M. (2008). Feedback systems: an introduction for scientists and engineers. Princeton University Press.

Brandt, S. C., Morbach, J., Miatidis, M., Theißen, M., Jarke, M., & Marquardt, W. (2008). An ontology-based approach to knowledge management in design processes. Computers and Chemical Engineering, 32 (1), 320-342.

Brandt, S. C., Morbach, J., Miatidis, M., Theißen, M., Jarke, M., & Marquardt, W. (2006). Ontology-based information management in design processes. In W. Marquardt & C. Pantelides (Eds.), 16th European symposium on computer aided process engineering and 9th international symposium on process systems engineering (pp. 2021–2026). Elsevier.

Callaos, N. 1992. A systemic system methodology. In International conference on system research informatics and cybernetics, Baden-Baden, Germany.

Callaos, N. & Callaos, B. (1994). Designing with a system total quality, in: Educational Technology, pp. 29–36.

Decker, B., Rech, J., Althoff, K. D., Klotz, A., Leopold, E., & Voss, A. (2005). Participative process learning–process-oriented experience management and conflict solving. Data and Knowledge Engineering, 52 (1), 5–31.

Checkland, P. (2000). Soft systems methodology: a thirty year retrospective. Systems Research and Behavioral Science, 17, 11-58.

DeLone, W. H. & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. Information Systems Research, 3 (1), 60–95

DeLone, W. H. & McLean, E. R. (2002). Information systems success revisited. In Proceedings of the 35th Hawaii international conference on system sciences (HICSS 02), January 7–10, Big Island, Hawaii.

Fernández-López, M., Suárez-Figueroa, M. C., & Gómez-Pérez, A. (2012). Ontology Development by Reuse. Ontology Engineering in a Networked World, 147-170.

Gaines B., (1990) Knowledge-support systems, Knowledge-Based Systems. 3–4, 192–203.

Gil R., Contreras L., & Martin-Bautista M.J. (2010). A systemic methodology for ontology learning: an academic case study and evaluation, IC3K, KEOD-2010, Valencia-Spain, vol. 1, pp. 206–212.

Gil R., & Martin-Bautista M.J. (2011). An ontology-learning knowledge support system to keep e-organizations knowledge up-to-date: a university case study, LNCS, vol. 6866, Springer, pp. 249–263.

Gil, R., & Martin-Bautista, M.J. (2012). A Novel Integrated Knowledge Support System Based on Ontology Learning: Model Specification and a Case Study. Knowledge-based Systems. Volume 36, December 2012, Pages 340–352.

Ilgen, D.R., Hollenbeck, J.R., Johnson, M., & Jundt, D. (2005). "Teams in organizations: From I-P-O Models to IMOI models". Annual Review of Psychology 56: 517–543.

Jennex, M. E. & Olfman, L. (2006). A Model of Knowledge Management Success International Journal of Knowledge Management (IJKM) IGI-Global, Issue 3. Volume 2, page 34-51.

Jennex, M. E. & Olfman, L. (2011). A Model of Knowledge Management Success. In M. Jennex, and S. Smolnik (Eds.), Strategies for Knowledge Management Success: Exploring Organizational Efficacy. pp. 14-31.

Kim, D. H. (1993). The Link between Individual and Organizational Learning. Sloan Management Review 35 (1): 37–50.

Kulkarni, U.R., Ravindran, S., & Freeze, R. (2007). A knowledge management success model: Theoretical development and empirical validation. Journal of Management Information Systems, 23(3), 309–347.

Lee H., Kim J., & Koh J. (2009). A contingent approach on knowledge portal design for rd teams: relative importance of knowledge portal functionalities, Expert Systems with Applications (36), 3662–3670.

Markus, M. L. (2001). Toward a theory of knowledge reuse: Types of knowledge reuse situations and factors in reuse success. Journal of management information systems, 18 (1), 57-94.

Maedche, A. & Staab, S. (2001) , "Ontology learning for the Semantic Web," Intelligent Systems, IEEE, vol.16, no.2, pp. 72- 79, Mar-Apr 2001.

Mora, M., Cervantes-Pérez, F., Garrido, L., Wang, F., and Angel-Sicilia, M. (2010). On KM, KMS and ontology-based KMS in the domain of SwE standards and models of processes: A conceptual survey. Intelligent Decision Technologies, 4(1), 75-98.

Nonaka, I. & Takeuchi, H. (1995). The knowledge-creating company: How Japanese companies create the dynamics of innovation. Oxford University Press, USA.

Nonaka, I. & von Krogh, G., (2009). "Tacit Knowledge and Knowledge Conversion: Controversy and Advancement in Organizational Knowledge Creation Theory". Organization Science 20 (3): 635–652.

Padma T. & Balasubramanie P. (2011). Domain experts knowledge-based intelligent decision support system in occupational shoulder and neck pain therapy, Applied Soft Computing. 11 (2), 1762–1769.

Petasis, G., Karkaletsis, V., Paliouras, G., Krithara, A., & Zavitsanos, E. (2011). Ontology population and enrichment: State of the art. Paliouras et al. (Eds.): Multimedia Information Extraction (LNAI), 6050 , 134-166.

Petter S. & McLean E. (2009). A meta-analytic assessment of the DeLone and McLean IS success model: An examination of IS success at the individual level. Information and Management, Volume 46, Issue 3, April 2009, Pages 159–166.

Petter, S. DeLone, W., & McLean, E. (2008). Measuring information systems success: Models, dimensions, measures, and interrelationships. European Journal of Information Systems, 17, 236-263.

Power, D. (2008). Decision support systems: a historical overview, in: Handbook on Decision Support Systems, International Handbooks on Information Systems, vol. 1, Springer, Berlin, Heidelberg, pp. 121–140.

Rai, A., Lang, S. S., & Welker, R. B. (2002). Assessing the validity of IS success models: An empirical test and theoretical analysis. Information Systems Research, 13(1), 50–69.

Ramaprasad, A. (1983), On the definition of feedback. System Research, 28, pp. 4–13.

Ramos L., & Gil R. (2010). Information system to support the management of the distance education (Spanish), Telematique, Venezuela, 9 98–119.

Ribiere, A., & Bechina, AAB, (2010). Knowledge management Technologies Chapter 12 In Search of Knowledge Management: Pursuing Primary Principles, Emerald Group Publishing Ltd.

Seddon, P. B. (1997). A respecification and extension of the DeLone and McLean model of Is success. Information Systems Research, 8 (3), 240–253.

Shigeyoshi H., Inoue S., Tamanoi K., Aoki S., Tsuji H., & Ueno T. (2011). Knowledge and transaction based domestic energy saving support system, LNCS, vol. 6884, Springer, Berlin, Heidelberg, pp. 242–251.

Stankosky M. (2005). Creating the discipline of knowledge management, Elsevier Inc., 2005.

Urbach N. & Müller B. (2012). The Updated DeLone and McLean Model of Information Systems Success Information Systems Theory Integrated Series in Information Systems, 2012, (28), 1-18.

Urbach, N., Smolnik, S., & Riempp, G. (2010). Improving the success of employee portals: A causal and performance-based analysis. In Proceedings of the 18th European conference on information systems (ECIS 2010), Pretoria.

Velasquez, N. F., Durcikova, A., & Sabherwal, R. (2009). Studying knowledge management system success in system administration. In Proceedings of the 42nd Hawaii international conference on system sciences (HICSS 09), Hawaii.

Villazón-Terrazas, B. & Gómez-Pérez, A. (2012). Reusing and Re-engineering Non-ontological Resources for Building Ontologies. Ontology Engineering in a Networked World, pp. 107-145.

Walsh, J. P. & Ungson, G.R. (1991). Organizational memory. Academy of management review, 57-91.

Wegner, D.M. (1995). "A computer network model of human transactive memory". Social Cognition 13 (3): 319–339.

2. THE SMOL DEVELOPMENT AND EVALUATION

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Towards a Machine of a Process (MOP) ontology to facilitate e-commerce of industrial machinery

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ABSTRACT

Adapting to user's requirements is a key factor for enterprise success. Despite the existence of several approaches that point in this direction, simplifying integration and interoperability among users, suppliers and the enterprise during product lifecycle, is still an open issue. Ontologies have been used in some manufacturing applications and they promise to be a valid approach to model manufacturing resources of enterprises (e.g. machinery and raw material). Nevertheless, in this domain, most of the ontologies have been developed following methodologies based on development from scratch, thus ontologies previously developed have been discarded. Such ontological methodologies tend to hold the interoperability issues in some level. In this paper, a method that integrates ontology reuse with ontology validation and learning is presented. An upper (top-level) ontology for manufacturing was used as a reference to evaluate and to improve specific domain ontology. The evaluation procedure was based on the systemic methodology for ontology learning (SMOL). As a result of the application of SMOL, an ontology entitled Machine of a Process (MOP) was developed. The terminology included in MOP was validated by means of a text mining procedure called Term Frequency–Inverse Document Frequency (TF–IDF) which was carried out on documents from the domain in this study. Competency questions were performed on preexisting domain ontologies and MOP, proving that this new ontology has a performance better than the domain ontologies used as seed.

1. Introduction

The development of new products[1] is a challenging activity that demands highly flexible and adaptable enterprises. Approaches, such as flexible manufacturing systems (FMS) [1], concurrent engineering (CE) [2] and design for manufacturing (DfM) [3] among others, aim to contribute to this challenge. Nevertheless, these approaches are centered in previously existing resources; that means they only consider available resources in a formerly given facility, and they discard the existence of newer resources which could give a better performance for a given production process. Thus, when new products are developed, the decision makers have fewer possibilities to have updated information about the real worldwide available resources for manufacturing. The situation described above becomes error-prone, given that the evaluation of a new product could conclude that an innovative product cannot be manufactured due to the lack of resources. When innovation is a key factor for success in the modern industry [4], this kind of decisions can lead to loss of business opportunities.

The Internet can be used as an information source of digital models of resources for manufacturing; e.g. industrial machinery, spare parts and raw materials. However, these resources require a different treatment from other resources commonly sold on Internet like clothes or other goods for personal use, for which a technical evaluation is unnecessary. Resources for manufacturing are designed for specific tasks and require skilled engineers and planners to decide about their acquisition and use. Thus, selecting such resources implies team work. Additionally, acquiring resources for manufacturing means disbursing considerable amounts of money, if we compare their costs with the cost of other products currently sold on the Web. Moreover, as we will demonstrate in Section 4, resources for manufacturing are becoming abundant on the Internet for sale. So, engineers and planners may require considerable amounts of time to decide among hundreds of similar resources. In fact, without specialized software tools for analyzing such information, taking an efficient decision becomes technically impossible [5]. An immediate consequence of this is the increase of cost to design and to develop new products.

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[1] In the definition of products industrial machinery can be included from Business to Business (B2B) approach.

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In this vein, ontologies and the Semantic Web are valid approaches to describe resources on the Web [6]. In the domain of manufacturing, ontologies have been used in several use cases [7], [8], but little work has been conducted to make a semantic representation of certain manufacturing resources such as machinery, raw materials, product designs, among others. Such semantic representation would simplify searching them on the Web, and to integrate their model in a virtual environment or factory for reasoning about production processes constrains, in order to determine if any virtual resource should be integrated in a physical factory to get the target product done. We have selected industrial machinery as a resource to model, because this resource was recently referred in research related to ontology development for manufacturing [9].

Because the information about industrial machinery is in a human readable format (html, txt, pdf, among others), links and semantic connections between content and document are missing, thus the adaptation to a machine readable format is necessary. We use ontologies to bridge the gap between the technical document and its content. In this vein, three ontologies and a corpus of technical documents were considered in this study: (i) the Manufacturing's Semantic Ontology (MASON) [10], defined by its developers as an Upper Level Ontology (ULO) for manufacturing; (ii) the Machine-Tool Model (MTM) [9]; and (iii) the machine ontology (MO) [11]. A corpus of 633 documents was extracted from the Internet and processed by text mining analysis tools to get significant keywords. The aforementioned ontologies were matched to each other in order to obtain similarities among them. Based on these results, an ontology learning (OL) [12] process was carried out with MTM and MO. In a semi-automatically way, relevant concepts and relations were extracted from MTM and MO to form a new ontology. The result was Machine of a Process (MOP), an ontology that represents industrial machinery as resources on the Web, satisfying the user's requirements of knowledge for economic evaluation, engineering design and production control for a given production process. In Sub Section 4.2 we will demonstrate how to evaluate the fulfillment of these requirements by means of performing some competency questions to the aforementioned ontologies [6].

This paper has been structured as follows: we present related work classified in three blocks, product description and Semantic Web, ontologies for enterprises, and ontology learning in Section 2; the general methodology, its tools and methods are described in Section 3; while we discuss our results in Section 4; and some conclusions and future work are outlined in Section 5.

2. Previous work

2.1. Product description and the Semantic Web

Semantic description of goods is a key factor for e-commerce. This is so, because nowadays, manufacturing of goods can take place almost anywhere at any time, but with different prices and levels of quality. This means that decision makers require computer-based systems to speed up the analysis of product data and take decisions. In this vein, ontology such as GoodRelations [6] illustrates the usability of product description on the Web to simplify e-commerce. Nevertheless, the scenarios in which GoodRelations is involved correspond to trading goods, and highly technical information related to machinery is not involved. In consequence, as for scenarios like the one drawn by us in Section 1, the requirements are not covered yet.

In addition, the World Wide Web Consortium (W3C) contributed by a Working Group for Product Modeling Using Semantic Web Technologies [13]. This initiative demonstrates the relevance of the topic for the Semantic Web community, but the proposal was limited to describe the role and scope of product data and an initial work on quantities, units and scale specification, together with product structure consideration. We consider necessary to highlight that they mention the requirement of interaction of the given product with other elements of the world, but without showing any course of action to deal with it. Thus, if we consider industrial machinery as a product, and additionally, we recognize that it has the possibility of interaction [14] with other components of the digital factory, then the specification of an ontology for industrial machinery remains as an enterprise requirement and an open issue.

2.2. Ontologies for enterprises

Some researchers propose to model the enterprise as a whole. For instance, Grüninger and Fox [15] proposed the Toronto Virtual Enterprise (TOVE). This model contained a set of related ontologies which represented the entire enterprise. TOVE was specified by means of situation calculus [16]. This formalism enables reasoning about dynamic domains. Given that actions, fluent and situations are the fundamental elements of this formalism, this could be used for modeling and reasoning over activities in the enterprise. Manufacturing resources ontology was mentioned, but machines as concepts were not referred to.

Lemaignan et al. [10] proposed MASON as a manufacturing upper ontology. They aimed to draw a common semantic model in a manufacturing environment. The resulting ontology was used as a part of a system that could estimate manufacturing costs in multiagent systems using the Java Agent DEvelopment framework (JADE) [17]. We used the vocabulary of machine given in MASON as a part of our study (see Section 4). Kjellberg et al. [9] proposed a machine-tool ontology model (MTM) to facilitate interoperability between machine-tool specification standards. They considered that an information model of machine-tool was required in process planning, factory planning and machine investment. They claimed that their machine ontology included concepts related to any type of machine. Nevertheless, they did not present a method to obtain such concepts, more than a brief analysis of the standards they mentioned (ASME B5.59 [18], AP239 [19], AP214 [20]) and the concepts referred to such standards, making special emphasis on Kinematics.

2.3. Ontology learning (OL), based on information extraction and evaluation

OL techniques can be divided into two approaches, constructing ontologies from scratch and extending the existing ontologies [19]. For both approaches, several tools and techniques have been proposed, for instance, Luther et al. [20] used text mining to supplement the development of ontologies. They supported their development with a commercial text miner tool, arguing that their contribution consisted on generating the vocabulary without an exhaustive customization effort.

Despite of the benefits of OL, Gil et al. [23] listed several of its shortcomings and proposed a Systemic Methodology for OL (SMOL) to overcome some of them. In our study we will implement and extend SMOL to the manufacturing scenario, but emphasizing the ontology reuse based on OL from another upper ontology, domain ontologies and from a selected corpus. Moreover, we will provide a criterion to determine when an OL process can be carried out with effective results for this particular case.

3. Methodology

We considered the following assumptions before designing our experiments and selecting the corresponding methods, software tools and materials involved in our methodology.

- Upper level ontologies facilitate the development of domain ontology [24].
- Reusing existing ontologies can considerably accelerate the development of a new ontology [25].
- Ontologies aim at modeling the fundamental concepts and relations in a specific domain of discourse [26]. That is, ontology pretends to model entities by means of a formal specification that includes their concepts and a logic to define them.
- Modular (small) ontologies improve understandability, maintainability and quality of interoperability of ontology-based systems for the benefit of the end user [21].
- With regards to the users participating in the process, we can distinguish among [22]:
- Knowledge Engineers/Developers: usually associated with ontology development and (re)structuring tasks.
- Expert-Users (Domain-Professionals): usually associated with ontology contents procurement and validation tasks. Additionally, they are involved with the user's requirement specification tasks.
- End-Users (Domain-Clients): usually associated with the ontology user's requirements and knowledge needs.

Based on the assumptions listed above, the methodology applied in this case (adapted from the SMOL [23]) is depicted in Fig. 1. This figure includes every activity and decision steps involved in our methodological workflow, moreover it has been clearly specified who performs them and how. To decide about how these actions are performed it is necessary to consider software tool availability and their efficiency. Thus, such actions can be performed complementing manual, semiautomatic and automatic techniques or applying them individually. These activities and decision steps are summarized in four phases and sub-steps, referred below.

3.1. Methodology strategy selection

In this stage, firstable the existence of upper level ontologies (ULO), by means of which the target domain concepts could be contained, is verified. In determining if a given ULO is suitable, a controlled vocabulary and a general model of the domain are obtained from selected documents. Additionally to this, in this stage the availability of ontology documentation, description of use cases in which the ontology could be involved, and its accessibility for manipulation and visualization should be also considered. The last criterion is closely related to the language in which the ontology is implemented and the available software tools. In the case that ontology development from scratch becomes necessary, this ontology can be developed by means of methodologies (e.g. Methontology, OL) using specific tools and techniques.

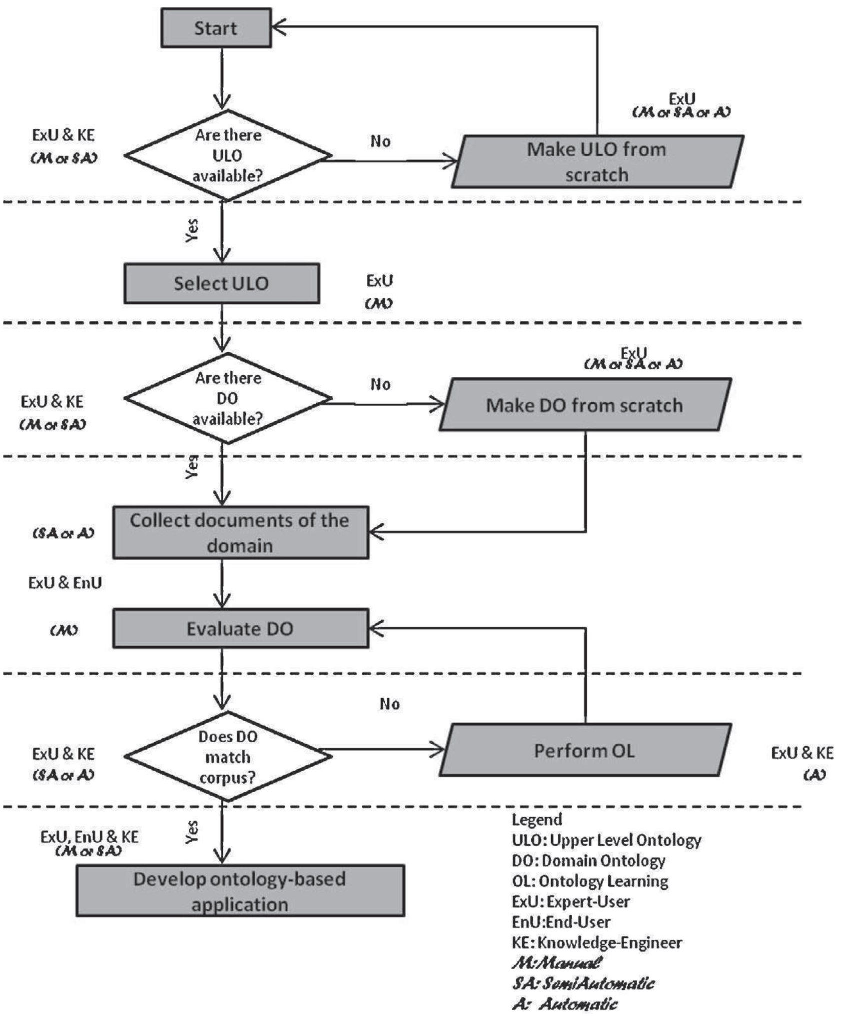

Fig. 1. Methodology description.

The selection of any of these methodologies is up to the knowledge engineer duty.

After granting an ULO, the existence of domain ontologies (DO) in which the domain is to be represented is verified and accordingly selected. The criteria are similar to the description in the previous step. Nevertheless, we have to take more into account the presence of concept definitions, axioms, properties, and rules in the target ontology, given that the domain ontology can be more restrictive than a ULO. After finishing the previous stages a corpus of documents is compiled from different general or specialized search engines. We have to select a methodology strategy according to the complexity of the domain and the knowledge sources found. Some learning tools have to be selected in this step to support the (semi)automatic ontology development and OL process.

3.2. Knowledge discovery, query requirements and selection

In this phase, a module in the ULO that could contain concepts presented in the domain ontology is identified and selected. Then the DO has to be evaluated after:

(i) Comparing the ontological structure of DO with corpus.
(ii) Setting up competency questions by domain expert-users (see Section 4.2).
(iii) Performing queries on DO to determine whether current ontologies can answer them.

3.3. Knowledge structure construction and reorganization

Then ontology objects, such as concepts, relations and attributes are identified through text mining on corpus. If the result of the structured evaluation is not satisfactory, then ontology learning (from ontologies and text) is performed on DO to obtain an improved ontology. Then, the expert user should return to the previous step and re-evaluate the ontology. During the re-evaluation, the user's requirements should be satisfied. The (non-)taxonomic or hierarchical relations of the MOP-ontology should be reviewed and last, but not least, the reorganized concept taxonomy should be validated/compared against the previously identified ontologies and the highlighted terms of the corpus.

3.4. Knowledge base system configuration

If the result of the structured evaluation is satisfactory, then the ontology-based application can be developed or improved, in case it already exists. This last step is out of the scope of this paper and is considered for future work.

In Fig. 1 a simplified workflow of our implemented methodology is presented. There, the user roles are highlighted through the methodological workflow, moreover we put forward how such action should be performed (manual, semi-automatic or automatic) according each role of the users.

4. Results

4.1. Methodology strategy selection

In this section we will describe the results obtained from the application of our methodology mentioned above. We started with an evaluation of the complexity of the domain. This analysis of this domain and an evaluation of software tools are outlined in a detailed technical report [24]. As a consequence of such analysis, a combination of deductive and inductive OL strategy (middle out) was selected. In other words, top-down and bottom-up methodological strategies were considered. In this vein, top-down strategies perform a feedback learning by a matching between ontologies, and bottom-up strategies let us perform a feed-forward learning by matching terms in the corpus against concepts in domain ontologies [25]. Furthermore, some processing tools were selected to support the ontological analysis, validation, and OL processes (Protégé-Prompt [26], Rapid-I [27], and GATE [28]).

In the literature we found that MASON and the Process Specification Language (PSL) [29] have been mostly reported on the development of ontology and applications in the manufacturing domain. Thus, we evaluated them in order to select one.

The two just mentioned ontologies are well documented with many use cases referred in the literature. The fundamental differences are: on the one hand, PSL is a process ontology; its core contains basic descriptions about processes, activities and activity occurrences, with the possibility of integrating extensions on it. It is not intended to represent objects or goods or to specify their features. PSL was implemented in knowledge interchange format (KIF) [30]. On the other hand, MASON was built upon three head concepts: entities, operations and resources. MASON was implemented in the Web Ontology Language (OWL) [31], thus it can be visualized and handled in ontology editors such as Protégé [32]. MASON resources include hierarchically: Material-resources, Machine-resources and Machine-tool. Machine-tool is related to the object we want to model in this proposal, the industrial machinery. Therefore, given that MASON contains terms closely related to our domain of interest and that is highly reusable, it was chosen so that we continue with our experimentation.

In Fig. 2, a module of MASON corresponding to machine-tools is presented. This visual representation was obtained by means of OntoGraph (a Protégé Plug-in [38]), thus the solid line arrows shown there correspond to subclass relations, and the dashed line arrows correspond to relations between concepts. Such concepts are represented as circles inside boxes, and certain instantiations are represented as diamonds inside boxes as well. Hereinafter an ontological view is presented, this meaning will be assumed.

The MASON's module presented there, contains a categorization of four kinds of Machine-tool, with 24 classes of machine-tools (concepts) in total. There is an object property, enablesRealisationof. Given that there is not more information related to a description of the attributes or concepts, MASON was used as a controlled vocabulary or thesaurus, and as a general manufacturing reference.

MTM, as DO referred in [9] and presented in Fig. 3, is proposed to describe machine tools information in a reusable way for process planning, factory planning and machine investment. MTM was tested in a use case for mapping industry standards, in order to facilitate interoperability. This ontology was implemented in OWL; it contains 13 concepts and 9 object properties. No rules or concept definitions were mentioned by [9]. Given the relation with industrial machinery, this ontology was selected as a base to use in our research.

The machine ontology (MO), depicted in Fig. 4, was developed before this research as a germinal version of MOP and is available at [11]. It replicates basic information about concepts commonly found in catalogs and brochures of industrial machinery. For instance, Model (of machine), Description (Operation_Features, Materials_Features and Market_Features), Location and Supplier. This ontology contains eight concepts that are related amongst one another by using ten object properties. Just to mention some concepts of MO and their relations, a Machine is_Located_in a given Location. They have a symmetric relation by means of Place_of_Origin.

The relation between the domain in the study and this ontology can be judged as evident, so we selected it to continue our research. However, later the content of MTM and MO will be compared against MASON. The competency questions will be performed and

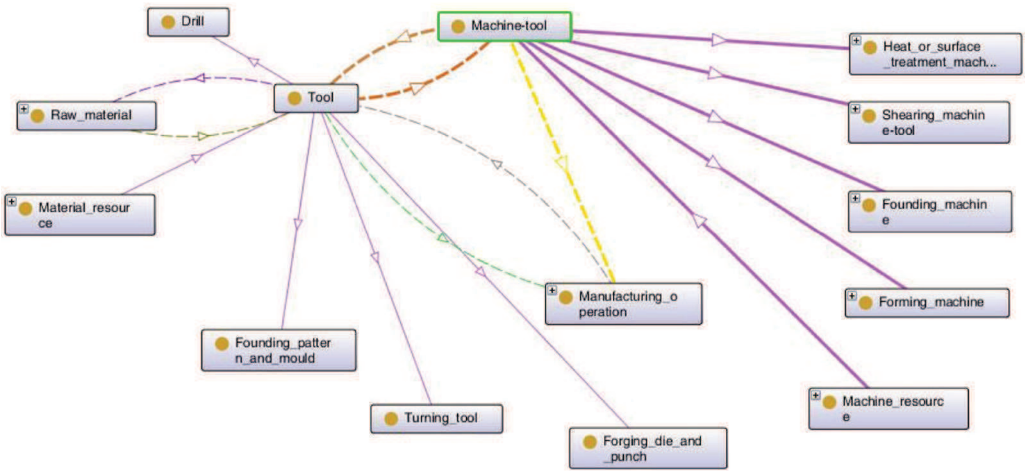

Fig. 2. Module of machine-tool in MASON.

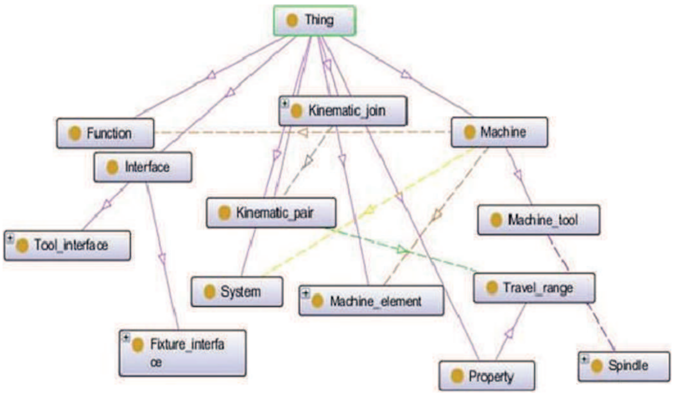

Fig. 3. Module of machine-tool in MTM.

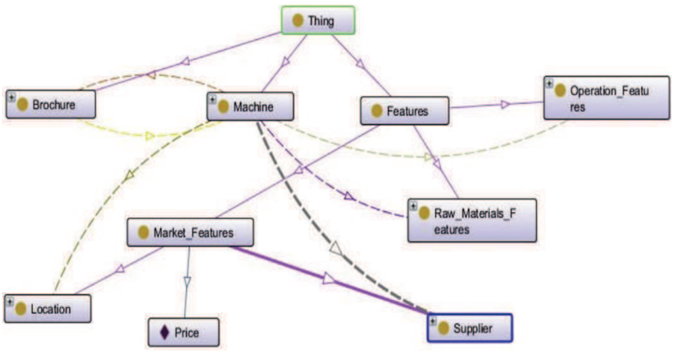

Fig. 4. Machine ontology (MO).

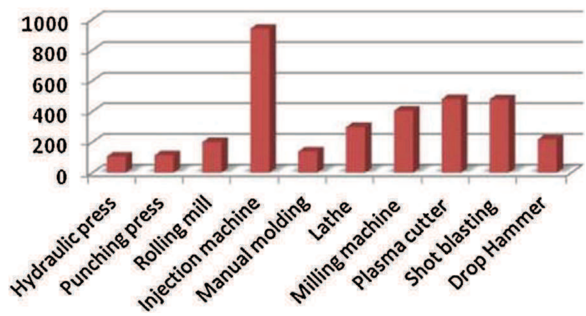

Fig. 5. Number of results obtained from specialized search engines.

additionally, the ontologies will be compared against a corpus of selected documents, in order to demonstrate that such a conclusion should not be taken *a priori*.

After having our selected ULO, and two DOs, we proceeded to generate a corpus of documents related to the domain. In our case study, MASON presents 24 concepts naming industrial machines. These concepts were used as significant keywords for performing a manual search by means of some specialized search engines on the Internet to get matching documents related to certain machinery which could be available for sale. The result of our search is presented in Fig. 5. In fact, the analysis of Fig. 5 makes evident that selecting industrial machinery can be an overwhelming task for a human being. On average, a decision maker has to evaluate at least 100 machines of any kind, contact the similar quantity of suppliers and perform the same number of technical evaluations. It is necessary to mention that some results were approximately 1000.

A sample of the retrieved documents, resulting from our search, was used to create a corpus. In order to obtain a representative corpus, the concepts distribution of MASON was used as a reference (Fig. 6a). In other words, the proportion of documents regarding specific concepts of MASON was maintained as much as possible in the obtained corpus (Fig. 6b). Moreover, some additional documents were included, such as documents corresponding to industrial standards (ASME [33]) and industrial safety requirements (OSHA [34]). Therefore, the resulting proportions were not equal, but very similar. The final corpus is in Extensible Markup Language (XML) format and was created by 633 documents in pdf, text, html and owl format.

The corpus was analyzed by means of RapidMiner [27]. It let us obtain (applying TF–IDF[2] techniques [35]) the most statistically significant sets of attributes into the corpus. In the following Section, we demonstrate how this set of terms (keywords) was used to determine the incompleteness of MTM and MO.

4.2. Knowledge discovery, query requirements and selection

MTM, MO and MASON content (concepts, properties, attributes and instances) were matched against each other by means of Protégé-Prompt [36]. This plug-in enables the realization of string and substring (concept/relations) matches across pairs of source ontologies. In other words, Prompt aims at finding common content and overlapping terms between ontologies, moreover it supports the creation of a new one or merged ontology based on the source ontologies.

[2] TF–IDF: Term Frequency–Inverse Document Frequency.

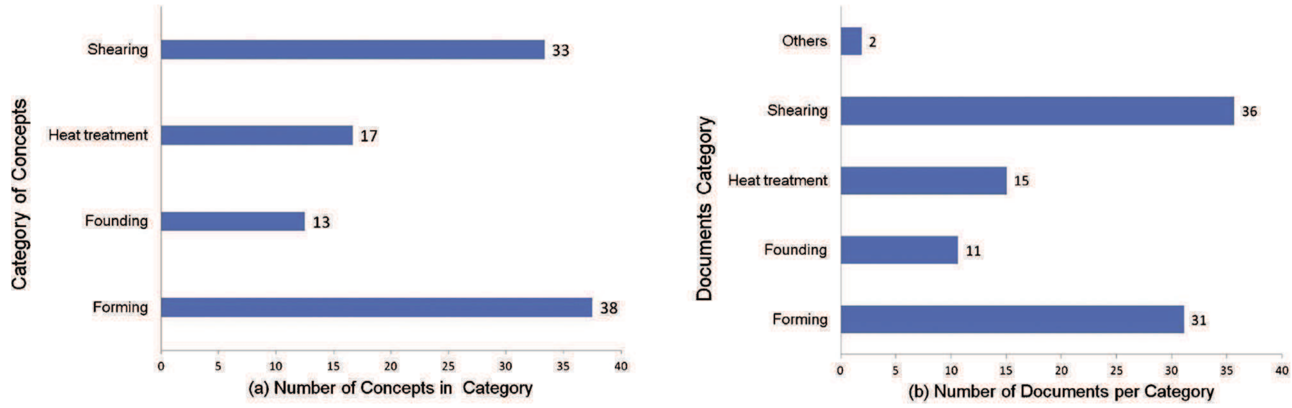

Fig. 6. Distribution of classes of machines (Concepts) in MASON and documents in corpus.

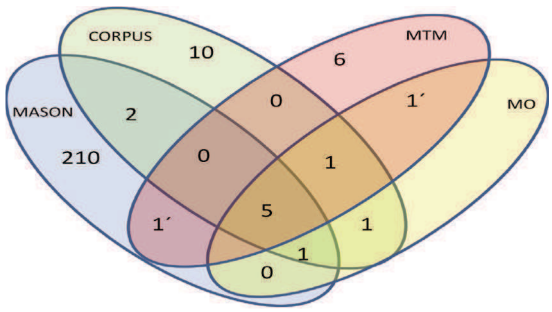

Fig. 7. Term relationships among ontology and corpus[3].

Because MASON has a level of abstraction upper than MTM and MO, it can contain them. That is, MTM and MO should be alignable as extending modules of MASON. We tried to find such a relation by means of Protégé – Prompt. Machine-tool was identified as the matching concept between MASON and MTM. Likewise, MTM had other matching of terms with MO. MASON had, though, no matching with (the current syntactical terms of) MO. From this perspective, MTM resulted as preferable to MO.

But, when ontologies were compared against the terms obtained from the corpus, the results were different. At first: all concepts of MO were coincident with some terms in the corpus, second: less than 50% of concepts of MTM were present in the corpus. In this step, MO had a better performance than MTM. That is, all concepts of MO were coincident with some terms collected from the corpus. However, the evaluation indicates that MO can contain less than 50% of the terms in corpus, which is still a low rate. Fig. 7 summarizes the result of this stage of the methodology.

Competency questions were also considered as a standard component of ontology development [37]. In this case study, MO and MTM were queried to try to get answers from. These queries were executed in Protégé for each ontology and the results are presented in Table 1. In this evaluation, MO had a better performance than MTM, given that its content could be used to answer four queries, while MTM answered only two of those.

As shown in Fig. 7, considering that each MO concept was related to some terms in the corpus, as long as MTM had six concepts not related with any term in the corpus, and that MO answered more competency questions than MTM, we decided to use MO as seed for OL, integrating relevant concepts of MTM into MO.

[3] Number with apostrophe indicates result of automatic mapping of ontology with Prompt.

Fig. 8. Merging Process with Protégé-Prompt.

In the following Subsection, we describe how the OL process was carried out and its results.

4.3. Knowledge structure construction and reorganization

This stage was carried out in two steps. First MO and MTM were merged. Seven classes of MTM were copied into MO, four object properties were also copied. This activity was supported by Protégé-Prompt merging capability. Fig. 8 shows the suggestions given by Prompt at the moment of loading and merging both ontologies in Protégé. The resulting ontology was named as MOP.

The second part of this stage consisted of enriching and populating the ontology with terms from the corpus either as concepts, instances or relations. In this sense, three concepts and two instances were added to this ontology.

Table 1
Results of applying competency questions on ontologies.

Competency question	MO	MTM	MOP
What kind of raw material can be processed with the given machine?	×	×	✓
What is the size of the machine?	✓	×	✓
What kind of power supply does it have?	✓	×	✓
What kind of operation does this machine perform?	✓	✓	✓
How much production can I obtain with it?	×	×	×
How many operations can I carry out on it?	✓	×	✓
What is the operational space required?	×	✓	✓

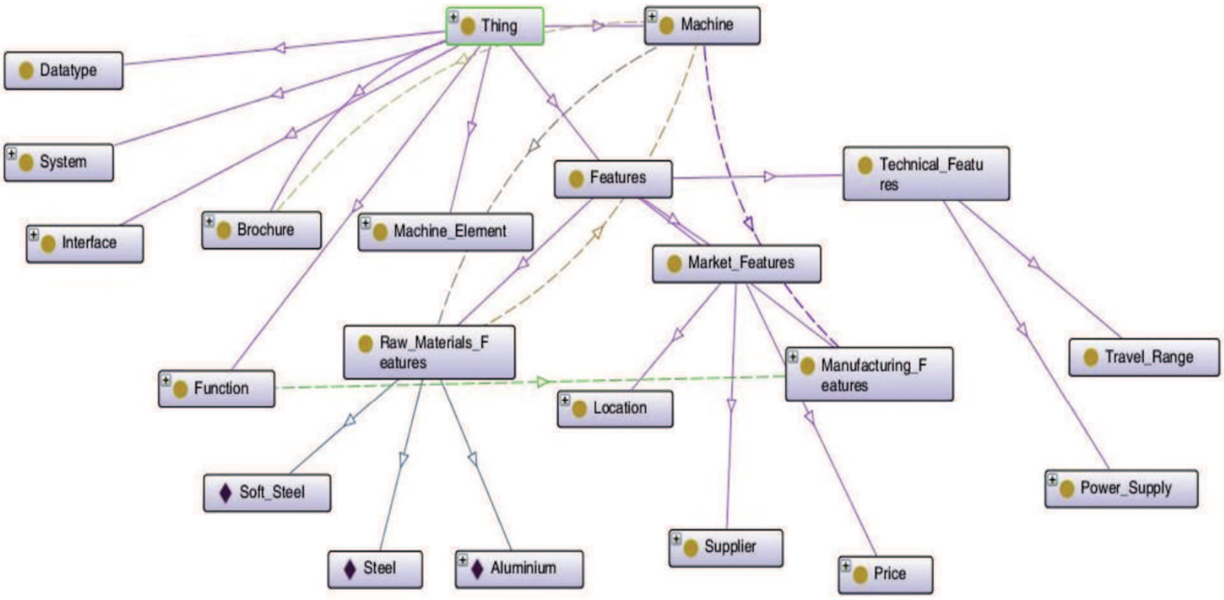

Fig. 9. Resulting ontology: Machine of a Process (MOP).

Fig. 10. Partial View of MOP in GATE.

The resulting MOP ontology is shown in Fig. 9, MOP contains 18 concepts and 11 properties. We calculated that MOP concepts were related to 85% of the terms in the studied corpus. Additionally, MOP presented a performance higher than MO and MTM when answering competency questions (See Table 1).

MOP was also tested against some documents randomly chosen from the corpus by means of GATE. Fig. 10 shows the result of this test. Identified terms were highlighted in different colors by this tool. This result demonstrates that a relation between a given document, related to the domain, and MOP was automatically found by this natural language processing (NLP) software tool. This ontology is available to download in [38].

5. Conclusions

Integration of the product life cycle is a key factor for enterprise success. Ontologies and the Semantic Web are currently being used to develop systems for the manufacturing industry. Nevertheless, many of the approaches, related to manufacturing, make ontology from scratch without considering the possibility of reusing ontology, although there is previous work developed in this field.

In this work, we have shown how to bind semantic of a manufacturing domain by an upper level ontology and a corpus. By analyzing the corpus, domain ontologies were validated. Our approach differs from other studies in the field of semantic manufacturing in that we aim at re-utilization of ontology, instead of discarding previously existing ontology. Our analysis was carried out by matching ontologies to one another and matching terms in the corpus against concepts in domain ontologies. The result demonstrated that MTM did not contain as many terms as MO in the corpus, but that MTM had a positive mapping with MASON, while MO did not.

Because MO had higher matching with corpus, it was enriched with concepts of MTM and terms of the corpus. So, we obtained a new ontology that we called MOP. This ontology can be used to describe industrial machinery and use this description in Internet. It contains a set of terms, whose likelihood of usability has been validated by means of text mining analysis in corpus.

We have also shown that, despite of having some ontologies closely related to one domain, in our case manufacturing, when they were evaluated several flaws were found. The first flaw was the lack of interoperability among ontologies as a consequence of having few mappings between them. The second flaw was the low level of interrelation between a set of terms automatically extracted from a corpus of documents whose content was related to the domain.

As future work, we consider developing the ontology-based search engine, and applying the methodology followed here to improve ontology of computer aided design (CAD) and ontology of raw materials.

References

[1] Abazari A.M., Solimanpur M., Sattari H., Optimum loading of machines in a flexible manufacturing system using a mixed-integer linear mathematical programming model and genetic algorithm. Computers and Industrial Engineering.

[2] T.P. Tsai, H.C. Yang, P.H. Liao, The application of concurrent engineering in the installation of foam fire extinguishing piping system, Procedia Engineering 14 (2011) 1920–1928.

[3] O. Kerbrat, P. Mognol, J.-Y. Hascoët, A new DFM approach to combine machining and additive manufacturing, Computers in Industry 62 (2011) 684–692.

[4] S. Ray, P. Kanta Ray, Product innovation for the people's car in an emerging economy, Technovation 31 (2011) 216–227.

[5] F. Jungermann, Information extraction with rapidminer, in: Proceedings of the Rapid Miner Community Meeting and Conference, 2010, pp. 67–72.
[6] M. Hepp, Goodrelations: an ontology for describing products and services offers on the web, Business 5268 (2008) 329–346.
[7] Y.-J. Chen, Y.-M. Chen, M.-S. Wu, Development of an ontology-based expert recommendation system for product empirical knowledge consultation, Concurrent Engineering 18 (2010) 233–253.
[8] M.G. Marchetta, R.Q. Forradellas, An artificial intelligence planning approach to manufacturing feature recognition, Computer-Aided Design 42 (2010) 248–256.
[9] T. Kjellberg, A. Von Euler-Chelpin, M. Hedlind, M. Lundgren, G. Sivard, D. Chen, The machine tool model–a core part of the digital factory, CIRP Annals – Manufacturing Technology 58 (2009) 425–428.
[10] S. Lemaignan, A. Siadat, J.-Y. Dantan, A. Semenenko, MASON: a proposal for an ontology of manufacturing domain, in: IEEE Workshop on Distributed Intelligent Systems: Collective Intelligence and its Applications, DIS 2006, (2006), pp. 195–200.
[11] Ramos L., Machine Ontology, Germany (2011), Available on: http://sourceforge.net/projects/ontomanufacture/files/mop/Machine_Ontology.owl/download.
[12] A. Maedche, S. Staab, Ontology learning, in: Handbook on Ontologies, Springer, Germany, 2001, pp. 173–189.
[13] W3C: Product Modelling using Semantic Web Technologies, http://www.w3.org/2005/Incubator/w3pm/XGR-w3pm-20091008/.
[14] Vei-Chung Liang, C.J.J. Paredis, A port ontology for automated model composition, in: Simulation Conference, 2003, Proceedings of the 2003 Winter. Vol.1, (2003), pp. 613–622.
[15] M. Gruninger, M. Fox, Enterprise Modeling, The American Association for Artificial Intelligence, Berkely, CA, 1998, pp. 109–122.
[16] Java Agent Development Framework, Telecom Italia SpA (2011).
[17] ASME B5/TC56: ASME B5.59-2: Draf: Information Technology for Machine Tools, Part 2, Data Specification for Properties of Machine Tools for Milling and Turning, (2005).
[18] ISO: ISO 10303-239 Industrial Automation System and Integration - Product Data Representation and Exchange – Part 239: Application Protocol: Product Life Cycle Support, (2005).
[19] C. Biemann, Ontology learning from text: a survey of methods, LDV-Forum 20 (2005) 75–93.
[20] S. Luther, D. Berndt, D. Finch, M. Richardson, E. Hickling, D. Hickam, Using statistical text mining to supplement the development of an ontology, Journal of Biomedical Informatics (2011).
[21] Bateman J., Castro A., Normann I., Pera O., Garcia L., Villaveces J.-M., OASIS common hyper-ontological framework (COF), http://www.oasis-project.eu/docs/OFFICIAL_DELIVERABLES/SP1/D1.2.1/OASIS-D121.pdf, (2009).
[22] B. Gaines, Knowledge-support systems, Knowledge-Based Systems 3–4 (1990) 192–203.
[23] R. Gil, M. Martin-Bautista, L. Contreras, Applying an ontology learning methodology to a relational database: university case study, in: 2010 IEEE Fourth International Conference on Semantic Computing (ICSC), 2010, pp. 313–316, IEEE.
[24] R. Gil, Techinical Report of MOP, 2011 https://sourceforge.net/projects/ontomanufacture/files/mop/.
[25] M. Fernández-López, Overview of methodologies for building ontologies, in: Presentado en IJCAI-99 workshop on Ontologies and Problem-Solving Methods, Stockholm, Sweden, 1999.
[26] N.F. Noy, M.A. Musen, The PROMPT suite: interactive tools for ontology merging and mapping, International Journal of Human-Computer Studies 59 (2003) 983–1024.
[27] RapidMiner, Rapid-I, USA, MA (2011).
[28] General Architecture for Text Engineering, The University of Sheffield (2011).
[29] The Process Specification Language (PSL) Theory and Applications, http://www.aaai.org/ojs/index.php/aimagazine/article/view/1719.
[30] Genesereth M., Knowledge Interchange Format, http://logic.stanford.edu/kif/dpans.html.
[31] W3C: OWL Web Ontology Language Semantics and Abstract Syntax, http://www.w3.org/TR/2004/REC-owl-semantics-20040210/, (2004).
[32] N.F. Noy, M. Sintek, S. Decker, M. Crubezy, R.W. Fergerson, M.A. Musen, Creating Semantic Web contents with protege-2000, Intelligent Systems, IEEE 16 (2001) 60–71.
[33] ASME: Engineering Standards, News and Resources for Engineers – ASME, http://www.asme.org/.
[34] OSHA: Occupational Safety and Health Administration – Home, http://www.osha.gov/.
[35] J. Davies, R. Studer, P. Warren (Eds.), Semantic Web Technologies: Trends and Research in Ontology-based Systems, Wiley, United States of America, 2006.
[36] S.K. Malik, N. Prakash, S.A. Rizvi, Ontology merging using prompt plug-in of protégé in Semantic Web, in: 2010 International Conference on Computational Intelligence and Communication Networks (CICN), IEEE, Bhopal, India, 2010, pp. 476–481.
[37] A. Gomez-Perez, O. Corcho-Garcia, M. Fernandez-Lopez, Ontological Engineering, Springer-Verlag New York, Inc, London, 2003.
[38] L. Ramos, R. Gil, Machine of a Process, Ontology, Germany, 2011.

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2.2. ***SMOL: A Systemic Methodology for Ontology Learning from Heterogeneous Sources.*** Journal of Intelligent Information Systems. (January 2014), Pages: 1-42, Springer

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SMOL: a systemic methodology for ontology learning from heterogeneous sources

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Abstract Organizations are demanding an efficacious knowledge management. Consequently, they are increasing their system innovation investments to turn information into useful knowledge for decision making obtained from heterogeneous Knowledge Sources (KSOs) such as databases, documents, and even ontologies. Methodological Resources (MRs) for the required knowledge discovering and recovering purposes have gradually become more elaborated and mature in the framework of Knowledge Engineering. Particularly, in the Ontology Learning (OL) field, there is a lack of integrated and open methodologies that could involve all the optional KSOs. In this sense, a systemic perspective is introduced combining MRs associated to diverse KSOs to improve the quality of an integral and continuous Knowledge Acquisition (KA) process. The main contributions provided by this work are on one hand, a novel Systemic Methodology for OL (SMOL) from heterogeneous KSOs which is applied for a case study and on the other hand, an evaluation of SMOL.

Keywords Ontology learning · Methodology · Knowledge acquisition · Evaluation · Case study

1 Introduction

Nowadays, companies and organizations are demanding an appropriate and efficacious knowledge management. To reach that, they are using data from internal and external sources and different organizational inter/intra -relationships to keep them operative and competitive. They are trying to respond more effectively (products and services) as well as to provide management innovations (as systems) to face the challenges of today's

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modern world. The organizational managers are developing and improving their own knowledge-task and decision-making support systems related to owners, employees, clients, and users (Abdullah et al. 2008).

Companies usually have much information accumulated and accessible in several structured, semi-structured, and unstructured formats associated with heterogeneous Knowledge Sources (KSOs) such as databases, texts, and even ontologies. This kind of sources has been used more frequently under semantic technologies for improving and updating their Knowledge Management Systems (KMS) (Bloehdorn et al. 2009).

Most of the organizational data are expressed in some of the cited formats. Usually, legacy organizational information is stored in databases of business information systems. Specifically, it is possible to convert this information into useful knowledge through the conceptual schemas, as well as through the data values.

Likewise, many of the new data are stored in texts and documents associated with the domain business applications. Natural Language Processing (NLP) and Text Mining techniques can be used to process this kind of data. Finally, we can find information stored in semantic formats such as ontologies about the system-domain. This information is available through the appropriate semantic technologies (Gómez-Pérez et al. 2004).

Methodological Resources (MRs) such as tools, methods, and techniques have gradually become more elaborated and mature in the framework of Knowledge Engineering. Particularly, in the Ontology Learning (OL) field, these MRs are usually related to a specific KSO (e.g., texts), but without any relation with the others KSOs. Therefore, reaching an adequate and dynamic methodology for the integration and organization of these sources and resources would be useful for KMS developers and users (Gómez-Pérez et al. 2004).

Dealing with the most "appropriate knowledge" to develop first a domain-ontology, as well as to keep it updated and enriched later, it will be required to cope with the following important underlying questions:

- Have the involved Users applied the appropriate MRs to reach efficaciously the *ontology development* (OD) and learning processes?
- Have they used several of the possible and complementary KSOs related to their specific domain for their ontology learning process?
- How could they do to keep periodically up-to-dated the ontology associated with their system-domain through an important updating process through these MRs?

New OL methodologies under a systemic approach (integrated, open, and flexible Callaos and Callaos 1994) from the aforementioned heterogeneous KSOs could be making the most of those combined MRs, and it may favourably impact the total quality performance of the associated Knowledge Based Systems (KBS). Specifically, those methodologies must be considered as an integral part of the referred systems. Thus, the continuous updating and enrichment of knowledge through OL processes for ontology would be globally more efficacious, accordingly to the complementary diversity of KSOs available.

Therefore, the *main motivation* for this work is:

1. Knowledge acquisition improvement through OL (iterative, incremental, and automatic) from heterogeneous but complementary KSOs such as: a) databases of organizational systems, b) texts and relevant documents, and c) previously developed ontologies (domains or uppers).
2. Combining inductive and deductive OL simplifies the learning process (Cerbah 2010). On one hand, OL from databases and text sources can be simplified through inductive reasoning/inference by data-mining and text-mining processes (bottom–up). On

the other hand, recoverable and deductive learning from other ontologies and databases can be simplified through matching and mapping processes (top–down) (Cerbah 2010; Buitelaar et al. 2009; Bai et al. 2011).

3. Reusing of explicit and implicit knowledge must be increased. Indeed, corresponding explicit knowledge as the one expressed in ontologies and implicit knowledge as the one expressed in routines or agents might be identified, qualified, and classified in catalogues for the purpose of reusing it. These types of knowledge could be obtained during OL processes associated with particular domains and/or use cases.
4. Systemic total quality must be ensured to users (Callaos and Callaos 1994). Under this paradigm, the quality of the OL Processes/Products must be checked as a whole, from the user perspective. Users have to understand the involved KSOs and MRs. Both elements must be explicitly considered/managed according to the expected results (Callaos and Callaos 1994).

The *main contributions* obtained from this work are:

1. Introducing a Systemic Methodology for Ontology Learning (SMOL) from heterogeneous sources through eight phases over a structured flow (based on Yao et al. 2007). Users can transit through this SMOL workflow under an iterated way, until completing a whole OL process for every KSO. Thus, we have an OL process for every KSO.
2. A user-centred methodology approach (flexible, iterative, and incremental) oriented to Experts Users and Knowledge engineers is outstanding in two ways:

   a) A dynamic selection of the methodological strategy can be drafted as an instanced and customized OL process, with the suitable MR. The methodology allows these kinds of users to design and select the "best strategy" based on the appropriate trade-off between the domain complexity versus the recoverable and useful knowledge from all types of KSOs (based on Zhou 2007). The method and technique suggested to draft the methodological strategy is detailed in SMOL Phase I.
   b) Implementing some user-based quality control mechanisms (named decision points) to improve the resulting semantic products. These OL products could be ontologies, semantic artefacts, or related agents (obtained procedures).

3. A SMOL application example of an academic case study is detailed. It helps us to show how the cycles of OL are performed from each KSO, by completing a whole Knowledge Acquisition (KA) process. A methodological evaluation of SMOL through methods based on further analysis is usually applied in the software engineering field.

In this article, we focus in an OL methodology under the systemic approach using important KSOs to keep updated ontologies of associated domain and KMS/KBS. Then, we describe how by using the appropriated combination of current MRs for OL according to the KSOs, following the SMOL workflow, it is possible to support integration and complementary KA processes. The article is structured in the following way: the OL related works and methodological perspectives are reviewed is Section 2. The design and description of the novel SMOL methodology can be found in Section 3. The SMOL application to the case study for each KSO is included in Section 4. The SMOL evaluation is explained in Section 5. Finally, some conclusions and future work are presented in Section 6.

2 Ontology learning under a methodological view

This section considers, on one hand, relevant insights about OL and a short review about the OL approaches regarding each KSO. On the other hand, it also considers some other issues: MR definitions are reviewed, the OL problematic is analyzed (based on OL Processes/Products), the systemic focus is introduced, and some evaluation methods to assess SMOL as a methodology have been included.

2.1 Ontology learning background

Condensing a general OL conception regarding this work, we have selected three associated definitions:

> *"The process of automatic or semi-automatic construction, enrichment and adaptation of ontologies is known as Ontology Learning.... Ontology enrichment is the task of extending an existing ontology with additional concepts and semantic relations and placing them at the correct position in the ontology...., Ontology population.... is the task of adding new instances of concepts to the ontology"* (Petasis et al. 2011).

The main technical advances and challenges of the OL technology are to find and identify *ontology-objects* (Buitelaar et al. 2009), such as Classes, Instances, (non-)taxonomic Relations, and Rules to be learned from KSOs (usually only one source) as the most efficient as possible objects. Commonly, these associated learning tasks are based in (semi-) automatic Artificial Intelligence approaches such as NLP, Pattern Recognition, Clustering, Data-mining, and so on (Wong et al. 2012).

Although other important definitions of Ontology Learning can be found in the literature (Gómez-Pérez and Manzano-Macho 2005), they are focused in OL from only one KSO (electronic documents or database schemas or by an ontology integration process from previously developed ontologies). However, there are not so many approaches that consider more than one KSO in the same KA process. For instance, recently in Simperl et al. (2008) up to two of these KSOs have been taken into account.

Important contributions for OL have been derived from the Ontology Evolution field particularly associated with the ontology management, modification, and versioning (Stojanovic 2004; Khattak et al. 2009). In this sense, we have focused our interest in some MRs of this field which could be applied in the SMOL design criteria and some developed methodologies (e.g., BOEMIE) which might be useful for comparison purposes (Petasis et al. 2011; Castano et al. 2007, 2009).

2.1.1 Ontology learning from heterogeneous KSO

There are several methodological alternatives in the literature about OL. The one suggested in (Gómez-Pérez and Manzano-Macho 2005). On the other hand, in Gliozzo et al. (2007) a different classification of the recommended techniques into two groups is given. The first group includes those MRs that allow the user to get knowledge and to retrieve information from electronic documents. The second group includes those MRs that allow the users to improve the semantics based on previous structured knowledge and ontologies such as dictionaries and thesauruses (Gómez-Pérez and Manzano-Macho 2005; Shamsfard and Abdollahzadeh 2003).

The different OL options according to the KSO are referred as:

- OL from other previously developed ontologies (Bai et al. 2011; Azzam and Zhou 2012).
- OL from documents (Cimiano et al. 2009; Massey and Wong 2011).
- OL from database schemas and their data-values (Cerbah 2010).

Despite the importance, continuous advances, and diverse variants of each of the cited OL approaches, most of the general MRs associated with each KSO have been synthesized due to space constraints, in the following subsection.

Ontology learning from ontologies Different learning approaches from ontologies are understood as processes to make use of the semantic matching between entities (concepts and relations) among diverse ontologies. This process of corresponding among entities is usually known in the technical literature as ontology integration and/or ontological matching; nevertheless, other authors divide the latter into variants such as ontological alignment and ontological mapping. In this way, it is possible to acquire a new knowledge domain (from other developed ontologies) for the updating of the target ontology (Bai et al. 2011)

Further details about the comparison of techniques, tools, methods, and methodologies for OL from ontologies can be found in Gómez-Pérez and Manzano-Macho (2005), Shamsfard and Abdollahzadeh (2003), and Azzam and Zhou (2012).

Ontology learning from texts OL from documents makes emphasis on the text-content information treatment under the following five processes: 1) Presentation, 2) Recovery, 3) Extraction, 4) Reasoning, and 5) Knowledge maintaining (Cimiano et al. 2009). All these processes operate over contents in text format, usually using NLP techniques (Wong et al. 2012; Castano et al. 2009; Gliozzo et al. 2007).

While some comparison studies consider the different MRs related with OL from texts (Wong et al. 2012; Gómez-Pérez and Manzano-Macho 2005; Shamsfard and Abdollahzadeh 2003), some other works emphasize methodological frameworks taking into account the knowledge domain and topic of importance (Massey and Wong 2011).

More recently, methodological proposals have also considered: a) KA through OL from texts (mainly) using dynamic phases (Nováček et al. 2008), and b) structured process-flows (Bai et al. 2011). Both proposals occasionally consider ontologies previously developed as another useful KSO, as well as the studies in Simperl et al. (2008). As far as we know, none of them had considered databases as KSO into their methodological proposals. Some relevant methodologies such as Simperl et al. (2008), DINO (Nováček et al. 2008), BOEMIE (Castano et al. 2007, 2009), and OntoCmaps (Zouaq et al. 2011) are included in Table 1 below and described in Section 2.5.

Ontology learning from databases Relational Databases (RDBs) have been contemplated as a possible knowledge source for different processes. In this work, the databases expressed as Relational Databases (RDBs) are used as another KSO. In an ontological framework, RDBs have been exploited to populate ontologies.. Moreover, some important tools have been developed considering the structured data (RDB-Tables) and including semantics obtained from their cell values (using data mining) to recover knowledge (inductive reasoning) using data-mining techniques as well (Cerbah 2010). Some representative methodologies are included in Table 1.

Table 1 Methodological resource for ontology learning from each KSO

Definition (Callaos 1992)	Ontologies	Texts (Corpus)	Databases
Technique:Subjective capabilities to handle a tool by users	- String matching - Graph based - Statistic analysis	- Linguistic patterns - Semantic relativity - Data mining algorithms	- Rule-based (similarity) -Taxonomic structure analysis - Clustering techniques
Method: A way to think/doing to achieve an objective	- Alignment - Structured & merging - Matching	- Statistical - Linguistics - Machine learning	- Attributes, - Instances & DB schemas. - Synonyms & inclusions - Classes (e.g RTAXON method)
Tool: Objective capabilities to apply techniques	ASMOV (Jean-Mary et al. 2010), MapPSO (Bock et al. 2011) Prompt (Noy and Musen 2003) FCA-Merge & H-CONE (Azzam and Zhou 2012)	CRSTOL (Jiang and Tan 2010) ASIUM (Faure and Poibeau 2000), GATE (Cunningham 2002) OntoLearn (Velardi et al. 2005) Text2Onto (Cimiano and Völker 2005)	ARTEMIS (Castano et al. 2001), DIKE (Palopoli et al. 2003), DataMaster (Nyulas et al. 2007), ODEMapster(Calbimonte et al. 2010) RDB-ToOnto (Cerbah 2010)
Methodologies: Set of techniques methods and tools	Approaches: - FOAM (Ehrig 2007) -OL: Protege-Prompt (Noy et al. 2004)	- OL Framework (Zhou 2007) - Structured (Simperl et al. 2008) - BOEMIE (Castano et al. 2007; Castano et al. 2009) - DINO (Nováek et al. 2008)	- Observer (Mena et al. 2000) - Garlic (Roth et al. 1996) - Rondo (Melnik et al. 2003) - RTAXON (Cerbah 2010)

2.1.2 Ontology learning methodological resources

There are some definitions regarding MR that allows us to understand the concepts associated with MR and to avoid confusions that sometimes happen in technical literature. The following definitions have been considered (Callaos 1992): a) Techniques, b) Methods, c) Tools, and d) Methodologies. All of them are in our work, the main set of MRs. A corresponding definition of each one is detailed in Table 1 (first column).

Regardless from the KSO studied in the technical literature, several MRs have been proposed to support users' needs in OL processes. In Table 1, without pretending to reach an exhaustive list, some OL representative MRs are summarized according to each selected KSO. Some suitable MRs for our case study has been selected and used, as can be seen detailed in Section 3.

2.2 Ontology learning problematic

Although there have been important technical advances in MR in the OL field according to each KSO, some works with emphasis on methodological features have reported a high dispersion and a little integration among those MRs to obtain some OL results from different KSOs (Petasis et al. 2011; Wong et al. 2012; Gómez-Pérez and Manzano-Macho 2005; Shamsfard and Abdollahzadeh 2003).

Therefore, to synthesize the general OL problems, a situational technical analysis, which is known as SWOT (Strengths, Weaknesses, Opportunities, and Threats), is used (Hill and Westbrook 1997). This technique simplifies the OL understanding from two broad perspectives. First, it addresses the knowledge development and reconstruction as an OL process and, second, it studies the quality of the results from a semantic point of view. Consequently, our suggested SWOT analysis about these methodological OL -Process and –Semantic Product problems are shown in Table 2.

In agreement with Gómez-Pérez and Manzano-Macho (2005), and Shamsfard and Abdollahzadeh (2003); two conclusions taken from those studies about OL methodologies can be summarized as follows:

- Regarding to OL Methods; a) there is not an established standard; b) the methods are not usually combined; and c) many methods are not associated with specific tools.
- With regard to OL Tools: a) all of them help to extract knowledge; b) a small group of them allows to retrieve a complete taxonomy; c) only some tools support specific OL methods; and d) some of those tools are difficult to be evaluated.

It is also possible to infer that OL methodological options do not exist as a complete integral and dynamic way to face the OL problems for identifying and selecting "knowledge-objects" from different sources as ontologies, texts, and databases. Nevertheless, recent works show the incorporation image and videos as useful KSOs (Castano et al. 2007, 2009). OL methodologies must offer a wide and suitable support to users for ontology updating associated with their KBS/KMS.

Regardless of the KSO, several MRs have been proposed to help during the OL process. Precisely, this wide variety of mechanisms and optional means make difficult -without a systemic approach- the definition and formulation of a unified OL standard methodology.

Finally, and not less importantly, the *Ontology Evaluation* (OE) feature and how it could affect the associated *KMS success* must be considered. Those are OE aspects in progress according to Strasunskas and Tomassen (2008), Fernández et al. (2009),

Table 2 SWOT analysis applied to ontology learning process and products

	OL processes	OL products
S	There are:	Main:
	- Some stable OL methods and techniques.	- Structured knowledge is Ontology-based.
	- Some stable OL tools.	- Some standard languages (RDF, OWL)
	- Structured methodological proposals.	- The generalized ontology - approach uses.
	- Some integrated OL Development Tools (i.e., Protégé-Prompt, Text2Onto)	- Users are learning about those resources.
		- Some GUIs browse the ontology and texts
W	There are:	There are:
	- Very few GUI & App. interfaces.	- GUI and App. are very inadequate.
	- Non methodological standard yet.	- Some system products neglect semantics and contexts aspects.
	- Many unknown methodological resources recently developed.	- Non customized store of partial products (as agents) for reuse purposes.
	- Dispersion about different resources and KSO.	- Other new and different options for knowledge representation.
	- Different users require to have some previous OL technical knowledge/experience	
O	May be...:	May be..:
	- New OL methodological options may emerge.	- A standard of quality of knowledge services and the involved ontologies are possible and needed.
	- MRs could be standardized for integration and purposes.	- Development of new MRs and Semantic products.
	- Methodological and technical resources could be developed by multi-disciplinary groups.	- Some previous developed partial/final knowledge support products (reuse storage) may be included.
T	May be..:	May be..:
	- OL technologies keep unconnected.	- Users sometimes have the feeling that they are relegated by knowledge itself.
	- Methodological resource dispersion tendencies can stay present.	- System designs are not considered as reuse way.
	- Keep technical-guided for the research line.	- Scientific community could change the interest for OL products as a means for knowledge representation
	- New different knowledge structure may emerge	

S strengths; *W* weaknesses; *O* opportunities and *T* threats

Sabou and Fernandez (2012), Tartir et al. (2005) and their effects on the KMS success (Jennex and Olfman 2011; Urbach and Müller 2012). We judge both of them as others intrinsic and essential problems associated with the semantic products derived from the application of OL methodologies. In fact, the OE aspects will be considered as a key criterion in the SMOL methodological evaluation in Section 2.4.2. Conversely, the effect on the KMS success, although nonetheless relevant, is beyond the scope of this study.

2.3 Methodological design under a systemic perspective

Methodological options used to get designs and knowledge product developments D (e.g., Systems, ontologies, or models) are associated with strategies and processes which are structured in some way. Many approaches closer to System and Software Engineering reflect the efforts dedicated in this direction (Sommerville 2006; Mens et al. 2010).

Some OD/OL methodological approaches have arisen. Some of them are oriented to Software Development (Gómez-Pérez et al. 2004) while some others are oriented to Knowledge Engineering (De-Nicola et al. 2009; De Leenheer and Mens 2008). However, these latter approaches suggest methodological options according to the requirements of efficacy which are suitable for ontology applications.

Our methodological perspective tries to conciliate the system/software development paradigms with user-centred services (adaptable and anticipative) to meet their demanded knowledge requirements. This conciliation is supported by systemic methodologies instead of systematic ones (Callaos 1992; Larman and Basili 2003; Boehm and Turner 2004).

- *Systematic methodologies* are oriented to the efficiency, with a predetermined behaviour, strict, and closed, e.g., Structured Life Cycle.
- *Systemic methodologies* are oriented to the effectiveness, with a non-predetermined behaviour, flexible and open, e.g., Agile Process/Methods.

The product (ontologies) and process (methodologies) must be developed in a balance between efficient and effective design suggested under the principle of systemic methodologies and/or the agile methods trends.

In this regard, we have combined in the SMOL design (workflow of phases) the Yao's proposal for a generic knowledge retrieval model (Yao et al. 2007) and the flexibility/adaptability of the methodology strategy selection (in SMOL phase I) according to the complexity of domain by extending Zhou's proposal (Zhou 2007). In addition, some MRs of ontology evolution (modification and versioning) have been considered for the workflow design of SMOL (Stojanovic 2004; Khattak et al. 2009). More details of these reference applications are included in the SMOL workflow description in Section 3.3.

Finally, the aim is for the users of this proposal of a systemic methodology for OL to be able to efficiently and effectively combine different MRs from diverse KSOs to keep the associated KBS/KMS updated. In this sense, we have classified in this work the different user groups according to the Gaines' KSS model (Gaines 1990). Specifically, they are grouped as end-users, expert-users, and knowledge engineers. More details are included in Section 3.4.

2.4 Methods to evaluate methodologies

There are not so many alternatives for the evaluation of methodologies applied to the Ontology Development and Learning field. One of the most accredited methods and also, one of the commonly referred ones in the Software Engineering area is the DESMET method (Kitchenham et al. 1997).

In this sense, we have used the combination of three methods suggested in DESMET to technically evaluate our integrated OL methodology proposal:

- *Qualitative screening*: A feature-based evaluation (Kitchenham et al. 1997, pg. 122) executed by a single individual who not only determines the features to be assessed and their rating scale, but also carries out the assessment. For an initial screening, evaluations are usually based on the literature describing the software method/tools rather than the actual use of them. In this case, the screening evaluation is divided into two: 1) Using a previous study about the evaluation criteria of users' usability and suitability, and 2) Using a comparison with other equivalent OL methodologies.
- *Qualitative experiment:* A feature-based evaluation implemented by a group of potential users who are expected to try out the methods/tools for typical tasks before delivering their evaluations.
- *Qualitative case study:* A feature-based evaluation performed by someone who has used the method/tool on a real project.

These selected methods are recommended by DESMET to be used when: a) there is a large number of methods/tools to assess, b) there is a short timescale for evaluation exercise, c) there are benefits which are difficult to quantify, d) there are benefits which are observable on a single project, e) there are stable development procedures, f) there are benefits which are directly observable from the task output, g) there is a relatively small learning time, and h) the popularity of the tools and methods by users is very varied but limited. The MRs associated to OL processes have similar characteristics found in some software engineering MRs as the ones identified above in Table 2.

Consequently, SMOL as methodology is evaluated applying these qualitatively DESMET's methods to assess their main characteristics and by comparison with other similar OD/OL methodologies.

Particularly, to apply these DESMET methods to SMOL in Section 5, we have used complementary a proposal of OD methodology assessment suggested in Dahlem and Hahn (2009) about ontology-oriented methodology usability criteria described in the following Subsection.

2.4.1 Usability criteria to evaluate methodologies

In Dahlem et al. (2009), thirteen criteria to evaluate the usability and suitability of the OD methodologies are considered. These criteria are: Adequate terminology (C1); Structure (C2); Descriptiveness (C3); Transparency (C4); Error avoidance (C5); Robustness (C6); Lookahead (C7); Consistency (C8); Hiding formality (C9); Expressiveness (C10); Conceptualization flexibility (C11). Ontology assumptions (C12); and Tool support (C13).

These criteria are combined also by the authors in the following five aspects:

- *Learnable:* (C1 & C9)
- *Efficiency:* (C2, C3, C5, C9, C10, C11, & C13)
- *Memorability:* (C1 & C8)
- *Error-Handling:* (C5, C6, C7, & C12)
- *Satisfaction*: (C3, C4, C5, & C7).

Two evaluation methods using these usability evaluation criteria have been applied to SMOL in Section 5.1; one of them, for a qualitative screening analysis cited in the DESMET approach and the other one, based on the other Dahlem's work about a comparative methodological benchmarking using the same usability criteria (Dahlem et al. 2009).

On the other hand, a screening through methodological comparison with other four equivalent and recent OL methodologies helps us focus on the main discriminator assessment criteria to compare them in Section 5.2.

So far, we have found no references either where an OL methodology has been previously evaluated using these formal DESMET methods or by the combination of it with other assessment methods for ontology-oriented methodologies similar to the Dahlem's proposals.

2.4.2 *Complementary ontological evaluation criteria*

The convenience to determine how well the OL methodologies can guarantee the *Ontological quality* must be involved with the explicitly standardized Ontology Evaluation (OE) mechanisms and their associated MRs must be prescribed according to the selected strategy for OL.

Particularly, the workflow and guideline suggested as an OE methodology to carry out the associated MRs activities has been adopted from Sabou and Fernandez (2012) in this work.

The cited OE methodology involves the following workflow-tasks: Task 1: selecting the individual components of the associated KMS ontologies (partial/group of ontologies); Task 2: selecting an evaluation goal and approach *(Domain coverage, Quality of the modelling, Suitability for an application/task, or Adoption and use);* Task 3: identifying a frame of reference and evaluation metric *(Gold standard, Topology-based, Data-driven, Assessment by humans, and so on);* and Task 4: applying the selected evaluation approach. This OE is applied to the case in Section 5.

Likewise, according to the MRs explicitly used/prescribed for OE (based on the previous workflow *Task 2* and *Task 3*), we have introduced a preliminary comparison about the ontological quality of our OL methodological proposal in relation to other equivalent OL methodologies suggested until now. A summary of this comparison is shown in Table 7 of Section 5.2.

2.5 A methodological focus: state-of-art

The main related work could be classified as follows: 1) the methodological features associated with *Ontology Development (OD),* and *Ontology Evaluation (OE)* used as reference for comparison and/or for evaluation purposes; 2) The derived ontology evolution and OL methodologies; 3) The importance and convenience of diverse KSOs useful to support OL processes; and the scope of our previous OL developed works.

Some different types of OD methodologies have emerged and evolved to turn into viable options for ontology building or construction. Many of them originally consider the MRs for OD from scratch (users' requirements).

However, a recent group of OD proposals has incorporated other optional KSOs and MRs (e.g., tools) to build the "wanted ontologies". Some instances of the former approach could be followed in methodologies such as Ontology-Guide-101 (Noy and McGuinness 2001), ONIONS (Gangemi et al. 1999), and Methontology (Gómez-Pérez et al. 2004). The latter group includes more recent OD methodologies and their variants such as UPON (De-Nicola et al. 2009), DILIGENT (Pinto et al. 2009), OntoClippy (Dahlem 2011), and NeON methodology (Suárez-Figueroa et al. 2012). Besides, a comparative work in

Islam et al. (2010) about OD methodologies has been considered as well to evaluate general SMOL usability features.

In fact, our SMOL proposal is more aligned with continuous KA processes (ontology enrichment and updating) in comparison with some of the most relevant OD methodology (to develop or to create ontologies). Thus, the previously cited OD methodologies can be useful as a reference for evaluating (by comparison) the most distinctive methodological characteristics of our proposal in Section 5.1.

Consequently, with this methodological focus, we have considered convenient to include the OE as another relevant element which may affect the quality of the ontology-associated semantic products (KBS/KMS success) obtained during any OD/OL methodology application. Thus, some comparative features suggested in Noy et al. (2004) and correlated with OE have been considered in Section 5.2.

2.5.1 Relevant OL methodologies

Some of the most recent and relevant OL methodologies which consider diverse MRs, KSOs, and/or media have been found in the literature and used to evaluate comparatively attribute qualities and properties of SMOL. So far, the derived Ontology evolution and OL methodologies selected for these feature comparing purpose are briefly described as follows:

a. Simperl et al. in (Simperl et al. 2008). This methodology incorporates some MRs in a structured way. The authors consider a couple texts and ontologies as main KSOs for OD and for updating the developed/created ontology. The methodology describes the major coordinates of these processes in terms of activities, actors, inputs, outputs, and support tools. From the feasibility study phase of ontology integration, up to eight faces are considered in the whole methodology workflow
b. BOEMIE (Castano et al. 2007, 2009). This methodology extends the OL approaches beyond text contents considering other media such as image, video, and audio. The applied methodological evolution approach is based on the updating pattern-driven identification. An automatic detection of an evolution scenario is identified on the basis of the result of the semantic interpretation activities (potential changes) against the knowledge background (from the previous domain-ontology version). The innovative knowledge representations and automatic mechanism (reasoning/ abduction) incorporated into the methodology reduce the expert user involvement. It has three general phases starting with an extracting process (ABoxes), the pattern selection (for populating/enrichment), and finally, some coordination activities (ontology is updating).
c. DINO (Nováček et al. 2008). This methodology is able to automatically process new knowledge from texts and web pages. It is able to be compared to the domain-ontology (master) to select the new knowledge accordingly. DINO automatically sorts the new knowledge corresponding with the user-defined preferences. According to the case study, the authors state that the population process requires little participation of expert users, while the enrichment process (integration) demands more careful expert involvement. The methodology is described according to a dynamic integrated scheme based on six phases.
d. OntoCmaps (Zouaq et al. 2011). This methodology extracts deep semantic representations from corpora. Acording to their authors, OntoCmaps generates rich conceptual

representations in the form of concept maps and proposes an innovative filtering mechanism based on metrics from graph theory. It relies on three main phases to learn a domain ontology: (1) extraction phase that performs a deep semantic analysis and extracts various chunks of knowledge; (2) integration phase that builds concept maps, which consists of terms and labeled relationships, and relies on basic disambiguation techniques, and finally, (3) filtering phase where various metrics are used to filter out the obtained concept maps. In this paper, the authors of the methodology use interchangeably the name OntoCmaps tools to describe the workflow phases as well as the diverse functionalities/services useful to support these phases.

Although we have not found previous and specific comparative works about OL methodologies, we have developed a comparative feature evaluation among these similar OL methodologies with SMOL in Section 5.2.

2.5.2 *KSOs management and our previous OL works*

Regarding the use of multiple and heterogeneous KSOs to support OL processes from diverse organizational contexts, it has been increasingly relevant in the literature (Argote and Miron-Spektor 2011; Wohlgenannt et al. 2012; Jimeno-Yepes et al. 2009). We have emphasised in the SMOL design the use of some (un-) structured useful and accessible KSOs such as texts, databases, and previous developed ontologies. These KSOs would be (semi-) automatically discovered and recovered according to the MRs for OL from diverse associated organizational context (local-unit, whole-organization, and external-environment) in line with the model suggested in Argote and Miron-Spektor (2011). It is important to point out that as far as we know, no other previous work has considered some optional MRs (tools) for OL from databases (Cerbah 2010) as significant into an integrated OL methodology,

Finally, our previous works have been related to an incremental designing process to develop SMOL as an integrated OL methodology. Particularly, we have developed successive and partial OL processes for each one of the KSOs in Ramos and Gil (2010), Gil et al. (2010a); a partial description of the case study and the SMOL evaluation was introduced in Gil et al. (2010b) and a variant of the SMOL application in another system domain (manufacture) was detailed in Ramos et al. (2013) where a technical report is used to explain a crucial phase (I) of the SMOL workflow (*Methodology strategy selection*) (Ramos and Gil 2011).

3 A systemic methodology for ontology learning

As far as we know, the lack of integrated methodologies covering the whole process of OL (using the aforementioned KSOs) leads us to propose and experiment with new methodological options. The design of this suggested *Systemic Methodology for OL (SMOL)* has focused in making it flexible, iterative, incremental, and adaptable to support the important knowledge-designing tasks of the Expert Users and Knowledge engineers using some MRs (previously developed) from heterogeneous KSOs. In this sense, SMOL is user-centred to support these kinds of user's needs. It must combine some MRs of OL for each specific KSO in a proper way, following the above mentioned systemic approach.

The general outline of the proposed methodology consists of eight phases that keep some precedence relationship during a conditional flow. Each phase in the OL process is characterized by the most suitable set of MRs for every KSO. This methodology is open to the possibility of generating the most adequate strategy (initial phase) under the technical criteria and available resources.

Thus, based on the needs of the process to support knowledge for a certain domain, the specific methods and techniques of each phase would vary. Moreover, these can be intentionally adjusted (at user's discretion according their skills) to conceive the aforementioned methodological strategy.

In short, in the cited initial phase (selection of strategy), the most suitable methods, techniques, and tools associated with the problem-domain become crucial parameters.

The suggested methodology strengthens the notion of user-centred KA that could turn selectively to use KSO in several phases according to the aforementioned strategic convenience. Specific MRs previously obtained (in cyclical phases) can be reused to achieve a better KA process.

These MRs may be:

- Methods, techniques, and tools created and catalogued as OL resources before OL applying processes.
- Explicit or declarative knowledge (re-usable) supported as structures (ontologies and other formats).
- Implicit or procedural knowledge such as Agents or Knowledge Artefacts, allowing to manage reusable knowledge for the specific cases. This process can be carried out via some automatic learning functions (procedures) which are adjusted or adaptable to the domain and which were previously conceived and scheduled for these purposes.
- Profiles that support some queries for reusable purposes from previous experiences made by the same or other Expert Users (such as advisory or recommendations).
- Track versions of previously updated ontologies (versioning) for supervised changing control and rollback purpose.

Indeed, *methodological versions* (selected combination of MRs according to the case-domain particularities such as methodological instantiations) derived from the proposed methodology during the SMOL strategy selection phase, shall be adaptable to the domain circumstances and available resources. Therefore, this methodological proposal must be more flexible, improving the desired product and therefore, helping the synergy and the overall efficacy.

3.1 SMOL objectives

The main objectives of SMOL are:

- Taking the most potential knowledge changes to be expressed as *ontology-objects* (instances, classes, and relationships) for each specific KSO using diverse MRs.
- Customizing a cost/effective methodology-strategy (MR combination) to be applied according to the heterogeneous KSOs which is available. Some costs would be associated to the tool acquisitions (non-open licenses) and the required user training (methods and techniques).
- Clear identification of user-activities to be followed during each phase (Objectives/Input/MR/Results).
- Improvement of the quality of updated ontologies by cyclical-control validation (Users' decision points).
- Reusing of knowledge based in cataloguing/storing of partial inputs/results of declarative and implicit/procedural knowledge.

3.2 SMOL design criteria

In this methodology design, we have considered some criteria based on previous studies:

- In the SMOL workflow design, we use the conceptual framework cited above (Yao et al. 2007). Some of these original Yao's process objectives were adapted and adjusted to our methodology as workflow. In this regards, the initial selection of strategy, the inclusion of cycles and decision points, as well as the details of the processes (tasks) have been introduced as improvements in comparison to Yao's framework. Let us remark that our proposal is user-centred, thus, the user's participation and the SMOL adaptation to the user (Experts/Engineers) are crucial points in comparison to Yao's proposal.
- The Methodology strategic selection phase has been designed considering that the users of SMOL may adjust the MRs according to the information available in the KSO. The purpose is to select a suitable strategy (Top–Down, Bottom–Up, or Middle-Out) after estimating a sort of domain-complexity. This domain-complexity estimation could be obtained by Expert Users using a heuristic about KSOs availability or by assessing it according to their own domain expertise and background. This germinal idea was previously presented in Zhou (2007) where only texts are considered as a source. In our proposal, other sources (ontologies and databases) are also included.
- Knowledge Sources (KSOs) are configured as flexible, adaptive, and incrementally reusable sources. For instance, ontologies and OL corpora about from texts could be also reused. For this purpose, the storage of these sources becomes a key point in our design.
- User/Task profiles are created and stored with the purpose of reusing them in recommending tasks. This process reinforces the intended user-centred aspect of our methodology.

3.3 SMOL workflow description

The workflow of the Systemic Methodology for OL is proposed emphasizing the methods and techniques recommended to be used in each specific phase. This methodology workflow applied for OL from each KSO is shown in Fig. 1.

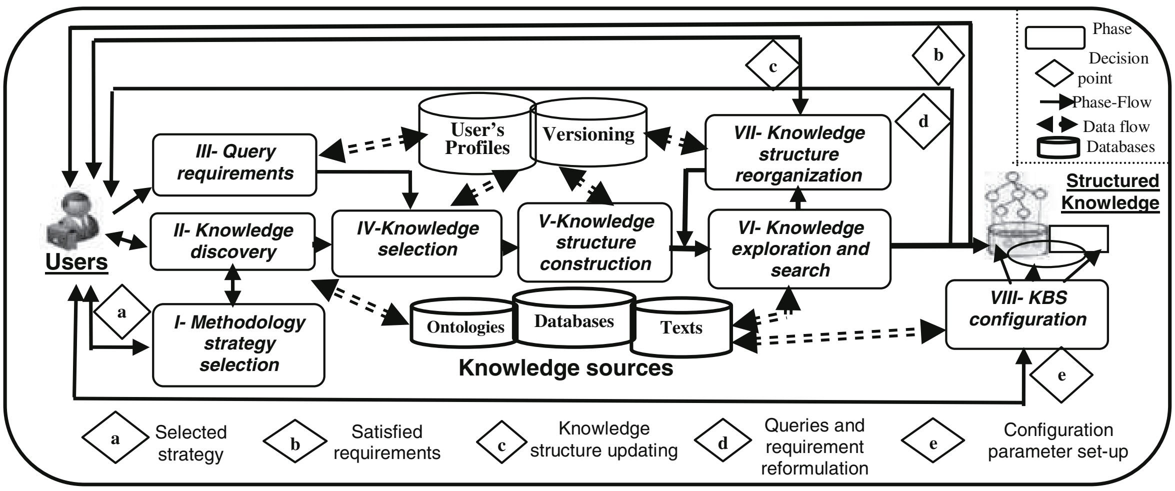

Fig. 1 Systemic methodology for ontology learning (SMOL)

The activities related to each original phase developed for SMOL are explained below:

I. *Methodology strategy selection*. The complexity of the domain is evaluated based on the availability of: a) the thesaurus and dictionaries for that domain, b) other previously developed ontologies, c) knowledge updating frequency, and d) the disciplines that cover this domain (Zhou 2007). This methodology strategy is user-drafted (top–down, bottom–up, middle-out) for inductive/deductive OL processes and selected using a suitable arrangement of MRs for each related KSO.
II. *Knowledge discovery.* The diverse MRs from different KSOs and their repositories (database graphic representation) are combined.
III. *Query requirements.* Different queries are formulated to the available KSO by browsers or other kind of applications. The queries are related to competence questions which the ontologies must support/respond (Castano et al. 2009).
IV. *Knowledge selection.* A selection of the retrieved data from the formulated queries to the sources and repositories is performed. The associated meaning (semantics) and the consistency of the format of some potential *ontology-object* retrieved from each KSO is checked by Expert Users. There are diverse MRs which can automatically check some type of ontology-object consistency (Castano et al. 2007).
V. *Knowledge structure construction.* Different structures such as ontologies and contexts can be interactively built with users' advice through MRs such as: ontology alignment, machine learning techniques, etc. The data-format conversions (automatic/manual) of the potential *ontology-objects* retrieved from each KSO are verified occasionally by Expert Users (depending on the tools' capabilities).
VI. *Knowledge exploration and search.* The knowledge structures are explored, verified, and validated and the search can be refined (automatic/manual according the available MRs).
VII. *Knowledge structure reorganization.* OL Processes such as grouping of instances, ontology population, and other similar tasks are performed in this phase.
VIII. *Knowledge system configuration.* Users set up the main modules/components of the KBS/KMS that have ontologies associated with the users' domain.

Decision points have been included in the user's participation in the checking the semantic quality during the OL process. Some of them are shown in Fig. 1 -in rhombi- such as:

a) *Selected strategy:* This decision point is introduced together with a new phase called OL strategy selection to choose the strategy based on the domain complexity.
b) *Satisfied requirements:* This decision point verifies that the strategy is the right one if the requirements have been satisfied. Users can interact with the system again to help with this verification.
c) *Knowledge structure updating:* It verifies whether there is consistency between the ontology which we have at this point and other ontologies that can be found in the sources by searching and exploring. An OE activity may be increasingly developed by automatic tools.
d) *Queries and requirement reformulation*: Once the final ontology is obtained, the user can check for more queries or requirement of reformulation.
e) *Configuration parameter certification:* Users can check the parameters configured for their KBS modules or components.

A more detailed SMOL phase description, including *Objectives, Input, Output, Phases-steps* and the main optional *tools* to be used during each phase have been incorporated in the Appendix A.

3.4 Users' profiles according to knowledge activities

Users have been grouped in this work (Fig. 1) according to their information and knowledge needs based on the Gaines' model (Gaines 1990): (a) end-users – information and knowledge task-workers related to a specific domain such as the application of ontologies; (b) expert-users – designers of knowledge structures (ontologies and others) and guarantors to update them; (c) knowledge engineers – technical support managers responsible for the development and updating of processes through the appropriate means (MR), using the adequate technology.

Those corresponding users' profiles have been associated and described in the academic case study in Section 4.2, according to the specific involved KMS users' knowledge-tasks and responsibilities.

The expert-users are usually involved with *knowledge selection, construction, and re-organization phases* (IV, V, & VII). On the other hand, some associated phases with *knowledge searching and query* (II, III, & VI) usually involve both groups of users (end/expert).

4 An academic case study

In this section, we describe a case study in the academic domain in which two groups of Expert Users followed the SMOL methodology with the purpose of updating an ontology named DEA-Ontology. It was previously developed for a Decision-Support System in the National Open University (UNA-System) which supports Distance Education Administration (DEA) programs. This Decision-Support System was installed in some important University head offices across Venezuela (Jimeno-Yepes et al. 2009).

4.1 Contextual framework

The academic domain deals with knowledge about academic institution management. The subsystems that correspond to this semantic model are the following: 1) the Academic and Educational subsystem, 2) the Production and Extension subsystem, 3) the Company and Organizational subsystem, 4) the Administration and Management subsystem, and 5) the Research and Development subsystem. The ontologies used for integration in this academic case study are specifically related to subsystems 1 and 4 for SMOL application from all cited sources.

This Academic- Educational subsystem has been selected and created for the cited Venezuelan University. Thus, in the original decision-support proposal (Jimeno-Yepes et al. 2009), some relationships among relevant components are identified such as: i) different cognitive styles of students, ii) distance educational modalities (Administration), iii) educational technology, and iv) the social-economic variable (student purchase power).

On the other hand, the selected host-ontology for updating and enrichment purposes (called DEA-ontology) is in a supervised evolutionary stage. Thus, the Expert Users have the responsibility to keep updated this ontology under quality parameters in this evolutionary stage. In a later ontology evolution stage, where the users are not experts, ontology qualities MRs (such as Racer-pro tools) are needed. Similarly, as happens with other ontology-based application developed to support real users' requirements, the DEA *ontology-object* components are very specific and specialized. For this reason and before applying the whole KA processes (updating and enrichment by OL), this host-ontology is counted with 45 Classes, 64 Instances, 26 Relationships (properties), and 14 Rules (axioms).

4.2 Objectives of the case study and SMOL application

The main objective of this experimental case study is to update/enrich the DEA-Ontology in an incremental and iterative way, with knowledge acquired from each cited KSO. The aim is the identification of the shortcoming of the current available SMOL application as regards its usability during this KA process. This main objective is subdivided into three partial sub-goals (steps) to reach a whole KA process from each KSO. The main users identified are: Expert-users (*Professors*), Knowledge Engineer (*Know.Eng*) and End-users (Advisors/*Student*).

These three steps are represented in Fig. 2 and described as follows:

1) OL by comparing/updating with other ontology domain located and recovered from the Internet. From this recovered ontology, the Academic management DEA-Ontology is updated by users through ontology-matching methods (FOAM) and tool (Prompt).
2) OL from a selected set of texts from specialized Educational journals. Moreover, these users help the Knowledge engineers to evaluate the keywords obtained from the corpus using "unsupervised learning" under an automated agent developed for this case, as well as to validate the ontology updated in advance.
3) OL from a Relational Database (RDB) that belongs to another local University. It is converted from this RDB into a temporary ontology by inductive and deductive learning, using varied conversions-tools for turning RDB into ontologies.

Some interesting results associated with this SMOL application are described and summarized in the Section 4.3. The four subsubsections below essentially describe the MRs used during the SMOL workflow process according to each one of the involved KSOs as well as the methodological strategy followed in the case of completing the associated OE activities.

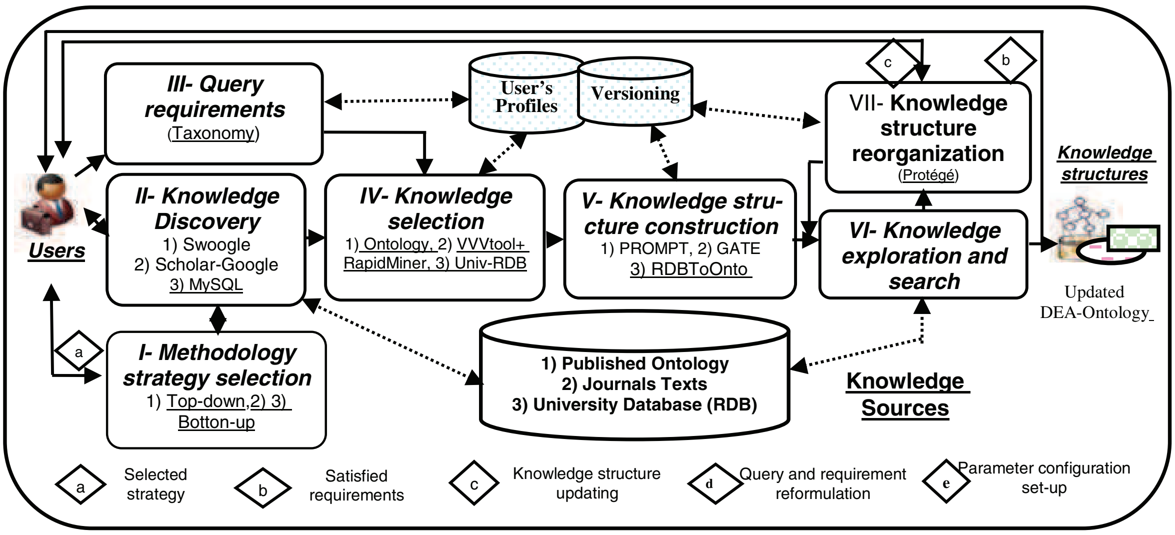

Fig. 2 SMOL applied to the case study from each knowledge source

4.2.1 SMOL from ontologies

According to the SMOL workflow, the Methodology strategy selection (Phase I) is firstly developed. The drafted and selected strategy mainly addresses the availability of previously developed ontologies related to the domain to be updated (Administration and Management model). Particularly, the host-ontology is updated based on a matching top–down approach. The SMOL-phases are grouped and summarized as follows:

a) Finding and selecting a published ontology as a KSO by Internet using Swoogle. This task was developed by *Professors* and the *Know.Eng*.

   One of this published ontology, among the three found (by Know.Eng), was chosen according to the potential knowledge that it could provide to the domain of the case study. The selected ontology, based on the opinion of the *Advisors* and *Professors*, was LUBM-Ontology for two reasons: its potential as a source of useful knowledge (in the administrative sub-domain), and because it is commonly used for assessing or evaluating the ontology capabilities of automated systems associated with diverse academic domains (Phases I & II).
b) EuroWordNet thesaurus is used *(Know.Eng/Professors)* as language dictionary resource to translate the terms (concepts and relations) from the Spanish to English language. So, the original DEA-ontology that was translated have a semantic mapping with equivalent terms with the selected LUBM-Ontology during the next ontological matching process (Phases III & IV).
c) The *Professors* and *Advisors* (in Phase IV) have checked the consistency of the format and the ontology-object meaning of the LUBM-Ontology to try and reach at least syntactic matching with the DEA-Ontology *objects*. For instance, the classes *Professor* and *Management* in LUBM were respectively validated to match with the classes *Professor* and *Administration* in DEA.
d) The Protégé-Prompt tool plug-in was used (by *Professors* and *Advisors*) for ontological matching purposes due to the following reasons: i) this tool includes the popular and common facilities for ontological edition purposes, ii) it has a graphical interface that simplifies the process of the visual-interactive integration by the user (CogZ plug-in), iii) it implements the FOAM method, iv) it keeps on updating versions and tracking the resulting ontology, and v) it produces as output under user commands a final resulting ontology (DEA+LUBM), without affecting any of the input ontologies (Phase V & VI).
e) Finally, the RACER-Pro tool is used (by *Know.Eng*) under an educational license to verify the overall resulting class taxonomy and relationship consistency (Phase VII). The obtained host-ontology has some updating improvements learned through the Ontological Matching between the DEA-Ontology with the LUBM-Ontology.

4.2.2 SMOL from texts

Regarding to the Methodological workflow established in SMOL, a bottom–up or deductive learning strategy (Phase I) was drafted and selected by users considering the following key factors/activities: a) finding and selecting a set of texts from the Internet based on the users' recommendations, b) identifying from the corpus of texts, via a Machine Learning agent, the most relevant keywords (up to 10) for ontology updating, and c) applying the OL from texts through text annotations and ontology population.

The rest of the phases are grouped and developed as follows:

a) Text selection with the user's participation (*Professors* and *Advisors*) is carried out in Phases II & III. Users take part on the recovering of the texts for the corpus building, by means of Google Scholar. From an initial set of 1000 retrieved texts found, a final set of 480 texts is selected by these users by their potential contents and a minimal length established (files larger than 10 Kb.).
b) A learning agent was developed (in RapidMiner) by the *Know.Eng* and used later by experts to classify and mine texts through a text clustering technique to obtain relevant keywords. The purpose is to add these terms to the corpus for future updating (Phases III & IV). Moreover, different tokenization, stop-word removing, and stemming processes were performed. A TF-IDF term weighting schema has been applied. From the obtained list of words, users selected the most important ones. Among the keywords found by the agent and later selected by experts *(Professors* and *Advisors)* are: *accredit, style, distance, institute, programming, program, online, faculties, course,* and *student*. The Meta-algorithm agent is shown in Algorithm 1 and this specification was developed with RapidMiner with the WVTool plug-in. For instance, this procedure for knowledge implicit discovering could be recorded later (in some type of "Knowledge Repositories System") as a reusable agent for other OL from texts in the same domain or for another similar system-domain.

Algorithm 1 Meta-algorithm for keyword vectorization and selection

```
Require: Corpus-texts < − Set of texts in txt format
Require: Normalized-word-list < − function to normalize a list of words from texts in a
         corpus
Require: CorpusBasedWeighting < − function to characterize a corpus by features
         (Normalizedword) from higher to lower weights
Require: Word-list-selection < − Function to select the feature (Normalized-word) that
         fulfils a given condition
Corpus-texts < − copy (480 txt)
Word-list < − Normalized-word-list (Corpus-texts)
Word-list-weighted < − CorpusBasedWeighting(Word-list)
Word-list-to-selection < − Word-list-selection (Word-list-weighted, top 10)
for Word $ Word-list-to-selection do
    Words-list-selected< − InteractiveAttributeWeighting(Words chosen by users)
end for
Return Selected-word-list
```

c) Users (*Advisors)* validate the consistency and the meaning of the terms from the corpus (in Phase IV). These users make the most of the GATE annotation tool capabilities to integrate these terms with the ontology-objects in the DEA-Ontology. This tool can automatically highlight the DEA-Ontology Concepts and Instances correlating them (e.g., the University class) with the corresponding terms in the texts.
d) Keywords selected by the automatic-agent are used as inputs (manually included by *Know.Eng*) to the next process in GATE via Onto Gazetteers (Phase V). The central purpose is to identify (by *Professors* and *Advisors*) specific and representative terms and concepts about the academic domain in the texts of the corpus together with the

corresponding annotation which is highlighted from the standard of the gazetteers (e.g., places, dates, and names).

e) An ontology graphical tool option for ontology management was configured (by *Know.Eng*) and used in GATE to display annotations for *Advisors* and *Professors* and to help them to support ontology updating from texts (Phases VI & VII).
f) The RACER-Pro tool is applied by the *Know.Eng* to verify the host-ontology overall consistencies.

4.2.3 SMOL from databases

This specific SMOL application stresses in Phase (I) the Methodological strategy selection, which combines different instrumental resources -tools and techniques- to achieve an as efficacious as possible OL process for an RDB academic management case study. The host-ontology used as the input of the case study for OL updating from RDB was developed during the three cited studies (Gil et al. 2010a, b).

SMOL from this RDB was completely applied to the case study through seven phases, including three decision points. Some specific details about the process to assess and select each conversion-tool can be found in Gil et al. (2010a). These conversions-tools comparison and evaluation (referred in Gil et al. 2010a) were considered as the background to support the methodological strategy selection (Phase I). It was proposed under bottom–up and top–down approaches, supported by two learning cycles based on two specialized conversions-tools such as RDBToOnto and ODEMapster.

The SMOL phases are developed as follows:

a) The corresponding RDB called RDB-IUTEPAS was found and used (*Professors* and *Know.Eng*) as the KSO. RDB-tables have been selected by Expert-users from this RDB, which was previously developed for a real academic information system that currently operates in a small-scale university institution, identified by its acronym: IUTEPAS, which is established in Cagua city (Venezuela). At present, it has about 1,000 registered students and 110 professors. A set of 12 RDB-IUTEPAS tables related to the professor's sub-domain has been chosen and transformed by the *Know.Eng* from its original format (Excel) into two equivalent small and medium-size RDB models (MS-Access and MySQL, respectively). These new obtained and validated RDB-format models have a technical link compatibility (JDBC/ODBC) with the two selected conversions-tools.
b) Both Expert-users make throughout Phase IV the most of the RDBtoOnto and the ODEMapster tool capabilities to generate (automatically) *ontology-objects* equivalences and some type of correspondences between the DEA-Ontology and the RDB-IUTEPAS respectively. Both tools help users during the RDB data-consistency checking (batch or interactively). They suggest to the Expert-users, some optional Classes that were found (associated or mapped respectively) against RDB-Attributes (columns) of the RDB-IUTEPAS.
c) In the first learning cycle (bottom–up), RDB-IUTEPAS and RDBToOnto tools have been used to discover and recover knowledge from the system database. Then, semantic entities in the RDB-IUTEPAS were compared later through Protégé-Prompt, by means of ontology matching. For instance, an ontology-subclass (university location/name) about where the specific instances of the professor's class earn their grades was obtained by running the RDBToOnto tool.
d) In the second learning cycle (top–down), using the knowledge learned in the first cycle about relevant classes, subclasses, and some relationships from this RDB, the

ODEMapster tool has been applied for refining semantic correlations between the RDB-entities within the DEA-ontology. Therefore, ODEMapster automatically helps *Advisors* and *Professors* to learn more about the previous (sub-) concepts and to establish a better correlation between the table attributes of the RDB-IUTEPAS and the properties of the concepts in the host-ontology.

e) Finally, the RACER-Pro tool is applied by *Know.Eng* also to verify the overall resulting class taxonomy and relationship consistency.

4.2.4 Ontology evaluation workflow and implementation

The case study host-ontology (DEA-ontology) has been ontologically evaluated following the workflow established in Sabou and Fernandez (2012) considering the suggested *Topology-based* and *Assessment by human* frameworks. The corresponding OE tasks are detailed as follows:

Task-1 the *Quality of modelling* is the selected OE strategy. Apart from the user possibility to guarantee the quality of the whole OL process through the SMOL cyclical mechanism (using *Decision points)*, they can also determine ontological qualities (structure and population) and check the host-ontology consistency through the OntoQA metrics and the reasoner Racer-pro respectively.

Task-2 The applied evaluation frames are based on the *Topology-based frame* and the *Assessment by humans*. The former uses the OntoQA metrics and the latter applies direct interviews to the Expert-users (*Professors*) and some End-users (*Advisors*).

Task-3 The *Topology-based* frame is supported by metric such as Relationship and Attributes Richness, Cohesion, or average population (Tartir et al. 2005). About the evaluation made by humans, the *Syntactic* and *Trust* metrics have been essentially considered.

Task-4 The results of the applied OntoQA metrics have been shown below and their related analysis is included in Section 4.3 (letter f).

Consequently, the main OE metrics derived from the OntoQA application according to the DEA-ontology structure (schema) and population (instances) are summarized in Table 3.

Aligned with the purpose and meaning of the metric in Tartir et al. (2005), the *Relation Richness* on 38.80 would state that most relationships are class-subclass type (i.e., ISA). Conversely, the *Class Richness* 95.55 indicated that the data in the knowledge-base represent most of the knowledge in the schema.

Table 3 Schema and knowledge-based metrics from OntoQA tool

Schema metrics		Knowledge-base metrics	
Total Classes	45	Total Instances	64
Total Relationships	26	Class Richness	95.55
Relation Richness	38.80	Average Population	1.42
Inheritance Richness	3.15	Instance Coverage	1.81
Tree Balance	1.29	Heigh Distribution	0.00
Attribute Richness	0.00		

4.3 Some representative case study results

Some results obtained in each cited OL process by the SMOL application in the previous subsection are summarized as follows: a) The four main classes and subclasses of the DEA-ontology were reviewed/updated; b) some professors' categories and student profiles were defined and correlated with the Cognition-Dimension subclass in the host-ontology through OL from LUMB-ontology; c) some repetitive instances of locations and places where the professors obtained their degrees were identified as subclasses; d) a new and extended subclass was formed into the DEA-ontology through this OL process from a database of another University (IUTEPAS); e) some corresponding mapping with places between the RDB and the host-ontology were found by expert-users to test the validity and consistency of the result; and f) the analysis of the OntoQA metrics corresponds with the quality property of the DEA-ontology used to support a KSS application (a hierarchical structure of classes-subclasses, representing the knowledge basically in the same class-structure).

Some specific details as evidence of the SMOL process and some partial semantic results (described as DEA-Ontology objects) have been included in Table 4. In addition, part of these results expressed in the DEA-ontology is shown in Fig. 3.

Finally, a derived multi-format *Knowledge Repository System* has been suggested also in SMOL to support future OL processes and knowledge reusing needs (Ramos and Gil 2011) such as: a) Some partial *KSO repositories* (corpus, group of ontologies, the RDB-IUPEPAS); b) Agent repositories (a relevant word identifier was developed as an agent in RapidMiner); and c) the MR repositories (instances of tools: Protégé-Prompt, GATE, RapidMiner, and so on).

4.4 The case study lessons learned

The following aspects are considered the most relevant "lessons learned" from the Case Study: (a) flexibility of the SMOL methodology; (b) advice for users about how they can

Table 4 Case study summary: some evidences about SMOL application from each KSO

Knowledge source	Structured knowledge	SMOL tools applied	Enriched & populated DEA-ontology object	Data pre-processing
Ontologies (LUBM from Web)	- Ont. Enrichment - Ont. Comparison - LUBM as KSO	- Swoogle - Prompt - Racer-Pro	+Class: Cognition\Dimension\Professor *Classes: Person\Student& Administration\University	- WordNet/Synset - Spanish to English Dictionary.
Documents (480 texts of journals)	- Ont. Population - Knowledge agent - Corpus as KSO	- RapidMiner - GATE (Ont.) - Racer-Pro	+Class: Cognition\Dimension \Professor\UniversityCity \\+Instances: City	- Google-Scholar - WordNet/Synset - GATE-Gazetteers
Databases (RDB of IUTEPAS University)	- Ont. Enrichment - Ont. Population - RDB as KSO	- RDBToOnto - ODEMapster - Protégé - Racer-Pro	+Class:\\PostgradeTitle & \\gradeTitle #Class:\\UniversityCity by \\UniversityTitle&UniversityCity +Instances:\\UniversityTitle &\\City	- FoxPro - MS-Excel - MS-Access - MySQL

Ont.=Ontology, Ontology' Object= +Added, *Reviewed, #Changed

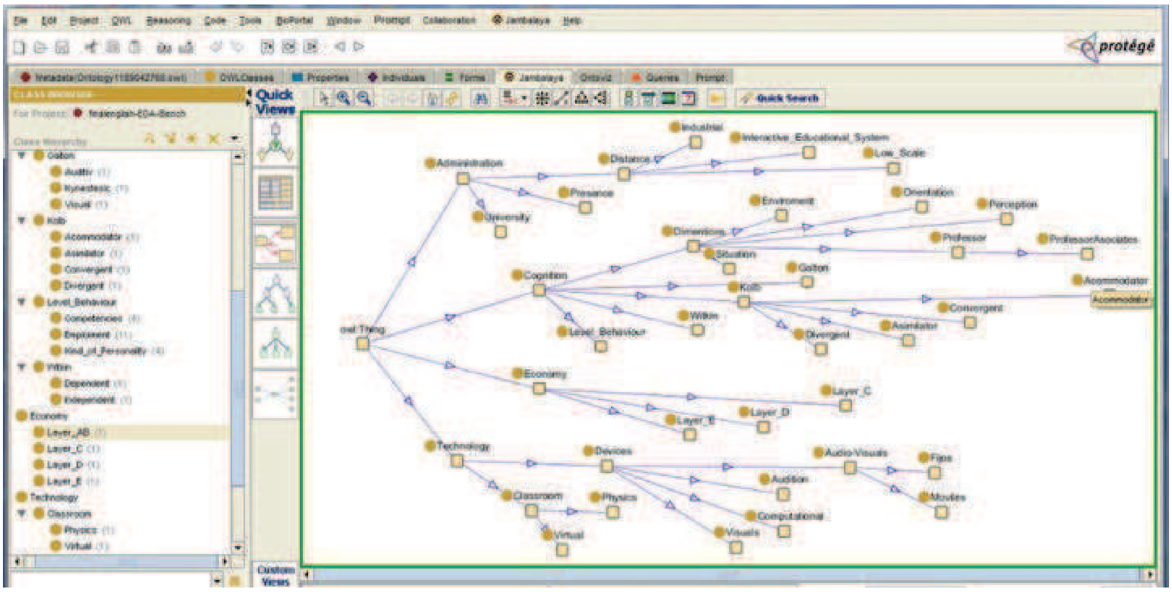

Fig. 3 DEA-ontology updated: enriched and populated classes (Protégé 3.5)

overcome errors during SMOL Processes; (c) some foresight for integration, consistency, and content extraction; (d) scope of the mechanisms of a user's interaction.

a. The flexibility of the SMOL helped users in different activities related to the updating of the knowledge of the associated ontologies. The effectiveness of OL from diverse KSOs has been improved and it is possible to reach new knowledge through inductive and deductive automatic learning (by data, text-mining, or ontology-matching). The incorporated SMOL possibilities to knowledge storage and recovery have been enabled, thus reducing the corresponding manual effort. Some important results (dynamic knowledge) expressed as *Semantic Products* and *KSOs* (e.g., agent, selected KSOs, and MRs) can enhance the future efficiencies of additional *OL Processes* and help users to procure continuous updating (rising effectiveness) of their *Semantic Products*.
b. To avoid errors and mistakes related to data and knowledge processing, the documentation related to each KSO is made available: (1) it is needed for the documentation associated with each potential KSO to correct and/or adjust incompatibilities (format/domain) with the host-ontology that is to be updated; (2) it is also used to track the updating facts that must be recorded in log-files; and (3) it is recommended that some MRs for OE are applied (e.g., OntoQA or Racer-pro tool) to keep-track of the ontological quality after completing any OL updating/enriching process.
c. Adequate integration of data-models, consistency of validation, and content extraction are recommended (Bloehdorn et al. 2009): (1) ontology mapping is proposed (and used for each KSO) as the main data-model mechanism for the integration of OL from diverse KSOs; (2) consistency of the ontology can be reached by at least two ways, firstly, by using highlevel rule-languages for reasoning expressively (OWL-DL used in DEA-ontology) and secondly, by applying a reasoner tool (Racer-pro) to repair inconsistencies; (3) users must be open to learn/apply new MRs to reach automatic OL extraction of relevant contents from each KSO.
d. With regards to selecting the most convenient OL strategy (in Phase-1 of SMOL), some critical features must be assessed. The most pertinent ones are the following: (1) useful and available KSOs; (2) reuse of involved MRs/KSOs (e.g., OL-tools); and (3) the users' expertise (Expert-user and Knowledge Engineer skills) and their associated

techniques. Complementary, some details for another SMOL case application over the manufacture domain are found in a technical report in Ramos and Gil (2011).

e. Appropriate communication mechanisms among the involved Users help to support user-expert's interactions with: (1) the end-users to gather their knowledge-task requirements and (2) the KSS specialists (System Engineers) to explain the (re) configurations of the subsystems required by the associated KMS once the host-ontologies have been updated.

5 SMOL methodology evaluation

The application of the cited and selected three DESMET methods (Qualitative Screening, Qualitative Experiments, and Qualitative Case study) in combination with the Dahlem's usability/suitability criteria to evaluate the SMOL methodology.

Attempting to apply the Qualitative screening of the DESMET method of evaluation, we have followed the two options explained in Section 2.4. Firstly, we have jointly performed a complementary evaluation approach by applying the usability/suitability criteria assessment of Kitchenham et al. (1997) to measure our novel methodological proposal by comparing it with other relevant methodologies.

Secondly, we have developed a comparison of SMOL (using some criteria) with four specific and similar OL methodologies recently published (Simperl et al. 2008; Novacek et al. 2008; Castano et al. 2007, 2009; Zouaq et al. 2011).

5.1 Screening through usability criteria

Firstly, we combining the DESMET methods for Quality Screening with the usability criteria cited to assess the SMOL methodology characteristics. It is shown in Table 5.

Afterwards, we performed the criteria comparison among other OD methodologies for ontology creation and maintaining with similar features and open trends such as DILIGENT, DynamOnt, NeOn, On-To-Knowledge (OTK), and UPON. Some of them have been evaluated methodologies at Dahlem's work (Dahlem and Hahn 2009). Methodologically, despite the fact that they are OD oriented, they have some characteristics in common with the SMOL usability. These following ones are worth mentioning: a) User-centric evolution (updating) of ontologies. b) A clear structure but not a fixed life cycle. c) KSO may be (re)used. And, d) Some MRs may be (re)used.

The result of including NeOn, UPON and our SMOL methodology to assess in the benchmarking schema about the prior methodology comparison developed by Dahlem and Hahn (2009) is shown in Table 6. Thus, SMOL has up to ten of the thirteen representative criteria for methodology usability/suitability according to Dahlem's proposal, in this Table 6.

Some particular criteria have apparently not been included by SMOL also, just as happens with other methodologies, which have not been compared to (C1, C11, and C12). Under our systemic interpretation, this may happen because at least two of these criteria (C11 and C12) could be associated mainly with semantic result-product processes (ontologies) instead of OL processes related to methodological properties.

Regarding the usability evaluation criteria applied by the Qualitative Screening method under a uniform presence among any of them, it is important to point out that the result of the evaluation of Efficiency and Satisfaction Dahlem's aspects for SMOL are 0.85 and 0.75,

Table 5 Usability evaluation criteria applied to SMOL

	Evaluation and assessment
C1: Adequate terminology	SMOL uses standard ontology engineering terminology.
C2: Structure	SMOL has a flexible structure which is not a fixed life cycle but optional learning iterative cycles according to the domain characteristics.
C3: Descriptiveness	SMOL description is medium; knowledge acquisition is described in detail.
C4: Transparency	SMOL Phases are described with input, output, methods, and tools.
C5: Error avoidance	Control cycles (decision points) are defined for user satisfaction certification when some key workphases are completed.
C6: Robustness	It is considered through evolution capability.
C7: Lookahead	The SMOL phases (VI & VII) are trying to detect consistency about knowledge re-structuring and updating. It is explicitly considered using quality evaluation tools such as Racer-Pro and OntoQA.
C8: Consistency	The terms related to the methodological resources are specifically set. SMOL Phases and Cycles components are defined in detail.
C9:Hiding formality	The formality has been hidden partially according to the user's experience.
C10: Expressiveness	The expressivity is at the level of light-weight ontologies.
C11:Conceptualization flexibility	SMOL Conceptualization is related to the used Tools for each specific OL method (recovery, matching, and so on). It is not explicitly considered.
C12:Ontology assumptions	It is not explicitly considered.
C13: Tool-support	Open-source tools could be used as support in some Phases. Some of them are suggested according to the knowledge source.

respectively. Those values are, at least, equivalent and/or higher than the other OL methodologies. Likewise, their related Learnable, Memorability, and Error-Handling criteria all fit into the average value (0.5).

In any case, SMOL as OL methodology has been compared by usability (in Table 6) to other OD methodologies which have technical foundations and backgrounds.

5.2 Screening through OL methodological comparison

Although some of the most discriminating criteria for OD methodologies as suggested above by Dahlem have been included in SMOL, we have also considered convenient to compare them with the most recent proposal of methodologies specially designed to deal with the OL problematic. In fact, we have made a comparison of SMOL among the Simperl

Table 6 Benchmarking: OD methodology usability evaluation including SMOL

OD Methodology	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
DynamOnt	-	-	-	-	X	X	-	X	X	X	-	-	X
OTK	-	X	X	-	X	X	-	X	-	-	-	-	X
UPON	-	X	X	X	X	X	X	X	X	X	-	-	-
NeOn	-	X	X	X	X	X	X	X	X	X	-	-	X
SMOL	-	X	X	X	X	X	X	X	X	X	-	-	X

Table 7 Some methodological features among OL methodological proposals

	Simperl et al 2008	BOEMIE (Castano et al. 2007, 2009)	DINO (Nováček et al. 2008)	OntoCmaps (Zouaq et al. 2011)	SMOL
Asu	A useful and available knowledge in texts & ontologies	Useful and available knowledge can be fused from diverse media	A useful and available knowledge in texts & ontologies	A useful and available knowledge in texts	A useful knowledge in texts, ontologies, & databases
OriP	OD & OL oriented	Automatic OL population & enrichment from a corpus	OD by OL & Ontology integration oriented	OL (by conceptual maps technique) for OD purpose	OL & Enrichment/ updating oriented
WF	Focused Semantic Processes using structured cycles: 8 process	Semantic Product focused on an updating pattern-driven identification: 3 general phases	Semantic Product focused on dynamic cycles: 4 phases	Semantic Product focused on a workflow: 3 phases	Semantic Processes/ Product by flexible cycles: 8 phases.
KSOs	OL from text/ontologies for updating & enrichment	Multimedia sources from a corpus of documents/texts	OL from texts/ontologies for OD	OL from texts and filtering for OD	OL from text, ontologies, & databases to keep up-to-date
Ob	Ontology created from text & used as reference. It could be also updated from ontologies	The target domain-ontology is used (as background) to obtain Aboxes as input to reach a new evolved ontology	The developed ontology used as a reference (master) to be updated from prior ontologies	The ontology obtained by this OL process can be recursively extended	The associated KMS/ KBS-ontologies are used to be updated from various KSOs
MRs	Some MR could be selected/ combined by users	New MRs (methods/tools) have been developed to support the OL process	MR for OL may not be combined by users. Just for OE	The tool developed by the authors (OntoCmaps) is used	The MR and KSo may be combined/ customized by users

Table 7 (continued)

	Simperl et al 2008	BOEMIE (Castano et al. 2007, 2009)	DINO (Nováček et al. 2008)	OntoCmaps (Zouaq et al. 2011)	SMOL
ReqE	OL requirements are specified though a specific document.	OL requirements are derived/refined by the interpretation of a reasoning document	OL requirements are partially specified formally	OL requirements are not specified formally	OL requirements are specified in advance at SMOL-phase 1
DocD	It includes suitable Doc. details for OL process support	It includes few Doc. details for OL process support. The BOEMIE's MRs formality is very adequate	It includes partial Doc. details for OL process support	It includes few Doc. details for OL process support	It includes suitable Doc. details for OL process support
EvaD	It includes a specific OE process stage. Primarily, it is based on*the assessment by humans*	Apart from the OL expecting derived qualities, no OE details are included	It is an open issue in DINO. Some suggested MRs for OE are cited but not applied	Apart from the OL expecting derived qualities, no OE details are included	It includes OE: a) in phase-flow; b) after OL from each KSO; & c) after KA process

Asu assumptions; *Ori-P* orientation profile; *WF* workflow focal-point; *KSOs* knowledge sources; *Ob* ontology base; *MRs* MR uses; *ReqE* requirement explained; *DocD* documentation details; *EvaD* evaluation details et al. (2008), the DINO (Nováček et al. 2008), BOEMIE (Castano et al. 2007, 2009), and OntoCmaps (Zouaq et al. 2011) proposals. The feature comparative summary is detailed in Table 7.

In that sense, we have firstly considered some pertinent comparing features such as: *main assumptions (Asu), methodological orientation profile (OriP), workflow focal-point (WF), ontology base of reference (Ob)*, and the involved *KSOs and MRs* for OL. Additionally, some other comparative characteristics of the work in Islam et al. (2010) which may affect the ontological quality and OE such as *Requirement explained (ReqE), Documentation details (DocD),* and *Evaluation details (EvaD)* have been considered as well to develop the comparison among these OL methodologies.

As a result of Table 7 analysis, we can state that SMOL has more elaborated MR options to support OL processes from complementary KSOs. The main options are: 1) SMOL explicitly considers the assessment of the domain-complexity characteristics; 2) the OL strategy selection is based on a learning approach starting not always from texts, but from other KSOs, such as databases and prior developed ontologies from the beginning of the KA process; 3) just SMOL includes databases as another important KSO for OL; 4) the flexibility of SMOL and the Simperl et al. (2008) proposals to include MRs resources (efficacious methods/tools) aligned with the OL problematic; and 5) Some OE resources have been explicitly considered during the KA process.

Finally, Our SMOL proposal is suggested as an optional OL methodology in the KM context, that (re) uses KSOs under a systemic view according the MRs (available and/or updated) which are available or reachable by the modern organizations. The other cited OL methodologies have their own relevant qualities and characteristics, which maybe useful according to the organizational users' insights, backgrounds, and/or purpose.

5.3 Qualitative experiment and qualitative case study methods

The main way to test the SMOL functionality is based on the case study, because we can check the user's validation and experiment with related methods/tools.

The application of these DESMET methods has revealed that some of the more distinctive and representative designing features or properties about the SMOL qualities can be tested and validated for this academic domain.

For each KSO (ontologies, texts, and databases), an evaluation strategy has been designed considering: context setting (goals/constrains), planning and design, preparation, execution, data analysis, dissemination, and decision-making.

Expert Users were trained/familiarized with some OL methods/tools (e.g., Protégé, Prompt, GATE, RDBToOnto, or ODEMapster) to be used during the OL processes using real KSOs. Some specific tools for pre-processing and format conversion purposes such as Excel, MS-Access, MySQL, and GATE were selected and used by Knowledge Engineers.

Knowledge was recovered from specific academic domains according to each KSO. In the case of the ontology source, the knowledge was obtained from an ontological matching process (between DEA-Ontology and LUBM-Ontology of SWAT-Project). In the case of the text source, they were recovered by Google-Scholar. As for the case of the database source, an OL comparison process from a database of another institution was performed.

An interview-questionnaire (about syntactic and trust metric) was given to users (up to 6) during the OL cycle according to each KSO. A feature-based analysis was applied to those results associated with the used MRs (methods/tools). Particularly, they were asked them about the functionality of the tools and Input/Output related to the applied OL methods/techniques.

Table 8 SMOL advantages according to OL processes and OL products

OL processes advantages	OL product advantages
Knowledge availability from useful/qualified KSOs	Partial Product/Process can be stored (KRS) for reuse
The Database as another effective KSOs for OL	Partial MRs/KSOs can be stored (KRS) for reuse
Flexibility to start the OL process through any KSO	Users' log / tracks can be stored (TMS) for users' sharing
Flexibility to adopt MRs, including the emergent ones	Another type of knowledge-representation can be included
MR's standardization is easy due to the systemic focus	Tools' GUI may be extended to manage stored MRs/KSOs
Standardized workflow-phases & quality OE means	Some new kinds of MRs for OE can be included
MR for OE can be included due to this systemic view	User's lesson learned can be replicated in other cases

KR knowledge repository system, *TMS* transative memory system (Kulkarni et al. 2007)

5.4 SMOL evaluation: discussion of results

After completing the evaluation process using the three cited DESMET methods, a summary of the main obtained results has been analyzed in this subsection.

Consequently with the systemic quality perspective adopted (Callaos and Callaos 1994), and for simplifying the discussion of the results, they are explained below according to each applied method. This explanation is given in terms of the favourable impact of some SMOL features assessed over the efficiencies and the effectiveness related to the *KA Processes* and their associated *Semantic-Products.*

The Qualitative screening evaluation results (individually and comparatively) allow us to ponder the following elements:

1) SMOL contains many of the relevant criteria (10 of 13) suggested by Dahlem and Hahn (2009) just as it happens with any other equivalent "open" methodologies (Tables 5 and 6).
2) Regarding the comparison of Table 6, SMOL contains, at least, the same criteria as any other similar OD methodology. Likewise, based on other more specific criteria related to this systemic methodology such as (C3) Descriptiveness, and (C9) Hiding formality, SMOL is better than various of them. Peculiarly, the (C4) Transparency, (C7) Look-ahead criteria, and (C9) are considered by SMOL as well as the other two significant recently launched ones for OD purposes.
3) Concerning Dahlem's approach, the SMOL aspects about *Efficiency, Satisfaction, and Error-Handing* have been additionally reinforced by the presence of some of the assessed criteria (C4, C5, C6, and C7). The former two have specifically improved the efficiency and effectiveness of the *KA Processes* and the latter, the efficiency of the *Semantic-Products*.
4) Complementary, the SMOL methodological screening comparison to another four OL methodologies in Section 5.2, reveals some outstanding features about SMOL; firstly, it considers MRs as customizable and reusable means according to users' objectives

to select dynamically a methodological strategy to reach more effectiveness of *KA Processes;* secondly,

5) KSOs such as database options have been included in SMOL as a key factor in the knowledge recovery about organizational facts (RDB-schemas) and some historical trends (data mining). In this sense, none of the selected OD and OL methodologies for the comparison with SMOL takes into account (explicitly) the domain databases as another significant KSO. The importance of the MRs' customization for the involved KSOs during the SMOL application is linked to the efficiency of *KA Processes*; and thirdly,
6) Some OE activities have been included explicitly into SMOL such as *Decision point* for phases tracking task developed by users; a workflow for OE control; and a couple of tools for automatic ontological quality checking/measuring (Racer-pro/OntoQA). Specifically, all of them have been applied to this case.

On the other hand, under the evaluation of DESMET applying the Experimental and Case study, the most distinctive and prominent design properties about the SMOL qualities have been tested and validated. Some details about the SMOL assessing results are explained as follows:

1) The MRs selection (associated with SMOL Phase I) was tested through the SMOL application. It was useful primordially to identify the *ontology-objects* required for enriching/populating the host-ontologies from each of the cited KSOs. This cited identification would favourably affect both *Semantic-Product* measures.
2) As another distinctive difference in comparison to other open OL methodologies, it has been tested and validated that SMOL users could combine diverse methodological strategies in relation to the selected MRs and KSOs or by reusing some of them which were previously catalogued. Knowledge engineers can include some new MRs (e.g., tool) which would be incorporated according to their tested technical capabilities or by replacement of any other previously used one. These features would impact on the efficiency and effectiveness of the *KA Processes*.
3) The users' recommendations and the ontology versioning considered as the SMOL design properties are tested and validated as useful resources to improve both *KA Processes* and Semantic-Product efficiencies.
4) Some favourable survey results about the user' satisfaction experimentally tested and validated regarding the flexibility of SMOL associated with the capability of the systemic MR integration and reusing is considered as an attribute that enhances both *KA Processes* and *Semantic-Products* effectiveness.

Regarding these DESMET methods, both individually and comparatively applied for SMOL evaluation, they reveal that SMOL could be considered as another tested and validated methodology for OL purposes under a systemic view. Moreover, SMOL presents additional high-quality ranked attributes to reach the best possible *Semantic-Products* through efficacious and integrated *KA Processes*.

Finally, some of the most relevant advantages of SMOL as a novel methodology to support OL processes from heterogeneous and complementary KSOs in comparison with other previous approaches have been tested/inferred according to the real/potential effect over the OL Processes and OL Products obtained. A summary of the most representative advantages has been included in Table 8.

6 Conclusions

There is a lack of integrated methodologies for knowledge acquisition through OL processes, regardless from the sources which are considered: ontologies, texts, or databases. A Systemic Methodology for OL named SMOL was designed, validated, tested, and evaluated taking into consideration advantages and drawbacks of the previous OL methodological proposals. The result is an integral, flexible, open, and iterative OL methodology that can support integrated and efficacious KA processes.

The new SMOL methodology was applied and validated in an academic case study for diverse KSOs. Some different kinds of partial KA approaches were applied through OL specific and incremental strategies. Particularly, inductive and deductive learning was combined through corresponding data/text -mining processes (bottom–up) with ontology/database matching/ mapping processes (top–down) under three complementary methodological strategies. The updated/enriched ontology by the user's participation helps us for SMOL validation and testing.

Furthermore, the SMOL application for the cited case reveals, in the first place, the feasibility of it as an instance of new methodological perspectives for OL from heterogeneous KSOs, and secondly, an optional way to keep the ontologies associated to KBS of the user's domain updated and consequently, to improve their involved knowledge management activities.

Likewise, the evaluation of SMOL as a methodology was developed through different DESMET methods, helping us to determine and to confirm, on one hand, its usability and suitability to users at different levels, and on the other hand, some comparison differences and advantages regarding to other similar OL methodologies.

In this sense, we must point out the SMOL flexibility, openness, and ontology quality-oriented when SMOL is compared to any other methodology criteria (Descriptiveness, Transparency, Hiding formality, and Lookahead) or aspect (Efficiency, Satisfaction, and Error-Handling) to manage and organize the optional MRs according to the available knowledge acquired -and updated- from heterogeneous but complementary KSOs.

The systemic global quality approach adopted which is partially formulated in SMOL to support KA processes must be considered in future works about KMS as a complementary and convenient mechanism to guarantee the global efficiency and effectiveness of the *Semantic-Products* during the *KA Processes* from different KSOs.

Specialized subsystems, useful for semantic product versioning as well as some feature registering during updating and enrichment OL processes, such as user profiles mechanisms, will be developed in the future.

Appendix A: a specific description of the SMOL phases

Phase I: Methodology strategy selection

Objective: In this phase, the best methodological strategy to follow is selected according to the available or recoverable data from the KSO related to the specific domain.

Input: Information about the KSO and user's domain: First, the information which is more strongly related to the explicit and implicit knowledge from previously stored or new KSOs; secondly, information coming from the opinion of Expert Users to characterize the domain and KSO.

Output: Methodological strategy drafted and selected (MR for each KSO) among the possible options (inductive/deductive) for OL: Top–down, Bottom–up, Middle-out, or a combination of them.

Steps Methods and techniques:

1. Identifying domain-complexity, assessing partial characteristics of that domain according to the cited Zhou's proposal. A Rule-based decision approach is applied about the domain-complexity attributes (Established, Conventional, Technological independence, and Interdisciplinary features). Users could select the Methodology strategy applying an optional heuristic suggested in two ways: a) based on the user's expertise assessing the domain-attributes in Fig. 3, or b) using any decision-rules about the availability of KSOs related to previously developed ontologies or RDBs shown in Algorithm A.1, under the premise that OL from texts are mostly available.
2. Identifying and selecting the KSO available in the own DB (based on phase II cycles). The potential knowledge already available (both explicit and implicit) as well as new knowledge coming from accredited Internet sites is obtained.
3. Obtaining previous system recommendations for users about optional methodological strategies, showing the possible options. The key point is that, just as more domain information and knowledge is available and able to be integrated, the uncertainty is reduced consequently; in this case, the recommendation is to use top–down strategies.
4. Recording (in the user profile) the strategy selected by users for each potential knowledge source, which would be later reused as resource candidates for learning purposes.

States (s_i) of the world

Domain Attributes	S_0	S_1	S_2	S_4	S_8	S_3	S_5	S_6	S_9	S_{10}	S_{12}	S_7	S_{11}	S_{13}	S_{14}	S_{15}
1) Established/Under-developed domain	0	1	0	0	0	1	1	0	1	0	0	1	1	1	0	1
2) Conventional/Emerging domain	0	0	1	0	0	1	0	1	0	1	0	1	1	0	1	1
3) Technological (Indepen)/(Depen)dent domain	0	0	0	1	0	0	1	1	0	0	1	1	0	1	1	1
4) Self-contained/Interdisciplinary domain	0	0	0	0	1	0	0	0	1	1	1	0	1	1	1	1
N= uncertainty	0	1	1	1	1	3	3	3	3	3	3	7	7	7	7	15

0= Option of lower uncertainty
1= Option of upper uncertainty

a1 = Top-Down (TD) a2 = Middle-Out (MO) a3 = Bottom-Up (BU)

UNCERTAINTY CONDITIONS
$N = 2^n - 1$
IF $N \leq 1$ => Top-Down
IF $N = 3$ => Middle-Out
IF $N \geq 7$ => Bottom-Up

Fig. A.3 Methodology strategy selection according to domain complexity assessment

Algorithm A. 1: Heuristics suggested for the setting up of the domain attributes (Corpus is feasible)

```
CASE Corpus of Texts is available DO
 IF (Domain-Ontology or Upper is found)  ≥  1 THEN
    a. IF (RDB Public or RDB private is found          ≥ 1)  (➔ At least 3 domain-attributes are 0's) THEN  Top-Down
    b. IF (RDB-scheme or Domain-Ontology is found  = 1)  (➔ At least 2 domain attributes are 0's) THEN  Middle-Out.
    c. IF (RDB is not found                             = 0)  (➔ At least 1 domain attribute is  0)      THEN  Bottom-Up
 ELSE (%No Ontology)
    d. IF (RDB-scheme or RDB is found                  = 1)  (➔ At least 2 domain attributes are 0's) THEN  Middle-Out.
    e. IF (RDB is not found                            = 0)  (➔ At least 1 domain attribute is  0)      THEN  Bottom-Up
 ENDIF
 IF (RDB Public or RDB private is found)              ≥  1 THEN
    f. IF (Domain-Ontology or Upper is found          ≥ 1)  (➔ At least 3 domain-attributes are 0's) THEN Top-Down
    g. IF (Upper-Ontology (not domain) is found       = 1)  (➔ At least 2 domain attributes are 0's)  THEN  Middle-Out.
    h. IF (Ontology is NOT found                       = 0)  (➔ At least 2 domain attributes are 0's)  THEN  Bottom-Up
 ELSE (%No RDB)
    i. IF (Domain-Ontology or Upper is found          ≥ 1)  (➔ At least 2 domain attributes are 0's) THEN  Middle-Out.
    j. IF (Upper-Ontology (not domain) is found       ≤ 1)  (➔ At least 1 domain attribute is  0)      THEN  Bottom-Up
 ENDIF
ENDCASE
```

Tools: Protégé, Swoogle (and others), Google/AltaVista, Wikipedia, (Euro)WordNet, SUMO, Cyc, ERwin case, RDBToOnto, etc.

Decision-point: <a> Selected strategy.

Phase II: Knowledge discovery

Objective: Identifying and pre-selecting potential knowledge from previously structured and recorded KSOs in the FDB catalogues of the associated KBS. Likewise, other potential knowledge can be recovered from other accredited sources through the Internet (e.g., documents, ontology-catalogues, public databases, websites, and so on).

Input: a) Knowledge regarding the KSO (explicit and implicit) previously recorded in DBs of the associated KBS (Corpora, DBs, ontologies, procedures, etc). b) Public knowledge that may be recoverable from KSOs (ontologies, corpus-texts, RDB-Schemas, websites) associated with the domain. Some of these sources could be identified and preselected in Phase I.

Output: Potential knowledge preselected as a candidate KSO (from one of the three types of KSOs cited above) regarding: taxonomic and non-taxonomic relationships, semantic correspondences (thesaurus), RDB-schemas and their cell-data values, some procedures as agents of knowledge processing and updating, and any other useful MR considered as well.

Steps Methods and techniques:

1. For each type of structured KSO (ontology, corpus, DB, agent, or any MR), some potential explicit and implicit knowledge (content, MR, or agent) must be identified and recovered.
2. For each KSO which is not processed by users yet (such as texts, ontologies or DBs-schemas, found on the Internet), new knowledge can be incorporated.
3. Some recovered knowledge resources (either structured or not) may be reorganized in any structured format (such as taxonomies and RDB-schemas). For instance, selecting parts of the domain ontologies using tools such as Text2Onto or Protégé.

4. Asking users to validate the knowledge recovered according to their correspondence with the case or domain study. The suggestions of these users are stored in the user's profile.
5. The potential knowledge considered by users as suitable for the selected strategy in Phase I is registered in the KSO catalogues.

Tools: O*L from ontologies*: ASMOV, GeRMeSMB, MapPSO, RiMOM, Prompt, TaxoMap, etc. *OL from texts*: Asium, SVELAN, Text2Onto, etc. And, *OL from databases*: S-Match, Cupid, COMA, and RDBToOnto.

Phase III: Query requirements

Objective: Allowing users to make different queries (through a standard format as a browser) such as the structured knowledge already acquired on the host-ontology as well the one available in the KSO catalogued into the associated KBS. Likewise, users would be able to turn these queries into general search options on the Internet that could lead to obtaining additional knowledge.

Input: Some users' queries and requirements that could be interesting, expressed in natural or pseudo-Natural language (uses cases) regarding some information, knowledge, or taxonomic structure.

Output: Some tentative text corpora or ontologies about sub-domains, database candidates, users' agreements, and consensus among several MRs.

Steps Methods and techniques:

1. Querying about knowledge structures, terms, and meanings to match the actual ontology with previous versions.
2. Consulting on the potential knowledge, according to each KSO (ontology, text, RDB-schema) to add new knowledge to structures.
3. Validating the existence of reusable, similar, or equivalent queries previously carried out by users (in users' profiles) for the same domain or for a similar one.
4. Registering in the associated KSO repositories, the potential knowledge considered useful by users according to the selected strategy in Phase I.
5. Registering user's profiles and ontology versioning for new queries and changing requirements demanded by users.

Tools: Google, Journal subscriptions, LabelTranslator, Protégé, QuicRDF, GATE, ERWin, PowerDesigner and others.

Phase IV: Knowledge selection

Objective: Selecting a ranking of potential knowledge based on the previous queries and the knowledge discovered in Phase III.

Input: Tentative Corpus, optional sub-domain ontologies, some RDB-scheme candidates and some agreements and consensus among tentative users.

Output: Selected Corpus, ontologies, RDB-schemes and any other MR.

Steps Methods and techniques:

1. Selecting structured potential knowledge (ontologies, corpus, RDB-schemes) from the registries in the KSO of the KBS previously registered as useful in the users' profile.

2. Selecting non-structured potential knowledge (content of texts, other DBs, other ontologies) from the previously preselected registries.
3. The Expert Users check the consistency of the format and data meaning of the already identified and selected data from the KSOs. This data could be used for OL to update the host-ontology *objects*.
4. Selecting the preselected MR definitively from the KSO to be used in the workflow of SMOL. Occasionally, the selected tools can include some user's options for (semi-)automatic format conversion and consistency checking of the potential selected data for OL.
5. Showing to the Expert Users a rank of "potential knowledge level" to improve the OL process once that this potential level is calculated by the system.
6. Asking users about their opinions and decisions of the KSO (content and MR). According to the specific case, some of these opinions and decisions may be considered by users as an appropriate recommendation to face similar cases by other users, using user's profiles. This recommendation system is not included in this work, but will be developed in the future

Tools: GATE, Text2Onto, Asium, OntoLern, Terminae, RapidMiner, ERWin.

Phase V: Knowledge structure construction

Objective: Selecting potential novel *ontology-objects* such as concepts, relations, and instances regarding structured knowledge correspondence, from potential knowledge selected as a candidate one.

Input: Selected corpora and ontologies, RDB-schemes. Terminology verified as significant by users for the domain and context (re-validated).

Output: Structured knowledge updated, validated corpus, ontologies and RDB-schemes, and tested MR.

Steps Methods and techniques:

1. Applying the selected MR for each possible and potential KSO.
2. Validating by Expert Users the data/information format obtained through the conversion-tools associated to each KSO to guarantee the compatibility needed for the OL processes (e.g., mapping or populating). Also, the Knowledge engineers have to support any other possible data adjusting associated with formats.
3. Consistency verification of the semantic result or proposing knowledge structures (according to previous steps) using any reasoning tool for testing ontology consistencies.
4. Validating the consistency of the structure of the resulting knowledge (as ontology), querying the users and registering their opinions in user's profiles
5. Applying ontology quality evaluation tools (e.g., Racer-pro).
6. The ontologies' changes are registered for rollback and versioning purposes. Likewise, the user's profile updated with the user's actions.

Tools: *OL from ontologies:* ASMOV, GeRMeSMB, MapPSO, RiMOM, Prompt, TaxoMap, etc. *OL from texts:* Asium, SVELAN, Text2Onto, etc. *OL from databases*: Cupid, COMMA, RDBToOnto, ODEMapster.

Phase VI: Knowledge exploration and search

Objective: Exploring the structured knowledge (both acquired and potential) to be reviewed by users for verification, whether the requirements are satisfied and if they are still valid. Besides, testing of consistent results from the changes added to the structured knowledge.
Input: Structured knowledge updated, corpus tested, ontologies validated, RDB-schemes, selected MR and user's queries recorded.
Output: Structured knowledge updated and evaluated (verified and validated), user's consensus, agents for discovering and updating purpose, etc.
Steps (Methods and techniques):

1. Browsing the novel structured knowledge (updated), exploring its semantic and new meaning (using Word-Net tool, for instance).
2. Comparison and evaluation of the novel structured knowledge. Comparing it, for instance, with the meaning of other upper level or domain ontologies, supported by the opinion of users (by validation), or using other automated forms (by verification) such as pattern validating, agents for consistency checking, etc.

Tools: Protégé-Prompt, OntoStudio, Text2Onto, GATE, RacerPro, WordNet.
Decision-Point: <b> Satisfied requirements. <d> Query and requirement reformulation.

Phase VII: Knowledge structure reorganization

Objective: Reorganizing the structured knowledge, checking that both the acquired and the potential one are correct.
Input: Structured knowledge updated and evaluated (verified and validated). Criteria of users registered in the user's profiles.
Output: Structured knowledge updated and evaluated. Some quality issues are tested. Some novel agents/procedures are registered as KSOs for future reorganization purposes.
Steps Methods and techniques:

1. Reorganizing knowledge structures (e.g., the host ontologies, their connections/links with texts, with other KSOs, etc).
2. Comparing different ontology versions (visually or automatic tool).
3. Applying MRs for quality *OE* (e.g., based on tools such as Racer-pro and, OntoQA). Some details of the OE workflow for the case has been included in Appendix B.
4. Registering the user profiles and the ontology changes of the previous version.

Tools: *OL from ontologies*: ASMOV, GeRMeSMB, MapPSO, RiMOM, Prompt, TaxoMap, etc. *OL from texts*: Asium, SVELAN, Text2Onto, GATE, *OL from databases:* COMMA, ODEMapster, RDBToOnto.
Decision-Point: <c> Knowledge structure updating.

Phase VIII: Knowledge-based system configuration

Objective: Establishing functionality parameters for the different modules related to the KBS and their components (regarding KSOs, user profiles, logs, etc). Essentially, the configuration of these parameters helps users to manage the KBS and the KSO appropriately.
Input: The structured knowledge expected by user. Some additional system functionalities required by users.
Output: System improvement and adaptation (user interface setup, procedures as agents' inclusions, and so on.)
Steps: Configuration of some Knowledge-base system modules such as:

1. Graphic User Interface options.
2. Updating/Recovering from any KSO options (ontologies, text, RDB-schemes).
3. Profiles Coordination/administration of (users, security, management).

Tools: Text2Onto, GATE, Agents as possible RM tool.
Decision-Point: <e> Configuration parameter setup.

References

Abdullah, R., Selamat, M., Jaafar, A., Abdullah, S., Sura, S. (2008). An empirical study of knowledge management system implementation in public higher learning institution. *International Journal of Computer Science and Network Security*, *8*, 281–290.

Argote, L., & Miron-Spektor, E. (2011). Organizational learning: from experience to knowledge. *Organization Science*, *22*, 1123–1137.

Azzam, S.R., & Zhou, S. (2012). Assessment of ontology alignment methodology. In *Internet technology and secured transactions, 2012 international conference for IEEE* (pp. 759–764).

Bai, R.J., Wang, X.Y., Yu, X.F. (2011). Study of the methods and tools for ontology integration. *Advanced Material Research*, *187*, 716–727.

Bloehdorn, S., Haase, P., Huang, Z., Sure, Y., Volker, J., van Harmelen, F., Studer, R. (2009). Ontology management chapter 2. In *Semantic knowledge management*. Berlin: Springer.

Bock, J., Danschel, C., Stumpp, M. (2011). MapPSO and MapEVO results for OAEI 2011. In *Proceedings of 6th ISWC workshop on ontology matching (OM)* (pp. 179–183). Bonn (DE).

Boehm, B., & Turner, R. (2004). Balancing agility and discipline: evaluating and integrating agile and plan-driven methods. In *Software Engineering, 2004. ICSE 2004. Proceedings of 26th International Conference on IEEE* (pp. 718–719).

Buitelaar, P., Cimiano, P., Haase, P., Sintek, M. (2009). Towards linguistically grounded ontologies. In *The semantic web: research and applications* (pp. 111–125). Berlin: Springer.

Calbimonte, J.P., Corcho, O., Gray, A.J. (2010). Ontology-based access to streaming data. In *Poster at the 7th extended semantic web conference (ESWC2010)*. Greece: Hersonissos.

Callaos, N. (1992). A systemic system methodology. In *International conference on system research informatic and cybernetics*. Germany: Baden-Baden.

Callaos, N., & Callaos, B. (1994). Designing with a systemic total quality. In *Educational technology* (pp. 29–36).

Castano, S., Antonellis, V.D., di Vimercati, S.D.C. (2001). Global viewing of heterogeneous data sources. *IEEE Transaction on Knowledge and Data Engineering*, *13*(2), 277–297.

Castano, S., Espinosa, S., Ferrara, A., Karkaletsis, V., Kaya, A., Melzer, S., Petasis, G. (2007). Ontology dynamics with multimedia information: *The boemie evolution methodology* (p. 41). IWOD-07.

Castano, S., Peraldi, I.S.E., Ferrara, A., Karkaletsis, V., Kaya, A., Möller, R., Wessel, M. (2009). Multimedia interpretation for dynamic ontology evolution. *Journal of Logic and Computation*, *19*(5), 859–897.

Cerbah, F. (2010). Learning ontologies with deep class hierarchies by mining the content of relational databases. In *Advances in knowledge discovery and management* (pp. 271–286). Berlin: Springer.

Cimiano, P., & Völker, J. (2005). Text2Onto. In *Natural language processing and information systems* (pp. 227–238). Berlin: Springer.

Cimiano, P., Mädche, A., Staab, S., Völker, J. (2009). Ontology learning. In *Handbook on ontologies* (pp. 245–267). Berlin: Springer.

Cunningham, H. (2002). GATE, a general architecture for text engineering. *Computers and the Humanities*, *36*(2), 223–254.

Dahlem, N. (2011). OntoClippy: a user-friendly ontology design and creation methodology. *International Journal of Intelligent Information Technologies*, *7*(1), 15–32.

Dahlem, N., & Hahn, A. (2009). *User-friendly ontology creation methodologies-a survey* (pp 1–9). California: 15th American Conference on Information Systems.

Dahlem, N., Guo, J., Hahn, A., Reinel, M. (2009). Towards an user-friendly ontology design methodology. In *International conference on interoperability for enterprise software and applications China, i-esa* (pp. 180–186).

De Leenheer, P., & Mens, T. (2008). Ontology evolution. In *Ontology management* (pp. 131–176). US: Springer.

De-Nicola, A., Missikof, M., Navigli, R. (2009). A software engineering approach to ontology building. *Information Systems, Elsevier*, *34*, 258–275.

Ehrig, M. (2007). *Ontology alignment: bridging the semantic gap* (Vol. 4). Springer.

Faure, D., & Poibeau, T. (2000). First experiments of using semantic knowledge learned by ASIUM for information extraction task using Intex. In *Proceedings of the 1st workshop on ontology learning*.

Fernández, M., Overbeeke, C., Sabou, M., Motta, E. (2009). What makes a good ontology? A case-study in fine-grained knowledge reuse. In *The semantic web* (pp. 61–75). Berlin: Springer.

Gaines, B. (1990). Knowledge-support systems. *Knowledge-Based Systems*, *3–4*, 192–203.

Gangemi, A., Pisanelli, D.M., Steve, G. (1999). An overview of the ONIONS project: applying ontologies to the integration of medical terminologies. *Data and Knowledge Engineering*, *31*(2), 183–220.

Gil, R., Martin-Bautista, M., Contreras, L. (2010a). *Applying an ontology learning methodology to a relational database: University case study*. Pittsburgh: 4th IEEE Int. Conf. (IEEEICSC-2010).

Gil, R., Contreras, L., Martin-Bautista, M. (2010b). *A systemic methodology for ontology learning: an academic case study and evaluation* (Vol. 1, pp. 206–212). Valencia: IC3K, KEOD-2010.

Gliozzo, A.C., Caracciolo, M.S., D-Aquin, M., Peter, W., Voelker, J., Dzbor, M., Mota, E., et al. (2007). Results from experiments in ontology learning including evaluation and recommendation (Tech. Rep.). NeOn-Project.org.

Gómez-Pérez, A., & Manzano-Macho, D. (2005). An overview of methods and tools for ontology learning from text. *Knowledge Engineering Review*, *19*, 187–212.

Gómez-Pérez, A., Fernando-López, M., Corcho, O. (2004). *Ontology engineering*. London: Springer.

Hill, T., & Westbrook, R. (1997). Swot analysis: it's time for a product recall. *Long Range Planning*, *30*, 46–52.

Islam, N., Abbasi, A.Z., Shaikh, Z.A. (2010). Semantic Web: choosing the right methodologies, tools and standards. In *Information and emerging technologies (ICIET)*, (pp. 1–5). 2010 International Conference on IEEE.

Jean-Mary, Y.R., Shironoshita, E.P., Kabuka, M.R. (2010). Asmov: results for oaei 2010. Ontology Matching. 9th International Semantic Web Conference (ISWC-2010) Workshop, 129–136. Shanghai, China, November 7–11.

Jennex, M.E., & Olfman, L. (2011). A model of knowledge management success. In M. Jennex & S. Smolnik (Eds.), *Strategies for knowledge management success: exploring organizational efficacy*(pp. 14–31). Hershey-New York: Information Science Reference.

Jiang, X., & Tan, A. (2010). CRCTOL: a semantic-based domain ontology learning system. *Journal of the American Society for Information Science and Technology*, *61*(1), 150–168.

Jimeno-Yepes, A., Jiménez-Ruiz, E., Berlanga-Llavori, R., Rebholz-Schuhmann, D. (2009). Reuse of terminological resources for efficient ontological engineering in life sciences. *BMC Bioinformatics*, *10*(Suppl 10), S4.

Khattak, A.M., Latif, K., Lee, S., Lee, Y.K. (2009). Ontology evolution: a survey and future challenges. In *U-and E-service, science and technology* (pp. 68–75). Heidelberg: Springer.

Kitchenham, B., Linkman, S., Law, D. (1997). Desmet: a methodology for evaluating software engineering methods and tools. *Computing and Control Engineering Journal*, *8*(3), 120–126.

Kulkarni, U.R., Ravindran, S., Freeze, R. (2007). A knowledge management success model: theoretical development and empirical validation. *Journal of Management Information Systems*, *23*(3), 309–347.

Larman, C., & Basili, V.R. (2003). Iterative and incremental developments. A brief history. *Computer*, *36*(6), 47–56.

Massey, L., & Wong, W. (2011). A cognitive-based approach to identify topics in text using the Web as a knowledge source. *Ontology Learning and Knowledge Discovery Using the Web: challenges and Recent Advances*.

Melnik, S., Rahm, E., Bernstein, P.A. (2003). Rondo: a programming platform for generic model management. In *Proceedings of the 2003 ACM SIGMOD international conference on management of data* (pp. 193–204). ACM.

Mena, E., Illarramendi, A., Kashyap, V., Sheth, A.P. (2000). OBSERVER: an approach for query processing in global information systems based on interoperation across pre-existing ontologies. *Distributed and Parallel Databases*, *8*(2), 223–271.

Mens, T., Guehéneuc, Y.G., Fernández-Ramil, J., D'Hondt, M. (2010). Software evolution. *IEEE Software*, *27*(4), 22–25.

Nováček, V., Laera, L., Handschuh, S., Davis, B. (2008). Infrastructure for dynamic knowledge integration—automated biomedical ontology extension using textual resources. *Journal of Biomedical Informatics*, *41*(5), 816–828.

Noy, N.F., & McGuinness, D.L. (2001). Ontology development 101: a guide to creating your first ontology.

Noy, N.F., & Musen, M.A. (2003). The PROMPT suite: interactive tools for ontology merging and mapping. *International Journal of Human-Computer Studies*, *59*(6), 983–1024.

Noy, N.F., Rubin, D.L., Musen, M.A. (2004). Making biomedical ontologies and ontology repositories work. *IEEE Intelligent Systems*, *19*(6), 78–81.

Nyulas, C., OConnor, M., Tu, S. (2007). DataMaster–a plug-in for importing schemas and data from relational databases into Protege. In *Proceedings of the 10th international protege conference*.

Palopoli, L., Terracina, G., Ursino, D. (2003). Experiences using DIKE, a system for supporting cooperative information system and data warehouse design. *Information Systems*, *28*(7), 835–865.

Petasis, G., Karkaletsis, V., Paliouras, G., Krithara, A., Zavitsanos, E. (2011). Ontology population and enrichment: State of the art. In Paliouras et al. (Eds.), *Multimedia information extraction* (LNAI) (Vol. 6050, pp. 134–166).

Pinto, H.S., Tempich, C., Staab, S. (2009). Ontology engineering and evolution in a distributed world using DILIGENT. In *Handbook on ontologies* (pp. 153–176). Heidelberg: Springer.

Ramos, L., & Gil, R. (2010). Information system to support the management of the distance education (Spanish). *Télématique*, *9*, 98–119. http://www.publicaciones.urbe.edu/index.php/telematique/issue/view/143.

Ramos, L., & Gil, R. (2011). https://sourceforge.net/projects/ontomanufacture/files/mop/.

Ramos, L., Gil, R., Anastasiou, D., Martin-Bautista, M.J. (2013). Towards a Machine of a Process (MOP) ontology to facilitate e-commerce of industrial machinery. *Computers in Industry* (in Press).

Roth, M.T., Arya, M., Haas, L.M., Carey, M.J., Cody, W., Fagin, R., Schwarz, P.M., Thomas, J., Wimmers, E.L. (1996). The garlic project. *Sigmod Record*, *25*, 557. http://www.informatik.uni-trier.de/~ley/db/conf/sigmod/RothAHCCFSTW96.html.

Sabou, M., & Fernandez, M. (2012). Ontology (Network) evaluation. In *Ontology engineering in a networked world* (pp. 193–212). Heidelberg: Springer.

Shamsfard, N., & Abdollahzadeh, A. (2003). The state of the art in ontology learning: a framework for comparison. *The Knowledge Engineering Review*, *18*(4), 293–316.

Simperl, E., Tempich, C., Vrandecic, D. (2008). *A methodology for ontology learning the book: Chapter of book ontology learning and population*. Amsterdam: IOS Press.

Sommerville, I. (2006). Software engineering. In P. Education (Ed.), *Pearson education*.

Stojanovic, L. (2004). Methods and tools for ontology evolution. Doctoral dissertation, Karlsruhe, University, PhD.Diss, Germany.

Strasunskas, D., & Tomassen, S.L. (2008). Empirical insights on a value of ontology quality in ontology-driven web search. In *On the move to meaningful internet systems: OTM 2008* (pp. 1319–1337). Heidelberg: Springer.

Suárez-Figueroa, M.C., Gómez-Pérez, A., Fernández-López, M. (2012). The NeOn methodology for ontology engineering. In *Ontology engineering in a networked world* (pp. 9–34). Springer.

Tartir, S., Arpinar, I.B., Moore, M., Sheth, A.P., Aleman-Meza, B. (2005). OntoQA: metric-based ontology quality analysis. In *IEEE workshop on knowledge acquisition from distributed, autonomous, semantically heterogeneous data and knowledge sources* (Vol. 9).

Urbach, N., & Müller, B. (2012). The updated DeLone and McLean model of information systems success information systems theory. *Integrated Series in Information Systems*, *2012*(28), 1–18.

Velardi, P., Navigli, R., Cuchiarelli, A., Neri, R. (2005). Evaluation of OntoLearn, a methodology for automatic learning of domain ontologies. *Ontology learning from text: methods, evaluation and applications* (pp. 92–106).

Wohlgenannt, G., Weichselbraun, A., Scharl, A., Sabou, M. (2012). Dynamic integration of multiple evidence sources for ontology learning. *Journal of Information and Data Management*, *3*(3), 243–254.

Wong, W., Liu, W., Bennamoun, M. (2012). Ontology learning from text: a look back and into the future. *ACM Computing Surveys (CSUR)*, *44*(4), 20.

Yao, Y., Zeng, Y., Zhong, N., Huang, X. (2007). Knowledge retrieval. In *Proceedings ieee/wiz/acm international conference on web intelligence* (pp. 729–735).

Zhou, L. (2007). Ontology learning: state of the art and open issues. *Information Technology and Management*, *8*(3), 241–252.

Zouaq, A., Dragan, G., Marek, H. (2011). Towards open ontology learning and filtering. *Information Systems*, *36*(7), 1064–1081.

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Applying An Ontology Learning Methodology To A Relational Database: University Case Study

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***Abstract*—Important knowledge can be recovered from relational database (RDB) associated with some information system-specific domains and converted to semantics. Studying the processes and Methodological Resources (MR) for this conversion has gained relevance in Knowledge Engineering and, particularly, in the Ontology Learning (OL) field. Such MR, organized in an appropriate manner under a methodological strategy, will make it possible to take advantage of existing tools for converting the cited RDB to domain ontologies. A comparative conversion-tool analysis, having considered the tools capabilities, learning levels and some advantages, has been useful for selecting and aligning those tools with the methodology applied to the case study. Finally, the methodological strategy design and its application under a Systemic Methodology for OL (SMOL) is shown.**

I. Introduction

There are several alternative methods for Knowledge Acquisition (KA) and discovery from specific domains associated with the information systems of companies and organizations. Such knowledge can recovered from the Relational Database (RDB) of such systems and expressed semantically.

The recent technical literature about the diverse options available for retrieving knowledge from RDB sources has been reviewed, including the RDB models and the schemes, as well as the knowledge that underlies the data which can be retrieved and processed using data mining techniques.

Some RDB conversion-to-ontology tools have been analyzed, with the intention of designing a strategy compatible with the Systemic Methodology for Ontology Learning (SMOL), which can be applied to the academic management domain. Such preliminary analysis will make it possible to gain some experience (insights) about the abilities of conversion tools to achieve certain levels of learning capabilities and their possible adoption in the cited strategy. The new SMOL methodology is briefly described and applied to the case study.

The article is structured in the following way: A technical review of the literature related to OL, particularly about conversion from the RDB towards the ontologies; in section II; A conversion-tools comparison and selection in section III; A description of the SMOL methodology in section IV; Some details about SMOL applied to the case study in section V; And, finally, Conclusions presented in section VI.

II. Background

According to the definition of OL given in [1], the process is the application of a set of methods and techniques used for improving a previous ontology with heterogeneous Knowledge Sources (KSo), avoiding the complete Ontology Development process. These sources can be previously developed ontologies, texts and database [2][3][4].

Nowadays, KA from diverse sources using OL processes is of interest for research in the methodological field. Several Methodological Resources (MR) such as methods, techniques and tools have been previously studied for OL from prior developed ontologies and electronic documents relative to the system domain [5].

Here, more specific reviews about MR for OL conversion from RDB to ontologies have been analyzed [6][7][8].

A. Problematic about Ontology Learning

Although important technical advances in MR in the OL field, according to each KSo, have demonstrated the main OL strengths and opportunities, authors recently have reported high dispersion and little integration among those MR producing OL results from the same KSo. Specifically, in agreement with [1][9] and [10] some conclusions associated with those studies about OL methodologies can be summarized.

Regarding OL Methods: a) There is not an established standard. b) The methods are not usually combined, and c) Many methods are not associated with specific tools. Respecting OL Tools: a) All of them help to extract knowledge; b) A small group of them allow the retrieval of a complete taxonomy; c) Only some tools support specific OL methods; and d) difficult to evaluate the KA tools similarly using texts as KSo.

B. Ontology Generating and Updating from RDB

First, we must distinguish between two mechanisms that are usually cited for conversion [11]

"*The difference is that the **mapping** assumes the existence of both an RDB and an ontology, and produces a set of correspondences between the two... By contrast, **transformation** assumes that only a relational database exists, while an ontology is produced from the RDB*" [12].

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There are several approaches to *mapping* [13][14] as well as *transforming* from the RDB [15], which is roughly and schematically grouped [16]. Specifically, in [4] is presented a taxonomic framework that groups conversion/mapping approaches. The main identified are: mapping creation, mapping representation/accessibility, mapping implementation, query implementation, application domains and data integration.

C. Methodological Resources for OL from RDB

Various terms relative to MR are defined in [17]: *Technique:* subjective capabilities such as abilities and skills to handle properly a tool. *Method:* a manner or way of thinking or doing using a tool to achieve an objective. *Tools*: capabilities aimed at properly using the logical and physical resources to apply techniques. And *Methodology:* a related or "relatable" set of methods, with their respective techniques and tools which could be used for achieving certain objective(s).

1) Techniques: Conversion techniques from RDB to Ontology usually to conform the following steps/rules : 1) Each RDB-table becomes a class concept. 2) Each RDB-sub-table becomes a subclass. 3) Each column of each table (not foreign key), becomes data type property. 4) Each column associated with a key, becomes a property object. 5) Each table row data become an instance associated with the corresponding class. Furthermore, some tool based in data mining have included new rules from the table-data values such as: 6) Building subclass categories from cell-values of RDB-tables in the specific classes of the ontologies, and 7) Generating indirect subclass categories from RDB table-value attributes[18][19].

2) Methods: Four steps to building an ontology from RDB are usually described as follow [12]: 1) Extract the ER model from the RDB using database tables querying system or reverse engineering. 2) Analyze the RDB model obtained in the previous step 1 and to transfer it to the intended ontology model, using conversion schemas and mapping rules for tables, columns, data types, row values, functional restrictions, etc. 3) Transfer data values from the cells of RDB table to their corresponding instances in the classes of ontologies using data conversion mechanisms. This is usually executed by batch processes. 4) Verify and validate logic integrity over the file obtained or generated as an output within mapping results [20].

3) Tools: The report mentioned above [4] has studied 15 conversion-tools (projects) to complete a tool comparative synthesis. Conversion-tools from this survey-report include: ASIO, DB2OWL, SOAM, ODEMapster, Dartgrid, Triplify, and DBToOnto tool. There are other tools referred to in the technical literature with similar proprieties such as: Vis-A-Vis, DataMaster and OntoBase (Protégé plug-in) that were also reviewed and considered as candidates.

III. Conversion-Tools Comparison and Selection

This tool-selection process below, is used as an illustrative example about how these MR can be evaluated/combined in the SMOL methodology for strategy drafting and selection.

DataMaster, RDBToOnto and ODEMapster were considered conversion-tools candidates due to: 1) ease of alignment with suggested OL methodology, 2) the scope of the current project and 3) all of them were available and accessible by Internet. Thus, these tools were studied, installed and tested experimentally to better understand the mapping and transformation capability of each. The feature summary of each tool tested can be seen in Table I.Each tool is described as follow:

TABLE I
Conversion-tools according capabilities parameters [4]

Conversion Tool	Mapping creation	Mapping representation	Mapping implementation	Query implementation	Application domain	Data integration
DataMaster (Portégé)	Automatic	Logic rules	Static		Generic/ Specific	Possible
RDBToOnto	Automatic (user-interation)	Constrain rules (data-mining)	Without explicit registration	Potential SPARQL ontology population	Generic	None
ODEMapster (R2O)	Both (auto- and by user)	R2O Lenguage	both (Static & dynamic)	SPARQL -> RDF/SQL -> RDB.	Generic	Potential multiple

DataMaster: A Protégé plug-in to support conversion of RDB schemes and data to the ontology editor. DataMaster allows new ontology conversion which could help user to update some previously developed ontologies [21].

RDBToOnto: A tool that enables configurable method implementation for ontology acquisition from RDB. Furthermore, it allows the updating of ontology instances. Learning parameters could be selected by users (data-mining/control-process) through a stable user interface [18].

ODEMapster: A NeOn Toolkit plug-in. It is based on a declarative language such as XML to express the elements which match between the RDB and the ontology. It is supported by R2O pseudo-language implementation. It used to detect inconsistencies/ambiguities in mapping definitions[13].

A. Learning Levels Supported by Conversion-tools

The tools in question must be considered according to the learning levels that they can reach or meet. In this sense, Buitelaar et al [22] have presented a semantic hierarchy about OL aggregation based on the following levels: terms, synonyms, concepts, taxonomy, relations and rules or axioms. This proposal has been adapted selecting five as references to qualify those tools. In Table II an approximation to different learning levels that may be supported by each tool is shown.

Likewise, based on users operational skills acquired with each tool during training-practices, some relevant comparative advantages and disadvantages when using them for conversion purpose had discussed. Despite the important results, they were not included due the limited number of paper-pages.

Finally, to summarize the selection process and due the similarities between DataMaster and RDBToOnto, the two conversion-tools selected to achieve partial and complementary learning from RDB are: a) **RDBToOnto** should be used to understand the system domain as a knowledge source. It could be used (through a provisional ontology) as a knowledge source to recover and to identify semantic terms and expressions. Also, it helps to infer those implicit relationships from the RDB table-attributes by a data mining approach and b) **ODEMapster** should be used by users through interactive GUI options to define direct mappings between RDB-attributes of the data model with the ontology elements which are intended to be updated, particularly under the referred learning levels.

TABLE II
CONVERSION-TOOLS COMPARED BY LEARNING LEVELS

Learnig level	DataMaster	RDBToOnto	ODEMapster
1) Terms	Table Attribute/cell	Table Attribute/cell	User asociation
2) Concepts	Table denomination	Table denomination	User asociation
3) Taxonomies	User specifications No data mining	Key principal and subclases Data mining by columns	User asociation No data mining
4) Relations	User specifications	Foranea key & subclases Maybe user specified	User specification Attribute combining
5) Axioms & rules	None	Rule deduction by redundancy	No predefined

IV. METHODOLOGY FOR ONTOLOGY LEARNING

Systemic Methodology for OL (SMOL) is a new proposal based under the systems approach which combining properly a variety of MR for OL under user-oriented approach. SMOL is purposed as useful for some kind of Knowledge-based Systems (KBS) to keep updated from diverse KSo (ontologies, texts and databases) related with the system domain [23].

This systemic methodological proposal to combine some MR previously developed, must be flexible, iterative, incremental and adaptable to end users, experts and knowledge engineers. It has some proper-cyclical-control mechanism according to quality approach cited in [24].

A. SMOL Phase-flow Summary

For the methodology flow design, we adapted a knowledge retrieval framework cited in [25]. The phases-flow of SMOL are proposed emphasizing the MR recommended to use in each specific phase. The application from RDB is shown in Figure 1. The activities related to each original phases are summarized as follow: *I. Methodology strategy selection.* The complexity of the domain is evaluated [3]. *II. Knowledge discovery.* The MR from different KSo and repositories are combined. *III. Query requirements.* Different queries are formulated to the knowledge sources available by browsers or other kind of applications. *IV. Knowledge selection.* A selection of the retrieved information from the formulated queries to the KSo and repositories is performed. *V. Knowledge structures construction.* Different structures such as ontologies and contexts can be built interactively with users advisory. *VI. Knowledge exploring and searching.* The knowledge structures are explored, verified and validated. *VII. Knowledge structures reorganization.* Processes such as grouping of instances, ontology population and others activities similarly are performed. *VIII. KBS Configuration.* Users to set-up modules-components of KBS with ontologies associated.

Other activities for SMOL drafting/testing were developed: a) KSo are configured as storage component for knowledge reuse purpose. b) User/Task profiles are configured as storage component to queries-operations registration for MR reuse and for user's recommendations purpose. c) Decision points have been included for cyclical-quality-check purpose (Figure 1; in rhombus). d) SMOL was applied for the case study from each KSo. And, e) a methodology evaluation through DESMET was performed [26].

V. CASE STUDY

SMOL was applied for an academic management case study using the RDB of another university institution as KSo.

The host-ontology to be used as the input case study has been developed/updated during three previous studies. The previous semantic processes are summarized in this way: 1) The Ontology-DEA was obtained from a University of Venezuela that operates under a Distance Education Administration [27]. 2) This ontology was an input for a SMOL application from a previously published ontology (LUMB) retrieved via Internet (Swoogle). Through ontological matching a new version of this host-ontology was updated. And, 3) This ontology updated, was enriched through another SMOL from a corpus-texts (480 files) [28]. This ontology attained was used as host. SMOL applied is shown in Figure 1.

Furthermore, a RDB named DB-IUTEPAS has been used as a KSo. This RDB has been developed since 7 years ago for an academic information system that currently operates in a small-scale university institution, identified by its acronym as IUTEPAS (About 1000 students and 110 professors) [29].

A set of 12 RDB-tables related with the professor subdomain has been chosen and has been transformed (preprocessing) to equivalent small and medium-size RDB models. These new RDB-format models obtained and validated, have technical link compatibility with the two selected tools.

Phase-I Methodological strategy selection: Considering the conversion-tools comparison/selection referred to above, a strategy was proposed which is supported by two learning cycles; In the first cycle, the RDB and RDBTo-Onto have been used to discover, to recover and to compare -matching-semantic entities that are found in the RDB. For instance, a ontology-subclass (university location/name) about where the professors earn their grades was obtained by data-mining. In the second one, using the lessons learned in the first cycle about relevant classes, subclasses and some relationships from this RDB, ODEMapster has been applied for refining semantic correlations between the RDB and the host-ontology.

Therefore, through ODEMapster users supports OL about the previous (sub)concepts, converted taxonomies found, and to establish better correlation between the RDB-tables-attributes with those concept property equivalents (such as dataproperty) in the host-ontology that is is restructuring.

This strategy selection was conceived from a combination of bottom-up (inductive) learning discovery for the first flow cycle cited, with another top-down (deductive) from the learning recovery (information obtained) from RDB during the second flow cycle. A complete updated and validated ontology was obtained, with important semantic results.

The lesson learned shows some relevant aspects: a) Several MR might be combined and used in SMOL. b) The activities -tasks- were registered (log) to support users in future related decisions reuse. c) The RDB used was registered (cataloged) to support future decisions associated with the host-ontology querying and updating. d) Users are satisfied with the SMOL characteristics, enabling them to participate in the OL strategy. And, e) Despite of data pre-processing involved had demanded user's skills about the tools, they had obtained OL inductive-

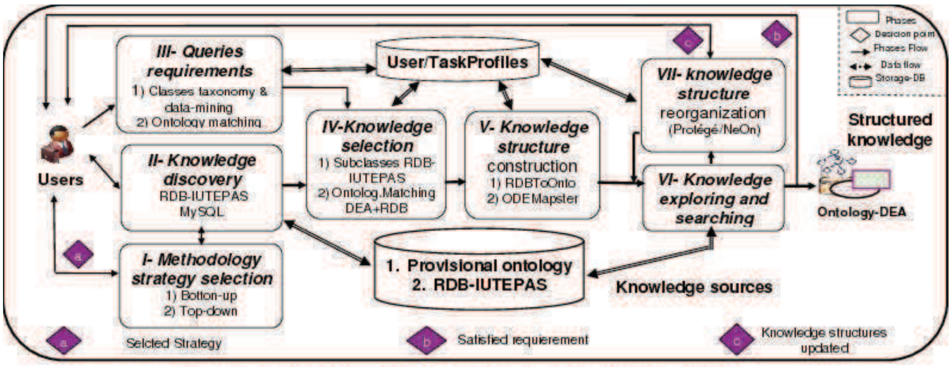

Figure 1: Systemic Methodology for Ontology Learning applied from RDB

automatic from the RDB-tables (near 60%) and the rest, in deductive-interactive way (40%) using mapping-definitions.

VI. Conclusions

Possibilities for better OL processes from RDB are improving recently, taking advantage of the new conversion-tool capabilities with adequate knowledge discovery and recovery results. Conversion-tools evaluated using the hierarchical learning level model for OL similar to that proposed by Buitelaar, was useful as a practical resource to qualify the tool capacities and selection.

SMOL applied to the case study has allowed the drafting and selection of a suitable strategy (bottom-up/top-down) according to instrumental available resources, leveraging a complementary combination of potential learning levels.

Structured knowledge incorporated into the host-ontology was achieved on the one hand, by comparative semantic shape, using a provisional ontology generated from RDB for that purpose. Thes two learning cycles have allowed the users: a) to identify different concepts and taxonomy as well as category results obtained via data mining using value redundancy attributes, and b) to achive new knowledge structures, based on users' expert opinions. Those were expressed in explicit matching, using mappings between specific RDB data-attributes with corresponding classes in the host-ontology.

References

[1] A. Gómez-Pérez and D. Manzano-Macho, "An overview of methods and tools for ontology learning from text," *Knowledge Engineer. Rev.*, vol. 19, pp. 187–212, 2005.
[2] M. Ehrig, *Ontology Alignment: Briding the Semantic Gap*. Springer-Verlag, 2007.
[3] L. Zhou, "Ontology learning: state of the art and open issues," *Information Technology and Management*, vol. 8, no. 3, pp. 241–252, 2007.
[4] S. Sahoo, W. Halb, S. Hellmann, I. Kingsley, T. Thibodeau, S. Auer, J. Sequeda, and A. Ezzat, "A survey of current approaches for mapping of relational databases for rdf," *W3C RDB2RDF incubator Group.*, 2009.
[5] P. Buitelaar and P. Cimiano, *Ontology Learning and Population: Briging the Gap Between Text And Knowledge*. IOS Press, Netherland, 2008.
[6] F. Cerbah, "Learning highly structured semantic repositories from relational databases: The rdbtoonto tool," *Lecture Notes in Computer Science Springer Berlin / Heidelberg*, vol. 5021, pp. 777–781, 2008.
[7] C. De-Laborda and S. Conrad, "Relationalowl - a data and schema representation format based on owl," *Conceptual Modelling*, vol. 43, pp. 89–96, 2005.
[8] S. Kiran and K. Sharifullah, "Building local ontology from database relation in data integration," *IEEE*, 2007.
[9] N. Shamsfard and A. Abdollahzadeh, "The state of the art in ontology learning: a framework for comparison," *The Knowledge Engineering Review*, vol. 18 (4), pp. 293–316, 2003.
[10] H. Zargayouna and A. Nazarenko, "Evaluation of textual knowledge acquisition tools: a challenging task," *Lenguage Resources Evaluation Conferences*, vol. 1, pp. 435–440, 2010.
[11] I. Astrova and A. Kalja, "Towards the semantic web: Extracting owl ontologies from sql relational schemata," *Proceedings of IADIS International Conference WWW/Internet (2006)*, vol. 1, pp. 62–66, 2006.
[12] I. Astrova, N. Korda, and A. Kalja, "Rule-based transformation of sql relational databases to owl ontologies," *Proceedings of the 2nd Inter. Confer. on Metadata & Semantics Research.*, vol. 1, 2007.
[13] J. Barrasa and A. Gómez-Pérez, "Upgrading relational legacy data to the semantic web," *www 2006, ACM*, vol. 1, 2006.
[14] N. Konstantinou, D. Spanos, M. Chalas, E. Solidakis, and N. Mitrou, "Visavis: An approach to an intermediate layer between ontologies and relational database contents," *International Workshop on Web Information Systems Modeling (WISM2006) Luxembourg.*, 2006.
[15] N. Cullot, R. Ghawi, and Yetongnon, "Db2owl: A tool for automatic database to ontology mapping," *In Proc.of 15th Italian Symposium on Advanced Database Systems (SEBD 2007)*, vol. 1, pp. 491 – 494, 2007.
[16] Q. Trinh, K. Barker, and R. Alhajj, "Rdb2ont: A tool for generating owl ontologies from relational database system," *AICT-ICIW '06. Inter.Confer. on Internet and Web Applications and Services.*, 2006.
[17] N. Callaos, "A systemic system methodology," in *International Conference on System Research Informatic and Cybernetics, Baden-Baden, Germany*, 1992.
[18] F. Cerbah, *RDBToOnto User Guide, Version 1.2 Beta From relational Database to Fine-Tuned Populated Ontologies*. TAO-Project, 2009.
[19] D. Pan and Y. Pan, "Using ontology repository to support data mining," *Proceedings of the 6th World Congress on Intelligent Control and Automation , June 21 - 23, 2006, Dalian, China, IEEE*, 2006.
[20] He-Ping, H. Lu, and C. Bin, "Research and implementation of ontology automatic construction based on relational database," *2008 Inter. Confer. on Computer Science and Software Engineering*, vol. 1, 2008.
[21] C. Nyulas, M. O'Connor, and S. Tu, "Datamaster - a plug-in for importing schemas and data from relational databases into protege," *10th Intl. Protege Conference, Budapest (2007).*, 2007.
[22] P. Buitelaar, P. Cimiano, M. Grobelnik, and M. Sintek, "Tutorial: Ontology learning from text," in *In conjunction with the ECML/PKDD 2005 Workshop, Porto-Portugal*, 2005.
[23] M. Abdullah, C. Kimble, I. Benest, and R. Paige, "Knowledge-based systems: a re-evaluation," *Journal of Knowledge Management*, vol. 10 Nro 3, pp. 127–142, 2006.
[24] N. Callaos and B. Callaos, "Designing with a system total quality," in *Int. Conference on Information System Analysis and Synthesis, (ISAS'06), Orlando-USA* (I. C. on Information System Analysis and I. . Synthesis, eds.), pp. 15–23, 2006.
[25] Y. Yao, Y. Zeng, N. Zhong, and X. Huang, "Knowledge retrieval," in *Proceedings IEEE/WIC/ACM International Conference on Web Intelligence*, 2007.
[26] B. Kitchenham, "Evaluating software engineering methods and tool part 1: The evaluation context and evaluation methods," *ACM SIGSOFT Software Engineering Notes*, vol. 21, pp. 11–14, 1996.
[27] UNA, "Plan estrategico de la universidad nacional abierta:presente y futuro desde un punto de vista colectivo," tech. rep., Universidad Nacional Abierta-UNA. Retrieved from http://www.una.edu.ve/, 2005.
[28] R. Gil, A. Borges, L. Ramos, L. Contreras, and M. Martín-Bautista, "Improving ontologies through ontology learning: a university case," in *World Congress CSIE'09, IEEE Computer Society, L.A.-USA.*, 2009.
[29] IUTEPAS, *Instituto Universitario de Tecnologia Pascal (IUTEPAS).* Acta Constitutiva, Retrieved from http://www.iutepas.8k.com/, 1996.

REFERENCES

1. Abdullah, R., Selamat, M., Jaafar, A., Abdullah, S., and Sura, S. (2008). An empirical study of knowledge management system implementation in public higher learning institution. Int. J. Computer Science and Network Security , 8 , 281-290.
2. Alavi, M. and Leidner, DE. (2001). "Review: Knowledge Management and Knowledge Management Systems". MIS Quarterly25 (1): 107–136.
3. Alquier, L., McCormick, K., and Jaeger, E. (2009). KnowIT, a semantic informatics knowledge management system. In Proceedings of the 5th international symposium on Wikis and open collaboration (p. 20). ACM.
4. Ammari A., Dimitrova V., Lau L., Tzagarakis M., Karacapilidis N., (2011), Augmented collaborative spaces for collective sense making: The dicode approach., in: The International Workshop on Adaptive Support for Team Collaboration 2011, held in conjunction with the International Conference on User Modeling, Adaptation, and Personalization (UMAP2011), Spain, July 15, 2011, Vol. 743, pp. 3-13.
5. Argote L., and Miron-Spektor E. (2011). Organizational Learning: From Experience to Knowledge, Organization Science, September/October 2011 22:1123-1137.
6. Brandt S. C., Morbach J., Miatidis M., Theiÿen M., Jarke M. and Marquardt W. (2006), Ontology-based information management in design processes, Computer Aided Chemical Engineering 21 2021-2026.
7. Bloehdorn, S., Haase, P., Huang, Z., Sure Y., Volker, J., van Harmelen F., Studer R., (2009). Ontology management chapter 2, in: Semantic Knowledge Management, Springer-Verlag, Berlin, Heidelberg,
8. Boehm, B., and Turner, R. (2004). Balancing agility and discipline: evaluating and integrating agile and plan-driven methods. In Software Engineering. ICSE 2004. Proceedings. 26th International Conference on(pp. 718-719. IEEE.
9. Bunge, M. (1979). A world of systems (Vol. 4). Dordrecht: Reidel.
10. Buitelaar, P., Cimiano, P., Haase, P., and Sintek, M., (2009). Towards linguistically grounded ontologies. In The Semantic Web: Research and Applications, Springer Berlin Heidelberg. pp.111-125.
11. Callaos, N. (1992). A systemic system methodology. In International conference on system research informatic and cybernetics, Baden-Baden, Germany.
12. Callaos, N., and Callaos, B. (1994). Designing with a systemic total quality. In Educational Technology. p. 29-36.
13. Castano, S., Espinosa, S., Ferrara, A., Karkaletsis, V., Kaya, A., Melzer, S. and Petasis, G. (2007). Ontology dynamics with multimedia information: The boemie evolution methodology. IWOD-07, pp.41.
14. Castano, S., Peraldi, I. S. E., Ferrara, A., Karkaletsis, V., Kaya, A., Möller, R., and Wessel, M. (2009). Multimedia interpretation for dynamic ontology evolution. Journal of logic and computation, 19(5) 859-897.
15. Cerbah, F. (2010). Learning ontologies with deep class hierarchies by mining the content of relational databases. In Advances in Knowledge Discovery and Management (pp. 271-286). Springer Berlin Heidelberg.

16. Chakrabortya, B., Maji, R. K., and Ghosh, D. (2011). An object oriented programming platform for ontology based KMS. Journal of Computational Methods in Sciences and Engineering, 11(3,1), 139-148.
17. Chen, J., Wu, Y., Li, M., Li, S., and You, J. (2009). Rules driven object-relational databases ontology learning. In Interoperability for Enterprise Software and Applications China, IESA'09. International Conference on (pp. 169-174). IEEE.
18. Cheng, H., Lu, Y., and Sheu, C. (2009). An ontology-based business intelligence application in a financial knowledge management system. Expert Systems with Applications, 36(2) 3614-3622.
19. Dahlem, N., Guo, J., Hahn, A., and Reinel, M. (2009). Towards a user-friendly ontology design methodology. International Conference on Interoperability for Enterprise Software and Applications China, i-esa, 180-186.
20. Dahlem. N. (2011)."OntoClippy: A user-friendly ontology design and creation methodology" International Journal of Intelligent Information Technologies 7.1 15-32.
21. De-Nicola, A., Missikof, M., and Navigli, R. (2009). A Software engineering approach to ontology building. Information Systems, Elsevier, 34, 258-275.
22. DeLone WH. and McLean ER., (2002). Information systems success revisited, in: System Sciences, HICSS. Proceedings of the 35th Annual Hawaii International Conference. p. 2966-76.
23. Gaines. B, 1990.Knowledge-support systems, Knowledge-Based Systems.3-4,192-203.
24. Gallupe, B. (2001). Knowledge management systems: surveying the landscape. International Journal of Management Reviews, 3(1), 61-77.
25. Gangemi, A., Pisanelli, DM., and Steve, G. (1999). An overview of the ONIONS project: Applying ontologies to the integration of medical terminologies. Data and Knowledge Engineering, 31(2) 183-220.
26. Garruzzo S., Rosaci D., Sarne G., (2007). Mars: an agent-based recommender system for the semantic web, LNCS, , Springer, vol. 4531, pp. 181–194
27. Gil, R., Borges, A. M., Contreras, L., and Martin-Bautista, M. J. (2009). Improving ontologies through ontology learning: a university case. In Computer Science and Information Engineering, 2009 WRI World Congress on (Vol. 4, pp. 558-563). IEEE.
28. Gil, R., Martin-Bautista, M. J., and Contreras, L. (2010). Applying an Ontology Learning Methodology to a Relational Database: University Case Study. In Semantic Computing (ICSC), 2010 IEEE Fourth International Conference on (pp. 313-316).
29. Gil R., Contreras L., and Martin-Bautista M.J. (2010), A systemic methodology for ontology learning: an academic case study and evaluation, KEOD-2010, Valencia-Spain (1) 206-212.
30. Gil, R., and Martín-Bautista, MJ. (2011). An Ontology-Learning Knowledge Support System to Keep e-Organization’s Knowledge Up-to-Date: A University Case Study. In Electronic Government and the Information Systems Perspective. Springer, Berlin-Heidelberg (p.249-263).
31. Gil, R., and Martín-Bautista, MJ. (2012). A novel integrated knowledge support system based on ontology learning: Model specification and a case study. Knowledge-Based Systems (36), 340-352.

32. Gil, R. and Martin-Bautista, MJ. (2013a), SMOL: A Systemic Methodology for Ontology Learning from Heterogeneous Sources, (Journal of Intelligent Information Systems, Accepted Nov/13).
33. Gil, R. and Martin-Bautista, MJ. (2013b), Toward A Process-Based KMS Success Framework Improved Through Ontology Learning Technology, Information System Frontiers, Submitted Dec-2013.
34. Godoy C.P., Knowledge-based reasoning over the web, Ph.D. thesis, Departamento de Lenguajes y Sistemas Informaticos de la Universidad del Pais Vasco, Spain, 2005.
35. Gomez-Perez, A., and Manzano-Macho D. "An overview of methods and tools for ontology learning from texts." The knowledge engineering review 19.3 (2004): 187-212.
36. Gomez-Perez, A., Corcho-Garcia, O., and Fernandez-Lopez, M. (2003).Ontological engineering. Springer-Verlag New York, Inc..
37. Hill, T., and Westbrook, R. 1997. Swot analysis: It's time for a product recall. Long Range Planning, 30, 46-52.
38. Holsapple C., (2008). DSS architecture and types, Handbook on Decision Support Systems, vol. 1, Springer, pp. 163–189.
39. Huang, H. Designing a knowledge-based system for strategic planning: a balanced scorecard perspective, Expert Systems with Applications 36 (2009) 209–218.
40. Jennex M. and Olfman L. (2006). A model of knowledge management success, International Journal of Knowledge Management (2) 34.51.
41. Jennex, M. E. (2013). Knowledge Management Success in an Engineering Firm. Engineering Management Reviews, 2(3).
42. Kitchenham, B., S.Linkman, and Law, D. 1997. Desmet: a methodology for evaluating software engineering methods and tools. Computing and Control Engineering Journal, 8(3), 120-126.
43. Kulkarni, U.R., Ravindran, S., and Freeze, R. 2007. A knowledge management success model: Theoretical development and empirical validation. Journal of Management Information Systems, 23(3), 309-347.
44. Larman, C., and Basili, V. R. (2003). Iterative and incremental developments. a brief history. Computer, 36(6), 47-56
45. Leung, N. K., Lau, S. K., and Tsang, N. (2013). An ontology-based collaborative inter-organisational knowledge management network (CIK-NET). Journal of Information & amp; Knowledge Management, 12(01).
46. Markus M. L., (2001). Toward a theory of knowledge reuse: Types of knowledge reuse situations and factors in reuse success, J. Manage. Inf. Syst. 18 (1) 57-93.
47. Maedche, A. and Staab, S.: 2001, Ontology learning for the semantic web, Intelligent Systems, IEEE 16:2, 72–79.
48. Meier R., (2007). Knowledge Management Systems: Information and Communication Technologies for Knowledge Management, Springer.

49. Mora, M., Cervantes-Pérez, F., Garrido, L., Wang, F., and Angel-Sicilia, M. (2010). On KM, KMS and ontology-based KMS in the domain of SwE standards and models of processes: A conceptual survey. Intelligent Decision Technologies, 4(1), 75-98.
50. Nasir, S.A., and Noor, N. L. (2010). Integrating ontology-based approach in Knowledge Management System (KMS): construction of Batik Heritage Ontology. In Science and Social Research (CSSR), 2010 International Conference on (pp. 674-679). IEEE.
51. Nováček, V., Laera, L., Handschuh, S., and Davis, B. (2008). Infrastructure for dynamic knowledge integration—Automated biomedical ontology extension using textual resources. Journal of Biomedical Informatics, 41(5), 816-828.
52. Noy, NF., and McGuinness, DL. 2001. Ontology development 101: A guide to creating your first ontology.
53. OAEI. Ontology Alignment Evaluation Initiative (2013) http://oaei.ontologymatching.org/
54. Padma T. and Balasubramanie P. (2011), Domain experts knowledge-based intelligent decision support system in occupational shoulder and neck pain therapy, Applied Soft Computing 11 (2) 1762–1769.
55. Pavel, S., and Euzenat, J. (2013). Ontology Matching: State of the Art and Future Challenges. IEEE Transactions on Knowledge and Data Engineering, 25(1), 158-176.
56. Petasis, G., Karkaletsis, V., Paliouras, G., Krithara, A., and Zavitsanos, E. 2011. Ontology population and enrichment: State of the art. Paliouras et al. Multimedia Information Extraction (LNAI), 6050, 134-166.
57. Petter S., McLean ER., (2009) A meta-analytic assessment of the Delone and Mclean {IS} success model: An examination of {IS} success at the individual level, Information & Management 46 (3) 159 -166.
58. Pinto, H., Tempich, C., and Staab, S. (2009). Ontology engineering and evolution in a distributed world using DILIGENT. In Handbook on Ontologies (p.153-176). Springer Berlin Heidelberg.
59. Power D., Decision support systems: a historical overview, in: Handbook on Decision Support Systems, International Handbooks on Information Systems, vol. 1, Springer, Berlin, Heidelberg, 2008, pp. 121–140.
60. Rajsiri V., Lorre J., Benaben F., Pingaud H. (2010), Knowledge-based system for collaborative process specification, Computers in Industry 61161–175.
61. Ramos L., Gil R., Information system to support the management of the distance education (Spanish), Telematique, Venezuela, 9 (2010) 98–119.
62. Ramos L., and Gil R. Technical Report of MOP, (2011) in the Web-page; https://sourceforge.net/projects/ontomanufacture/files/mop/,
63. Ramos L, Gil R., Anastasious D., and Martin-Bautista MJ. (2014) Towards a Machine of a Process (MOP) ontology to facilitate e-commerce of industrial machinery, Computer in Industry, (65), 108-115.
64. Ribiere V., Bechina A., Knowledge management Technologies Chapter 12 In Search of Knowledge Management: Pursuing Primary Principles, Emerald Group Publishing Ltd., 2010.
65. Sabou, M., and Fernandez, M. 2012. Ontology (Network) Evaluation. In Ontology Engineering in a Networked World (pp. 193-212). Springer Berlin Heidelberg.

66. Santoso, HA., Haw, SC., and Abdul-Mehdi, ZT. (2011). Ontology extraction from relational database: Concept hierarchy as background knowledge. Knowledge-Based Systems, 24(3) 457-464.
67. Shamsfard, N., and Abdollahzadeh, A. 2003. The state of the art in ontology learning: a framework for comparison. The Knowledge Engineering Review, 18 (4), 293-316.
68. Shigeyoshi H., Inoue S., Tamanoi K., Aoki S., Tsuji H. and Ueno T. 2011, Knowledge and transaction based domestic energy saving support system, LNCS, vol. 6884, Springer, Berlin, Heidelberg. 242–251.
69. Simperl, E., Tempich, C., and Vrandecic, D. 2008. A methodology for ontology learning. Chapter of book: ontology learning and population. IOS Press, Amsterdam
70. Stankosky M., Creating the discipline of knowledge management, Elsevier Inc., 2005.
71. Suárez-Figueroa M. C., Gómez-Pérez A., and Fernández-López, M., 2012. The NeOn Methodology for Ontology Engineering. Ontology Engineering in a Networked World, Springer-Verlag, 9-34.
72. Sure, Y, Staab S, and Studer R. 2003. "On-to-knowledge methodology (OTKM)." Handbook on Ontologies, International Handbooks on Information Systems.
73. Triche, J., Cao, Q., and Thompson, M. (2012). Using Multiple-case Studies to Investigate Relationships among Knowledge Management Systems, Business Process and Business Performance: A Task Technology Fit Perspective.
74. UoY. (2011). University of York. Artificial Intelligence Group: 2011 Group Seminars. Speaker: Richard Gil Herrera. Wednesday 22nd June 2011. http://www.cs.york.ac.uk/aig/seminars/11.php
75. Urbach N. and Müller B., The updated Delone and Mclean model of information systems success, in: Y. K. Dwivedi, M. R. Wade, S. L. Schneberger (Eds.), Information Systems Theory, Vol. 28 of Integrated Series in Information Systems, Springer New York, 2012, p.1-18.
76. Walsh J. P., and Ungson G. R., (1991) Organizational memory, Academy of management review p. 57-91.
77. Wand, Y., & Weber, R. (1995). On the deep structure of information systems. Information Systems Journal, 5(3), 203-223.
78. Wong, W., Liu, W., and Bennamoun, M. 2012. Ontology learning from text: A look back and into the future. ACM Computing Surveys (CSUR), 44(4), 20.
79. Yao, Y., Zeng, Y., Zhong, N., and Huang, X. (2007). Knowledge retrieval. In Proceedings ieee/wiz/acm international conference on web intelligence (p. 729-735).
80. Zhang, F., Ma, ZM., Fan, G., and Wang, X. (2010). Automatic fuzzy semantic web ontology learning from fuzzy object-oriented database model. In Database and Expert Systems Applications Springer Berlin Heidelberg. (p16-30).
81. Zhou, L. 2007. Ontology learning: State of the art and open issues. Information Technology and Management, 8 (3), 241-252.
82. Zouaq A., Dragan G., and Marek. H., 2011. "Towards open ontology learning and filtering." Information Systems 36, no. 7, 1064-1081.