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A bi-level interactive decision support framework to identify data mining-oriented electronic health record architectures

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ABSTRACT

Nowadays, many healthcares are generating and collecting a huge amount of medical data. Due to the difficulty of analyzing this massive volume of data using traditional methods, medical data mining on Electronic Health Record (EHR) has been a major concern in medical research. Therefore, it is necessary to assess EHR architectures based on the capabilities of extracting useful medical knowledge from a huge amount of EHR databases. In this paper, we develop a bi-level interactive decision support framework to identify data mining-oriented EHR architectures. The contribution of this bi-level framework is fourfold: (1) it develops Interactive Simple Additive Weighting (ISAW) model from an individual single-level environment to a group bi-level environment; (2) it utilizes decision makers' preferences gradually in the course of interactions to reach to a consensus on an data mining-oriented EHR architecture; (3) it considers fuzzy logic and fuzzy sets to represent ambiguous, uncertain or imprecise information; and (4) it synthesizes a representative outcome based on qualitative and quantitative indicators in the EHR assessment process. A case study demonstrates the applicability of the proposed bi-level interactive framework for benchmarking a national data mining-oriented EHR.

1. Introduction

Medical knowledge is the most valuable asset of a healthcare organization. Extracting hidden knowledge from patients' raw data helps physicians to identify effective diagnostic and treatment methods. In simpler terms, the efficacy of patient care can be improved with turning medical data into medical knowledge. Clearly, it is not surprising that healthcare organizations have been interested in medical data mining to support physician decisions.

Nowadays, many healthcare organizations are generating and collecting a huge amount of medical data such as demographics, vital signs, laboratory data, radiology reports, and progress notes in EHR architectures. Therefore, there is an urgent need to assess EHR architectures based on the capabilities of extracting useful medical knowledge from a huge amount of EHR data.

There are two main challenges in turning data from EHR architecture into medical knowledge:

(1) EHR data may not be optimal for medical data mining operations. EHR data quality determines whether the data mining process is successful or not;
(2) traditional methods cannot be used to analyze massive volumes of EHR data. This explosive growth of patients' raw data requires an automated way to extract useful knowledge from EHRs.

In order to overcome to the above challenges in the EHR architecture, we must consider the first challenge prior to the second one.

Several papers in the current literature have focused on implementation of EHR in healthcare information technologies [9,10,16,5,19]. A study of a number of papers indicates adoption of electronic health records [13,14]. Further studies have been applied to assess performance of an Electronic Health Record and the right expectations for the EHR standard [29,37,22,25].

Academic researchers have established a link between medical data mining techniques and EHRs [20,4,2,17,24,8].

A number of studies have focused on the application of interactive approaches [35,33,28,36,1,7,18,30,6,27,31,32].

To our best knowledge, there is no model in the existing literature to response to the mentioned challenges. This paper develops a bi-level model to assess different EHR architectures in order to identify a data mining-oriented EHR architecture.

This bi-level model consists of the following two sub-models:

(1) Leader sub-model: we assess the data quality of EHR architectures based on a data mining approach. In other words, the

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Table 1
The comparison of advantages and disadvantages of MCDM methods.

Method	Description	Advantages/disadvantages
No-preference method	This method can rank EHRs without any additional preference information	Such no-preference methods must be used if no preference information is available
A priori method	In this method, decision makers express preference information before the data mining-oriented EHR identification process	The difficulty here is that decision makers do not necessarily know the limitations of the EHR identification problem. Therefore, the feasible order of the EHRs generated may be far from the team's preference
A posteriori method	In this method, a set of feasible orders of the EHRs is generated and then decision makers must select the most preferred one	It may be difficult for decision makers to analyze a large amount of medical information
Interactive method	In interactive methods, decision makers can specify and adjust its preference information progressively during the interactive process	The advantage of interactive methods is that decision makers can specify and correct its preferences during the data mining-oriented EHR identification process

leader sub-model objective is to eliminate the less favorable EHR architectures with respect to EHR data quality indicators;

(2) Follower sub-model: we assess the rest of EHR architectures based on the capabilities of extracting useful medical knowledge from a huge amount of EHR data. In other words, the follower sub-model objective is to select the EHR architecture with the most applicable data to discovery medical knowledge.

A difficulty of the EHR architecture identification decision originates from the presence of more than one criterion at each sub-model. Therefore, we develop a bi-level Multiple Criteria Decision Making (MCDM) model to identify the data-mining-oriented EHR. Table 1 compares advantages and disadvantages of MCDM methods:

As shown in Table 1, the weaknesses of both *a priori* and *a posteriori* methods can be overcome if decision makers can direct the EHR identification process according to their preferences. Thus, we formulate the data mining-oriented EHR identification problem using a novel bi-level interactive model. As decision makers express their judgments using linguistic terms, the bi-level interactive model is considered in the fuzzy environment.

This paper is organized into six sections. In Section 2, we illustrate the details of the proposed framework. In Section 3, we present a case study to demonstrate the applicability of the bi-level interactive framework. In Section 4, we validate the bi-level interactive model. In Section 5, we compare the bi-level ISAW model method with the single-level ISAW method. The paper presents conclusions and future research directions in Section 6.

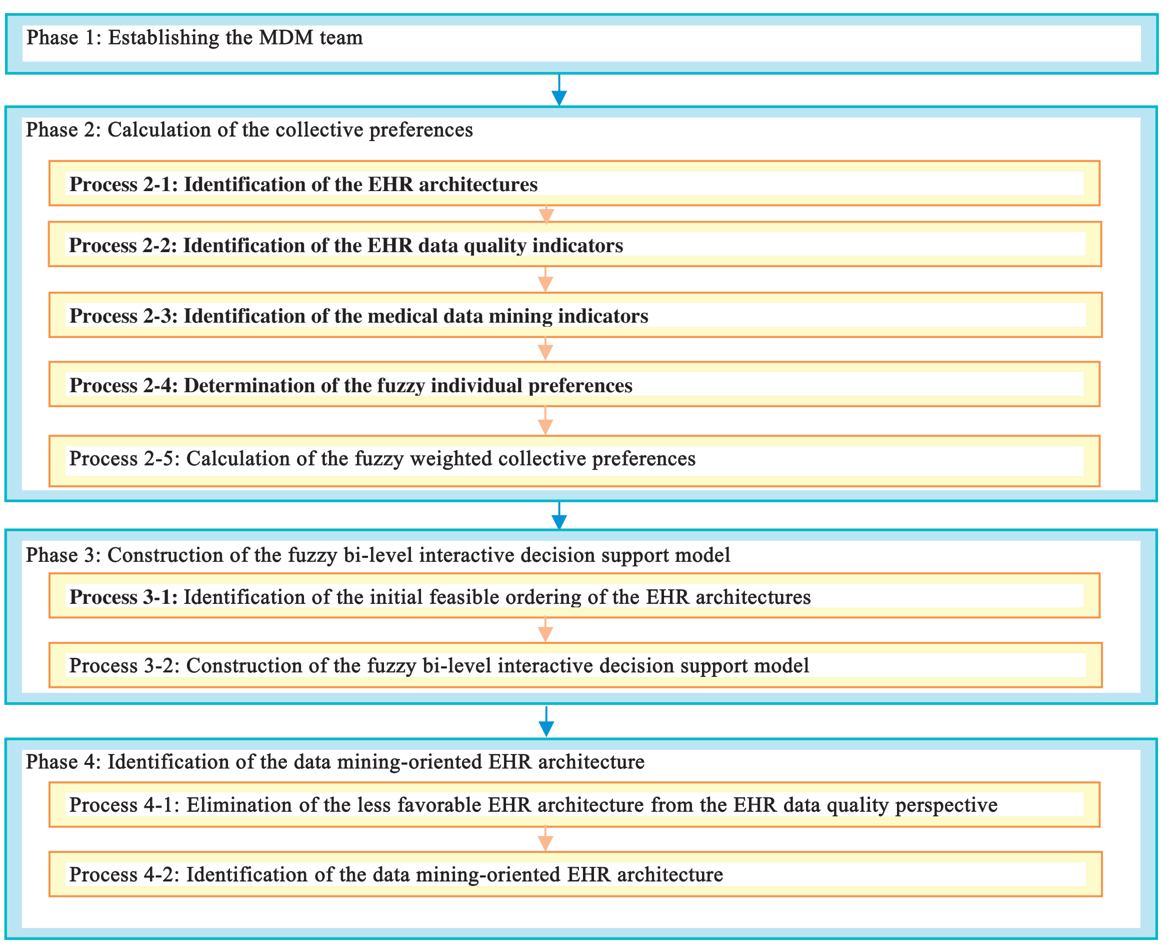

Fig. 1. The bi-level interactive decision support framework for the identification of the data mining-oriented EHR architecture.