CogBPMN: Representing Human-computer Symbiosis in the Cognitive Era

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Abstract: The human-computer symbiosis is a core principle of Cognitive Computing where humans and computers are coupled very tightly, and the resulting partnership presents new ways for the human brain to think and computers to process data. Business Process Management (BPM) provides methods and tools to represent, review, and discuss business domains, considering their knowledge, context, people, computer systems, and so on. Such methods and tools will be affected by advances in Cognitive Computing. Business Process Modeling notations need to support discussion and representation of human-computer symbiosis in any given organizational context. We propose CogBPMN, a set of cognitive recommendation subprocesses types that can be used to represent human-computer symbiosis in business process models. With CogBPMN, business stakeholders and Cognitive Computing specialists can understand how business processes can thrive by considering cognitive empowerment in organizations' core processes. We discuss the proposed cognitive subprocesses in a medical domain use case.

1 INTRODUCTION

In the past, Cognitive Computing aimed to develop a coherent, unified, universal mechanism inspired by the mind's capabilities (Modha et al., 2011). It focused on investigating the development of self-learning systems, which naturally interact with humans in complex environments, and are capable of adapting themselves to context. More recently, the idea of a human-computer symbiosis is gaining momentum in the Cognitive Computing research (Kelly, 2015) where humans and computers collaborate, using their unique and powerful capabilities, to build an environment where knowledge is created and evolves considering environment events. Computers bring their capability to deal, in different ways, with large sets of data, which is impractical for the human brain. On the other hand, humans provide their capability to judge and make decisions, to assess situations considering their intuition and all kinds of knowledge (structured, unstructured, subjective, etc.), and their ability to innovate in a given domain. Understanding this human-computer symbiosis is the key to the application of proper Cognitive Computing resources in any business domain.

The relationship between humans and computers is intricately established in any business and society. However, to understand and discuss it, considering the advantages of Cognitive Computing resources to the modeled business, we need to represent that relationship. Business Process Management (BPM) practices already present process modeling notations to represent business domains. BPM also investigates the bridge between business context and software systems, considering business process models as a source of early software system's requirements (Alotaibi and Liu, 2017). Therefore, business process models are a representation that can be used to express the human-computer symbiosis necessary to define artifacts for the development of cognitive systems. However, BPM still requires a "cognitive layer" above its practices to address the evolution and adaptation to the Cognitive Era. Cognitive BPM, coined in (Nezhad and Akkiraju, 2014), refers to a new paradigm in BPM, which encompasses all BPM contexts and aspects of its ecosystem that are impacted and enabled by Cognitive Computing technologies (Hull and Nezhad, 2016).

Any business process, from transaction-intensive to knowledge-intensive (Di Ciccio et al., 2015),

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has the potential for cognitive empowerment through human-computer symbiosis. Several organizations have their business processes designed with Business Process Model and Notation (BPMN) - the *de-facto* standard for business process modeling (Chinosi and Trombetta, 2012). BPMN already deals with human-computer relation, *e.g.*, the user representation supported by system task characterizes a human performing a task with the assistance of a software system (OMG, 2011). However, we believe that BPMN needs resources to support the discussion, representation, and specification of human-computer symbiosis necessary to develop cognitive systems.

The relation between humans and computers deals with other aspects of Cognitive Computing. For example, machine learning techniques support various human tasks involved in interpretative-intensive activities (Kelly, 2015). Some of those tasks, as depicted in (KPMG, 2015), are the identification of concepts in massive data, ranking web searches, pattern recognition, trend finding, and sentiment analysis on social media. With the immediate dissemination of such technologies, the relationship between humans and AI algorithms in daily tasks is undoubtedly becoming more transparent. The relationship between humans and computers in these cognitive scenarios is symbiotic: the quality of such cognitive systems increases because of the interaction itself. In this paper, we propose CogBPMN – four recommendation cognitive subprocesses types to represent human-computer symbiosis in business process models. The subprocesses indicate activities to represent actions for recommendation, creating evidence from the reasoning used to reach recommendations, and getting user feedback. Besides, the subprocesses suggest representations for the involved data and knowledge. We exemplify the use of CogBPMN, designing a business process of the medical domain scenario.

Our main motivations to propose CogBPMN are: (i) explore the representation of processes focusing on the modeling of Cognitive Computing activities; and, (ii) use BPMN to allow the analysis and (re)design of organization models containing such processes. Represent human-computer symbiosis in a business process that can be used by stakeholders and Cognitive Computing specialists to (re)analyze and (re)think processes and decide where the Cognitive Computing resources can make a strategical difference for businesses. In the current version of CogBPMN presented in this paper, we have chosen to focus on the modeling of recommendation processes (Rich, 1979), which is a classic standard process coming from experts and recommendation systems.

The remainder of this work is divided as follows. Section 2 presents the background. Section 3 presents our proposal. Section 4 presents an example of the use of the proposal. Finally, Section 5 concludes and presents future work.

2 BACKGROUND

Cognitive Computing refers to software (cognitive) systems that learn at scale from their interaction with humans and the environment. One of the defining characteristics of cognitive systems is that they are capable of improving their performance over time by leveraging its understanding of their users and application domain. Some requirements are: (i) interactions should be (at least partially) recorded; and, (ii) models should learn from previous interactions.
The research and development of cognitive systems involve multiple computer science areas of expertise. There must be a constant technical collaboration from different professionals to tackle the challenges of building a cognitive system. The areas involved depend on the problems that the cognitive system aims to solve. At least HCI (Human-Computer Interaction) experts (UX designers and HCI professionals) and developers need to work closely together to build a cognitive system. Designers and HCI professionals, working together with industry experts, place the new system in real scenarios; and developers and machine learning experts define the algorithmic strategy and datasets for solving the scenario problems. This multidisciplinary technical approach applied to Cognitive Computing differs from other current approaches of Artificial Intelligence (AI) that focus on algorithmic accuracy and not on the people that work with the system (Kelly, 2015). Cognitive systems allow humans and computers to collaborate and produce better results, each one bringing their superior skills to the partnership: computers with rational and analytics and people with intuition, empathy, and judgment. That is why this is such a multidisciplinary approach (Kelly III and Hamm, 2013). HCI (Human-Computer Interaction) is an important research area to investigate and explore human-computer symbiosis. HCI and AI expertise have been combined for some time (Grudin, 2009). The combination of HCI and AI research has been a concern of major tech companies like Google[1], which launched an initiative to study and redesign the ways people interact with AI systems (Holbrook, 2017).

We argue that a cognitive system learns whenever the output of a given model evolves due to

[1]https://ai.google/pair/

changes in the knowledge base. Therefore, one requirement is that models, in principle, should use the acquired knowledge in their predictions. This definition of learning is loosely based on (Mitchell and et al, 1997). In particular, we relax the performance measurement requirement, since evaluating "how good is the human-computer symbiosis" is a non-trivial task: *A computer program is said to learn from experience **E** with respect to some class of tasks **T** and performance measure **P**, if its performance at tasks in **T**, as measured by **P**, improves with experience **E**.*

Recommendation and Expert systems are references in AI for Cognitive Computing approaches. Recommendation, or recommender systems, are software tools and techniques that provide suggestions to support users' decisions (Adomavicius and Tuzhilin, 2005). Recommendation systems deal with the problem of estimating ratings for current items, usually based on the ratings given by the user to other items and/or by other users to the same items. Expert systems reconstruct the expertise and reasoning capabilities of qualified specialists within limited domains. The underlying assumption is that experts construct their solutions from single pieces of knowledge, which they select and apply in a proper sequence. Hence, expert systems require detailed information about the domain and the strategies for applying this knowledge to problem-solving. Those systems simulate problem-solving tasks over static representations of some knowledge domain (Kidd, 2012).

Although recommender systems include concepts of cognitive science (Rich, 1979), they handle recommendation problems that explicitly rely on rating structures. On the other hand, Cognitive Computing enables "knowledge acquisition at scale", *i.e.*, deeper than ratings of items, using emerging methods in natural language understanding and machine learning techniques (Hull and Nezhad, 2016). Expert systems, different from cognitive systems, do not aim for human-computer symbiosis, but to emulate human thinking and problem-solving abilities (Kidd, 2012).

The discussion, mapping, modeling, and representation of business scenarios are rich topics to be developed by the BPM research area. Those topics are related to the research of Cognitively-enable BPM (Hull and Nezhad, 2016), and referenced in our work as Cognitive BPM. Particularly those scenarios where people need to harvest insights from vast quantities of data to understand complex situations, make accurate predictions, and anticipate the unintended consequences of actions and other human-centered processes.

There are also important concepts and key abstractions for Cognitive BPM and Knowledge-intensive Processes (KiP's) research (Di Ciccio et al., 2015)(Hull and Nezhad, 2016)(Netto et al., 2013). Cognitive Computing presents the possibility of "knowledge at scale" (Hull and Nezhad, 2016). KiP's process representation deals with the life-cycle of knowledge in business processes. In that way, large amounts of knowledge relevant to a process instance can be considered as input for new process' instances and the model itself. Moreover, cognitive potential can be present in structured workflow processes to unstructured and knowledge-intensive ones (Hull and Nezhad, 2016). Also, the practice of software systems early requirement derivation from business process models (Alotaibi and Liu, 2017) can be applied for cognitive systems' specifications.

BPM has been used in different industries for over a decade (Van der Aalst, 2013). Hence, there is a large amount of pre-existing knowledge legacy of business processes models in organizations. The knowledge presented in those business models and their instances is a crucial asset for each organization that wants to advance to the Cognitive Era. Questions like "What and how can we learn through discussing and revising old business processes in the light of Cognitive Computing technologies?" and "What can happen to transactional processes once there is a technology to handle more volume of data and unstructured data?" are going to guide the Cognitive BPM research agenda. BPM activities, like mapping, modeling, and analysis of processes, can gain with Cognitive Computing technology abilities to explore and get insights from large amounts of business process data.

3 CogBPMN

This section describes CogBPMN, our proposal for representing cognitive subprocesses using BPMN. We focus on subprocess types that include recommendations, evidence that support those recommendations, and the handling of user feedback. The recommendation subprocesses are a guide since they contain activities that should be used when modeling a system that provides recommendations. We also present an abstract view about how to perform those activities, although it is not the focus of this work. Our current proposal of CogBPMN comprises four subprocesses types: (i) Recommendation subprocess; (ii) Recommendation with evidence subprocess; (iii) Recommendation with feedback subprocess; and, (iv) Recommendation with feedback and evidence subprocess.

Section 4 presents an example of the proposal for a cognitive application in the medical domain. In the following, we present the proposed BPMN four subprocesses types, and their abstract representation using BPMN subprocesses.

We decide to explore BPMN specification (OMG, 2011), which is the *de-facto* standard modeling language for business process modeling (Chinosi and Trombetta, 2012), to identify definitions and visual representations that could support our proposal for CogBPMN. Table 1 presents the elements and corresponding icons we are using in this work.

Table 1: BPMN elements used in this work.

Element	**Icon**
Service task	
User task	
Data store	
Data object	

We selected service and user tasks to represent advisor and user's tasks, respectively. A service task is a task that uses some sort of service ((OMG, 2011), pp.158). Its definition already covers our need to represent a task performed by an algorithm or service. We choose the user task element to represent tasks where humans execute an activity with the advisor's aid. A user task is a typical workflow task where a human performs the task with the assistance of a software application ((OMG, 2011), pp.163). In CogBPMN, the software application is the advisor for the represented subprocess.

We used the data store element to represent a generic knowledge base in the main process and also the specific data stores in the cognitive subprocesses. A data store provides mechanisms to retrieve or update stored information that will persist beyond the scope of the process ((OMG, 2011), pp.208). We created a specific data store called process instances' data store, which represents the data of the previously executed process' instances. The cognitive subprocess has the potential capacity to learn from its execution and the main process execution. We used the data object element ((OMG, 2011), pp.205-206) to represent specific instances data, and collection of instances data. Those elements are present in the main process model and the subprocesses.

BPMN is a flexible notation that allows its users to add more semantics to its elements, like addressing different meanings to the same element represented in different colors. For CogBPMN, there are specific demands that the notation specification needs to address. For example, the data store for process' instances usually needs to be handled on cognitive subprocess' new instances. Data stores remain generic and central for cognitive processes, representing data and knowledge generated and consumed throughout the process' instances. We argue that CogBPMN specification is a conservative extension (Turski and Maibaum, 1987) of BPMN to represent specific activities that define a pattern, as a specialized type of subprocess like Transaction, *Ad-Hoc* and Event Subprocesses ((OMG, 2011), pp.173-183). We are proposing a visual representation that does not interfere with the model notation specification but makes explicit and enriches the representation for identifying and discussing when the human-computer symbiosis happens in business processes.

3.1 Cognitive Recommendation Subprocesses

We present in this section, the four Cognitive Recommendation subprocesses. They are abstract representations, corresponding to suggestions of activities to be modeled in each case, *i.e.*, the process modeler designs those activities according to the scenario being modeled.

3.1.1 Recommendation Subprocess

Figure 1 illustrates an abstract representation of the *Recommendation* subprocess. This subprocess is extended by the other three by defining new activities and other elements. It is the simplest proposed subprocess.

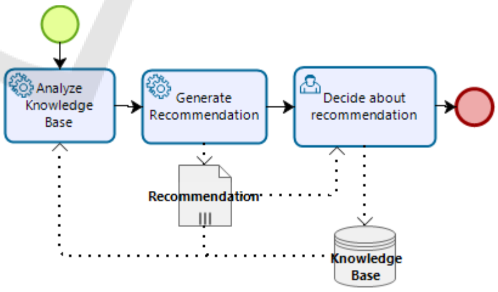

Figure 1: Recommendation subprocess abstract representation.

The first activity represents the advisor analyzing the knowledge base (KB) of the application to create hypotheses. The second activity represents the advisor generating the recommendations and storing such recommendations in (another) KB. These two activities can be merged into one activity if necessary, representing the analysis and the generation of recommendations. The third activity represents the actions of the user monitored by the advisor. This action could represent, for instance, the selection of an option from the list of options recommended by the advisor. They do not need to be executed immediately after the first two actions.

To provide recommendations to a user, the cognitive advisor analyzes available knowledge related to the application domain, the process being executed, and the process' instances already executed. Besides, the advisor can learn about the recommendations provided and the actions carried out by the user. For example, the advisor evaluates if the user has followed or not the recommendations and uses such information when making new recommendations. This example is a kind of implicit feedback produced by the user for the recommendations provided by the advisor. Some examples are:

- Using the history of actions executed by the user and his peers, the advisor recommends the next actions to be executed;
- Using previous recommendations and the most selected options in a specific context, the advisor suggests the ones the user may choose.

In both cases above, the advisor monitors the actions performed by the user to learn about its recommendations.

3.1.2 Recommendation with Evidence Subprocess

Figure 2 presents an abstract representation of *Recommendation with evidence* subprocess. It extends the *Recommendation* subprocess by making available to the user the evidence that supported each generated recommendation. Such evidence is relevant to the user to understand why the advisor has provided the recommendations. Recommendations and evidence are stored along with the actions taken by the user. The advisor can use these data to learn and make more precise recommendations. Examples of this type of process are:

- Besides recommending the next action, the advisor shows the user evidence like the history of previous interactions executed by him and by others;
- Besides suggesting options to the user, the advisor shows evidence like recommended and selected options in past similar contexts.

3.1.3 Recommendation with Feedback Subprocess

Figure 3 presents an abstract representation of *Recommendation with feedback* subprocess. It extends the *Recommendation* subprocess by allowing the user

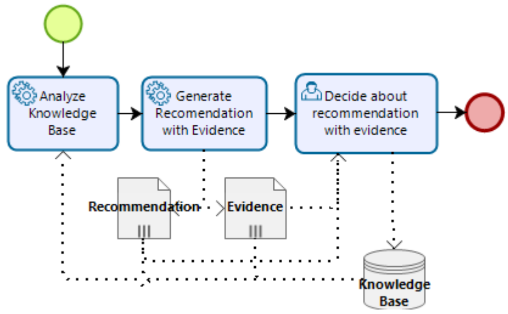

Figure 2: Recommendation with evidence subprocess abstract representation.

to provide feedback about the advisor's recommendations. This kind of feedback is explicit, different from the implicit feedback already present in the *Recommendation* subprocess. When given explicit feedback, the user informs if she/he likes or dislikes a recommendation. The advisor stores the recommendations, actions executed by the user, and the explicit feedback. It uses such knowledge to learn and to make improved recommendations. Examples of this type of process are:

- The user likes the recommended action and follows the recommendation;
- The user likes some of the recommended options and dislikes others;
- The user does not follow any of the recommended options.

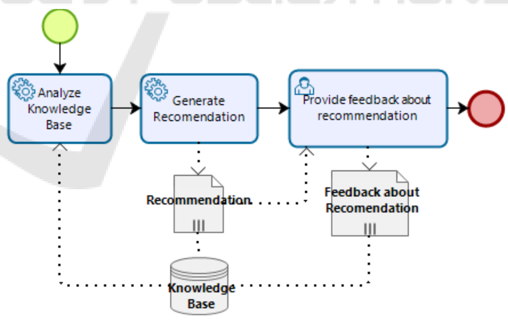

Figure 3: Recommendation with feedback subprocess abstract representation.

3.1.4 Recommendation with Feedback and Evidence Subprocess

Figure 4 presents an abstract representation of *Recommendation with feedback and evidence* subprocess. It combines the *Recommendation with evidence* and the *Recommendation with feedback* subprocesses by allowing the user to provide feedback not only about the recommendations made by the advisor but also about the evidence used to support them.

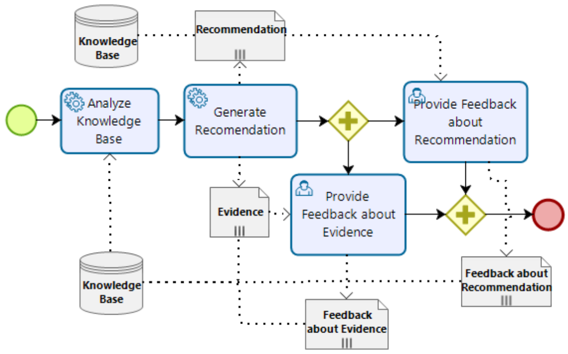

Figure 4: Recommendation with feedback and evidence subprocess abstract representation.

The advisor should store the recommendations, evidence, actions executed by the user, and also the feedback to provide a more precise recommendation. The feedback about evidence is essential, *e.g.*, to guide the advisor on the sources (knowledge-based, documents, etc.) it uses in its analyses. Some examples of *Recommendation with feedback and evidence* subprocess are:

- The user likes the recommended actions and also agrees that the previous actions executed in similar contexts are the correct evidence to be used;
- The user wants the recommended options but does not agree with the evidence. The user explains the context considered by the advisor is not similar to the context of the execution.

The *Recommendation with feedback and evidence* subprocess is the most complete proposed cognitive recommendation subprocess. The other subprocesses are simplifications of this one. The first and second activities (*Analyze Knowledge Base* and *Generate Recommendation*) are present in all recommendation subprocesses. To provide recommendations to a user, the cognitive advisor analyzes available knowledge bases (KBs) of the application domain and the process' instances already executed. Besides, the advisor can learn from previous recommendations and the actions carried out by the user stored in the process' instances KB. The advisor evaluates if the user has followed or not the recommendations and uses such information when making new recommendations. The information about the user's decisions for the recommendations is a kind of implicit feedback used by the advisor.

In the feedback, the user informs if she/he likes or dislikes the recommendation, and if she/he agrees or disagrees with the evidence used to support the recommendation. In both cases, the user should also be able to include comments (*e.g.*, expressed in natural language) about the recommendations and evidence. For instance, on the one hand, the user may like the recommendations but understands that the evidence supporting the recommendations are not adequate. In such a case, the advisor has provided the right recommendations based on the wrong evidence. On the other hand, the user may dislike the recommendations, but agree with the evidence. In this case, the advisor has provided the wrong recommendation based on accurate evidence.

The advisor should store the recommendations, evidence, actions executed by the user, and the feedback to provide a more precise recommendation. The feedback about evidence is essential, *e.g.*, to guide the advisor about the sources (knowledge-based, documents, etc.) it uses in its analyses.

4 EXAMPLE OF MODEL USING CogBPMN

This section presents an example using our proposal of cognitive subprocesses types (CogBPMN) to model the business process that represents the Doctor Oncology scenario (Figure 5). This scenario illustrates the use of IBM Watson for Oncology[2], the AI technology from IBM, which helps physicians quickly identify critical information in a patient"'s medical record, surface relevant articles and explore treatment options to reduce the unwanted variation of care and give time back to their patients.

The process *Perform Clinical Assessment for Oncology treatment* (Figure 5) starts the cognitive doctor advisor, which helps a doctor (*i.e.*, the user) to analyze patient's medical records and previous exams by highlighting the potentially significant aspects for a given patient disease. The advisor monitors the user's interactions to learn and provide recommendations.

The activity *Analyze Patient's Medical Records* is detailed following the CogBPMN's *Recommendation* subprocess type (Figure 1) through the subprocess presented in Figure 7. The advisor analyses the aspects visualized by the user about the patient current medical status (activity *Analyze Patient Current Medical Status*). The advisor learns from this (activity *Analyze Medical Knowledge*), and provides recommendations for future actions information. The user makes decisions about the provided recommendations (activity *Decide about Relevant Medical Recommendations*).

The next cognitive activity of the oncology process, *Analyze Analogue Cases* (Figure 5), is detailed

[2]https://www.ibm.com/products/clinical-decision-support-oncology

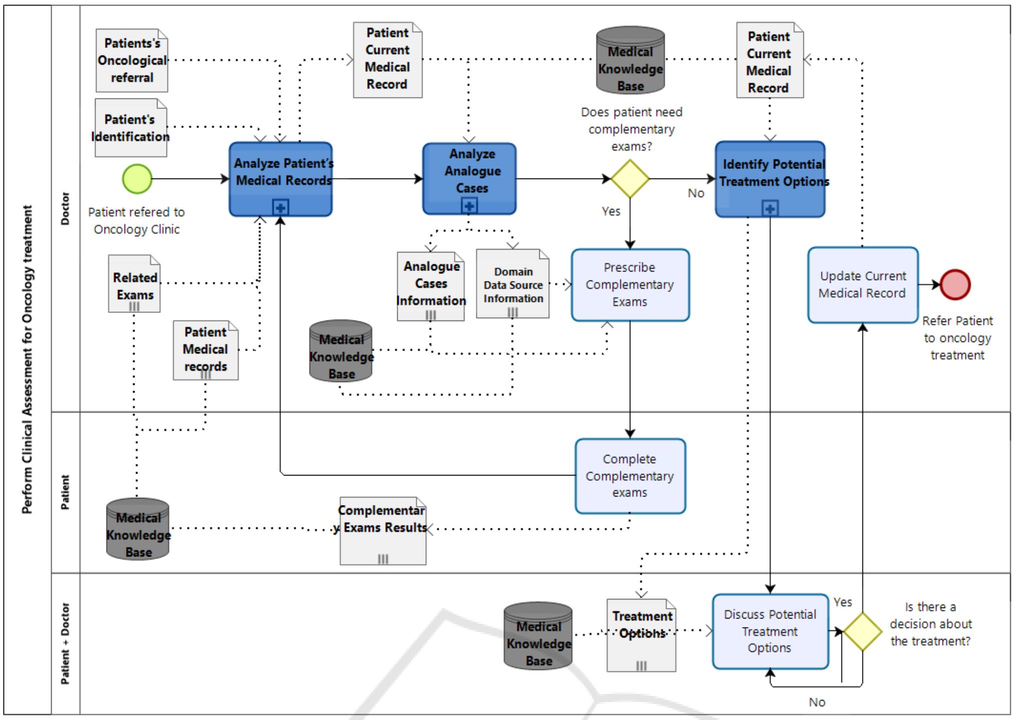

Figure 5: Perform Clinical Assessment for Oncology treatment process - main process.

following the CogBPMN's Recommendation with feedback and evidence subprocess (Figure 4) through the subprocess presented in Figure 6. The advisor analyzes characteristics of other patients' analog cases by taking into account: (i) the feedback about recommendations provided to such analog cases; (ii) the evidence used to support such recommendations and the feedback they received; and, (iii) the patient current medical record (activity Analyze Analogue Cases). Afterward, in the activity *Analyze Related Domain Data Sources*, the advisor uses the *résumé* about analog cases generated in the previous activity to provide recommendations about the current patient case and the evidence, such as books, papers or medical records of other patients, to support the recommendations. Then, the user provides feedback about the recommendations (activity *Provide Feedback about Recommendation*) and the evidence (activity *Provide Feedback about Evidence*). Back to the main process (Figure 5), the doctor decides if the patient should do complementary exams.

The next oncology process' cognitive activity *Identify Potential Treatment Options* (Figure 5) is detailed following the CogBPMN's *Recommendation with evidence* subprocess (Figure 2) through the subprocess presented in Figure 8. The advisor analyzes the case information and identifies a prioritized list of treatment options by associating then with a set of evidence that supports such a list (activity *Generating Treatment Options*). The advisor monitors the treatment chosen by the doctor and uses such information when making new recommendations about treatments. Then, the doctor explores the recommendations and evidence (activity *Explore Treatment Options and Evidence*).

Finally, the doctor discusses potential treatments with the patient (activity *Discuss Potential Treatment Options*), and, if a decision about the treatment rises, the doctor updates the patient's medical record (activity *Update Current Medical Record*).

5 FINAL REMARKS AND FUTURE WORK

Several works have evaluated the cognitive load to understand process models in specific BPM notations (Gruhn and Laue, 2006)(Gruhn and Laue, 2009)(Holschke et al., 2009). More recently, some authors have presented the impact of cognitive systems in BPM systems. Two major theoretical contributions on that subject are (Rich, 1979): 1. a framework of how cognitive systems will impact BPM; and, 2. a meta-model called *Plan-Act-Learn* for Cognitive-Enabled processes.

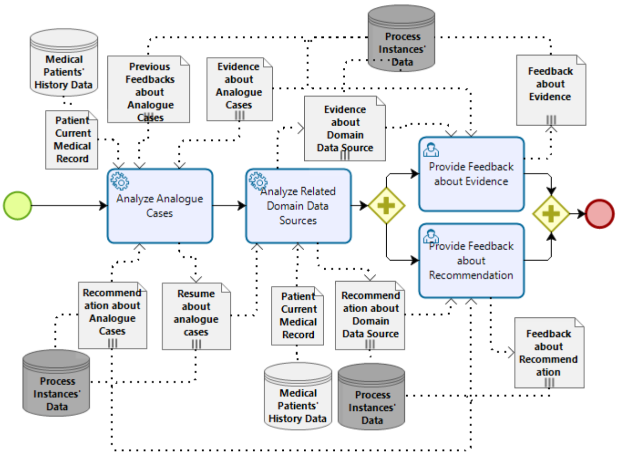

Figure 6: Recommendation with feedback and evidence subprocess of doctor advisor process.

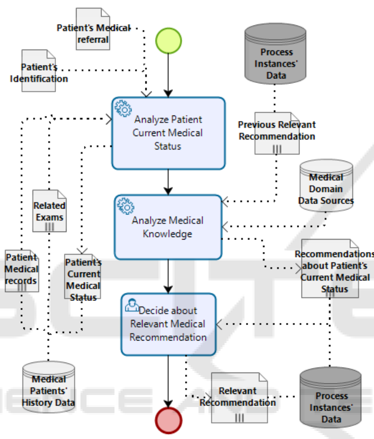

Figure 7: Recommendation subprocess of doctor advisor process.

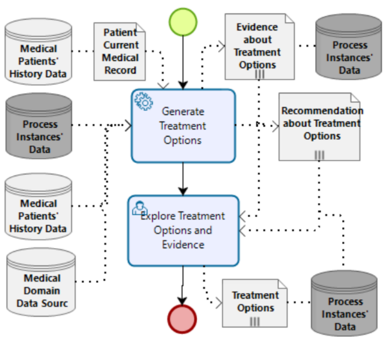

Figure 8: Recommendation with evidence subprocess of doctor advisor process.

However, to the best of our knowledge, no work proposed the extension of BPMN or other BPM notation to model cognitive related activities[3], which is the goal of this paper. Therefore, this paper introduces an innovative approach to model cognitive activities as BPMN subprocesses. The proposed approach encompasses four complementary recommendation subprocesses. The use of the approach to model the Doctor Oncology scenario makes clear those subprocesses should be used to model different kinds of recommendations.

Our proposal points out which parts of a process could be modeled as a cognitive subprocess along with which kinds of cognitive activities should be modeled if the process includes recommendations, evidence, or feedback. The proposal is in the abstract conceptual level presenting some directions on what should be considered by the subprocesses' activities. Hence it does not present how advisors should be combined nor which algorithmic approaches should be used to keep the knowledge base evolving, which is leveraged to the implementation phase.

We intend to extend CogBPMN to model other kinds of cognitive subprocesses, such as the learning process itself. In this work, the learning process is presented as an intrinsic characteristic of the recommendations subprocesses. However, the modeler should be able to represent which classes of learning algorithms (or models) that are more suitable for each type of subprocesses. Some goals are better or only achievable with particular algorithms. For example, if the subprocess requires that evidence should support the recommendations, neural networks[4] cannot be used (Adomavicius and Tuzhilin, 2005). The proposed subprocesses learn in the sense that previ-

[3] Research conducted using Google Scholar (http://scholar.google.com). It consisted of finding extensions for Business Process Models; several were found: for SOA (Service-Oriented Architecture), aspects, and model-driven BPM, among others.

[4] Weights in Artificial Neural Networks are not easily interpretable.

ously acquired knowledge are (or should be) leveraged by models in their predictions. Learning could be achieved by retraining the models.

Moreover, we are in the process of defining visual elements in BPMN to represent the four recommendations cognitive subprocesses. For example, we could use a specific icon (like the one depicted in Figure 9) for an activity expanded by a cognitive subprocess.

Figure 9: Icon for CogBPMN activity.

In the following, we intend to evaluate the proposed notation by surveying experts in BPM and BPMN, and domain experts to discuss real business processes exploring opportunities to take advantage of cognitive technology to empower human-computer interaction. We also intend to evaluate the proposal in modeling other kinds of processes like transactional and knowledge-intensive processes in the oil and gas domain. As another future work, we plan to evolve CogBPMN with other cognitive subprocesses types than the proposed four in the current approach, *e.g.*, conversation subprocess where the advisor identifies the willingness of the user by understanding the user's questions through tracking questions and the provided answers and the feedback of the user to which questions were correctly answered.

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