

Intelligent Risk Detection for Healthcare

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INTRODUCTION

In healthcare contexts, unfortunately for some diseases, surgery is not always considered a final cure, as it can result in a considerably high rate of disabilities, as well as the possibility of comorbidities; for example, types of cancer and even the development of bowel diseases. Further, there is the direct adverse impact on the patients and their families. Therefore, decision-making regarding such surgeries is multi-faceted and complex.

To facilitate the surgical decision making process, we contend that such contexts are appropriate for the application of real time intelligent risk detection decision support. We proffer a suitable solution which combines the application of data mining tools followed by Knowledge Discovery (KD) techniques to score key surgery risk levels, assess surgery risks and thereby help medical professionals to make appropriate decisions.

The aim of this study is to improve the outcomes and benefits of surgical interventions and support a healthcare value proposition of excellence for patients, their families, providers, healthcare organizations and society by developing an intelligent risk detection framework to improve surgery decision making processes. While such strategies have been used in other industries (i.e. banking and finance), it appears that this is one of the first studies focused on healthcare contexts.

To illustrate the power and potential of Business Intelligent and Data Mining techniques to support healthcare decision making scenarios, the following focuses on the contexts of Congenital

Heart Disease (CHD) in children as well as the Orthopaedic context of Hip and Knee interventions.

BACKGROUND

Clinical Decision Support Systems (CDSS) are computer driven technology solutions, developed to provide support to physicians, nurses and patients using medical knowledge and patient-specific information (De Backere, De Turck, Colpaert, & Decruyenaere, 2012). Decision Support systems can be found in widely divergent functional areas. However, in e-health contexts because of the importance of real time outcomes and the multi-spectral nature of care teams (Wickramasinghe, Bali, Kirn, & Sumoi, 2012), the following key features become most essential:

- Intelligent timing
- Multidimensional views of data
- Calculation-intensive capabilities

Hence, these systems will give advice and support rather than decision making replacing that of clinical staff. Studies have already proved that CDSS enhance quality, safety and effectiveness of medical decisions through providing higher performance of the medical staff and patient care as well as more effective clinical services (Garg, Adhikari, McDonald, Rosas-Arellano, Devereaux, Beyene, & Haynes, 2005; Fichman, Kohli, & Krishnan, 2011; Restuccia, Cohen, Horwitt, & Shwartz, 2012). A variety of CDSS programs designed to assist clinical staff with drug dosing,

health maintenance, diagnosis, and other clinically relevant healthcare decisions have been developed for the medical workplace (Haug, Rocha, & Rocha, 2007). On the other hand, patients' demand for participation in medical decisions has been increasing (Kuhn, Wurst, Bott, & Giuse, 2006). Therefore, to be respectful of patients and parents/guardians participation and decisions, shared decision-making (SDM) between health care professionals, patients, parents and guardians is widely recommended today (Lai, 2012). SDM is defined as the active participation of both clinicians and families in treatment decisions, the exchange of information, discussion of preferences, and a joint determination of the treatment plan (Makoul & Clayman, 2006; Légaré, Stacey et al., 2011; Barry & Edgman-Levitan, 2012).

Although SDM is supported in many disease management domains, some concerns and issues still remain regarding the adoption of SDM solutions such as a perception among some practitioners that the ultimate responsibility for treatment should remain under their authority (Schauer, Everett, Vecchio, & Anderson, 2007; Edwards & Elwyn, 2009). Moreover, client capacity to participate in decisions (O'Brien, Crickard, Rapp, Holmes, & McDonald, 2011), identifying the SDM components (Sheridan, Harris, & Woolf, 2004; Van der Weijden, Van Veenendaal, Drenthen, Versluijs, Stalmeier, Loon, & Timmermans, 2011) as well as SDM user acceptance (Scholl, Loon, Sepucha, Elwyn, Légaré, Härter, & Dirmaier, 2011) are main issues to promote this type of CDCS in the healthcare contexts.

On the other hand, SDM has also some limitations for example SDM is appropriate for situations in which two or more medically reasonable choices exist (O'Connor, Bennett, Stacey, Barry, Col, Eden, & Rovner, 2009), regardless of whether the degree of risk is high or low (Whitney, McGuire, & McCullough, 2004). Therefore, SDM is not appropriate in these cases while still patients or their families would like to have participation in the care process. Hence, more studies are needed to deepen the understanding of interactions be-

tween patient decision aid use and the patterns of patient-practitioner communication as well as format issues such as Web-based delivery of patient decision aids. (O'Connor, Bennett et al., 2009; Flight, Wilson, Zajac, Hart, & McGillivray, 2012; Parsons, Harding, Breen, Foster, Pincus, Vogel, & Underwood, 2012). Research on shared decision making is under way (Deegan & Drake, 2006; Barry & Edgman-Levitan, 2012), but much more is needed in this area.

Moreover, Medical decisions always have to be made in a tradeoff between benefit and risk. Unfortunately, many decisions are based upon an incorrect knowledge of risk (Weijden et al., 2007). Also different viewpoints concerning risks can result in different optimal choices because of different perspectives (Horn et al., 1985; Kuntz & Goldie, 2002).

Therefore the following suggest that an Intelligent Risk Detection (IRD) model which attempts to facilitate and provide decision support for clinicians and patients regarding the treatment risk factors might be beneficial. In developing such a solution, it is necessary to combine three key areas of business analytics, risk detection and decision support systems. This is an important contribution to both theory and practice in healthcare since, to date real time use of risk detection, while prevalent in many industries such as finance, has rarely if at all been incorporated into healthcare settings.

This in turn makes a real time intelligent risk detection framework the preferred choice. Thus, our study proposes an intelligent application for high-level surgery risk detection and outcome prediction to support surgical decisions. The model is designed based on two steps of the decision making process (surgical and personal) and, includes a decision support system which is suitable for high concentration prediction. Continual model updates inherent in the proposed system results in adaptive and more accurate risk detection and outcome prediction capabilities as compared to a fixed model.

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