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# Agents vote against Falls: The Agent Perspective in EPRs

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**Abstract.** In this work we present an agent-based fall-risk assessment tool which is self-learning. As part of a mobile electronic patient record (EPR) each patient is represented by its agent which helps to lift the treasure of data offered by combining multiple EPRs in order to reveal personalized health-care. To learn from the data provided by the population under care, we enabled the patient agents to negotiate about possible fall-risk indicators using a distributed information fusion and opinion aggregation technique.

## 1 Introduction

The prevention of falls is a priority objective of nowadays health-care professionals as falls do not only contract injuries and disabilities, but also lead to substantial economic burdens (0.8% - 1.5% of the yearly German health-care costs [8]). Usually health-care professionals utilize fall-risk assessment tools to conceive the individual fall-risk of the patients and as a consequence to initiate suitable retaliatory actions. Here the increasing dissemination of electronic patient records (EPR) offers new opportunities for a more personalized health-care as EPR contain a treasure of data [6]. Even so, the ubiquitous access to all patient information can overwhelm the professionals identifying relevant fall-risk indicators as the feature space is too huge to conceive for humans. Hence, we introduce a patient agent which observes the whole feature space in order to learn the influences of each feature on the fall-risk of a patient. Further, we enabled the patient agents to negotiate about possible fall-risk indicators using a distributed information fusion and opinion aggregation technique. The negotiation results are then used to adapt the fall-risk assessment tool to the population under care. The focus of this work is to demonstrate the capabilities of the application by providing insights into the approach as well as insights into the simulation accomplished for the evaluation and the final application as part of a mobile EPR developed within the project *agnes<sup>zwei</sup>* [2].

## 2 Main Purpose

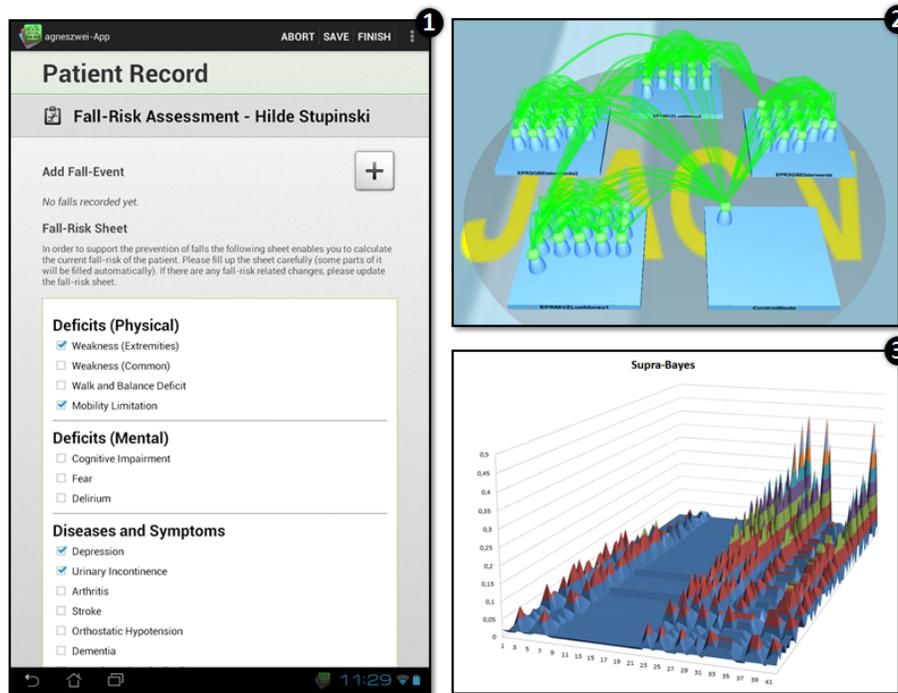
The environment we address consists of several health-care professionals, each one equipped with a Tablet which is the runtime for the mobile EPR. Every

Tablet is represented by an agent node containing several patients, where each patient is represented by its patient agent. The learning process is based on four steps: The occurrence of a fall, the local information fusion, the global opinion aggregation and the notification stage. Whenever a patient falls, the incident is documented in the associated EPR by the health-care professional. For each observed fall-event the patient agent elaborates the evidence for all features in the feature space using Bayesian information fusion [9]. Here, the prior knowledge about all features is linked with the current observation, where the initial knowledge of each agent where received from a literature research we conducted [11]. The received probability distribution can be seen as ‘degree of believe’ about possible fall-risk indicators [7]. Consequently each patient agent has an own expert opinion on which feature has influenced the fall observed. To receive a meaningful statement the challenge now ‘is to pool opinions in a rational way that yields a single probability distribution from which inference can be made’ [10]. Here, we first pool all opinions on a single Tablet and only pool the node opinion with the more global opinion of all Tablets if a feature reaches an experimentally established threshold. We decided to introduce this two stages as the communication on one Tablet is cheap and secure. As opinion aggregation technique we applied the ‘Supra-Bayesian Pooling Method’ [5] as it outperforms other evaluated pooling methods for the specific domain we address (rather small occurrence of events, fast convergence, linear time and space complexity). However, if the threshold of a feature is still exceeded after the global opinion aggregation the elaborated feature is forwarded to the health-care professional which has to decide whether this feature is a fall-risk indicator. For more details about the approach and the evaluation the interested reader is referred to *Ahrndt* and *Fähndrich* [1].

### 3 Demonstration

The goal of the demonstrator is twofold. To start with, we want to show how the overall system works and how the negotiation process between the single agents and the agent platforms operates. Therefor we will show the simulation environment we setup for the evaluation of the approach at runtime utilizing the ASGAR agent viewer [12] (see Fig. 1.2). We utilized the simulation runs in order to test the applicability and validity of the system and further to evaluate the performance of different distributed information fusion techniques. Here, we will show the progress of the probability distribution during runtime (see Fig. 1.3). To create meaningful results, each patient-agent where equipped with a set of fall-risk indicators received from a literature research [11] and the data model of the EPR developed within the *agnes<sup>zwei</sup>* project [2]. To initiate the negotiation we further implemented a simulation agent which represents the role of the health-care professionals. This agent adds fall-events to the population under care based on the current fall-risk of each patient and changes the values of the patient record as it would be during the use of the EPR system. The

simulation of the aging process of each patient is based on the research results of prior studies with risk-equivalent patients [3, 4].



**Fig. 1.** (1) Screenshot of the fall-risk assessment tool as part of the EPR. (2) Visualization of the simulation environment consisting of four Tablets with (with multiple patient agents, approximately 70) and a single agent platform simulating the health-care professionals. (3) Temporal progress of the probability distribution of 50 features during the first 80 voting rounds.

In addition to the simulation we want to introduce the final fall-risk assessment tool itself as part of the agnes<sup>zwei</sup> application. Fig 1.1 shows a part of the initial assessment tool enabling the health-care professional to add new fall-events and to calculate the current fall-risk of the patient. Here, we will show the notification stage of the approach reached if an elaborated feature is forwarded to the health-care professional which has to confirm whether it is a fall-risk indicator and should be added to the fall-risk assessment sheet or not.

## 4 Conclusion

We presented a self-learning agent-based fall-risk assessment tool as part of an EPR. The goal of the approach was to adapt the fall-risk assessment tool to the population under care to provide a more personalized health-care. We utilized an agent-based approach to model the system whereby each patient is represented by its patient agent. Consequently, the patient agents negotiate about possible fall-risk indicators. In order to demonstrate the approach we will utilize the simulation environment developed within the evaluation and show the system at runtime using the ASGARD agent viewer. Further we will present the final assessment tool as part of the agnes<sup>zwei</sup> App for Tablets.

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