HUMAN FACTORS IN DYNAMIC E-HEALTH SYSTEMS AND DIGITAL LIBRARIES

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"When dealing with people, remember you are not dealing with creatures of logic, but with creatures of emotion, creatures bristling with prejudice, and motivated by pride and vanity"

Dale Carnegie (1888-1955)

ABSTRACT

E-health systems and digital libraries deal with human health, requiring fast responses and real-time decision-making. Human intervention can be seen in the whole life cycle of biomedical systems. In fact, relations between patients, nurses, lab technicians, health insurers, and physicians are crucial in such systems, and should be encouraged when necessary. However, there are some issues that affect the successful implementation of such infrastructures. Man-machine interaction problems are not purely computational and need a deep understanding of human behavior. Many integrated health knowledge management systems, have employed various knowledgebases and ontologies as their conceptual backbone to facilitate human-machine communication. Ontologies facilitate sharing knowledge between human and machine; they try to capture knowledge from a domain of interest; when the knowledge changes, the definitions will be altered to provide meaningful and valid information. In this chapter, we review and survey the potential issues related to the human factor in an integrated dynamic e-health system composed of several interrelated knowledgebases, bio-ontologies and digital libraries by looking at different theories in social science, psychology, and cognitive science. We also investigate the potential of some advanced formalisms in the semantic web context such as employing intelligent agents to assist the human user in dealing with changes.

INTRODUCTION

During the last two decades, many advances in healthcare have required the development of artificial intelligence (AI) techniques in the biomedical domain. Several biomedical systems, such as Acute Care Systems, Medical Decision Support Systems, Educational Systems, Quality Assurance and Administration, Laboratory Systems, Medical Imaging, and so forth, are recruiting large digital libraries, knowledge-bases and ontologies (Gruber, 1993) as their backbone to facilitate human-machine communication and capture knowledge from the domain of interest. When the knowledge changes the definitions will be altered to provide meaningful and valid information. E-health systems and digital libraries deal with human health, requiring fast responses and real-time decision-making. These systems usually have a very complex structure, with many elements tightly coupled to one another and organized in distributed, lattice-like networks. In such structures, changing one component can have unpredictable effects on the whole system. As can be seen from state-of-the- art change management in existing biomedical knowledge-bases and digital libraries, this problem is inadequately addressed by available tools and algorithms, mostly because dealing with change is mainly a social, linguistic, and philosophical problem, rather than computational one. A key issue in managing current dynamic biomedical systems relates to users' behavior and the cultural and disciplinary assumptions (Forsythe, 1998), which can determine the success or failure of a system. The change management phase in current systems is largely addressed implicitly, and followed with human supervision and intervention.

Human intervention can be seen in the whole life cycle of biomedical systems. In fact, relations between patients, nurses, lab technicians, health insurers, and physicians are crucial in such systems, and should be encouraged when necessary. The human contribution improves rationality and plays an important role in controlling the quality of the results. However, there are several applications where human intervention is difficult, impossible, or simply undesirable (Flouris et al, 2006) (e.g., due to security issues). Also, differences in background knowledge, views, or preferences are other obstacles for consensus between people. In this sense, a result might not be accurate or reproducible. In addition, the system's outcome might be highly dependent on human behavior, which makes it difficult for evaluation in terms of efficiency or correctness.

The existing well-known biomedical systems and digital libraries usually affect large and heterogeneous groups of people, with different levels of background knowledge and dissimilar interests. Therefore, an efficient user-centered approach, along with psychological and organizational proficiency should be taken to reduce the behavioral side-effects and successfully manage changes in healthcare applications. An ideal e-health system should be able to automatically coordinate human factors, processes, tools and knowledge-bases while coping with different changes. There are some issues that affect the successful implementation of such infrastructures. In this paper, we review and survey the role of the human factor in a dynamic e-health system, and we address following issues:

- The organizational and social impacts of human-driven changes in e-health systems;
- Different sources of change;
- Human errors due to change and alteration;
- Responding to change in a dynamic e-health environment;
- Safety;
- User interface issues;

We also investigate the potential of some advanced formalisms in the semantic web context (such as using intelligent agents to assist computational inferencing) to assist the human user in decision making and dealing with changes.

BACKGROUND

A large body of literature exists on the importance of human-machine interactions in various domains of interest. Life science and biomedical fields are challenging domains in knowledge management. Biomedical data are highly dynamic, and the large biomedical knowledge sources contain complexly interrelated elements, with various levels of interpretation. Considering the dynamic nature of current volatile digital libraries, which need real-time decision-making and proper action from human agents, the concept of change and the ability to cope with various alterations play important roles in biomedical knowledge bases. Lorenzi & Riley (2000) presented an overview of change management efforts in informatics showing the roles of people and the organizational issues (i.e., the interruption of a known routine) that were counterproductive to the implementation and management of major information systems.

Based on their research, the main reasons for system failure can be categorized under miscommunication, cultural barriers, underestimation of complexity, inadequate or low-quality training, lack of organizational change management strategies, and weak leadership. Considering the dynamic nature of current knowledge-bases, which need real-time decision-making and proper action from human agents, the concept of change and the ability to cope with various alterations play important roles in biomedical knowledge-bases. Lewin (1947) with his social psychology perspective focused on the motivational concepts that underlie an individual's behavior. He believed that psychological needs in humans cause tension until they are fulfilled. Lewin indicated three major conflict situations: the choice between two positive goals of equal strength, two equally negative goals, or opposing positive and negative forces of different strengths. Lewin's field theory, commonly used in healthcare systems, allows one to identify different types of conflict situations and to analyze the effect of a change in a knowledge-based environment (Lorenzi & Riley, 2003).

TYPES OF USER-DRIVEN CHANGES

Watzlawick et al (1974) used two theories to explain first-order and second-order changes, namely the theory of groups and the theory of logical types, from philosophy and logic. A first-order change is defined as the logical extension and incremental improvements of past and current practices in a given system, leaving the system’s core belief relatively unchanged (Examples such as recovery from system failure, and generating new reports). A second-order change occurs when the system itself is changed. This change usually involves a redefinition or re-conceptualization of the ideas, tasks, domains, or roles in an organization. First-order change involves improving the existing procedures, while second-order change alters the core methods of conducting business, or even the basic business itself. The change from paper-based medical records to electronic medical records represents a second-order change in biomedicine (Lorenzi & Riley, 2000). Golembiewski et al (1976) added a middle-order level of change, to represent a middle ground for changes greater than first-order that do not affect the strategic goal and nature of the system.

For any alteration in a system, users, designers and developers can play various roles, which will influence their conceptualization about the change and their reaction to it (Lorenzi & Riley, 2000). So, in making decisions and taking action within dynamic biomedical systems, the users' behavioral aspects associated to each role should be controlled.

HUMAN ERROR IN CLINICAL SYSTEMS AND CHANGE MANAGEMENT

Studies (Lorenzi & Riley, 2000) on people working with health-related systems imply that due to high stress and pressure in the field they are relatively more resistant in confronting with changes. Changes can potentially increase the chance of error in a system by routine disruption. One factor urging system change is the need to deal with human error, present in all stages of a system's life cycle. Human error should be considered in clinical application development's life cycle, along with many other aspects of design. Studying human error provides valuable information for analyzing human behavior and reveals user requirements and misunderstandings. Human error is defined by Barfield (1993) as an error caused in some way by the user of the system, in contrast to a system error, where there is a physical fault in the system. Based on the user's mental model, he grouped the errors into two categories: errors of action (error in the translation between a user's intention and their action) and errors of intention (the user doing the wrong thing on purpose). This classification is comparable with Norman's categorization of errors (Norman, 1988) into mistakes and slips: if a person has intent to act that is inappropriate, it is a mistake; if the action was not what was intended, it is a slip. In order to deal with human error, Norman highlighted the needs for better consistency in describing the errors and better feedback for capturing and reporting them (Lorenzi & Riley, 1994). In dynamic environments with several external and environmental parameters such as evolving e-health systems, the rates of unintentional errors can increase greatly. Bés (1997) and Decortis (1993) have worked on the effects of temporal characteristics on users' activities in dynamic environments. Decortis stated that temporal errors can originate from incorrect estimates about the sequence or duration of actions and/or failure in choosing the right time to act, in anticipation of an event or in synchronization of collective actions (Decortis, 1993). In addition, De Keyser (1995) identified other sources of temporal errors, such as the absence of high-quality indicators to highlight the change, the presence of micro-changes too short to be received, and the existence of distracters capturing the users' attention (Bés, 1999). Heifetz et al (2002) made the distinction between two methods for change management: the technical method that can be understood and addressed with available knowledge (mostly used for managing first-order change) and the adaptive method that is beyond the existing and available techniques of operation.

Several efforts such as (Forsythe ,1998) and (Lorenzi & Riley, 1994, 2000, 2003) have been made for applying knowledge of human and organizational behaviors derived from psychology, sociology and cognitive scienceto the implementation and management of healthcare systems.

Safety

The six principles was defined by Committee on Quality of Healthcare in America (2001), to be followed by any e-health knowledge-based system to provide high-quality services, focus on safe, effective, patient-centered, timely, efficient, equitable environments. User and patient safety is a challenging issue that needs to be addressed with proper real-time control and feedback mechanisms in the systems. User interfaces can play a vital role in this case by providing appropriate forms of messages and warnings in a timely manner. The number of potentially hazardous errors can be reduced by employing intelligent safety devices, accurate alerts, and effective user-friendly interfaces. To cope with changes in the constantly evolving knowledge-based e-health environments, one must have a formal model of human reactions to change, enabling cognitive error analysis. Beitler et al (1995) designed an interface that provides a virtually simulated multimodal user control environment, based on the knowledge of a reactive planner to allow "autonomous planning as well as planning through human-machine interaction". The system acts like a human agent and can be used in situations unsafe for people. This approach is especially useful in assisting people to perform repetitive tasks, which potentially increase the chance of error for human.

Trust and Security Issues

Kini et al (1998) observed various aspects of human trust in computer-dependent systems, according to personality theory, sociology, economics, and social psychology. They defined trust as "a belief that is influenced by the individual's opinion about certain critical system features". Their study does not support the problem of trust between humans and processes involved in knowledge-based interactions, but focuses on the human factor as the "truster" instead of system. Gambetta (2000) defined trust as an estimation that can be determined by the probability of an action being successfully performed. Jøsang et al (2007) look at trust in a user-centered framework where '*one party is willing to depend on something or somebody in a given situation with a feeling of a relative security, even though negative consequences are possible'*. In this sense, human-agent interactions play important roles in the security process, which usually includes authentication, authorization, and confidentiality. Relying only on human factors in the security process, especially in complex health systems, may lead to unpredictable, inaccurate, and inconsistent results that often may not be reproducible. So, in modern e-health knowledge bases, security management must be carried out automatically, with minimal human intervention.

User Interface Issues

Since biomedical knowledge bases and applications are most often used by lab technicians, nurses, and physicians, a formal logical language is not well-suited. Therefore, special attention is given to the design of the operational user interface, based on natural language processing and intuitive graphical representation. Currently available tools do not provide complete support for dealing with the complexity of evolving medical systems, which go beyond the capabilities of existing user interfaces. One method for dealing with the representation of changes in user interfaces is to employ ontology in capturing the knowledge about evolving concepts. In this way, changes to the user interface can be made by changing the underlying ontology. Taboada et al (1996) and Gupta et al (1999) undertook two efforts devoted to modeling user interface for biomedical applications. Pohl et al (2007), Leitner et al (2007), and Carrigan et al (2007) also recently demonstrated their advances in the usability of user interfaces of available information systems in medicine and healthcare. In general, a user interface based on human factors is a key to the acceptance of a system (Nielsen, 1993) in medicine. In creating a graphical user interface (GUI), the level of expertise and the operational habits of the medical staff should be considered.

Hartson & Boehm-Davis (1993) specified behavioral and construction domains for implementing a user interface. The behavioral domain includes the design and development of the interactive part of an interface, and the construction domain includes the development of the graphical environment. The development process of a usable GUI is not possible without active participation of physicians, psychologists, and other end-users of an e-health system. It also requires the consideration of important human factors, such as intuitiveness, functionality, accessibility, flexibility, and adaptability of the user interface. However, design criteria based on human factors do not automatically guarantee a solid, usable interface (Taboada et al, 1996). As the GUI development for dynamic environments is always an iterative process (Hartson & Boehm-Davis, 1993), it requires the occasional modification of initial system specifications based on new requirements or newly obtained knowledge.

For defining any behavior change procedure, we first need to specify behavioral patterns to capture current behavior, the behavior upon change, and the advantageous replacement behaviors. For this purpose, we introduce our agent-assisted framework, meant to assist humans in performing changes automatically.

AN AGENT-ASSISTED FRAMEWORK FOR PARTICIPATIVE CHANGE MANAGEMENT

A dynamic health knowledge-base usually deals with spatial and temporal data, metadata, documents, and data warehouses while working in an integrated web-based system that includes databases, ontologies, and software agents. To overcome some of the existing challenges in current knowledge-based systems, there is an emerging trend to design systems based on human behavior and needs (Brazier & Treur, 1994; Duribreux-Cocquebert & Houriez, B, 1996).

Recruiting intelligent agents can assist users in coping with change in evolving environments. Change management starts with specifying the type of potential change. Then an individual can act alongside agents to capture, represent, and manage the alterations. In this approach, special attention should be paid to agent-human interactions. Intelligent agents are able to discover, identify, and collect information about a variety of actions under changing conditions from multiple distributed resources (Devedžic, 2001). They have ability to work rationally, to capture different alterations in frequently changing environments, and to react appropriately to these changes (Li et al., 2005). In our proposed RLR (*R*epresentation, *L*egitimation and *R*eproduction of a change) framework (Shaban-Nejad & Haarslev, 2008), we have used four types of agents, the Change Capture agent, Learner agent, Reasoning agent, and Negotiation agent, to assist an ontology engineer in coping with change in dynamic knowledge-bases. Figure 1 demonstrates the interactions between the agents and the human factor. The collaboration between human and software agents can lead towards participative evolution which is defined as managing incremental change through collaboration (Dunphy & Stace, 1990).

Change Capture Agents

They work like triggers in database and can find, capture, and track different alterations in a knowledge-based system, by processing the associated change logs. These agents perceive the changes – either random or scheduled- in the real-world and report them as new facts to update the new knowledge. In the RLR framework, we have defined three different types of change-capture agents: action control agents, explorer agents, and log-reading agents.

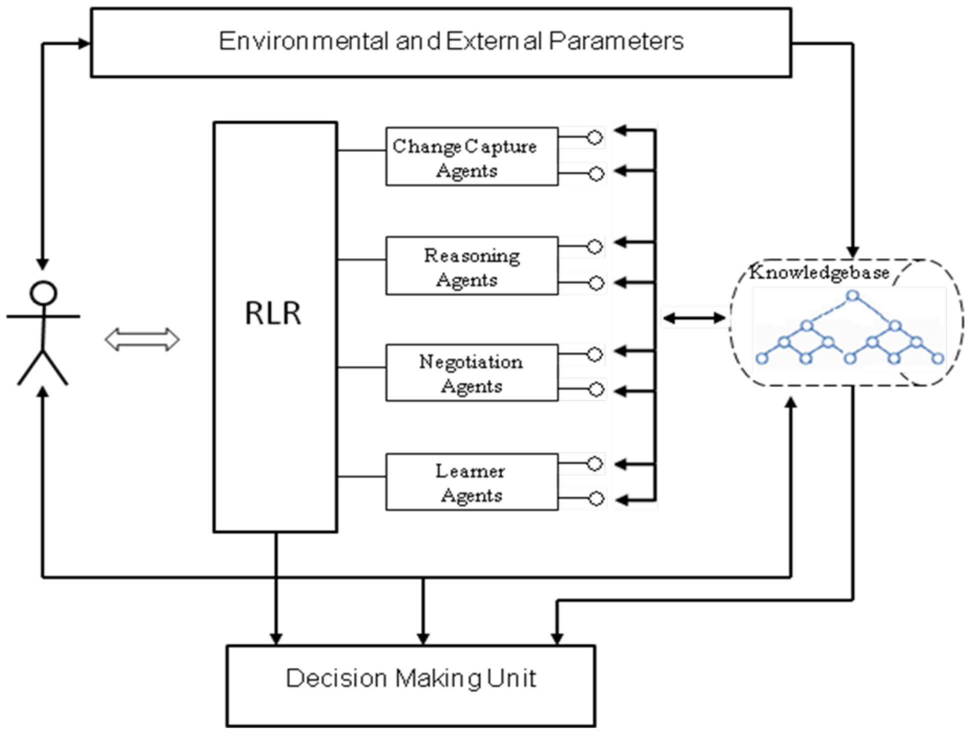

Figure 1. The Decision making mechanism for user-centric change management

Action Control Agents (ACA): consist of user activities and legal operations for capturing and storing (within change logs) basic changes such as deletion, insertion, and updates to knowledgebase elements.

Explorer Agents (EA): capture changes by processing and reading accumulated data in change logs within a specific time period and submit proper messages for the corresponding services.

Log-Reading Agents (LRA): read the information stored in the log files within two time points and send them to a learning agent in order to create patterns for different changes.

Learner Agent

One approach to minimizing the side-effects of a change is to concentrate on a limited number of changes until they gradually become part of the routine. In this way, the system can improve its learning abilities over time and adapt to new conditions. With active human and machine participation in the change management process, the necessary skills for bootstrapping the whole process can be achieved by the adaptive learner agents. As a knowledge-based system is used and evolves, the designed change logs accumulate invaluable data and information about various types of changes. An intelligent learner agent can then exploit these records of changes that happen frequently in a process to develop a pattern, which can be used to predict - with a realistic degree of certainty - the rate and direction of change.

The learning agent starts with a limited, uncertain knowledge of the domain and tries to improve itself; it relies on adaptive learning, based on the semantics provided by the ontological backbone. The adaptive learning agent plays an important role in the reproduction phase, where we look for patterns to bootstrap the process of change management.

Reasoning Agent

The new inputs (based on different changes) for a system force an agent to revise its conceptualization accordingly, by reasoning out the consistency of the change through the use of both prior and new knowledge. A reasoning agent controls and verifies the logical consistency of a system, by revealing inconsistencies, hidden dependencies, redundancies, and misclassifications. We use RACER (Haarslev & Moller, 2001) as a description logic reasoning agent, along with other semi-formal reasoners in the RLR framework.

Negotiation Agent

Negotiation happens when agents have conflicting interests and a desire to cooperate to settle the conflict (Rahwan et al., 2003). In RLR infrastructure, the negotiation agent handles all the negotiation between agents to determine the best approach for implementing a particular change. The final decision for confirmation, deletion, or modification of a proposal can be made by human experts based on the application's goal. In RLR, the negotiation is defined in accordance to the conceptual model of argumentation (van Eemeren et al, 1996) and an argument is described as a piece of information that allows an agent to backup and justify its negotiation stance or to influence that of another agent (Rahwan et al., 2003).

FUTURE TRENDS

With the increasing popularity of open source knowledge-based systems and advances in web-based applications and technologies, such as intelligent agents, online annotated knowledge-bases, and search engines, as well as in the popularity of collaborative media including blogs, social networking systems, wikis, podcasts, and RSS feeds, the current World Wide Web is heading towards its next incarnation, Web 2.0 (O'Reilly, 2005). Web 2.0 offers many facilities for e-health, such as satellite conferences, personalized learning environments, and blog meetings for educator and learners. A new trend in online biomedicine, e-health 2.0, will facilitate intelligent interaction between the users and computers. It will allow for active participation and contribution by different users, enabling them to add/modify information and knowledge to/from online biomedical knowledge-based networks through web interfaces. Also with advances in neural network and so called ambient intelligence (Riva et al, 2005), which rationally support human in performing various tasks, users will be more in charge and have direct influence in driving and defining the needs. It seems that research on the role of human factors as fundamental constructors of the social semantic web and e-health will continue to aid in the success of e-health 2.0. There is also a growing need to re-engineer our conceptualization of users, developers, trust, security, and traditional user interfaces for new mobile and dynamic e-health applications.

For overcoming on issues related to user-interface, recent advances in brain-computer interface (BCI) (Lebedev & Nicolelis, 2006) and human ergonomics (Bridger, 2008) offers promising results, which will enhance the quality of user-centric modelling.

DISCUSSION

As dynamic knowledgebases are becoming huge and complex, operations have to be automated, that needs a fine-tuned collaboration between human (user, operator or developer) and machine. The man-machine interaction problems are not purely computational and need a deep understanding of human behavior. To understand and analyze underlying behavioral issues in modern health systems, we studied some of the theories in social science, psychology, and cognitive science. This will enable us to apply knowledge of human behavior to the implementation and management of knowledge-bases in a healthcare environment. Life sciences in general and the health industry in particular are still highly dependent on human factor playing various roles, so it won't be sufficient to focus entirely on technology and machinery for modelling and implementing knowledge-based systems without considering various human behavioral aspects. To enhance the quality of our knowledge-based systems, human behavior and its limitations should be reflected in any defined change management strategy. In frequently evolving systems and knowledge-bases, this case would be even more critical. For example in modern e-health systems, security management must be carried out automatically, with minimal human intervention. Our proposed multi-agent change management framework presents a collaborative, realistic and future-oriented approach to facilitate human-agent interactions in dynamic environments.

The RLR framework acts as a basis for a web based decision making and recommender system which allows different users to control and analyze the consequences of their actions in a knowledge-based system. Then they can follow the most beneficial or the least harmless recommended actions to perform a change. Due to the multi-disciplinary nature of research on dynamic knowledge-bases, any advances in this field would be highly dependent on those in various others, such as human-computer interactions, user interface design, neural network, knowledge-base integration, translation, , alignment, and prediction of the semantic closeness of concepts in different knowledge-bases.

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KEY TERMS

RLR: A multi-agent framework for Representation, Legitimation and Reproduction of changes

Action Control Agents (ACA): Consist of user activities and legal operations for capturing and storing (within change logs) basic changes such as deletion, insertion, and updates to knowledgebase elements

Explorer Agents (EA): Changes by processing and reading accumulated data in change logs within a specific time period and submit proper messages for the corresponding services.

Log-Reading Agents (LRA): read the information stored in the log files within two time points and send them to a learning agent in order to create patterns for different changes.

Learner Agent: Exploit the records of changes that happen frequently in a process to develop a pattern, which can be used to predict the rate and direction of change.

Reasoning Agent: Controls and verifies the logical consistency of a system, by revealing inconsistencies, hidden dependencies, redundancies, and misclassifications.

Negotiation Agent: Handles the negotiations between agents to determine the best approach for implementing a particular change.