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# Predictive monitoring of clinical pathways

Zhengxing Huang[a,*], Wei Dong[b], Lei Ji[c], Huilong Duan[a]

[a] College of Biomedical Engineering and Instrument Science, Zhejiang University, Zhou Yiqing Building 512, Zheda road 38#, Hangzhou 310008, Zhejiang, China
[b] Cardiology department of Chinese PLA General Hospital, Fuxing road 28#, Beijing 100853, China
[c] Information Technology Department of Chinese PLA General Hospital, Fuxing road 28#, Beijing 100853, China

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ABSTRACT

*Objective:* Accurate and timely monitoring, as a key aspect of clinical pathway management, provides crucial information to medical staff and hospital managers for determining the efficient medical service delivered to individual patients, and for promptly handling unusual treatment behaviors in clinical pathways (CPs). In many applications, CP monitoring is performed in a reactive manner, e.g., variant treatment events are detected only after they have occurred in CPs. Alternatively, this article presents an intelligent learning system for predictive monitoring of CPs and from a large volume of electronic medical records (EMRs).
*Methods:* The proposed system is composed of both offline analysis and online monitoring phases. In the offline phase, a particular probabilistic topic model, i.e., treatment pattern model (TPM), is generated from electronic medical records to describe essential/critical medical behaviors of CPs. Using TPM-based measures as a descriptive vocabulary, online monitoring of CPs can be provided for ongoing patient-care journeys. Specifically, this article presents two typical predictive monitoring services, i.e., unusual treatment event prediction and clinical outcome prediction, to illustrate how the potential of the proposed system can be exploited to provide online monitoring services from both internal and external perspectives of CPs.
*Results:* The proposed monitoring services have been evaluated using a real clinical dataset pertaining to the unstable angina CP and collected from a large hospital in China. In terms of unusual treatment event prediction, the overall precision and recall of our system are 0.834, and 0.96, respectively, which is comparable to identify unusual treatment events in CPs in comparison with human evaluation. In terms of clinical outcome prediction, the stable model was characterized by 0.849 accuracy, 0.064 hamming-loss and 0.053 one-loss, which outperforms the benchmark multi-label classification algorithms on clinical outcome prediction.
*Conclusion:* Extensive evaluations on a real clinical data-set, typically missing from other work, demonstrate that the proposed system, as a crucial advantage over traditional expert systems for CP management, not only provides an efficient and general surveillance of CPs, but also empowers clinicians with the capability to look insights into CPs to gain a deeper understanding of the situations in which the proposed prediction technique performs well.



## 1. Introduction

Clinical pathways (CPs), as evidence-based patient-care algorithms, describe the process of care for specific medical conditions within a localized setting (Huang et al., 2014d; Panella, Marchisio, & Di Stanislao, 2003; Rotter et al., 2010). In clinical practice, patient-care journeys are generally subject to the recommended treatment interventions which are regulated in CPs (Blaser et al., 2007; Ghattas, Soffier, & Peleg, 2014; Huang, Lu, & Duan, 2013a; Hunter & Segrott 2008). For example, a certain type of PCI surgery, as a well-defined step in the unstable angina CP, is recommended to an unstable angina patient. However, unexpected scenarios often occur in patient-care journeys and have a dramatic impact on health service delivery of CPs. In order to be able to quickly adapt to arising problems or deviations during the execution of CPs, it is very important to be able to monitor CPs in a near real-time manner so as to obtain a current overview over patient-care

* Corresponding author. Tel.: +86 57187951792.
*E-mail addresses:* zhengxinghuang@zju.edu.cn, zhengxing.h@gmail.com, loveproxy@hotmail.com (Z. Huang), 301dongw@sina.com (W. Dong), jilei_nudt@163.com (L. Ji), duanhl@zju.edu.cn (H. Duan).

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journeys, and subsequently guarantee/improve the performance of health service delivery.

CP monitoring is an emerging imperative in healthcare organizations (Huang, Juarez, Duan, & Li, 2014c; Huang, Lu, Gan, & Duan, 2011a; Uzark, 2003). Accordingly, a range of proposals have addressed the problem of monitoring CPs, which refer to specific requirements imposed on the execution of a CP that separates compliant from non-compliant treatment behaviors (Huang et al., 2011a; Huang, Bao, Dong, & Duan, 2014a). In fact, most existing techniques monitor ongoing patient-care journeys by assessing whether they comply with the treatment regulations in the established CP specification (Huang et al., 2014a). However, these approaches are from the reactive perspective, in that they allow clinicians to identify an unusual treatment event only after it has occurred rather than supporting them in preventing such variations in advance.

Recently, with the rapid development of hospital information systems, a large collection of electronic medical records (EMRs) has become available, which provides the opportunity to study medical cases, evidence and knowledge for CP analysis (Huang et al., 2014a) As a systematic collection of electronic health information about individual patients in their care journeys, EMRs conceal an untapped reservoir of knowledge about particular treatments and the way these are applied for patients with specific conditions. It is therefore possible to mine EMRs, extract non-trivial treatment knowledge from EMRs, and exploit these for helping clinicians improve and optimize CPs, and make the practice better for the care of individual patients (Peleg, 2013).

In clinical practice, healthcare organizations are gradually using EMRs to manage and measure CPs from an external observation, e.g., length of stay (LOS), cost, infection rate, and so on (Rotter et al., 2010; Okita et al., 2009). As valuable as these measures, they are all preceded in an offline manner and lack of management during the CP execution. In terms of CP management, it is more important to monitor the execution of CPs in real-time and look insight into the essential/critical treatment behaviors of CPs than only to inspect the outcome after the execution of CPs.

In this study, we present a learning system to provide predictive monitoring services in CPs. The proposed system takes into account the fact that predictions often depend on both patient conditions and performed treatment activities at any time points during the execution of CPs. The core of the proposed system is a technique to recognize essential/critical treatment behaviors in CPs (Huang, Dong, Bath, Ji, & Duan, 2015a; Peleg, Mulyar, & van der Aalst, 2012). In line with the principle of utilizing the heterogeneous EMRs to assist CP monitoring, the proposed system proceeds according to a two-phased approach. In the first phase of offline analysis of CPs, a specific probabilistic topic model, i.e., treatment pattern model (TPM), which is presented in our previous work (Huang et al., 2015a), is generated describe essential/critical treatment behaviors of CPs. Based on TPM-based measures as a descriptive vocabulary of CPs, predictive monitoring services of CPs can be provided on ongoing patient-care journeys from both external and internal perspectives. In particular, we present two typical predictive monitoring services in our learning system. The one is an unusual treatment event prediction service, which looks insight into CPs to map the prediction task to a classification task such that unusual variant executions of treatment activities can be timely predicted in an ongoing patient-care journey. The other is a clinical outcome prediction service, which is from an external perspective to forecast multiple clinical outcomes across various stages of CPs. The proposed predictive monitoring services have been validated using a real clinical dataset pertaining to the unstable angina CP in a large hospital in China.

The remainder of the paper is organized as follows: Section 2 depicts the case study of the unstable angina CP. Sections 3–5 present the proposed learning system for predictive CP monitoring, the employed probabilistic topic model for recognizing essential/critical treatment behaviors in CP, and two typical predictive CP monitoring services, as well as the case study results thereof, respectively. We then discuss some possible improvements in Section 5. Finally, Section 6 draws conclusions and perspectives.

## 2. Case description

The CP of unstable angina is selected in the case study. Unstable angina or sometimes referred to as acute coronary syndrome is a warning sign that a heart attack may happen soon, and causes unexpected chest pain, and usually occurs while resting (Dong, Huang, Ji, & Duan, 2014). The population of unstable angina is huge, especially for aged people and those with associated disease such as hypertension and diabetes (Dong et al., 2014). Numerous factors impact on unstable angina patient treatment strategies and the application of interventions, such that variations could occur in a mandatory manner for unstable angina CP. Thus, predictive monitoring and analysis on the unstable angina CP will be of significant value and interest since it could provide physicians comprehensive understanding on the expected results of the pathway, and explicit suggestions for the adjustment and improvement of the pathway in concern for the patient's benefits (Catherwood & O'Rourke 1994).

In this case study, a collection of EMRs of 12,152 patients following the unstable angina CP (from 2004 to 2013) was extracted from EMR system of Chinese PLA general hospital to demonstrate the ability of the proposed learning framework for CP understanding. The collected EMRs have 144 patient features, and 704,004 clinical events within 606 treatment activity types. The average length of stay (LOS) recorded in the collection of EMRs is 10.14 days, which some patient treatment journeys take a very short time, e.g., only 1 day in the hospital, and other treatment journeys take much longer, e.g., more than 6 months in the hospital, which implicitly indicates the diversity of treatment behaviors in the unstable angina CP.

## 3. A learning system for predictive monitoring of clinical pathways

In this study, we propose a learning system for predictive monitoring of CPs. As shown in Fig. 1, the proposed system can provide online monitoring services in CPs from both internal and external perspectives, by automatically extracting non-trivial CP knowledge from EMRs.

The basis of our learning system is a large collection of EMRs $\mathcal{D}$, which conceals an untapped reservoir of knowledge about particular treatments and the way these are applied for patients with specific conditions. Each EMR $d$ in $\mathcal{D}$, corresponding to a particular patient treatment journey of a CP, consists of the descriptions on both patient clinical information and treatment events performed on the patient given his/her clinical conditions and during the pathway execution.

Formally, a patient treatment journey of a CP is described as a set of $N_d$ ($N_d = N_d^f + N_d^e$) treatment words consisting of both $N_d^f$ patient features with their values and $N_d^e$ treatment events with their occurring time stamps. In this sense, an EMR $d$ recording typical treatment information about a particular patient treatment journey is represented as $d = \{\langle \boldsymbol{f}_d, \boldsymbol{v}_d \rangle, \boldsymbol{e}_d\}$, where $\boldsymbol{f}_d = \{f_{di}\}_{i=1}^{N_d^f}$ represents patient features that are measured on a particular patient,