Personalized Fall Risk Assessment Tool by using the Data Treasure contained in Mobile Electronic Patient Records

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Abstract. This work presents a novel approach for combining multiple Electronic Patient Records (EPRs) to a self-learning fall risk assessment tool. This tool is used by a new type of home-visiting nurses to track the fall risk of their patients. In order to provide personalized healthcare for elderly people, we combine multiple EPRs using an agent-based architecture, where each patient is represented by an associated agent. The patient agents are enabled to negotiate about possible fall-risk indicators recognized in the specific patient population under care. We use distributed information fusion and opinion aggregation techniques to elaborate new fall-risk indicators and in consequence to adapt the fall risk assessment tool.

Keywords. Electronic patient records, fall risk assessment, personalized healthcare, agent-based, self-learning

Introduction

Over the last decade, there has been an exponential growth in the healthcare costs due to the aging population in many countries. One of the important economic burdens is caused by falls, which are a common cause of injury, and contribute significantly to the costs of injuries in old age. In Germany, the rate of costs due to falls is around 0.8% - 1.5% of the yearly German healthcare costs. These fall-related costs are expected to increase to 3.85 billion Euros a year by 2030 due to the demographic change towards aging population [1]. Besides this economic and social dimension, falls also introduce psychological and medical ramifications for the individuals. The prevention of falls is required to overcome these burdens. Additionally, in Germany, the early detection of risks and the prevention of outset incidents are required by law. For this purpose a magnitude of prevention tools exist aiming to determine the actual risks of a patient to reduce e.g., fall-related injuries. Here, the increasing development of Electronic Patient Record (EPR) systems offers new opportunities as EPRs contain a huge amount of data [2]. This data can be used to analyze the population under care proactively by observing the data set and achieve the goal of “personalized healthcare” [2]. In more detail, personalized healthcare is about the tailoring of the healthcare process to the individual patient. Therefore, it would be beneficial if the tools used in healthcare can

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adapt themselves to the population under care. As a result, leading to personalized healthcare provided not only by professionals but also supported by these semi-automatically adapting tools. This work introduces such a tool in the form of a fall-risk assessment tool [3, 4] developed as part of the agnes^{zwei} mobile application software [5]. Presenting this tool, we want to emphasize that existing approaches in different areas of computer science (e.g., agent-based systems, information fusion) can contribute to the challenges associated with personalized healthcare and that such approaches can be used to adapt tools online.

1. Methods

The goal of our study is to implement a personalized fall-risk assessment tool as part of the agnes^{zwei} Tablet App, which is a mobile EPR system [5]. This process started with a state-of-the-art analysis to identify the common practice in Germany. Here, we found that there is no standard available yet to develop a fall risk assessment tool for commonly usage and institutions mostly use a fall-risk assessment instruments developed by their own [6]. We proceeded with a literature research to identify fall-risk indicators and their influence through the actual fall risk of a patient. Using the results we were able to develop an initial fall-risk assessment instrument comprising 28 indicators and able to determine the actual fall-risk of a patient based on these indicators in terms of a traffic-light [6]. To adapt the list of indicators through the population under care, we have utilized an agent-based self-learning approach by using opinion aggregation techniques. The basic idea is that each EPR contains knowledge about possible fall-risk indicators of the represented patient and that multiple EPRs can be used to infer fall-risk indicators [3, 4]. In the following, we will provide more details about the methodology followed to reach our goal.

1.1. Meta-analysis of Initial Fall Indicators

We performed a meta-analysis to identify common fall-risk indicators using the keywords “fall”, “risk factors”, “older people” and “community-dwelling” querying the databases PubMed, DIMDI and Google-Scholar. At the beginning, we found more than a hundred confirmed fall-risk indicators. The filter process was done through comparing the statistical relevance and clustering/renaming of similar/synonymous terms. After this process, the literature research concludes with the advice to use 28 as initial indicators within the developed assessment tool. For more details about the meta-analysis, the interested reader is referred to Schenk et al. [6, 7].

The process of excluding risk indicators from assessment tools is common when creating such assessment tools while conducting/analyzing studies. It is implied by a trade-off between the statistical relevance of risk indicators examined in studies and the usability of an assessment tool. In consequence, this process prevents to provide personalized healthcare to the population under care.

1.2. Agent-Oriented Software Engineering

On top of the initial meta-analysis study, we have followed the Agent-Oriented Software Engineering paradigm to develop the approach, as it is a natural approach to model complex distributed software systems [8]. Here the major abstraction layer is that of an agent, which is an autonomous entity situated in an environment and encapsulating its knowledge and capabilities. Given an EPR system like the agnes[zwei] App, each patient (each EPR) can be modeled as an agent encapsulating the data of a specific patient. Furthermore, in agent-based systems, the agents involved typically cooperate with each other to achieve the system goal. We used this mechanism to establish a negotiation process about possible fall-risk indicators between the patient agents.

1.3. Agent-based Simulation

To evaluate the approach, we have developed an agent-based simulation environment using the agent-framework JIAC V [9]. Each patient agent has been equipped with the data model of the agnes[zwei] EPR. Furthermore, we have setup agents simulating the healthcare professional role, responsible to document fall events. Using this simulation environment, we were able to technically evaluate the approach and the applicability of different negotiation techniques in this circumstance. For more details about the technical evaluation, the interested reader is referred to Ahrndt et al. [3, 4].

2. Results

As mentioned above, we have utilized the agent-based approach to model the system based on several EPRs. A conceptual illustration is shown in Figure 1. Each patient is represented by a single agent and multiple patient agents run on a single platform representing a healthcare professional's Tablet. The population under care is supplied by several professionals meaning that the whole environment consists of several Tablets. Figure 1 also illustrates the negotiation process consisting of four different stages to determine whether adding new fall indicator is necessary or not: The occurrence of a fall, the local information fusion, the global opinion aggregation and the notification stage.

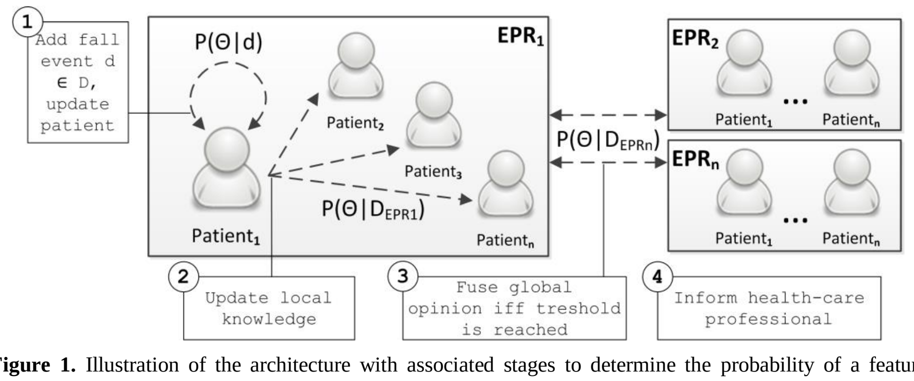

Figure 1. Illustration of the architecture with associated stages to determine the probability of a feature which influence the fall risk of a patient. The agent-based approach is a natural way to model such a system, viewing each patient as encapsulated entity [p. 4, 3].

The process starts when the healthcare professional documents a new fall event using the fall documentation sheet of the software application. **Fehler! Verweisquelle konnte nicht gefunden werden.** shows a part of the assessment tool enabling the healthcare professional to add new fall-event. The affected patient agent then elaborates the evidence of all features observed (all data-points available through the EPR) by analyzing which features has changed its value since the last observation. The probability of such features is then increased and a new probability distribution of fall indicators is built using Bayesian information fusion [10]. At this point, the affected patient agent publishes its new knowledge to all patient agents on the same Tablet updating their degree of believe about possible fall-risk indicators. As a result of this stage, each patient agent represents some kind of fall-risk expert. This means that each expert can express its opinion about the fall-risk indicators that influence the represented patient by voting for the new fall-risk indicator. Furthermore, the experts are able to express their opinion about the fall-risk indicators found in the population that is treated by a single healthcare professional (each nurse owns its own Tablet).

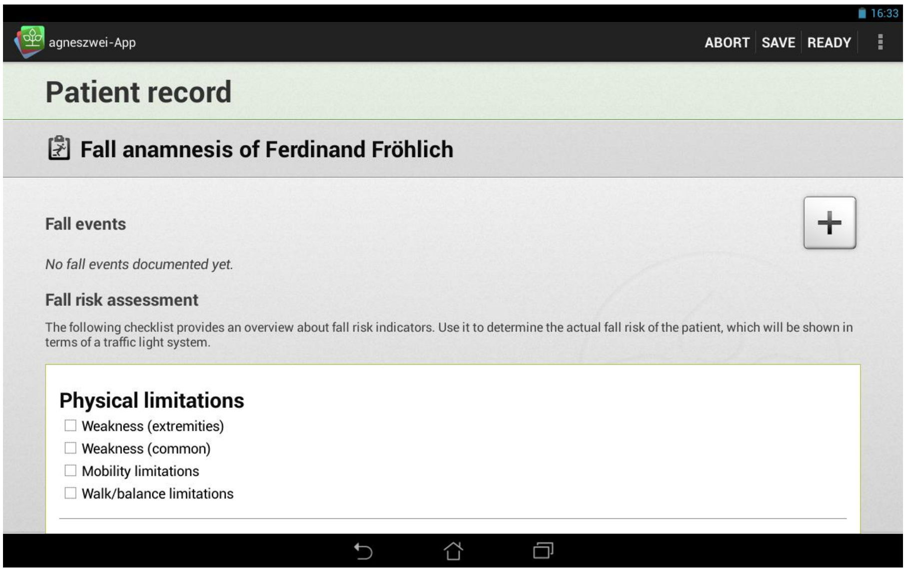

Figure 2. Screenshot of the fall-risk assessment tool as part of the EPR. The upper area contains the possibility to document fall events building a list of all documented incidents. The lower area shows a part of the fall-risk assessment instrument as checklist.

As a next step, the opinion aggregation starts if the probability of one of the features reaches a common threshold, which was empirical established using the agent-based simulation. Then the local believe is shared with all patient agents available through the population under care. To fuse these local expert opinions to a generalized view we have examined different opinion aggregation techniques [4]. After applying and evaluating some theoretically well-researched methods in the real world task, we decided to use the Supra-Bayesian Pooling Method [11] as it outperforms the other methods in time and space complexity.

As a last stage, if one of the features reaches the threshold after building the global opinion about fall-risk indicators, the healthcare professional gets notified. The nurse then has to decide whether this feature is a fall-risk indicator for the population under care or not. The result of this decision is communicated to all available Tablets and if necessary updates the fall-risk assessment tool with the new feature as a new fall-risk indicator that extends the prior checklist.

3. Discussion

Within the scope of this work, we have showed the applicability of our novel approach on top of the data provided by EPRs to achieve a more personalized healthcare. In order to adapt the assessment tool to the population under care, we have enabled the patients to be a part of the elaboration of arising fall-risk indicators. We have emphasized this using an Agent-Oriented Software Engineering approach to model the system in a distributed way. This approach is promising as it avoids the introduction of centralized entities occupying all data about a population under care. This is a special requirement when developing such applications in Germany considering the strict German privacy laws. This system can also be further improved by applying Natural Language Processing (NLP) techniques on the available free-text fields in EPRs containing a magnitude of data. Additionally, we have used a well-researched method to aggregate opinions about fall-risk indicators in form of probability distributions. We have shown here, that such methods can be applied using light-weight mobile technologies like Tablets, which means that we do not need massive computing power to infer knowledge from EPRs for such use cases in the healthcare domain. We have achieved technical applicability to estimate a fall risk of patients automatically while preventing the additional burden on healthcare professionals' work to find a possible fall-risk indictor. Regarding the evaluation of the fall risk assessment tool in a real healthcare practice from a medical point of view, we need to setup a case study to retrieve enough evidence for observing the fall events. This will be further tested and in future when the agnes^{zwei} app will be deployed as working appliances for the healthcare professionals.

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