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Tacit knowledge elicitation process for industry 4.0

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Abstract
Manufacturers migrate their processes to Industry 4.0, which includes new technologies for improving productivity and efficiency of operations. One of the issues is capturing, recreating, and documenting the tacit knowledge of the aging workers. However, there are no systematic procedures to incorporate this knowledge into Enterprise Resource Planning systems and maintain a competitive advantage. This paper describes a solution proposal for a tacit knowledge elicitation process for capturing operational best practices of experienced workers in industrial domains based on a mix of algorithmic techniques and a cooperative game. We use domain ontologies for Industry 4.0 and reasoning techniques to discover and integrate new facts from textual sources into an Operational Knowledge Graph. We describe a concepts formation iterative process in a role game played by human and virtual agents through socialization and externalization for knowledge graph refinement. Ethical and societal concerns are discussed as well.

Keywords Concept maps · Knowledge graph · Ontology · Tacit knowledge · Knowledge management · AI ethics

1 Introduction

Manufacturers migrate their processes to Industry 4.0 innovative practices, which include the adoption of recent technologies for improving productivity and efficiency of operations through visibility and analytics [1]. One of the major critical issues they face is capturing, recreating, and documenting the experience of the aging workers, the so-called *tribal knowledge* before they change their role or leave the company—This paper uses indifferently the terms of *tribal knowledge*, *tacit knowledge*, and *implicit knowledge*, although a subtle difference between *tacit* and *implicit* knowledge and the term *tribal knowledge* is jargon.

Tribal knowledge is a term widely employed in the industry to denote critical knowledge obtained by some senior staff subject matter experts (SME) who have gained deep expertise on types of equipment, a device, or a method. It is associated with action since it reflects *understanding how* more than *knowing what* [2]. The **Six Sigma Business Dictionary** describes tribal knowledge as *"any unwritten information that is not commonly known by others within a company. This term is used most when referencing information that may need to be known by others to produce a quality product or service"*. The tribal knowledge represents how people act unconsciously and intuitively. It is always tacit and never expressed [3] or not easily expressible since *we can know more than we can tell*, as stated by Polanyi [4]. Tribal knowledge is a subset of the institutional knowledge, which comprises all documented and undocumented knowledge in an organization [5]. It brings decades of hands-on experience acquired without direct instruction, self-study, or help from others. In this sense,

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it belongs to the company, but it is *stored within the heads* of the experienced workforce never transformed into the company knowledge base, and quantifiable only indirectly as a loss when senior workers leave and cannot get replaced by apprentices with comparable performance skills.

The process of extracting information *out of the head* of an expert is not new. It was part of the development process for expert systems. The method consisted of two phases: (i) knowledge elicitation, where the knowledge was extracted by the expert, and (ii) knowledge representation, where the knowledge was stored in a database. The techniques utilized in the past were somehow inefficient and based on direct interviews to develop rule-based systems without the support of contemporary cognitive psychology [6] or knowledge management principles [5].

Our contribution follows the same bi-partition, but to the best of our knowledge, this is the first work describing a framework for capturing tacit operational best practices of experienced workers in industrial domains based on a cognitive reasoning system and a role-playing game. We use domain ontologies for Industry 4.0 and reasoning techniques to discover and integrate new facts from textual sources for automatic Knowledge Graph (KG) generation. We describe a concepts-formation iterative process as a role game played by SMEs, knowledge engineers, and virtual agents to capture tacit knowledge through socialization and externalization for KG refinement. We defend the thesis that it is not possible to fully capture tacit knowledge (usually nonverbal and unexpressed) with a purely algorithmic approach. On the contrary, explicit and implicit knowledge transfer is made possible in a cooperative game where human experts and virtual agents play together according to the elicitation process described in Sect. 4. The synergy between SMEs and knowledge engineers from one side and the cognitive system from the other will lead to knowledge creation through constructive learning, reflective ability, active interaction, and collaboration of human and virtual participants. The conversion of tacit knowledge into organizational knowledge will be promoted by (i) the application of Concept Maps (CM) mining for concepts visualization [7], (ii) the application of domain ontology on a KG for knowledge representation and automatic knowledge generation [8, 9], and (iii) the application of logical and semantic reasoning to infer new knowledge in a continuous learning process for KG alignment and refinement [10] supervised by SMEs. The resulting KG capitalizes the full corporate business knowledge (implicit and explicit) into enterprise assets and can be the base for a conversational AI application for industrial domains such as maintenance operations, troubleshooting, reparations, on-site training, etc., or can be used as a unified base of expertise in an organization or as a unified enterprise semantic search for intelligent information retrieval.

Industry 4.0 is interdisciplinary and at the convergence of different capabilities that foster industrial innovations and social advances. In this respect, we follow the approach proposed in [11] for a convergence framework where people, objects, and organizations are connected to collect data from specific systems and processes and communicate with each other. In our work, we create value through the convergence of engineering methodologies (the cognitive system) and the convergence of the humanities and sociology (the cooperative game). In this way, our work can contribute to the transformation of the existing and complex relationships in the production process for Industry 4.0 with a better understanding of the technology-driven social mechanisms underneath.

The rest of the paper is organized as follows: In Sect. 2, we present some of the methods proposed for capturing tacit knowledge. In Sect. 3, we provide a functional description of our cognitive framework for capturing tacit knowledge into a KG. In Sect. 4, we describe the knowledge elicitation process using our game role approach for KG alignment and refinement. In Sect. 5, we discuss the societal and ethical concerns for the system proposed. In Sect. 6, we draw some conclusions. Future works are discussed in Sect. 7.

2 Related work

Tacit knowledge is the work-related practical knowledge learned informally on the job by workers. However, the importance of tacit knowledge is not systematically recognized by most companies, probably because the workforce age segmentation has never impacted companies as faced nowadays. According to the **US Bureau of Labor Statistics**[1], by 2029, around 25% of the workforce in the industry will be aged above 55 years and retire in the following years. As many qualified people retire, a wealth of information related to *best practices* and *efficient operations* is being inevitably lost. It will become increasingly difficult to find experts with 25 or more years in the workforce who know how to fix a critical

[1] www.bls.gov.

problem—assuming that it is non-trivial to transfer experience across jobs. Eventually, the better an organization can elicit tacit knowledge from its employees and share it across the organization, the more innovative it can be [12].

Many companies do not have any systematic approach to collect and incorporate the field experience of experienced workers and assess the role of tacit knowledge management on the success of Enterprise Resource Planning (ERP) systems implementation [13]. At best, the loss of tacit knowledge is mitigated by informal procedures [6]. The main approaches proposed are the following:

1. **Internal reports**: For most companies, the standard best practice for recording tacit knowledge is via internal reports and any other tribal exchanges such as conversations, forum postings, chats, emails, wikis, software repository issues. However, if not enforced, this procedure is ineffective and difficult to replicate. A critical aspect of this approach is related to workers' communication skills. SMEs who have previous experience expressing their expertise are far more able to share their knowledge than others. On the contrary, workers who lack minimal communication skills with similar domain expertise cannot externalize their knowledge correctly to others. A better approach is described in [14] without considering tacit knowledge.
2. **One-on-one mentoring**: Most companies prefer to organize a worker development program in the form of one-on-one mentoring [15], where a new apprentice shadows some veteran engineer, technician, or senior worker in the first 6 or 12 months on the job. The tacit knowledge is usually passed on during on-site training. However, due to the urgency of the assigned tasks, senior engineers typically do not have the time, energy, and motivation to carry out maintenance inspection and fault diagnosis and thoroughly explain *how they function while working* [6] to supervisors.
3. **On-site training**: Some companies prefer to provide on-site training to young engineers in the belief that they may better absorb and grasp domain knowledge from veteran engineers after they have a mental picture of the overall system or problem they are working to. However, most of the time, mentoring focuses on resolving an individual issue but fails to help trace the root cause of the problem in similar systems. It may often cause the inexperienced workers to jump directly to problem-solving using inefficient (sometimes dangerous) shortcuts for trial and error or opting for unwarranted large-scale parts or components replacement when charged with similar jobs.
4. **Rules collector system**: This method enables a process to capture an individual's expertise in a formalized manner updating hand-crafted rules and knowledge databases with information retrieved from the interaction with workers. It is the old approach from the time of expert systems. Unfortunately, rule-based systems are brittle and difficult to maintain. The rules captured can be contradictory and non-sufficient to ensure the consistency of the knowledge base. In our approach, we avoid the limitations of the rules collector system by reasoning in domain ontology to discover new knowledge.

KG construction is undoubtedly new for the tacit knowledge elicitation process that we describe for generating an *operational knowledge graph* in industrial domains. However, it is common practice for explicit knowledge transfer in other domains. For example, for the **biomedical domain**, in [16] the authors construct a *PubMed* KG to create connections among bio-entities, authors, articles, affiliations, and funding; in [17], the authors describe *KGen*, a KG generator from biomedical scientific literature using NLP techniques and ontology linking. For the **financial domain**, in [18] the authors present Enterprise Knowledge Graphs to illustrate a set of AI-driven applications strongly based on KGs for FinTechs; in [19] the authors introduce the *KnowEdu* system for the **education domain** that supports personalized teaching services and adaptive learning solutions using pedagogical data in a textual format for a neural network pipeline to generate a KG.

3 The cognitive framework functional architecture

In this section, we describe the cognitive pipeline for converting tacit knowledge into explicit knowledge. The mix of explicit and tacit knowledge allows organizations to make sense of their environment [20]. The continuous social interaction of tacit and explicit knowledge through dialogue and debate creates the institutional knowledge maintained on the internal technical documentation of the company. The implicit knowledge represents the industrial culture, the occupational traditions, and the cultural values of the workforce that uses, develops, administers, and operates the technology in the working environment [21]. In this sense, it is very reductive to think that the overall knowledge in a company belongs exclusively to one particular group of experts or a single individual as competence, skills, or know-how. It is far better to consider this knowledge as the result of social accomplishments of constructing and reconstructing

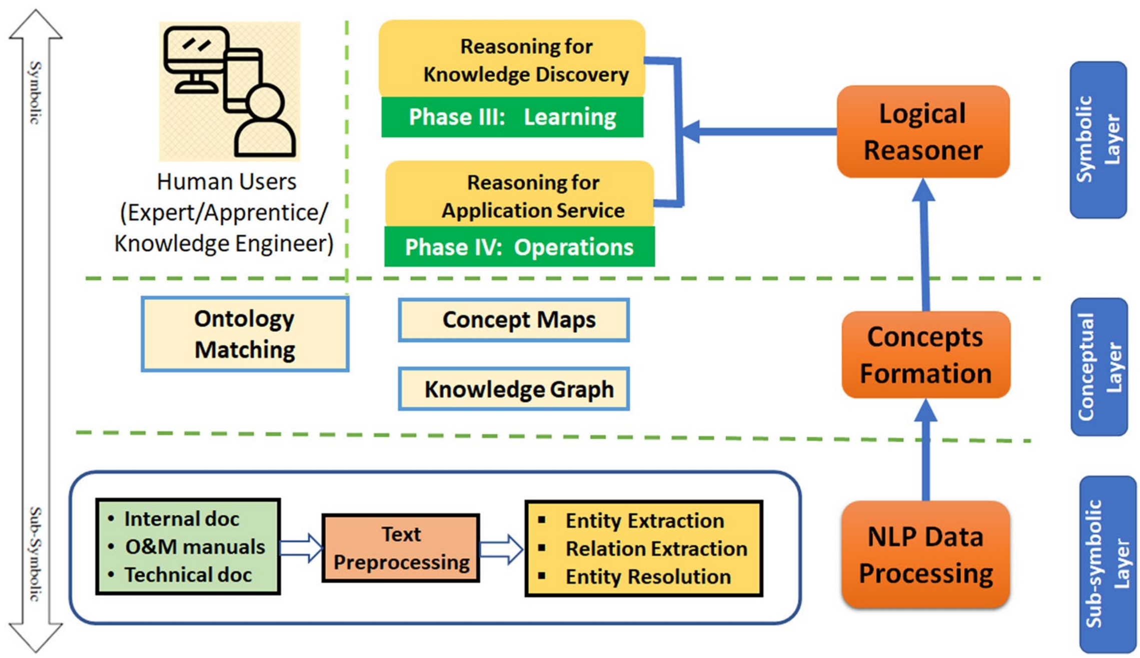


Fig. 1 Cognitive framework Functional Architecture for tacit knowledge elicitation

new knowledge as the ongoing product of practices that engage employees, promote collaboration, and expand the knowledge transformation towards a stronger company culture where background knowledge and implicit cognitive rules have a fundamental relevance. Tacit knowledge is a social and not an individual attribute [22], and the different forms of tacit knowledge [23] go beyond the reductive form of tacit knowledge as know-how. If we want to efficiently translate tacit knowledge into explicit knowledge, we shall also emulate the social working environment in which the workforce is acting. Insofar we assume the applicability of the *Nonaka-Takeuki model* [24] that postulates how knowledge in an organization is created through continuous social interaction of tacit and explicit knowledge, coupled with the four sequential modes of knowledge conversion of the SECI model: Socialization (from tacit to tacit), Externalisation (from tacit to explicit), Combination (from explicit to explicit), and Internalization (from explicit to tacit). It is outside the scope of this paper to discuss the limitations and the criticism raised by the SECI knowledge creation process. More detailed information on these aspects can be found in [25–28].

For the objectives of this paper, the SECI spiral model of knowledge creation perfectly justifies the role game we propose to convert tacit knowledge into explicit knowledge with human and virtual agents interacting in the process of knowledge transformation. It is worthwhile noting how the inability to formalize directly tacit knowledge does not exclude the possibility that a virtual agent (a computer system) might perform the same tasks using alternative representations or that tacit knowledge cannot be transferred to a machine [29, 30]. Nevertheless, no automatic cognitive system can capture the tacit knowledge or any other genuine human activity with a purely algorithmic approach—from workers' heads to corporate databases—without considering the social, cultural, legal, sociological contexts of the data collection and representation. The supervision of a human agent in the cooperative game described in Sect. 4 will ensure that non-algorithmic qualitative factors that require human appreciation may be considered during the knowledge transformation process, complementing the neuro-symbolic pipeline used to capture the quantitative algorithmic factors into an operational KG.

3.1 The neurosymbolic architecture

The architecture of the cognitive framework for tacit knowledge elicitation can be described as a hybrid neurosymbolic system where a neural network focused on sub-symbolic tasks interacts with a symbolic system— it can be classified as **Neuro;Symbolic** (Type 3) [31].

The functional architecture of the cognitive framework is presented in Fig. 1. It includes three main layers: (i) subsymbolic layer, (ii) conceptual layer, (iii) symbolic layer. The main difference with other neurosymbolic architectures is that the symbolic and the sub-symbolic layers are not coupled directly but interact through an intermediate layer (the conceptual layer).

3.1.1 Sub-symbolic layer

The sub-symbolic layer processes heterogeneous input data collected from the internal technical documentation, operation and maintenance (O&M) manuals, troubleshooting manuals, technical documentation, and reports from different structured or unstructured sources. Other input data types, such as video and audio, have not been scoped in this study but can be recorded for archival purposes and documentation.

NLP Data Processing One of the advantages of using input in textual format is the great availability of mature Natural Language Processing (NLP) methods. The raw input textual data is stored in files and processed using standard data mining tools for automatic knowledge extraction from text.

It is outside the scope of this paper to provide detailed information for KG construction from text using NLP tools and techniques. The reader can look at the specialized literature [9, 17, 32–34]. Nevertheless, we provide some basic NLP concepts practical for KG generation to extract information for KG construction, such as named entity recognition (NER), relation extraction (RE), and entity resolution (ER). A KG is a direct acyclic graph (DAG) defined as $KG = (V, E)$ containing a set of nodes or vertices *V* and a set of edges $E \subseteq V \times V$. Named entity recognition or entity extraction is about identifying entities of interest from textual sources to represent the nodes, while relation extraction is about extracting relations between two entities of interests identified in the text, i.e., how concepts and entities relate to each other to represent edges. Entity resolution identifies whether multiple mentions in a text refer to the same entity. Some preprocessing steps (tokenization, stemming, lemmatization, etc.) are performed using standard NLP tools such as Stanford NLP software [35], Apache OpenNLP [36], NTLK [37] to prepare the data sources for information extraction, . The modern way to perform NER is to take advantage of a pre-trained language model based on transformers (BERT [38]) because it can be adapted for the purposes of the specific domain even when few pre-training examples are available [39]. The classical approach to extract relations relies on Lexico-Syntactic Patterns and *Hearst Patterns* [40] as syntactic features, but many other methods are available [41]. Eventually, we can represent all the information extracted with a triple $subject \rightarrow predicate \rightarrow object$ to represent the relationships existing between subjects and objects where relations are the predicates, whereas entities are the subjects and the objects. This format can be stored as an RDF statement in a triplestore database.

3.1.2 Conceptual layer

The conceptual layer bridges the gap between symbolic and sub-symbolic representation with an intermediate layer that shares knowledge structures using a geometrical representation of knowledge [42]. The principal motivation for introducing this layer (Fig. 1) is the different abstraction levels between sub-symbolic and symbolic layers and the need to have an enterprise ontology for alignment and refinement of the heterogeneous KGs (triplestore databases) generated from texts in the sub-symbolic layer. The conceptual layer is an adaptation layer that facilitates the transformation of the information extracted from text (RDF triples) into symbolic objects (operational concepts) for composing new concepts and discovering similarities (concepts formation). We exploit this characteristic to fuse similar operational concepts and construct the operational KG. Actually, the raw KG composed of entities and relations in the RDF form generated in the sub-symbolic layer, is by its nature incomplete and based only on explicit knowledge found in the textual sources used during the generation process. Its associated ontological schema has to be alignment with an enterprise ontology and/or foundational domain ontologies for industrial domains [43] that are more general in supporting domain-specific applications. The entity alignment is part of the concept formation phase and can be achieved via joint KG embedding methods such as *OntoEA* [44] for higher quality and usability.

Concepts formation Concept formation is the construction of the ontology (the data graph schema) in a bottom-up approach that extracts knowledge instances from input textual data (ontology learning) and uses other knowledge resources coming from the CMs [45]. The operational KG is then created by ingesting data to the fused ontologies [46–48]. The interplay between CMs and the raw KGs leads to concepts formation by merging the knowledge representation for CMs and the knowledge representation for KGs (the ontologies). For the sake of completeness, we provide some background information for CM, KG, and ontology:

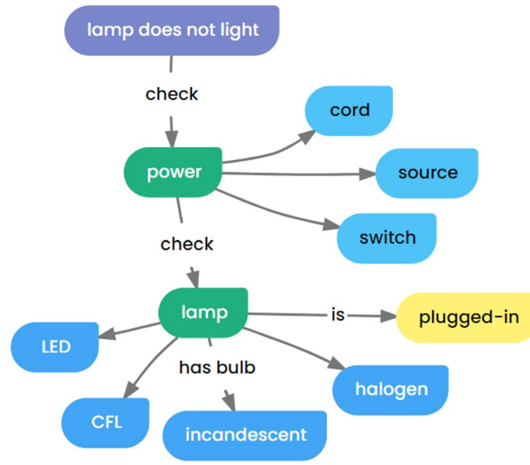


Fig. 2 Concept Map for the not-lighting lamp troubleshooting (*ContextMinds*)

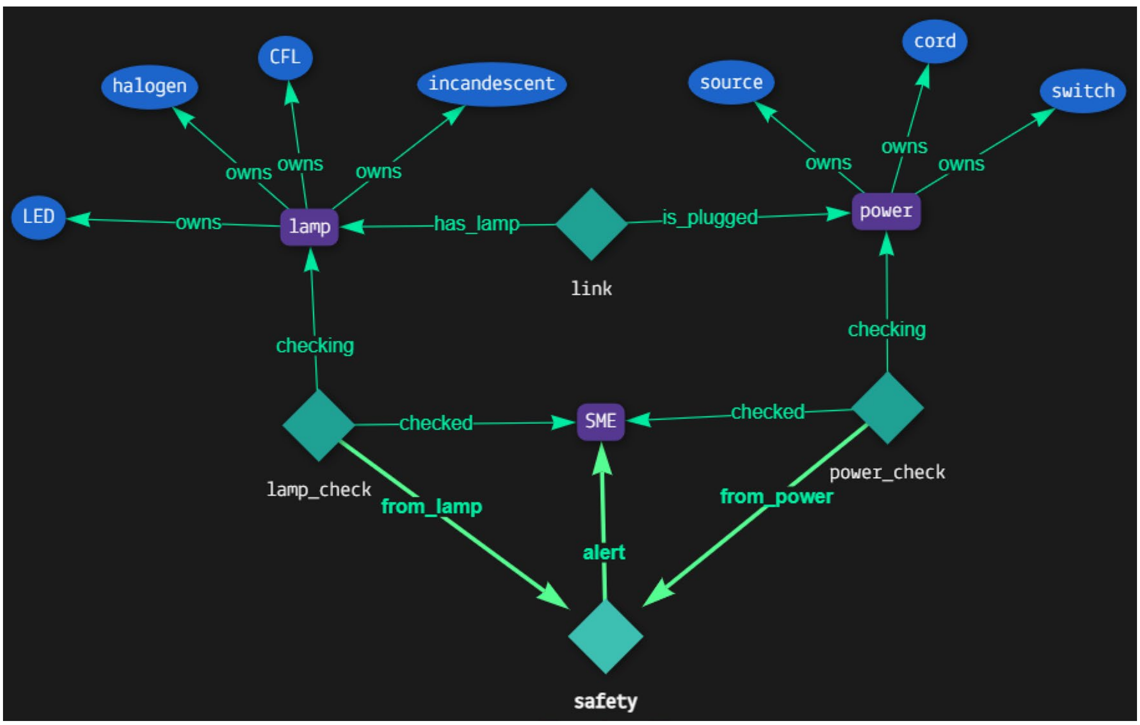


Fig. 3 Knowledge graph schema for the not-lighting lamp troubleshooting (*TypeDB* from Vaticle Labs)

- **Concept maps** or conceptual diagram is well-recognized approach [7] that uses both content knowledge and process knowledge to prompt users to create visual maps of a diagnostic strategy for identifying technical problems in complex environments [6]. A CM is a special type of propositional semantic network that is flexible, improves learning achievements, prompts constructive learning and active interactions [49, 50]. It is designed in the form of a directed graph where nodes represent concepts and edges represent relationships [51]. Despite being an old tool (1984), a CM visualizes the level of understanding and the level of thinking to assess the learning progress among human experts, displaying the structural nature and extent of knowledge, including misunderstandings of knowledge [49]. This aspect is quite important in our process because it facilitates human interactions and group synergies (Sect. 4). The CM [7, 52] is an alternative step for the automatic generation of concepts from texts to *operational knowledge graph* where we follow the CM mining frameworks described in [51, 53]. As an example, in Fig. 2 we present a fictitious example of a CM to illustrate the simple case of troubleshooting a not-lighting lamp.
- **Knowledge graphs** are more recent and adapted for automatic processing and machine reasoning than CMs. A KG acquires and integrates information into an ontology and applies a reasoner to derive new knowledge [8]. KGs can

efficiently express N-ary relationships between heterogeneous data in multiple domains using a hypergraph structure and clear denotation of entities, relations, and attributes. For example, in Fig. 3, we present the KG schema for the use case of troubleshooting the not-lighting lamp. The main difference with the equivalent CM in Fig. 2 is the new entity named *SME* and the nested relationships for the abstract roles played (safety and operational) introduced to capture the need for expert supervision.

A complete introduction to KG applications for different domains is in [9] with applications ranging from open KGs published on the Web, such as DBpedia, YAGO, Freebase, Wikidata, to proprietary enterprise KGs for a variety of different goals such as empowering business analytics, facilitating research and discovery, semantic search features and recommendations, detecting emerging events for FinTech, etc.

- **Ontology** promotes knowledge sharing [54] and offer a common communication mode for the knowledge elicitation process. The ontology describes and captures the domain knowledge [55], establishing the definitions of the technical concepts used by SMEs and providing the meaning of the relationships between technical terms and operational concepts. As such, ontologies aim to make domain knowledge explicit, remove contradictions and ambiguities, separate domain knowledge from operational knowledge, enable machines to reason and learn, and facilitate knowledge sharing between machines and humans [56]. Foundational domain ontologies have been developed for industrial domains such as aviation, aerospace, construction, steel production, chemical engineering, product development, and many others. A detailed presentation of the current state of ontologies for Industry 4.0 and reviews for existing ontological frameworks and ontological standardization efforts can be found in [43]. However, the typical condition is that a full ontology for a particular industrial domain does not exist or is available only partially. In this case, the enterprise domain ontology can be developed from the CMs [45], with the foundational ontologies used as baselines for the collaborative process described in Sect. 4.

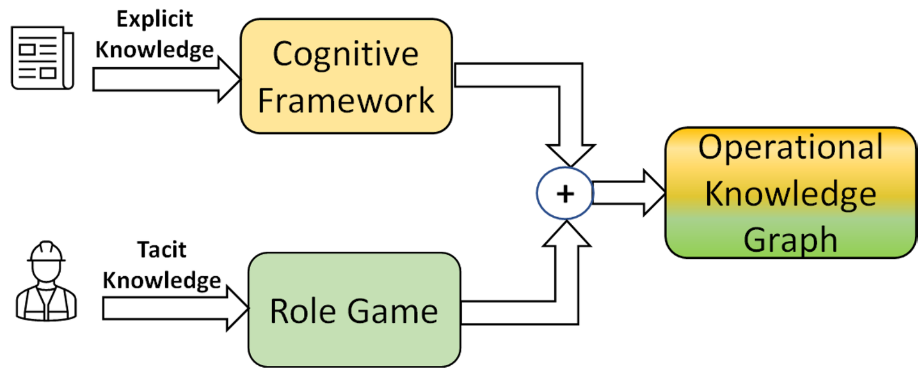
  Many methods for ontology learning from text or automatic ontology-population with NLP techniques have been investigated in the literature. For example, in [57], the author provides a knowledge repository of ontology learning tools; in [58], is presented how to populate an ontology with deep learning-based NLP methods from biological documents, and in [59] NLP techniques for ontology population using a combination of rule-based approaches and machine learning are discussed as well. However, only for specific and well-defined domains a fully automatic ontology construction using textual data is feasible [60]. Tacit knowledge is non-verbal and unexpressed; this makes the process of fully automating ontology learning an open research challenge, requiring human cognitive processing mandatory. We satisfy this requirement with a cognitive reasoning system and the role-playing game.

3.1.3 Symbolic layer

Once concepts have been formed in the conceptual layer, the SMEs and the knowledge engineers improve the knowledge models generated, adding new concepts and relationships in a collaborative knowledge construction process that takes into account the tacit knowledge. The symbolic layer is where the concepts initially formed in the conceptual layer (and sometimes ill-formed) are validated to create a consistent operational KG. Here we mainly refer to ontology alignment [61, 62] expressed for making integration into a data graph schema possible. The implicit knowledge is also converted into explicit knowledge and encoded in an ontological structure during the collaborative knowledge process (Sect. 4). We follow an iterative process of learning cycles for learning how to build an enhanced KG by improving the capabilities to integrate new fragments of knowledge extracted from the conceptual layer.

Logical reasoner Partial information is naturally stored in a graph where the relationships between operational concepts are integrated with an enterprise domain ontology, while the logical reasoner infers implicit knowledge. This paper, follows the KG life cycle described in [63] with three distinct reasoning phases. In particular, in the learning phase (see Fig. 5), we reason for knowledge integration and knowledge discovery (Sect. 4: Phase III), and we use the logical reasoner to derive new knowledge, add missing knowledge to identify conflicting information generated in the conceptual layer . We note how some aspects of tacit knowledge can be encoded in the KG model as logical rules. For example, in the non-lighting lamp problem (see Figs. 2 and 3), there is no direct relationship between incandescent lamp and filament condition (broken or intact), but it can be added to the data schema with a rule stating that when the filament for an incandescent lamp is broken, then the lamp does not light-up. Finally, reasoning for application service is related to the operational phase (Sect. 4: Phase IV), when knowledge is retrieved for knowledge base question answering (KBQA)

Fig. 4 Knowledge Elicitation Process functional diagram



services or for search services to provide on-site training to new hires. A detailed discussion of reasoning in KGs can be found in [63, 64].

3.1.4 Development software

We have used an exploratory programming approach to support the solution proposal described in this paper. We use the ContextMinds[2] tool to merge CM and KG. We use Text2Onto [65] for OWL ontology learning from text because knowledge is modeled at a meta-level and can be easily translated into different target languages. This tool also features algorithms for generating terms, synonyms, concepts, taxonomic and non-taxonomic relations. For the graph database, we use TypeDB[3] that provides a strongly typed knowledge representation system based on hypergraphs and enables modeling any type of complex network with an ontological schema. TypeDB ontologies do not work with RDF triples but with a concept level entity-relationship model, representing data with entities, relations, roles, and attributes. An embedded reasoning engine can interpret the resulting knowledge representation system with TypeQL query language. For KG reasoning, we have also explored RNNLogic [66] for its capability to train a reasoning predictor with logic rules. For NLP analysis, we also use Stanza [67], a Python NLP library for syntactic analysis.

4 Knowledge elicitation process

The knowledge elicitation process consists of a set of methods to elicit the tacit knowledge of a domain expert [68] with a mix of algorithmic techniques and a cooperative game. In particular, we focus on problem-solving knowledge [69], which is about capturing the domain knowledge of workers in a specific industrial structure during the accomplishment of tasks, such as maintenance operations, troubleshooting, and reparations. In management contexts, many different techniques have been proposed [12]. Our proposal goes beyond these techniques and describes a two-stages elicitation process based on (I) a cognitive framework that automatically transforms heterogeneous textual inputs and domain ontologies into a raw KG using explicit knowledge, and (II) a *role game* paradigm, in which human (H) and virtual (V) participants with different skill levels, from experts (E) to apprentices (A), play together to refine the KG using human cognitive processing for implicit knowledge integration (see Fig. 4). The primary motivation for our proposal is the incompleteness and inconsistency of KGs generated using only explicit data due to the heterogeneity and uncertainty of the textual sources and the evolution and acquisition costs of data and knowledge [70]. In order to infer and add missing knowledge to the KG or identify erroneous information, the KG refinement stage is needed. Several methods have been proposed [10] for the expansion and the enrichment of KGs, but we will be more interested in enriching the ontology of the KG since we use reasoning techniques as the main semantic operation during the KG refinement.

Moreover, in the case of tacit knowledge, a richer ontology is conditioned by human experts' supervision and human cognitive processing operated in the role-playing game (see also Sect. 3.1.2). Our configuration echoes the renowned Turing's imitation game but is significantly different. We implement a role-playing game where the objective is not to

[2] www.contextminds.com.
[3] vaticle.com.

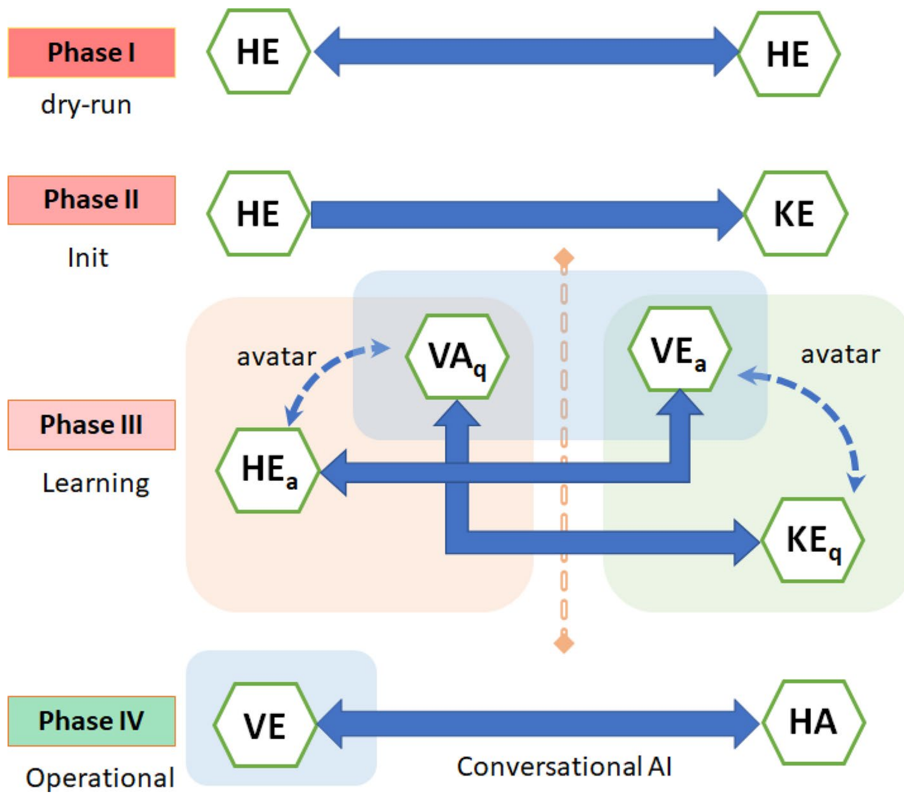


Fig. 5 Phases for the Knowledge Elicitation Process: *HE* is the Human Expert, *HA* the Human Apprentice, *KE* the Knowledge Engineer, *VE* the Virtual Expert, and *VA* Virtual Apprentice. KE_q and VA_q are the Knowledge Engineer and the Virtual Apprentice asking questions, while HE_a and VE_a are the Human Expert and the Virtual Expert giving answers, respectively. Phases I, II, and III capture tacit knowledge into a KG, while Phase IV is the operational setup-up when the human apprentice interacts with the virtual expert (the cognitive assistant)

assess if the virtual assistant has acquired some human characteristics, but rather to assess the correctness and reliability of the knowledge transferred between human and virtual agents and facilitate as much as possible the translation of SMEs tacit knowledge into valuable explicit knowledge through socialization and externalization (Sect. 3). The knowledge creation framework allows the transfer of insightful knowledge from SMEs to virtual agents in an iterative learning process under the supervision of human experts. This point is particularly critical because only human agents can diagnose why and how the virtual assistant may or may not be successful at specific tasks.

For completeness, this type of translation based on the SECI model is not new and has been described by other researchers [71]. The role game as a simulation of the professional activity with the participation of several experts has been described in [12] but without the involvement of the virtual agents. The participation of human experts in the knowledge elicitation process will also safeguard against possible collateral effects. In some instances, the tacit knowledge employed by SMEs is incorrect or dangerous and shall not be exposed to the virtual assistant during the learning phase. Incorrectly used equipment, incorrectly interpreted results, or procedural shortcuts can impose risks on the product and service quality and negatively impact employees' and consumers' safety. This aspect goes beyond the logical reasoning capability of the virtual assistant and a purely algorithmic approach. Therefore, the knowledge engineers—the game's referee, will double-check the practices used by the SMEs and determine which knowledgeable facts can be kept and stored in the KG and which others must be questioned and avoided because they are dangerous, unsafe, or illegal. In this way, we ensure that the human apprentices can eventually interact with the cognitive system in the operational phase without the risk of learning uncontrolled facts that may compromise their learning experience and future productivity in the organization.

4.1 Knowledge elicitation work-breakdown

The overall process for capturing tacit knowledge can be broken down into four phases (see Fig. 5). The objective of the first three phases is to capture tacit knowledge into a KG in a role-playing game similar to a video conference. The last phase is not scoped in this paper but is briefly described.

- **Phase I—Dry Run**: In this phase, two human experts (*HE*) generate reference CMs that are compared against the expert's CM generated on similar use cases. We will assess whether the experts can sustain a rich technical

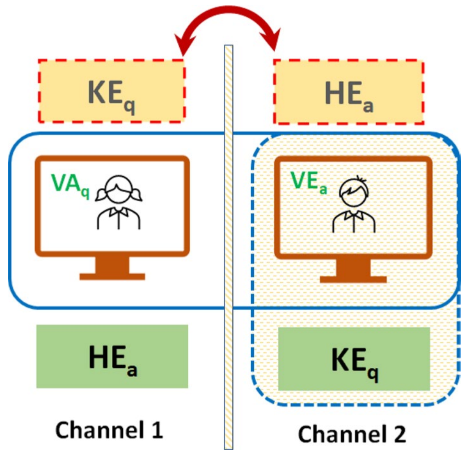


Fig. 6 Phase III—Learning. On channel 1, HE_a is the Human Expert giving answers, VA_q the virtual apprentice asking questions impersonated by its avatar on the screen masking the Knowledge Engineer asking questions KE_q. On channel 2, VE_a is the Virtual expert giving answers impersonated by its avatar on the screen masking the human expert HE_a accordingly. The rectangle with dashed border captures the configuration used in Phase IV (operations) where we eventually replace KE_q with the apprentice *HA*

exchange in a simulated working environment that may look unfamiliar. The rationale is to select the most knowledgeable experts on their subject of expertise and ensure optimal collaboration with the other team members (the apprentice and the knowledge engineer).

- **Phase II—Init**: We start by replacing the less performing *HE* with a knowledge engineer (*KE*) to coordinate the elicitation process. The *KE* will also impersonate the apprentice. Selecting the *HE* and the *KE* that fit better is critical for the rest of the process. There may be experts who know *how to do* but cannot explain the process they do. To mitigate this possibility, we introduce the role of the *game master* played by the *KE*, who facilitates the communication exchange with SMEs. The *KE* should be technically knowledgeable and possess a positive command attitude and directional authority to create a friendly environment and make knowledge transfer possible. The natural choice is to select the knowledge engineer from the pool of the best-performing SMEs, but other options that strongly depend on the corporate culture and personnel availability are possible. The *HE* and the *KE* will also create gold standards for quality assessment made of CMs extracted by human annotators from a set of tests [53].
- **Phase III—Learning**: In the learning phase, the virtual expert learns concepts and relationships from the role game technical session played by SMEs and knowledge engineers. We use CMs mining techniques [53] and ontology learning methods to generate an operational KG. The human expert (*HE*) is challenged by the *KE* impersonating the apprentice. The initial KGs are enhanced via an iterative Q&A session when the participants exchange technical information until the *HE* and the *KE* agree that a successful knowledge transfer has been completed. Typical examples are machine service, industrial troubleshooting, production processes control, etc. The decision process between the *HE* and the *KE* can be easily automated in case of conflicts introducing a majority vote mechanism.

  The human/machine interaction is done on two channels: *channel 1* between the virtual apprentice (*VA*) and the *HE*, and *channel 2* between the virtual expert (*VE*) and the *KE* (Fig. 6). The rationale is to isolate direct interactions of the human agents, which are gradually replaced by their virtual counterparts impersonated by *avatars* depending on the level of quality reached in the sessions. The quality of the concepts produced in this phase will be scored by measuring the semantic similarity between concepts generated by the apprentice and the expert [72]. In particular, *channel 1* isolates the interactions of the human expert giving answers (HE_a) and the knowledge engineer asking questions (KE_q) through the virtual apprentice (avatar) asking questions (VA_q), and *channel 2* isolates the interactions of the KE_q and the HE_a through the virtual expert (avatar) giving answers (VE_a). This arrangement in which humans are represented as avatars in a virtual environment and where each human sees the other as an avatar on their screen has been described in [73] in the context of an autonomous system for achieving artificial general intelligence. However, our arrangement aims to activate the experts' minds and reveal their tacit and implicit creative thinking procedures in a role-playing game [12] for KG refinement. Accordingly, the cognitive system learns to virtualize human agents for knowledge transfer. We also note that in the process described, some of the implicit cultural values of the organization—the tacit knowledge, are implicitly captured and encoded in the knowledge base schema.

- **Phase IV—Operations**: In the operational phase, the *VE* replaces the *HE*, and the *HA* replaces the *KE*. In this phase, the final KG is integrated into a cognitive system to allow new hires to formulate a technical problem as a collaborative task to the virtual expert, elicit mental models, and analyze the results [6] for knowledge retrieval and knowledge visualization [74]. Research done on regular classrooms has shown that learning with KGs resulted in better performance by students [49]. We expect the same improvements for workers in the industry interacting with this cognitive system for on-site training services.

5 Ethical and societal implications

Ethical and societal concerns are inevitable for the cognitive system we have described. Organizations should be vigilant about the knowledge management procedures for transferring tacit knowledge to be fair and equitable for human participants in the process. Once successfully trained, the cognitive system will operate in an industrial environment to allow new hires for on-site training. All the aspects of knowledge management shall be considered: from knowledge creation to knowledge transfer, from knowledge sharing to knowledge governance [75]. Should the system operate with a conversational AI user interface, impact assessment for the creation and use of the interface [76] shall be conducted by an independent organization before deploying the system. More specifically, from a societal and ethical standpoint, we can demarcate three points of interest that broadly track, data, model, and impact:

1. **Data** relates to concerns around what data is used and how the data is collected. Regarding what data is used, we note above that we propose using technical documentation and internal reports rather than video and audio assessment. Notwithstanding this, our approach lends itself to others using this kind of data. This is problematic because the collection of *emotive* data (such as verbal and facial expressions) requires surveillance of staff over long periods. The ethical concern here is one of consent and the appropriateness of the potential use of emotive data.
2. **Model** relates to the conceptual and symbolic layer we have discussed above. Here ground assumptions are made, which may be deemed contentious given that behavior analysis is occurring. Concerns with bias can be raised regarding the exclusion of various types of unconscious behavior such as routed in variations in customs, language use—here, the danger of excluding certain sources of tacit knowledge is what is of concern.
3. **Impact** relates to how tacit knowledge is used and the readiness with which the techniques of assessing non-algorithmic factors such as unconscious, unexplained knowledge can be abused. In essence, the rendering explicit of that which is implicit can be used to monitor *subliminally* and possibly thereby manipulate staff, a concern the EU AI Regulation draft (2021) raises as a critical concern [77]. In sum, these ethical and societal considerations can be addressed through accountability, transparency, and good governance mechanisms, such as those proposed in [78].

Allying with this board demarcation is the vibrant policy and regulatory debates and proposals relating to the ethical and societal implications and management of such systems. For example, at the state and federal levels of the United States, there are both existing and proposed regulations [79]; in the UK, worker and talent management is a case studied extensively as a critical area of legislative concern (moving beyond surveillance to include mental autonomy and well-being) [80]. Finally, the most advanced regulatory intervention is the proposed EU AI Act [77], which categorizes any algorithmic system used in the context of human resources as *high-risk* and thereby requiring the highest level of governance and assurance. The significance of these developments can be thought of as going beyond engineering validation and efficacy to one of societal impact.

We conclude with a real case about ethical and privacy implications concerning intellectual properties (IP) for tribal knowledge. We have discussed in Sect. 2 that one traditional method for capturing tribal knowledge is based on internal reports. The USPTO has granted recently (2019) a patent to IBM [81] about maintaining tribal knowledge for accelerated compliance control deployment building a tribal knowledge graph or knowledge base comprising a semantic level and an operational level, focusing on knowledge that does not exist or is not kept up-to-date in a traditionally structured, well-defined, coherent set of documents. We observe that the general idea to capture tribal knowledge into a KG is similar to ours, standing the different definition for tribal knowledge (Sect. 1). Moreover, it is a contrived trick to define tribal knowledge as *knowledge that does not exist* because even if unstructured, it is already explicit and can be easily captured by a process, machine, or computer system as it is claimed.

Nevertheless, this particular definition of tribal knowledge ensures the patent's claims eligibility since they are not directed towards managing personal behavior, relationships, or interactions between people. It removes all the complexity of the process described in Sect. 4. On the contrary, the ideas described in this paper are not patentable in the US because *methods which can be performed mentally, or which are the equivalent of human mental work, are unpatentable abstract ideas* [82]. Similar restrictions apply in other countries. In the UK, it is not patentable *a scheme, rule or method for performing a mental act, playing a game or doing business, or a program for a computer;* [83]. The rationale is to avoid patenting a system that will result in certain harmful adverse effects on technology related to concepts performed in the human mind, which can create unintended ethical and privacy challenges despite solving critical social issues [84]. Once again, these ethical considerations can be addressed through accountability, transparency, and good governance mechanisms but pose serious problems to those organizations that want to apply tacit knowledge management principles for their business.

6 Conclusions

We have described a solution proposal for capturing operational best practices of experienced workers (a.k.a. the tacit or tribal knowledge) in industrial domains for knowledge transfer. We use domain ontologies for Industry 4.0 and reasoning techniques to discover and integrate new facts into an operational KG. We describe a concepts formation iterative process to integrate explicit and tacit knowledge in a role game played by subject matter experts and knowledge engineers interacting indirectly with a virtual agent represented by an avatar. At the end of the learning phase, the expert is replaced by the virtual agent, and the knowledge engineer is impersonated by new hires or workers that need on-site training. Societal and ethical concerns have also been discussed.

7 Future directions

We plan to consolidate the investigations performed and develop the complete cognitive architecture to validate the method proposed in this paper. We also plan to extend the sensory input modalities to video stream sources for using T-Patterns analysis [85], adopting the approach described in [73] that may be used to improve the completeness of the operational KGs for troubleshooting tasks during the learning session with a better identification of temporal and sequential patterns—typical of manufacturing industrial processes.

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