Chapter 2
An Intelligence e-Risk Detection Model to Improve Decision Efficiency in the Context of the Orthopaedic Operating Room

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Abstract Decision making in healthcare is unstructured, complex and critical. Today, given the healthcare professionals are continually under immense time pressure to make appropriate treatment decisions. Moreover, in order to make such decisions it is necessary for them to process large amounts of disparate data and information. We contend that such a context is appropriate for the application of real time intelligent risk detection decision support system. To illustrate the benefits of risk detection to improve decision efficacy in healthcare contexts we focus on the case of the orthopaedic operating room for hip and knee replacements. In the orthopaedic operating room complex high risk decisions must be made which have for reaching implications on the success of the surgery and ongoing quality of life of the patient.

Keywords Data mining • Decision support system • Healthcare systems • Intelligent risk detection decision • Knowledge discovery

2.1 Introduction

Effective decision making is vital in all healthcare activities. While this decision making is typically complex and unstructured, it requires the decision maker to gather multi-spectral data and information in order to make an effective choice when faced with numerous options (Wickramasinghe et al 2009a). Unstructured decision making in dynamic and complex environments is challenging and in almost every situation the decision maker is undoubtedly faced with information inferiority. The need for germane knowledge, pertinent information and relevant data are critical and hence the value of harnessing knowledge and embracing the tools, techniques, technologies and tactics of knowledge management are essential to

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ensuring efficiency and efficacy in the decision making process. Recognizing this Wickramasinghe and Schaffer (Wickramasinghe et al. 2009a) developed the Intelligent Continuum, a systematic approach that enables the application of knowledge management (KM) principles and tools necessary for improving the decision making processes in healthcare and to ensure that the healthcare decision making process outcomes are optimized for maximal patient benefit. The following research-in-progress attempts to extend this idea, specifically focusing on the case of hip and knee replacements in orthopaedic operating rooms, an area that is not only of significance but also involves multiple risks and critical decision making processes and hence an appropriate environment to demonstrate the benefits of our approach. This work focuses on answering the research question of how to incorporate real time intelligent risk detection into healthcare decision support systems.

2.2 Background

Hip and knee replacements are procedures performed frequently to relieve pain and improve function in patients with advanced hip and knee joint destruction (Davidson et al. 2008). The Australian Orthopaedic Association National Joint Replacement Registry (AOANJRR) (Davidson et al. 2008) categorizes hip replacements as either primary or revision procedures. Primary hip procedures are further categorized as partial or total hip replacements. Partial hips are further sub-categorized depending on the type of prostheses used; these are monoblock, unipolar modular and bipolar procedures. Similarly, there are a number of different categorizations for knee replacement procedures. What is important is that these categorizations are made correctly and this requires a correct evaluation and assessment of various multi spectral data and information (Wickramasinghe and Schaffer 2006).

In general, knee replacement is more common in females (56.0%). There are however gender variations depending on the type of procedure. The indication for almost all primary knee replacement procedures is osteoarthritis (partial resurfacing 90%, unispacer 100%, patella/trochlear 98.9%, uni-compartmental 98.8%, bicompartmental 100% and primary total 96.8%). The principal cause for revision knee replacement is loosening (36.5%) (Davidson et al. 2008).

The most common knee procedure is a primary total knee replacement (78.7% of all knee procedures recorded by the Registry). The proportion of other knee procedures is 12.2% for unicompartmental, 0.5% for patella/trochlear and 8.5% for revision procedures. There are a small number of procedures recorded for the other types of primary knee replacement, partial resurfacing (90), unispacer (39) and bicompartmental.

The mortality associated with hip replacement varies as shown at Table 2.1, depending on the category and there has been little change in mortality trends over the 2007. As would be anticipated, crude cumulative mortality of primary partial hip replacement is high (45.4%) compared to primary total hip (6.6%) (Davidson et al. 2008).

On the other hand, trends previously reported for mortality following knee replacement remain unchanged. The cumulative mortality varies according to the extent of the procedure. There were no deaths recorded for unispacer, partial resurfacing and

Table 2.1 Mortality following primary hip replacement by type (Based on Davidson et al. 2008)

Type of hip replacement	Number deaths	Number patients	Cumulative mortality (% deaths)	Standardised mortality	Person years	Rate per 100 person years	Exact 95% Cl
Bipolar	2,789	7,749	36.0	26.2	20,176	13.8	13.32, 14.35
Unipolar monoblock	9,048	15,810	57.2	14.5	32,973	27.4	26.88, 28.01
Unipolar modular	2,013	6,924	29.1	18.8	12,242	16.4	15.73, 17.18
Partial resurfacing	0	8	0.0	0.0	12	0.0	0.00. 30.76
Total resurfacing	83	9,143	0.9	0.6	29,291	0.3	0.23, 0.35
Thrust plate	2	140	1.4	0.5	581	0.3	0.04, 1.24
Conventional total	7,580	106,540	7.1	2.6	349,195	2.2	2.12, 2.22
Total	21,515	146,314	14.7	3.8	444,469	4.8	4.78, 4.91

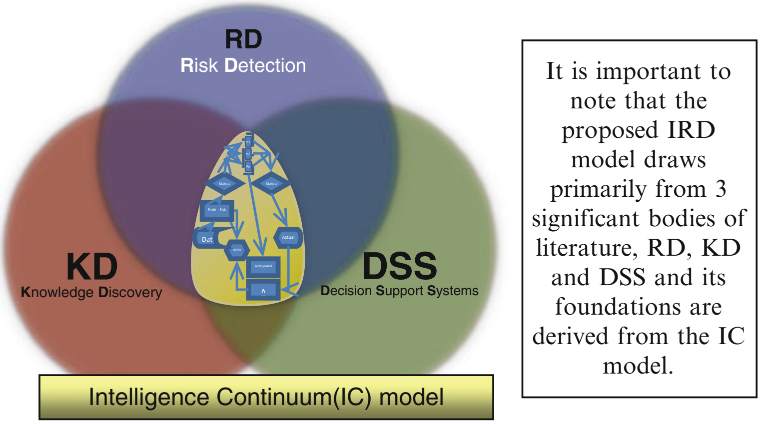


Fig. 2.1 The proposed IRD model

bicompartmental replacement. The cumulative mortality for patella/trochlear replacement is 2.3%, unicompartmental is 3.5% and primary total is 5.4% (Davidson et al. 2008). Hence, what on the surface seems to be simply a knee replacement is in reality much more complex. Table 2.1 summarises their issues.

In general total hip and total knee replacement surgeries are successful and very frequent procedures in the orthopedic or for people experiencing pain associated with degenerative joints. However the other types of partial hip and knee replacements are complex and involve with many different risk factors.

Since these risk factors are associated with decrease in quality of life (Dijkman et al. 2008), the importance of the decision making processes have increased significantly through hip and knee replacement.

In addition, Hip and knee implants are undergoing a constant state of innovation and improved technology (Wickramasinghe et al. 2009b). As can be seen, the critical decisions need to be made by both for orthopaedic surgeons and their patients.

Recognizing these risk factors, we have categorized the orthopaedic operating room issues, particularly hip and knee replacement, into four key components:

- Physiological issues followed by importance of quality of life.
- Technological issues based on new technologies and their performance.
- Biomechanical issues on conditions of patients' bones to do the surgery.
- Financial issues regarding the costs of these high-quality technologies and type of surgery.

We content therefore, that an Intelligence Risk Detection (IRD) model in support of better treatment decision making for this population of patients during and after surgery can provide superior healthcare outcomes for the patients and their families. In developing such a solution, it is necessary to combine three key areas of knowledge discovery, risk detection with decision support systems (Fig. 2.1). This is an important contribution to both theory and practice in healthcare.

2.3 Literature Review

The following section will outline the major issues pertaining to the key areas of decision support systems, risk detection and knowledge discovery and their importance to the design of our proposed real time intelligence risk detection model to improve healthcare decision making processes.

2.3.1 Knowledge Discovery in Data Bases (KDD)

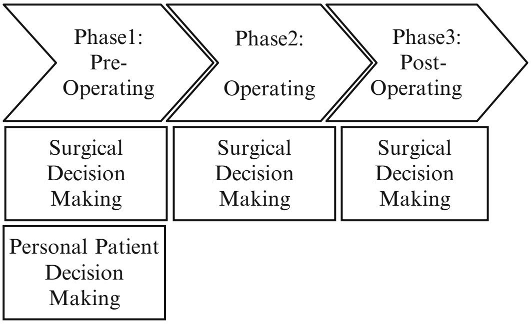
Knowledge discovery in data bases (KDD) is defined as the nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data (Cios et al. 2007). One of the most relevant applications of KDD for healthcare contexts is the model of the Intelligence Continuum (IC) (Wickramasinghe et al. 2006). The IC model includes but is not limited to applying the techniques of data mining, business intelligence/business analysis (BI/BA) and knowledge management (KM) to facilitate superior healthcare delivery add here on IC model. In order to maximize the value/utility of our IRD model and because the combined techniques of DM, BA/BI and KM are essential in the present context, we use the IC model as the foundation for our model as shown in Fig. 2.1.

2.3.2 Decision Support Systems (DSS)

Even though research in decision support systems in healthcare is relatively established, the use of DSSs in medical diagnosis and clinical practice is set to increase tenfold within the next decades (Miller 1994). Fundamentally this research covers clinical and medical aspects typically focusing on how information technology emulates and improves decision-making effectiveness for individual physicians (Fieschi et al. 2003). Specifically, computer based decision support systems focus on any software designed to directly aid in clinical decision making in which characteristics of individual patients are matched to a computerized knowledge base for the purpose of generating patient-specific assessments or recommendations that are then presented to clinicians for consideration (Hunt et al. 1998). In addition, the computer-based patient record, the Internet, shared decision-making processes, and new regulations also facilitate medical decision support systems (Fieschi et al. 2003). Therefore, for the purpose of our research the literature pertaining to Clinical Decision Support Systems (CDSS) and Medical Decision Support Systems (MDSS) is equally relevant as integral to both is the use of computer systems to promote decision support to healthcare professionals.

Decision-making regarding surgery for patients who needs hip or knee replacements is especially multi-faceted and complex. Patients may have a variety of symptoms, but are often quite functional. It is appealing to lean towards a complete

Fig. 2.2 Decision making framework across orthopaedic operating room



anatomical repair (Reddy et al. 1997). However, if the decision is for late repair, risks and benefits of surgery must be weighed against potential risks not proceeding with the surgery (Stamatis 2010). Moreover, the decision to treat replacement with either drugs, or surgery, or a combination of both depends on (Roy and Brunton 2008) a large number of factors.

The decision making process in the context of orthopaedic operating room can be divided into three phases (Fig. 2.2). In the first phase, or pre-operation phase, the surgeon, having received enough information about the patient and his/her medical condition, makes a decision relating to whether surgery is the best medical option. Once this decision has been made, and before surgery, the patients must decide whether to accept or reject the surgeon's decision in consideration of the predicted surgery outcomes. Once patients and surgeons have agreed to proceed, in phase 2, ad-hoc decisions pertaining to the unique situations during the surgery must be addressed. Finally, in the post operating phase, or phase 3, decision making is primarily done at two levels; level a, strategies to ensure a sustained successful result for the patient during aftercare and beyond, and level b, lessons to apply for future cases.

To capture this complexity, we define two steps of decision making in three different and key phases of the decision making process across orthopaedic surgery. The first type of decision making is called "surgical decision making" as it is primarily associated with the surgeons and the second type is called "personal decision making" as it is primarily associated with the patients because some surgery outcomes are related to "quality of life" that patients' decision is critical. Figure 2.2 shows the decision making framework we have developed based on the key phases in the orthopaedic operating room decision making process that it is required for our IRD model.

Although DSSs in the healthcare area is generally well discussed, unfortunately acceptance of such solutions tends to be low because doctors (the primary users) are reluctant to use computers (Baldwin 2001). Close consideration must also be paid to ensuring the clinical utility of any proposed solution. We contend that by incorporating real time risk detection the system is likely to then become more relevant and helpful which in turn will enhance its utility and thus adoption.

2.3.3 An Intelligence Risk Detection Framework in Healthcare Area

Surgical performance is usually indirectly measured by postoperative outcome of the initial hospital stay by means of risk-adjusted audits (Lacour-Gayet 2002). Although risk adjustment is important to assess performance and compare outcomes amongst individuals or institutions (Kang et al. 2004), statistical inferences alone cannot be used to determine what is considered acceptable performance (Gayet et al. 2005). Today's available methods look at the "big picture," from diagnosis to surgery and postoperative care (Larrazabal et al. 2007b). It is somewhat misleading, however, to judge an individual surgeon's performance by using postoperative outcome data such as 30-day survival or hospital survival (Larrazabal et al. 2007b). A poor outcome can be the result of a technical error, a nursing mistake, a drug error, or substandard intensive care monitoring (Larrazabal et al. 2007b).

Regarding to literature review, we find risk adjusters that meet these criteria have been under development since the 1980s and have been implemented by Medicare Choice program, numerous states, employer coalitions, and health plans (Keenan et al. 2001). Such systems have been based on many factors, including diagnosis, prior utilization, demographics, persistent diseases, and self-assessments of health and/or functional status. At Table 2.2, a review of selected risk adjustment systems in healthcare area is provided.

Table 2.2 A review of selected risk adjustment systems in healthcare area

Systems	Descriptions
ACG	This system was originally developed as a case-mix adjustment measure for ambulatory populations (Weiner et al. 1996). Later, it was extended to incorporate inpatient diagnoses as well. The system categorizes diagnoses based on duration, severity, etiology, diagnostic certainty and the likelihood that specialty services will be needed. ICD-9-CM codes are assigned to 32 ADGs (Adjusted Diagnostic Groups). The ACG system explains about 40–60% of the variation in concurrent health costs, and less for prospective health costs. The ACG system has been implemented by the Minneapolis Buyers Health Care Action Group. They reported a relatively smooth experience with the ACG system (Dunn 1998)
DCG	This system was developed as a health adjuster for HMOs that enroll Medicare populations (Pope et al. 2000; Ash et al. 2000). DCGs are clinically oriented and resource-based, and use demographic and diagnostic information. Initially, the model was calibrated on the Medicare population. It was later extended to commercial and Medicaid populations. This model estimates beneficiary health status (expected cost next year) from demographics and the worst principal inpatient diagnosis (principal reason for inpatient stay) associated with any hospital admission. The Washington State Health Care Authority also incorporated a DCG model

(continued)

Table 2.2 (continued)

Systems	Descriptions
CMS-HCC	CMS (Centers for Medicare and Medicaid Services) was required by Congress's BIPA (2000) to use ambulatory diagnoses in Medicare risk-adjustment, to be phased in from 2004 to 2007. To this end, CMS evaluated several risk-adjustment models that use both ambulatory and inpatient diagnoses, including ACGs (Weiner et al. 1996), the chronic disease and disability payment system (CDPS) (Kronick et al. 2000), clinical risk groups (CRGs) (Hughes et al. 2004), the clinically detailed risk information system for cost (CD-RISC) (Kapur et al. 2003), and DCG/HCCs (Pope et al. 2000). CMS chose the DCG/HCC model for Medicare risk adjustment, largely on the basis of transparency, ease of modification, and good clinical coherence
CDPS	The Chronic Illness and Disability Payment System was developed specifically to compensate more fairly for individuals with disabilities. It is a primarily resource-based system that is based on detailed clinical information for the disabled. The system has been developed for Medicaid and Medicare populations (Kronick et al. 2000, 2004). The system uses demographics and diagnostic information, and also used the length of enrollment, dates of services, type of provider, procedural information, and category of service. The model has over 700 diagnostic groups that are combined into over 50 diagnostic subcategories. The system predicts between 30% and 50% of the variance in a population with disability. However, it is important to note that this population is likely to have costs that easier to predict than the general population. The CDPS was implemented for the Medicaid population in Colorado. Plans did suffer from some selection, and required rates to be adjusted over time (Dunn 1998)
GRAM	The Global Risk Assessment Model is a clinically based, hierarchical model of health care use (Hornbrook and Goodman 1996). The model was developed on 100,000 individuals who were randomly selected from several HMOs. The model uses data on demographics, eligibility, diagnoses, and costs. The system uses Kaiser Permanente Clinical Behavioral Disease Classification System, which groups diseases by their clinical attributes and the expected responses to the disease. There are 350 diagnostic categories that are further grouped into 19 categories. The model explains 17% of the variance, or 70% of the explainable variance in prospective costs. This model has not been implemented to date
CRG	This system was developed to predict costs for individuals with congenital and chronic health conditions (Hughes et al. 2004). CRG is a categorical clinical system that classifies individuals into mutually exclusive categories and assigns each person to a severity level if he or she has a chronic health condition. The system uses demographic, diagnostic, and procedural information. The CRG grouper assigns each individual to a hierarchically defined health status group, and then to a specific CRG category and severity level if they are chronically ill. There are nine health status groups, and over 250 CRG categories. Unlike most other risk adjustment systems, the CRG is a categorical clinical model and not a regression model. The testing and refinement of CRGs included three large data sets representing different populations – Medicare, Medicaid, and an employer based population. Prediction performance varied depending on the population tested. For a Medicaid population, the CRG yielded a predictive power of 30%. CRG was implemented for several pediatric populations in Ohio and Maryland

An analytical review on these systems shows some limitations, most important of which are listed below:

- Focus on some risk factors related to cost management and financial issues rather than surgical issues.
- Applying such risk adjustment frameworks rather than risk detection frameworks.
- Without any function to apply some new risk factors.
- Having no look at on some procedures to evaluation the system.

Therefore, regarding these limitation through current systems, with an in depth review of risk detection in healthcare area, particularly in orthopaedic operating room, we find that applying some IT based techniques such as knowledge discovery followed by data mining would increase the performance of current risk adjustment methods significantly.

In order to find the relationships between the risk factors as well as relationships between these factors and surgery results, an intelligent model will be more effective and efficiency. It means, improving performance of surgery by applying the effect of the risk factors on surgery results is a significant advantage of an intelligence risk detection model.

Risk adjustment for hip and knee replacement operations, in itself, is challenging due to the great diversity of the patient population in terms of the diagnoses, indications for operation, the operation performed, the age at which an operation is deemed necessary and feasible, and other factors (Kang et al. 2004).

Regarding this issue, surgery-driven validated risk-adjusted outcome analysis can indeed lead to improvements in performance by both individual orthopaedic surgeons and orthopaedic surgery centres (Mavroudis and Jacobs 2002).

Although risk detection is an essential part of healthcare decision making, to the best of the authors knowledge there exist very few intelligence systems in healthcare with specific real-time risk detection component.

Table 2.3 serves to summarise the relevant studies. Given the importance of risk detection for the context of hip and knee replacement and the fact that real-time risk detection has not been significantly incorporated into healthcare decision support to date we believe this is an essential aspect of our proposed model.

2.4 Conceptual Model

Figure 2.3, depicts, the first stage in risk assessment. The output of the risk assessment process will help in determining important surgery risk factors and also predicting anticipated results based on the those risk factors.

The anticipated results enable the surgeons making informed decision whether to proceed with the surgery. If the decision is indeed to proceed with the surgery, all relevant information is passed on to the patients in order to allow them to make the final decision regarding the surgery. Any conflict in decision of the surgeon and that of the patients is an indication of high-levels of risk or some negative outcome of

Table 2.3 A list of relevant previous works in using knowledge discovery in healthcare area

Title	Technologies	Objectives
Analysis of health care data using different data mining techniques (Kumar and Gosain 2009)	The potential use of classification based data mining techniques such as decision tree and association rule to massive volume of health care data	In this study, our objective are to: (1) present an evaluation of techniques such as decision tree and association rules to Predict the occurrence of route of transmission based on treatment history of HIV patients; (2) demonstrate that data mining method can yield valuable new knowledge and pattern related to the HIV patient; (3) assesses the utilization of healthcare resources and demonstrate the socioeconomic, demographic and medical histories of patient
Intelligent heart disease prediction system using data mining techniques (Palaniappan and Awang 2008)	Data mining techniques, namely, decision trees, naïve bays and neural network	This research has developed a prototype Intelligent Heart Disease Prediction System (IHDPS) using medical profile such as age, sex, blood pressure and blood sugar it can predict the likelihood of patients getting a heart disease
Knowledge discovery approaches for early detection of decomposition conditions in heart failure patients (Candelieri et al. 2009)	Several KD algorithms have been applied on collected data	They propose an innovative knowledge based platform of services for effective and efficient clinical management of heart failure within elderly population

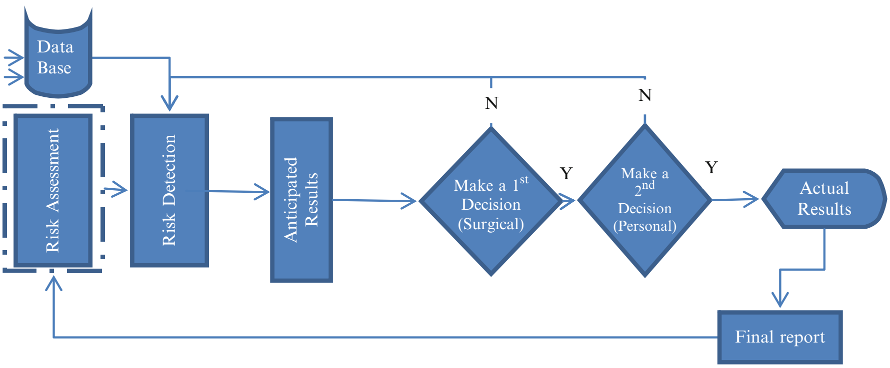


Fig. 2.3 The conceptual model

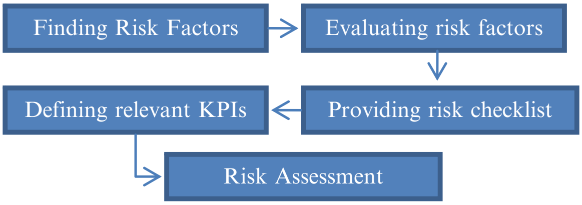


Fig. 2.4 The risk assessment process

surgery. Any such conflicts are fed back into the system for future risk assessments for the same or other patients.

After the surgery, actual outcomes are compared to the anticipated results. This comparison is an evaluation procedure for the model to ensure continual improvement of its predicting capabilities.

2.4.1 Risk Assessment

To assess hip and knee replacement surgery improvement, detecting risk factors is a useful method (Larrazabal et al. 2007a). To detect the risk factors, we will need to develop a multidimensional risk model to apply risk assessment.

Therefore, to address this issue, across our research, after finding some critical risk dimensions and factors from the literature, we use two experimental approaches, which required different degrees of the orthopaedic specialists' involvement in risk assessment.

In first approach, the orthopaedic specialists in a focus group are presented with certain risk factors based on the available literature. Then experts identify some main risk dimensions that should be used on the surgical decision making and the levels of these risk factors to provide a risk assessment checklist. In the second approach, the surgeons are asked to complete this risk assessment checklist to assess the risk factors and also define the relationships between these factors or between these factors and some actual and anticipated results and risk ranges to define some relevant KPIs (key performance indicators). Moreover, we document the surgeons' and specialists' recommended additional procedures and ask them to assess the responses provided by our subjects. The risk assessment process is shown in Fig. 2.4.

2.4.2 Risk Detection Using Knowledge Discovery

To incorporate an intelligent technology into the proposed risk assessment process, we suggest a data mining process followed by knowledge discovery. In the research case, the data types have a significant impact on the data mining tasks. Hence, after finishing the data collecting phase, the suitable tasks will extract such as neural networks and association rules. To apply the necessary data mining techniques, developing and then implementing the model, after the risk assessment process, we created a small database that included patients' data and also some data to show risk factors. Then we move through step 1 to step 6 (below).

The steps are:

Step 1. Understand business requirements, dataset structure and data mining task Knowledge-Rich Data Mining in healthcare Risk Detection. Designing a dimensional data mart will be more effective to apply data mining tasks on this data mart.

Step 2. Prepare target datasets: select and transform relevant features; data cleaning; data integration. Communicate any findings during data preparation to domain experts.

Step 3. Train multiple data mining models in randomly sampled partitions using Clementine[1] or Rapid miner.[2]

Step 4. Evaluate data mining models using a set of performance metrics.

Step 5. 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 findings with decision makers and determine appropriate actions.

Step 6. Go back to Step 1 if new business 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.

Data from a large hospital in Melbourne, Australia will be used to operate the procedure described above. Input to the system will be a dataset of hip and knee replacement surgery risk factors, and the outcome will be decision functions results of performance metrics; new and revised risk factors.

2.4.2.1 On-Line or Realtime Outputs to Create an e-Risk Detection Model

The mining process in not time-limited (Ting and Hui-Ju 2009), this risk detection process typically takes hours or days. So, choosing a real time processing technique should be a critical step to design a high performance application based on IRD model.

Services with more than a critical amount of user access traffic need to apply highly efficient, real-time processing techniques that are constrained both computationally and in term of memory requirements (Ting and Hui-Ju 2009). Web Usage Mining (WUM) is a great technique that provides solution to create a real-time intelligent model.

As shown in Fig. 2.5, user interaction with a web server are pre-proceed continuously and fed into online WUM systems that process the data and update the models in real-time.

Ting and Hui-Ju 2009, have stated that the out puts of this model are used to support online decision making as well as detecting some changes. They proposed a system to online monitor and improve website connectivity based on the site topology and usage data.

So, based on literature review, we find that using WUN technique is the best relevant and effective solution to create a realtime or online model to monitor decision

[1] A commercial software for data mining.

[2] An open source software for data mining.

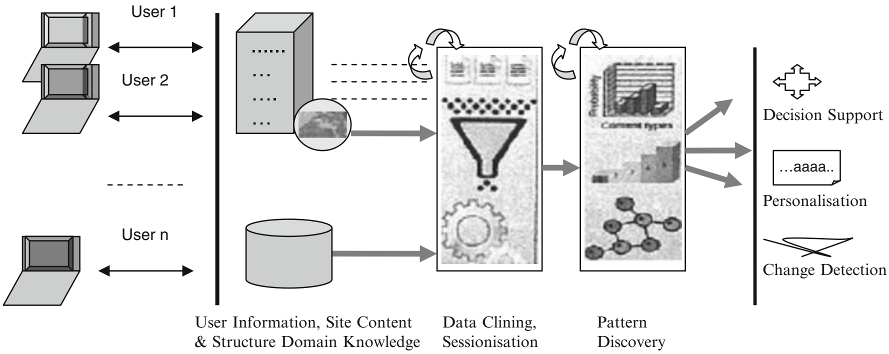


Fig. 2.5 An overview of online WUN (Source: Ting and Hui-Ju 2009)

making results. However, this technique still has some challenges to develop a novel web usage mining system.

2.4.3 Applying Anticipated and Actual Results

The decision making process for patient surgery is presented in Sect. 2.3.2. Based on this framework, two types of decision making, surgical and personal, are defined. Our model (Fig. 2.3) will enable contemporaneous and real time detection of risks factors and prediction of surgery results. The results will be a significant importance in forming surgical and personal decisions.

In the proposed conceptual model, to evaluate a risk detection process, the actual results will be compared to the anticipated results. This is because sometimes actual results present some new risk factors or new measurement to assess the risk factors. The business intelligence reporting tools would be the best solution to create a final report to show some important items, and finally apply them to the risk assessment process, for next iterations of evaluations.

2.5 Discussion

The above outlines a research in progress that is examining the merits of combining real time intelligent risk detection with decision support in a healthcare context. The case of orthopaedic operation room was chosen because of the complex nature of the decision making in this context as well as the many risks inherent with these decisions.

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

The hip and knee replacement risk detection has many dimensions and perspectives that their main focuses are usually on pathological process, physiological variables, some general health perceptions, social paradigm and also quality of life

(Wilson and Cleary 1995). So, detecting risk factors in all of these dimensions is not easy but based on our two approaches to assess the risks, with contribution of some orthopaedic specialists, we try to cover some main dimensions.

To best of our knowledge, this is the first study that directly examines the benefits of real time risk detection and outcome prediction in order to augment decision making process in healthcare area.

Also, using KPIs (key performance indicators) as a set of metrics is a novel idea to control the risk factors, finding its level and defining their relationships together, also with the other factors in such healthcare context. Furthers, KPIs will be so effective to monitor some key items during surgery for surgeons. It will be one of the valuable outcomes through this research that will be effective for orthopaedic specialist during all stages of patients' treatments.

Moreover, this research has the potential to contribute to understanding of the usefulness of involving orthopaedic specialists in designing an intelligent model when they has identified risk factors during the planning stages of the risk assessment and risk detection.

Additionally, it should reduce the burden of hip and knee replacement on its patients, their family and society is the other strategic benefits that will examined.

Being continuous is yet another advantage of this model. By comparing anticipant results and actual outcomes, risk factors will be amended to improve future predictions.

An important feature of our IRD model is the integration of the three IT solutions to solve a clinical issue in the definition and assessment of "outcomes" in patients, combined by some assessment measures. It is noted that the theoretical framework developed in this work needs to be tasted in a future research. However, empirical testing of the framework is likely to face a number of challenges such as:

1. The IRD model developed here will be used to identify common metrics for measuring the risk factors.
2. We have found a few instances where hospitals have well developed capabilities to develop and implement an intelligent model. However, our field research to date has found that the majority of hospitals who have implemented an IT infrastructure are employing some computerised clinical decision support systems (CDSSs) mainly to improve practitioner performance (Garg et al. 2005).

The transformation of the healthcare domain to develop capabilities to apply intelligence models to detect risks is likely to occur over an extended period of time and may be evident only in case studies. The willingness of hospitals to provide the required access for conducting such in-depth case studies is another challenge that needs to be overcome.

2.6 Conclusions

In this paper, we propose an intelligence risk detection model using knowledge discovery methods. Intelligent risk detection is a particularly challenging area for the healthcare industry while relatively common for fraud detection in finance, diagnosis in industry, and affect analysis in chemistry. This not only because building cases of training sets is difficult, but also because the cases may have many forms, causes, and unknown relations. We propose the application of knowledge discovery to high-level surgery risk detection and outcome prediction. The model designed is based on two steps of decision making process (surgical and personal) and, includes a decision support system which is suitable for high concentration prediction. Continual model update inherent in the proposed system results in adaptive and more accurate risk detection and outcomes prediction capabilities compared to fixed model. This study confirms that the selection of the risk detection, prediction by knowledge discovery and then decision making are also very important for hip and knee replacement surgical decision making process. The next phases for this research are to trial the model in appropriate clinical settings.

In closing, we contend that real time intelligent risk detection appears to be critical for many areas in healthcare where complex, high risk decision must be made and thus call for more research in this area.

References

Ash, A.S., Ellis, R.P., Pope, G.P., Ayanian, J.Z., Bates, D.W., Burstin, H., Iezzoni, L.I., MacKay, E. and Yu, V. (2000) "Using Diagnoses to Describe Populations and Predict Costs," Health Care Financing Review, 21(3), spring.

Baldwin, J. (2001) Automating patients' records. MD computing [cited May 2010]; Available from:www.technologyinpractice.com.

Candelieri, A., Conforti, D., Sciacqua, A., & Perticone, F. (2009). Knowledge discovery approaches for early detection of decompensation conditions in heart failure patients. In *Ninth international conference on intelligent systems design and applications*. IEEE.

Cios, K. J., Pedrycz, W., Swiniarski, R. W. & Kurgan, R. A. (2007) Date mining and knowledge discovery approach, Springer

Davidson, D., de Steiger, R., Ryan, P., Griffith, L., McDermott, B., Pratt, N. et al. (2008). Hip and knee arthroplasty. In *Annual report*. Adelaide: Data Management & Analysis Centre and University of Adelaide.

Dijkman, B. A., Kooistra, B. A., Ferguson, T. B., & Bhandari, M. A. C. (2008). Decision making open reduction/internal fixation versus arthroplasty for femoral neck fractures. *Techniques in Orthopaedics, 23*(4), 288–295.

Dunn DL. (1998) Applications of health risk adjustment: what can be learned from experience to date? Inquiry. Summer; 35,132–147.

Fieschi, M., Dufour, J. C., Staccini, P., Gouvernet, J., & Bouhaddou, O. (2003). Medical decision support systems: Old dilemmas and new paradigms? Tracks for successful integration and adoption. *Methods of Information in Medicine, 42*(3), 191–198.

Garg, A. X., Adhikari, N. K. J., McDonald, H., et al. (2005). Effects of computerized clinical decision support systems on practitioner performance and patient outcomes a systematic review. *JAMA, 293*(10), 1223–1238.

Gayet, F. L., Jacobs, J. P., et al. (2005). Performance of surgery for congenital heart disease: Shall we wait a generation or look for different statistics? *The Journal of Thoracic and Cardiovascular Surgery, 130*, 234.

Hornbrook M.C. & Goodman M.J. (1996) Chronic disease, functional health status, and demographics: a multi-dimensional approach to risk adjustment. *Health Service Research Journal*. 1996 August; 31(3), 283–307.

Hughes, J.S., Averill, R.F., Eisenhandler, J. (2004) Clinical Risk Groups (CRGs): A Classification System for Risk-Adjusted Capitation-Based Payment and Health Care Management. Medical Care 42, 81–90.

Hunt, D. L., Brian Haynes, R., Hanna, S. E., et al. (1998). Effects of computer-based clinical decision support outcomes: A systematic review systems on physician performance and patient. *JAMA, 280*(15), 1339–1346.

Kang, N., Tsang, V., Cole, T., Elliott, M., & de Leval, M. (2004). Risk stratification in paediatric open-heart surgery. *European Journal of Cardio-Thoracic Surgery, 26*, 3–11.

Keenan, P., Buntin Beeuwkes, M., McGuire, T., & Newhouse, J. P. (2001). The prevalence of formal risk adjustment in health plan purchasing. *Inquiry, 38*, 245–259.

Kronick, R., Gilmer, T., Dreyfus, T. and Ganiats, T. (2002)"CDPS-Medicare: The Chronic Illness and Disability Payment System Modified to Predict Expenditures for Medicare Beneficiaries" Final Report to CMS, June 24, 2002.

Kumar, A. and Gosain A. (2009) Analysis of Health Care Data Using Different Data Mining Techniques., International Conference on Intelligent Agent & Multi-Agent Systems(IAMA), Chennai, Print ISBN: 978-1-4244-4710-7. P1–6.

Lacour-Gayet, F. (2002). Risk stratification theme for congenital heart surgery. *Seminars in Thoracic and Cardiovascular Surgery. Pediatric Cardiac Surgery Annual, 5*, 148–152.

Larrazabal, L. A., del Nido Pedro, J., Jenkins Kathy, J., & Gauvreau, K. (2007a). Measurement of technical performance in congenital heart surgery: A pilot study. *The Annals of Thoracic Surgery, 83*, 179–184.

Larrazabal, L. A., Jenkins, K. J., Gauvreau, K., Vida, V. L., Benavidez, O. J., Gaitán, G. A., et al. (2007b). Improvement in congenital heart surgery in a developing country: The Guatemalan experience. *Circulation, 116*, 1872–1877.

Mavroudis, C. & Jacobs, J. P. (2002) Congenital heart disease outcome analysis: Methodology and rationale. *The Journal of Thoracic and Cardiovascular Surgery*, 123(7), 35–47.

Miller, R. A. (1994). Medical diagnostic decision support systems – past, present, and future: A threaded bibliography and brief commentary. *Journal of the American Medical Informatics Association, 1*, 8–27.

Palaniappan, S. and Awang R. (2008). Intelligent Heart Disease Prediction System Using Data Mining Techniques, International Conference on Computer Systems and Applications (AICCSA). IEEE/ACS, Doha, Print ISBN: 978-1-4244-1967-8, p. 108–115

Pope, G.C., Ellis, R.E, Ash, A.S., (2000) Principal Inpatient Diagnostic Cost Group Model for Medicare Risk Adjustment. Health Care Financing Review 21(3):93–118, Spring.

Reddy, V. M., McElhinney, D. B., Silverman, N. H., & Hanley, F. L. (1997). The double switch procedure for anatomical repair of congenitally corrected transposition of the great arteries in infants and children. *European Heart Journal, 18*(9), 1470–1477.

Roy, C. B., & Brunton, S. (2008). Managing multiple cardiovascular risk factors. *The Journal of Family Practice, 57*(3), 13–20.

Stamatis, G. (2010). Intensively lowering glucose: Possible benefits must be weighed against risks. ed. University Hospitals Case Medical Center.

Ting, I.-H., Hornbrook Hui-Ju, W. (2009). *Web mining applications in e-commerce and e-services*. Berlin: Springer.

Wickramasinghe, N., Bali, R. K., Capt. James Choi, J. H., & Schaffer, J. L. (2009a). A systematic approach optimization of healthcare operations with knowledge management. In *HIMSS*, USA.

Wickramasinghe, N., Bali, R., Gibbons, C., Choi, C., & Schaffer, J. (2009b). Optimization of health care operations with knowledge management. *JHIMS, 3*(4), 44–50.

Wickramasinghe, N., & Schaffer, J. (2006). Creating knowledge-driven healthcare process with the intelligence continuum. *Int J.Electronic Healthcare, 2*, 164–174.

Wilson, I. B., & Cleary, P. D. (1995). Linking clinical variables with health-related quality of life: A conceptual model of patient outcomes. *Journal of the American Medical Association, 273*, 59–65.

Weiner, J.P., Dobson, A., Maxwell, S.L., (1996) Risk-Adjusted Medicare Capitation Rates Using Ambulatory and Inpatient Diagnoses. *Health Care Financing Review* 17, 77–100, Spring.

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