EXPLORING THE POSSIBILITIES FOR INTELLIGENT RISK DETECTION IN HEALTHCARE CONTEXTS

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Abstract
Healthcare is an information rich industry where successful outcomes require the processing of multi-spectral data and sound decision making. The exponential growth of data coupled with a rapid increase of service demands in healthcare contexts today requires a robust framework enabled by IT (information technology) solutions as well as real-time service handling in order to ensure superior decision making and successful healthcare outcomes. Contemporaneous with the challenges facing healthcare, we are witnessing the development of very sophisticated intelligent tools and technologies. Therefore, it would appear to be prudent to investigate the possibility of applying such tools and technologies into various healthcare contexts to facilitate better risk detection and support superior decision making. The following serves to do this in the context of Orthopaedics and Congenital Heart Disease.

Keywords: clinical decision making, risk detection, Orthopaedics, Congenital Heart Disease.
1 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 co-morbidities (Jansson and Granath, 2011; Goossens et al. 2013); 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 (Landolt et al. 2011). Therefore, decision-making regarding such surgeries is multi-faceted and complex (Cook et al. 2012; Sox et al. 2013).

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 (ie. banking and finance) (Bhambri, 2011; Pulakkazhy and Balan, 2013), 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.

2 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 et al. 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, et al., 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 et al. 2005; Fichman, Kohli et al. 2011; Restuccia, Cohen et al. 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, Gardner et al. 2007).

On the other hand, patients’ demand for participation in medical decisions has been increasing (Kuhn, Wurst et al. 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 (Charles, Gafni et al. 1997; Makoul and Clayman 2006; Légaré, Stacey et al. 2011; Barry and 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 et al. 2007; Edwards and Elwyn 2009). Moreover, client capacity to participate in decisions (O’Brien, Crickard et al. 2011), identifying the SDM components (Sheridan, Harris et al. 2004; van der Weijden, van Veenendaal et al. 2011) as well as SDM user acceptance (Scholl, Loon et al. 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 et al. 2009), regardless of whether the degree of risk is high or low (Whitney, McGuire et al. 2003). 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 between 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; Cousin, Schmid Mast et al. 2012; Flight, Wilson et al. 2012; Parsons, Harding et al. 2012).

Research on shared decision making is under way (Deegan and Drake 2006; Barry and Edgman-Levitan 2012), but much more is needed in this area. Also, it is critical to address the importance of asking right questions in shared decision making process before looking for a right answer, as asking the wrong questions in clinical cases can generate seemingly right answers, but these answers may not be enough to reflect or predict real-life scenarios (Horwitz et al. 2014).

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 and 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.

3 Key Aspects of the Study

We note that while data mining is being utilized in various healthcare contexts including applications of text mining and secondary uses for data (Safran et al., 2012), infection control(Iakovidis et al., 2012), physician order entry and electronic health records(Wright and Sitting, 2006; Botsis et al., 2010; Batal and Hauskrecht, 2010) and even in the identification of high risk patients (Marschollek et al., 2012) the application of data mining and BI for risk detection is at a nascent state.

However, the lack of interaction between healthcare industry practitioners and academic researchers makes it hard to discover surgical risks, and limits opportunities for the application of BI techniques, and hence weakens the value that knowledge discovery and data mining methods may bring to healthcare risk detection.

In the context of surgical risk detection many dimensions and perspectives (Yoshio et al 2012) are of importance and these mainly focus on pathological process, physiological variables, some general health perceptions, social paradigm and also quality of life (Rizzo and Kintner 2012).

Naturally, detecting the risk factors in all of these dimensions is not easy or trivial but based on two approaches to assess the risks, with contribution of clinical experts; this research aims to cover these main dimensions.
4 Research Design and Methodology

Throughout this research a mixed method approach is conducted incorporating well established qualitative and quantitative data collection techniques. Qualitative and quantitative data are collected by two distinct method; namely, individual semi-structured interviews and questionnaires. Figure 1 provides a detailed schematic of the complete research design.

To capture the inherent complexities of surgery interventions, the conceptual model (figure 1) has been developed. Integral to this model are the two steps of decision making defined over the three key phases of the decision making process for the surgery. The first type of decision making is called “surgical decision making” and is primarily associated with the surgeons while the second type is called “personal decision making” as it is primarily associated with the patients or their family.

In the first phase, or pre-operative phase, the surgeon, having received information about the patient and his/her medical condition, needs to make decisions relating to whether surgery is the best medical option. Once this decision is made but before the surgery, the parents/patients must then decide whether to accept or reject the surgeon’s decision in consideration of the predicted outcomes. Thus, already at stage one of the decision making process already two, key decisions must be made. Once parents/patients and surgeons have agreed to proceed, in phase two (pre-operative phase), critical decisions during the surgery must be addressed. Finally, at the post-operative phase, or phase three, decision making is primarily done at two levels; a) strategies to ensure a sustained successful result for the patient during aftercare and beyond, and b) a record of lessons learnt for use by clinicians in future similar cases.

The first block in figure 2 depicts the first stage of risk assessment. The output of the risk assessment process will then be used to facilitate the determination of important surgical risk factors and also in predicting anticipated outcomes (in the risk detection block) based on specific risk factors.

The anticipated results enable the surgeons to then make better informed decisions regarding whether (or not) to proceed with the surgery in phase one. If the decision is indeed to proceed with the surgery, all relevant information then needs to be passed onto the parents in order to allow them to make their final decision regarding the surgery. Depending on their decision one move to either the second phase or the process is concluded.

Any conflict or differences in the decision of the surgeon and that of the parents form feedback into the system for future risk assessments for the same or other similar patients. In this way, the risk assessment process is continually updated and reflective of the latest outcomes and learning. After the surgery, actual outcomes are compared to the anticipated ones predicted by the system. This comparison serves as an evaluation process in the model; thus ensuring continual improvement of the system’s predicting capabilities.

Table 1. Key Data mining Steps

<table>
<thead>
<tr>
<th>Step</th>
<th>Activity</th>
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<tbody>
<tr>
<td>1</td>
<td>Understand surgical requirements, dataset structure and data mining task i.e. Knowledge-Rich Data Mining in healthcare Risk Detection.</td>
</tr>
<tr>
<td>2</td>
<td>Prepare target datasets: select and transform relevant features; perform data cleaning and data integration. Communicate any findings during data preparation to domain experts.</td>
</tr>
<tr>
<td>3</td>
<td>Train multiple data mining models in randomly sampled partitions using Business Intelligence software.</td>
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<tr>
<td>4</td>
<td>Evaluate data mining models using a set of performance metrics.</td>
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<tr>
<td>5</td>
<td>Discuss the data mining results with domain experts. Explore potential patterns from data mining results. If new risk factors or patterns are identified, communicate the rule(s) with decision makers and determine the appropriate actions.</td>
</tr>
<tr>
<td>6</td>
<td>Go back to Step 1 if new clinical questions are raised during the process or new KPI, rule(s) or risk factor are discovered after comparing the actual and anticipate results. Otherwise, finish and exit the process.</td>
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</table>
Figure 1: Research Design

Figure 2. The Conceptual Model. Source: adapted from (Moghimi, Wickramasinghe et al. 2011)
4.1 Risk Assessment and Detection

Detecting risk factors based on a risk assessment process using BI tools is a useful way to assess improvements in surgery (Larrazabal, Jenkins et al. 2007). Therefore, after first identifying important risk factors in the literature, we will seek expert input at two distinct stages to address this subject. The specific stages involved in the risk assessment process include the following: In the first stage, the specialists in an expert group of clinicians and surgeons are presented with risk factors identified from the literature. The experts will then nominate (or introduce) some main risk categories or dimensions as well as risk factors to be used in the surgical decision making process. In the next stage, the expert group is asked to assess the risk factors and also evaluate the effects of these factors in surgery outcomes. It is also important to document the surgeons’ and specialists’ recommendations and advice in order to improve the Model.

To incorporate an intelligent technology into the proposed risk assessment process, data mining tasks followed by knowledge discovery will be trained. In the research case, the data types have a significant impact on the data mining tasks. Hence, after completing the data collection phase, techniques such as neural networks and association rules will be used. After the risk assessment process, applying the necessary data mining techniques, and the development and implementation of the model, a database of the patients’ data will be used in order to detect risk factors (Table 1).

4.2 Applying Anticipated and Actual Results

To evaluate a risk detection process in the proposed conceptual model, the actual results will be compared with the anticipated results. This provides feedback to assess the accuracy of the process and also provide appropriate modification as new factors are identified. Lastly, the BI reporting tools will be used to create a final report to show important items, and finally apply them to the risk assessment process, for subsequent iterations of evaluations.

5 Case Studies

To illustrate the benefits of our proposed IRD Model, we look at two specific healthcare contexts: case one, Orthopaedic interventions and case two, Congenital Heart Disease. The following serves to examine the technical and conceptual layers of the IRD Model and also defines some of the associated knowledge driven healthcare services which are supported by the IRD model in order to facilitate superior healthcare delivery.

- **Case 1: Incorporating IRD Model to Hip and Knee intervention:**
  In general, total hip and total knee replacements are successful solutions for people experiencing pain associated with degenerative joints (Graves, 2011). In fracture care for broken hips however, there are other risk factors involved which impact on both the choice of treatment and on patient outcomes. (Graves, 2011; Dijkman, 2008). This makes the decision process connected with this surgery of significant importance. In addition hip and knee replacements continue to undergo innovation with improvement in technology and it needs to be monitored (Moghimi and Wickramasinghe, 2012a). Taken together, this serves to underscore that performance management in this context is clearly complex, dependent on multi spectral data and information and has far reaching consequences. Therefore, our IRD Model should be an effective and efficient solution in such a context.

  Thus, to illustrate the role for our IRD Model, we have categorized the hip and knee interventions, particularly for hip and knee replacement, into four key components as follows in an attempt to systematically capture four key risk factors (Moghimi and Wickramasinghe, 2012b):
  - Prosthetic issues: specific to implant that may impact on the outcome of surgery.
  - Financial issues: regarding the costs of these devices in relationship to outcome and type of surgery.
- Physiological and co-morbidities: patient specific issues that may impact on the outcome of surgery
- Clinical issues: to medical/provider intervention that may impact on the outcome of surgery.

Table 2 then, serves to illustrate how the key BA techniques depicted in figure 2 can then be transformed and translated into a specific context; in this instance the context of the hip and knee interventions specifically focussing on hip and knee replacements.

Implicit in this conceptualisation is that the proposed IRD Model is sufficiently flexible to cover all process from pre operative, operative and post operative. In so doing it will then provide most benefit to all key stakeholders.

Table 2: The role of IRD components to improve performance management in hip and knee interventions

<table>
<thead>
<tr>
<th>IRD components</th>
<th>Improvements subjects</th>
<th>Description (How)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Balanced scorecard</td>
<td>- To improve financial issues</td>
<td>By developing relevant measurements and KPIs</td>
</tr>
<tr>
<td>Service line analysis and reporting</td>
<td>- To improve financial issues</td>
<td>By making analytical and multidimensional reports</td>
</tr>
<tr>
<td>Health and wellness service line management</td>
<td>- To improve biomedical issues</td>
<td>By real-time monitoring and controlling patients’ clinical conditions</td>
</tr>
<tr>
<td>On-Line Analytical Processing (OLAP)</td>
<td>- To improve biomedical issues</td>
<td>By making ad-hoc and real-time analytical reports</td>
</tr>
</tbody>
</table>

- **Case 2: Incorporating IRD Model to the Congenital Heart Disease (CHD):**

Congenital Heart Disease (CHD), as a common health problem affecting many children around the world (Marino et al 2012), is involved a multi-faceted set of considerations including the immediate medical result, the ongoing increased risk of sudden death, exercise intolerance, neuro developmental and psychological problems as well as long-term impacts on the family unit (Long et al 2012). This multi-faceted consideration is important because of the far reaching consequences that can result post-surgery or even mortality or morbidity.

The decision making process in the context of CHD surgery can be divided into three broad phases. In the first phase, or pre-operative phase, the surgeon, having received information about the patient and his/her medical condition, needs to make a decision relating to whether surgery is the best medical option. Once this decision is made but before surgery, the parents must then decide whether to accept or reject the surgeon’s decision in consideration of the predicted outcomes. Typically, parents have met many medical staff before they meet the cardiac surgeon. Thus, already at stage one, two key decisions must be made. Once parents and surgeons have agreed to proceed, in phase two, critical decisions pertaining to the unique situations that may arise during the surgery must be addressed. For example, in CHD cases sometimes due to the clinical conditions, surgeons have to change the shunt size during the surgery and regarding this ad-hoc decision, they have to choose the best suitable shunt size with fewer risks, in a very short time. Finally, in the post-operative phase, or phase three, decision making is primarily done at two levels; a) strategies to ensure a sustained successful result for the patient during aftercare and beyond, and b) a record of lessons learnt for use by clinicians in future similar cases.
To clarify the function of the decision making framework across CHD surgery for this study, we summarize current surgery steps and the associated decision making process in one of the common CHD classifications; Hypoplastic Left Heart Syndrome (HLHS) in figure 4. HLHS patients, usually have three types of surgery during their childhood treatment period. Norwood, BCPC and Fontan are most recent surgeries that are conducted to patients in different age and conditions. However, the Norwood surgery is still much more complex and risky with a high rate of mortality and morbidity. As is depicted in figure 2, in the current state, typically the parental decision, while significant, is often not recognized as a key component of the healthcare outcome, whereas the surgical decision making process is clear in all critical steps. Thus, our proposed IRD Model will be a valuable Model to apply in the highlighted steps in all three surgery phases and surgery types to predict the operation results by detecting risk factors to assist parents as well as surgeons to make superior decisions.

Figure2. Flow Diagram of Key Steps with CHD Surgery in the case of HLHS to Demonstrate the Importance of the IRD Model (Highlighted boxes in the current procedure represent proposed situations to use the IRD Model)

6 Discussion and Conclusion

This study has outlined an exploratory research study aimed at trying to examine the potential benefits of combining a real time intelligent risk detection solution with decision support in a healthcare context. The outcomes from this exploratory research include, early identification of risk factors, providing superior decision support, developing key performance indicators to detect the surgery risk factors, predicting surgical results to identify patients at risk during surgery, standardizing clinical risk assessment and management processes to facilitate superior health outcomes, developing a risk profile for patients, improving risk information sharing, developing a true picture of risk categories and factors, creating a "Risk Aware" alarm to control the risk factors and monitoring the risk factors by using dashboards. Emphasizing the importance of knowledge sharing between clinicians as well as between clinicians and patients; clinicians' involvement during systems development; acceptability and capability of the system and high demand of outcome predictions to improve decision efficiency are the major contribution to practice.

Providing analytical report to clinicians and patients in three phases of preoperative, operative and post operative, through different and secure access level, is the other advantages of the IRD model.

In addition, using KPIs as a set of metrics not only is a novel idea to control the risk factors, finding the level and defining their relationships, but it also enables effective monitoring of several key items during surgery.
Another advantage of the proposed IRD model that should be noted is its continuous nature. Most importantly, by comparing anticipated results and actual outcomes and also performing risk auditing, risk factors will be amended to improve future predictions.

A further and final important feature of the proposed IRD model is the integration of the three IT solutions to solve a clinical issue in the definition and assessment of “outcomes” in patients with CHD, combined by some assessment measures. Thus, we believe it will also be one of the valuable contributions to both theory and practice of this research.

The next step for this research is to test the theoretical framework and conceptual model developed. In closing, we contend that real time intelligent risk detection appears to be critical for many areas in healthcare where complex and high risk decisions must be made and our future research will include testing of our proposed solution against specific clinical contexts.

7 References


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