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Journal of Biomedical Informatics 41 (2008) 217–223

Journal of Biomedical Informatics

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Tracing and cataloguing knowledge in an e-health cardiology environment

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Received 26 September 2006

Available online 14 September 2007

Abstract

In an e-health cardiology environment, the current knowledge engineering systems can support two knowledge processes; the knowledge tracing, and the knowledge cataloguing.

We have developed an n-tier system capable of supporting these processes by enabling human collaboration in each phase along with, a prototype scalable knowledge engineering tactic. A knowledge graph is used as a dynamic information structure. Biosignal data (values of HR, QRS, and ST variables) from 86 patients were used; two general practitioners defined and updated the patients' clinical management protocols; and feedback was inserted retrospectively. Several calibration tests were also performed.

The system succeeded in formulating three knowledge catalogues per patient, namely, the "patient in life", the "patient in time", and the "patient in action".

For each patient the clinically accepted normal limits of each variable were predicted with an accuracy of approximately 95%. The patients' risk-levels were identified accurately, and in turn, the errors were reduced. The data and the expert-oriented feedback were also time-stamped correctly and synchronized under a common time-framework.

Knowledge processes optimization necessitates human collaboration and scalable knowledge engineering tactics. Experts should be responsible for resenting or rejecting a process if it downgrades the provided healthcare quality.

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Keywords: Scalable knowledge process; e-Health; Knowledge engineering; Collaborative system

1. Introduction

In a medical environment, current knowledge engineering systems are able to support two knowledge processes: *knowledge tracing*, the processes that the system executes to produce knowledge; and *knowledge cataloguing*, the processes that the system executes to classify existing knowledge [1–5]. These processes cannot be sustained without dynamic dealing with the vast amounts of heterogeneous data and knowledge existing distributed in the environment [6].

However, several systems [2,3] still use the following: (i) resident assessment tactics to trace biosignal data, (ii) generic criteria within the resident assessment tactics to catalogue knowledge, (iii) predetermined non-personalized risk criteria to activate generic alarms, and (iv) limited feedback insertion. The first cause is that physicians on-duty due to their heavy workload, do not have the time to define and update the patients' clinical management protocols (CMP) and then check the outcomes by considering multiple variable values, following complex operating logic, and physically manipulating software modules [7]. The second cause is that usually there are differences in knowledge, skills, and orientation among the various healthcare providers (such as physicians, general practitioner etc.) [7,8]. Therefore, although the potential of the knowledge engineering systems is great, their outcomes often are insufficient [4,5].

Continuous human-agent collaboration and scalable knowledge engineering tactics, may be a solution. However, they necessitate heterogeneous human-machine inter-

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doi:10.1016/j.jbi.2007.09.001

action and, tasks that allow the collaborators to surpass the need of working at the same place and time [1,9]. Furthermore, data and feedback have to be time-stamped under a common framework [4,10] while the human factor needs to be investigated [11,12].

In an e-health cardiology environment, the investigation of issues referring to the aforementioned requirements is relative to the thorough understanding of the interrelationships between collaborators (e.g., patient, general practitioner, physician, expert) [13], the data they use, the typical and atypical tasks they perform, and the structure (portable biosignal devices, human-machine interfaces, modules etc.) in which they collaborate [7,14,15]. Following this understanding, specific pathways of continuous multi-level collaboration and scalable knowledge engineering tactics can be established, resulting in personalized data assessments [16,17]. Tasks that can be hazard-related and are not anticipated can also be recognized [15]. This is important as it is extremely difficult to identify all significant hazards in advance [4,11,18–20].

After these steps, knowledge processes outcomes can possibly be optimized, hazard can be mitigated or controlled, and patient's risk-level can be identified more efficiently.

In this study, we propose a system able to support the tracing and cataloguing of the knowledge in an e-health cardiology environment, by utilizing the human collaboration in each phase of a process, and a scalable knowledge engineering tactic, called self-paring tactic. Our objective is to minimize errors, ensure that intended collaborators are able to perform the essential tasks safely and effectively throughout the knowledge processes, so as to maximize the quality of healthcare.

2. Methods and materials

2.1. System implementation

In the present system, a number of physicians and general practitioners are able to contribute to the accumulation of the knowledge, software agents support their contribution by enabling the self-paring tactic [21], experts evaluate the knowledge processes providing feedback and, knowledge is built over time.

The system is structured on an n-tier architecture (Fig. 1) to support simultaneously the following data exchanges: (i) incoming data using the web forms, (ii) data requests by the Web Services [22], (iii) data submissions from the patients, and (iv) the expert-oriented feedback.

A module, called Analyzer, is responsible to create comprehensive XML-formatted data [23] by analyzing the heterogeneous data inputs. Moreover, JAVA APIs [24] are used to (i) establish communication among XML-formatted data, (ii) enable collaboration based on Web Services, and (iii) support data analysis and knowledge tracing.

The human-agent collaboration is established via several levels of abstraction and dynamically created levels of specification. The abstraction is achieved by using state-of-the-art JAVA technologies (Sun Microsystems, Santa Clara, US) [25] and XML features, whilst the specifications on each process are derived from on-demand enabled Web Services [22]. Finally, the necessary web interfaces are constructed "on the fly" by using PHP and MySQL features [26,27].

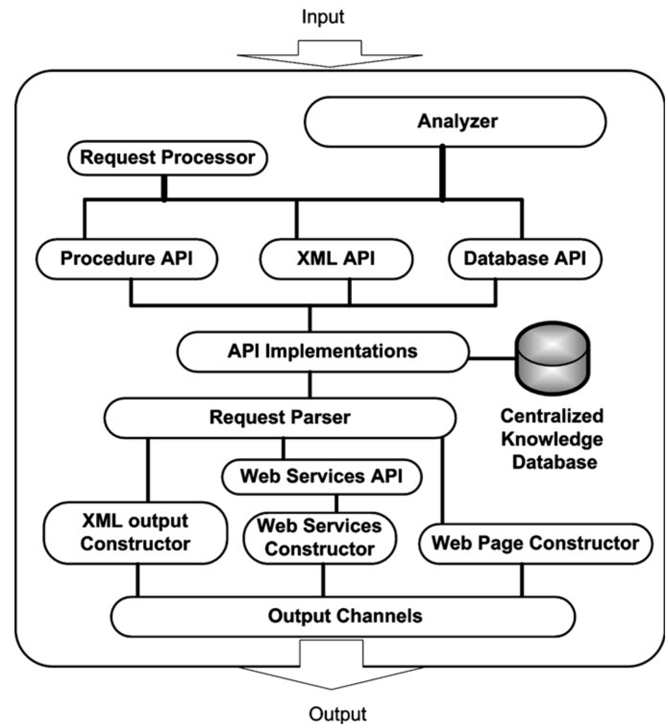

Fig. 1. System n-tier architecture.

2.2. The knowledge tracing process

During the time the patient first visits the Cardiology Department, the on-duty physician reviews the paper-based patient medical history (PMH), and defines an electronic CMP for the patient (initial CMP on the system), using an individual web form, as shown in Fig. 2. The CMP includes information regarding when new measurements should be performed by the remote patient and how; which variables (e.g., heart rate, QRS complex, ST segment) should be obtained; the expected upper threshold (V_{UP}) and the expected lower threshold (V_{LO}) per variable; and the timeline of CMP re-appraisal.

In case of emergency, or according to timeline, the patient performs the specified measurements, by using portable devices, and submits the biosignal values to the system, via a communication channel. The incoming data are parsed, classified, and checked by a software agent. Noisy data or data judged as irrelevant to the patient are discarded. Valid data are stored at a knowledge database (KDB), as a new record including the patient's identification number (ID), a time stamp, and values regarding the following variables: heart rate (HR), QRS complex (QRS), ST segment (ST), or/and QT interval, or/and QT

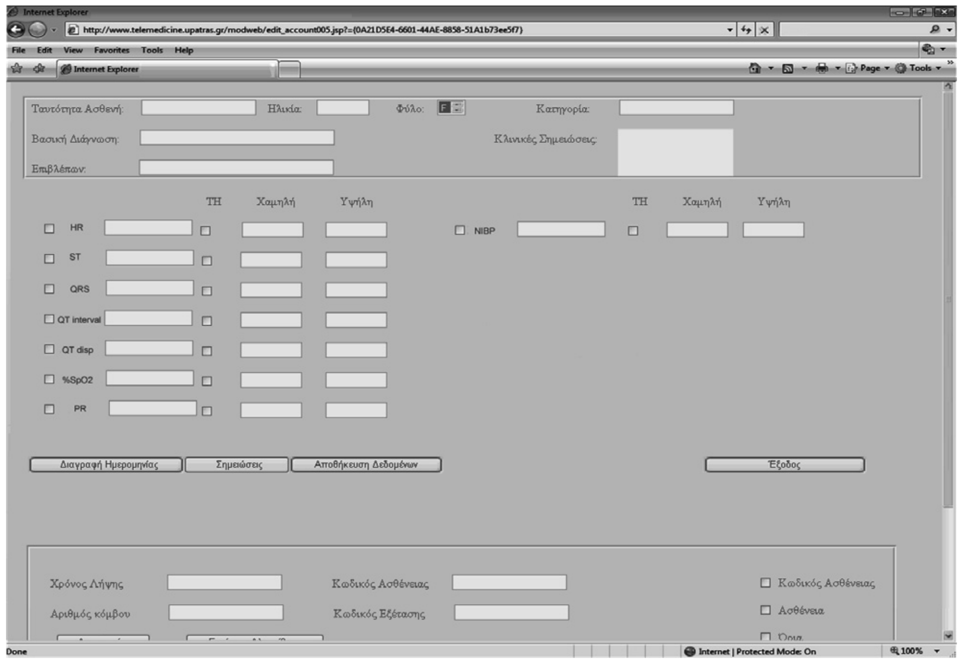

Fig. 2. Web form for defining patient CMP.

dispersion, or/and blood oxygen saturation (%SpO2), or/and pulse rate (PR), or/and non-invasive blood pressure (NIBP).

The system responds to specific requests and derives the first round of results. These results are then evaluated by an experienced physician (expert) and the knowledge cycle is completed, as shown in Fig. 3. The cycle is supported by a knowledge graph [21] that is used as a dynamic information structure [28]. The knowledge graph utilizes either data that are created by writing from scratch, or data retrieved by a client module, in order to formulate an abstraction level of information hierarchy ("know it and know why").

The knowledge graph consists of a layer of an input node (patient), two intermediate layers of nodes (variables, abnormalities), and a layer of output nodes (diseases). The

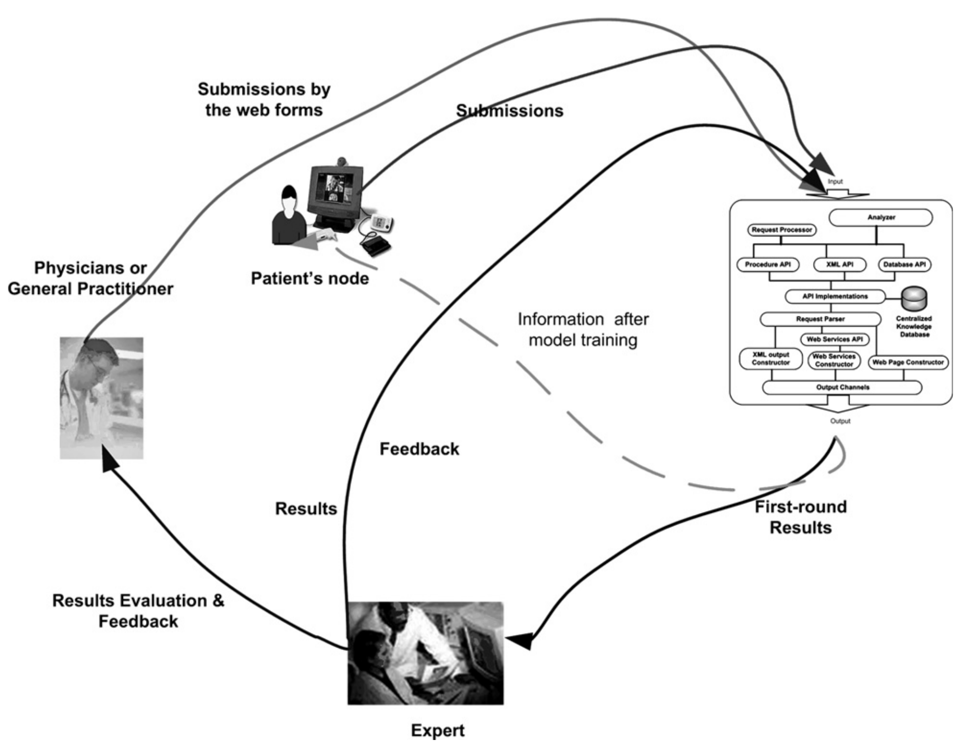

Fig. 3. The knowledge cycle.

Variables layer represents the values of biosignals obtained from the patient. The abnormalities layer represents possible abnormalities implied by the value of one or more variables. According to the incoming biosignal data, or to a specific request, each node calculates the value of the corresponding attribute. Subsequently, this output feeds into nodes in the next layer with a specific weight, and this weighted value becomes the input of the next node. The software agents locate the appropriate path from the node "Patient" to the node "Disease", as shown in Fig. 4, leading to the creation of an output and in turn to the recording of information in the KDB.

2.3. The knowledge cataloguing process

The system utilizes a prototype scalable self-paring tactic to structure the following three knowledge catalogues per patient: (a) the "patient in life", (b) the "patient in time", and (c) the "patient in action". The "patient in life" catalogue contains data provided by the physician(s). The "patient in time" catalogue includes information regarding the evolution of patient measurements over time and also assessment (control) values per measured variable that are calculated based on the distribution of measurement data (biosignal values), and the current thresholds per variable as defined by the physician (reference values). New information is added to the catalogue every time a CMP is updated or the results of new measurements are obtained. The "patient in action" catalogue includes information regarding the patient's risk level over time, as calculated by the system using the incoming measurements.

Specifically, each time a physician at the Cardiology Department or a general practitioner examining the patient at his/her home, updates the individual CMP using the web form, new information is provided for the formulation of the "patient in life" catalogue.

Using the individual KDB record sets per variable, the responsible software agent calculates the standard deviation (SD). Subsequently, using the current physician-oriented V_{UP} and V_{LO}, and the SD (entire distribution), the agent calculates for the patient the current "normal" limits of variable, and provides information for the "patient in time" catalogue. This calculation is based on a mathematical Eq. (1), called the patient current equation (PCE).

$$\mathrm{PCE} = \mathrm{mean}[(V_{\mathrm{UP}}), (V_{\mathrm{LO}})] \pm \mathrm{SD} \tag{1}$$

Finally, comparing each incoming value per variable with the corresponding PCE-oriented limits, the system receives information for the "patient in action" catalogue.

If the result is identified as "abnormal", an alarm is initiated depending on the identified risk level. Three discrete risk-levels can be identified by the system:

- Red risk level: when the PCE-oriented limits are exceeded.
- Orange risk level: when the current personalized normal thresholds (V_{UP}, V_{LO}) are exceeded.
- Yellow risk level: when the value is abnormal (>mean value).

2.4. The expert-oriented feedback

As mentioned previously, the individual who provides the feedback is an expert, usually the head of the Department, which has the depth of pathophysiological knowledge necessary to interpret complex cases properly. The expert reviews the patient's knowledge catalogues and his/her current CMP periodically, and evaluates the knowledge outcomes providing feedback. More specifically, the expert can decide to discard an outcome that was extracted via a process, indicate in the CMP additional variables to be measured, or update the physician-oriented descriptions of an abnormality or a disease. This feedback is obtained via a client module, as shown in Fig. 5.

3. Results

We investigated the feasibility and effectiveness of the present system using data from 86 patients including their PMHs and ECG findings (values of HR, QRS, and ST). The data were assessed once by the on-duty physician during the routine daily examination (Cardiology Department of the University of Patras). Three additional ECG measurements per patient were acquired by using an accurate 12-leads portable device, and two general practitioners defined and updated the CMP by reviewing the data. The assessment by the on-duty physician was then inserted retrospectively via the expert's client module as feedback.

Our findings indicated that the majority of biosignal values (~95%) were within the PCE-oriented limits and the risks-levels were identified accurately. Fig. 6 shows two characteristic diagrams regarding the HR from two patients with similar abnormalities. The PCE-oriented limits that were identified, are illustrated with dotted lines.

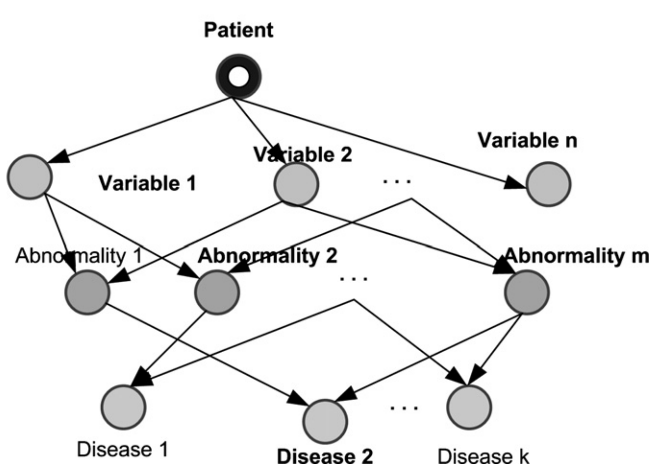

Fig. 4. The knowledge graph.

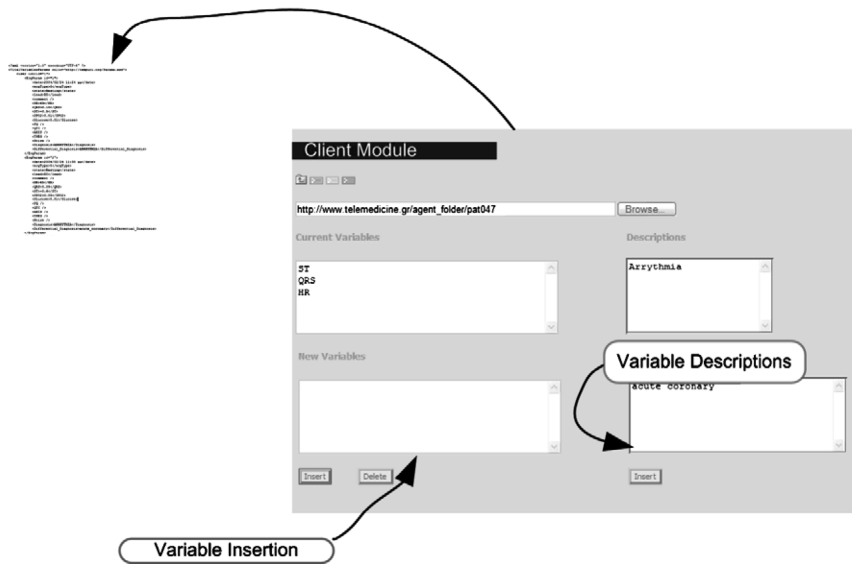

Fig. 5. The client module.

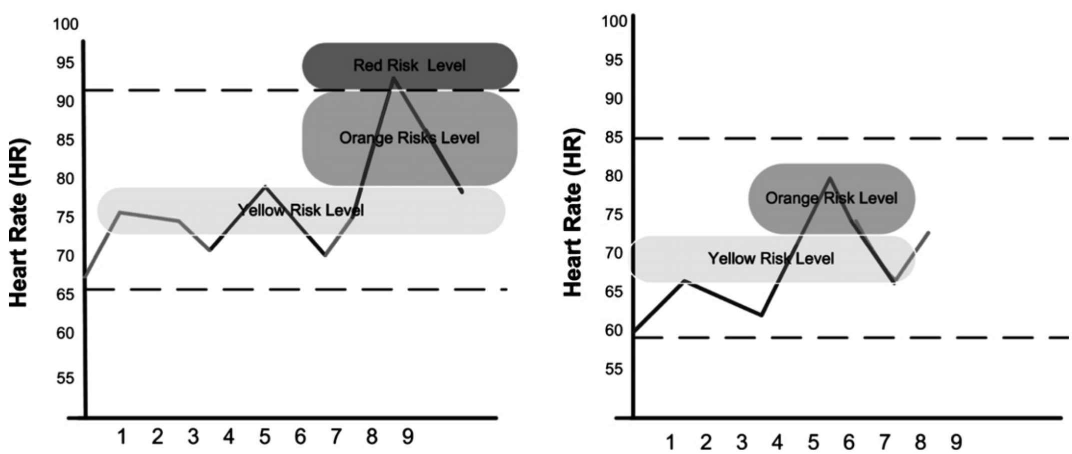

Fig. 6. Characterisitic diagrams regarding the HR from two individual patients with similar abnormalities.

They also indicated that by utilizing feedback, the system corrected several errors producing optimized outcomes.

Following the trials, the involved general practitioners were asked to assess the processes. They noted that (i) it was easy to define and update the patients' CMP via the individual web-forms, and (ii) the physicians formed the typical assessment about the patient's risk-level by examining the PMH and the ECG findings whereas the system achieved a risk-level hypothesis with sufficient information provided by the system's catalogues.

To investigate the overall system functionality, several calibration tests were also performed wherein the observer served as a user of the system modules. We observed that both the CMPs and the feedback were time-stamped correctly and synchronized under a common time-framework. We also observed that insufficient values were obtained to the system due to displacement of the peripheral ECG electrodes or due to incorrect electrodes placement were the most common causes leading to false process.

4. Discussion

It is generally assumed that health care teams function in a collaborative manner and deliver health care efficiently and effectively [1,7,9]. In this study, we propose a collaborative system that is capable of tracing and cataloguing knowledge in an e-health environment, and we investigate its feasibility and effectiveness.

One of the key characteristic of the system is that it enables the collaboration at four different levels. First, remote patient performs measurements and submits biosignal data to the system. Second, physician or general practitioner defines the patient's CMP. Third, the software agents support the knowledge processes maintaining synchronicity throughout. Fourth, expert retrospectively attaches feedback, correcting the outcomes to optimize the knowledge process.

While the importance of involving experts in all strategies to improve services has been repeatedly stressed, only few studies incorporated any mechanism for the doctors themselves to evaluate appropriateness [29,30].

Several knowledge engineering systems use machine learning methods to trace the knowledge [31]. Feedback usually is not inserted by any means. The expert systems, on the other hand, are entirely based on the knowledge of the experts (beliefs, rules, ontologies etc.), that "a priori" exists in the environment [32]. In the present system, the "knowledge tracing" results not only from acquiring the "a priori" existing knowledge, but also from continuous collaboration and a scalable knowledge engineering tactic.

Our findings indicated that the system optimized the knowledge processes and succeeded to reduce the errors. More precisely, the system did not activate alarms when a generic abnormality was detected, but only if a true risky situation for a specific patient was identified.

In this study, we argue that the collaborative knowledge processes, necessitate the investigation of several "environmental issues" [1,7,9], in common, although the methods that are used to address the investigation and result may vary for each one. The "types of human" in such environment are typically patients, physicians, general practitioners, and experts. In this heterogeneous "human puzzle" the role of each patient is major [7] for two reasons: (i) he/she is actively involved by performing measurements and (ii) he/she is finally the subject under investigation. Considering this assumption, we utilize three levels of cataloguing regarding each patient in the present system; the "patient in life", the "patient in time", and the "patient in action".

In addition, we should consider the role of the on-duty physician. The mental workload imposed on physicians on-duty by the e-health environment can exceed their abilities to support knowledge engineering processes properly [7]. The patients, the CMPs, and in turn the alarms, could be too many and if he/she must follow complex operating logic, or physically manipulate software modules, hazards are likely. Considering this assumption, this system enables the human-agent collaboration in all phases of a knowledge process.

The question of what makes for a quality knowledge process is always a difficult for a physician on-duty to answer. In many ways, it is easier to answer in the negative, that is, it is often easy to describe what a process of poor quality is. Therefore, it is doubtful to eliminate the expert role [33]. Experts axiomatically should be responsible for resenting or rejecting a process if it downgrades the provided healthcare quality [34]. The expectation is that they will collaborate to support such systems, providing continuously the appropriate contribution.

It ought to be observed that this study expands the existing approaches dealing effectively with knowledge processes optimization by enabling the collaboration in each phase. On the other hand, it also ought to be observed that a collaborative system offered advantages and disadvantages [8]. Thus, the clinical collaborators should choose the mode of the system that best meets their goals, e.g., the time for feedback insertion, the responsibilities and the rights of the general practitioners, and the amount of CMP that a physician is able to manage.

Further evaluation is also needed to determine in more detail the system feasibility by incorporating more biosignal variables. Finally, we should take into consideration that there are significant technical and regulatory issues surrounding the data insertion via free-text format, which need to be settled. Our future work will use text mining methods and dynamic ontologies in this direction.

5. Conclusions

In an e-health environment, knowledge processes necessitate human collaboration and scalable knowledge engineering tactics. Collaborative knowledge processes, in general, necessitate the investigation of several "environmental issues", in common, although the methods that are used to address the investigation and result may vary for each one. Experts should be responsible for resenting or rejecting a process if it downgrades the provided healthcare quality.

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