Bayesian knowledge modelling for healthcare practices

Eugene Santos Jr., Keum Joo Kim, Fei Yu and Deqing Li

Dartmouth College, Thayer School of Engineering,
8000 Cummings Hall, Hanover, NH 03755-8000, USA
E-mail: esj@dartmouth.edu

Joseph Rosen

Dartmouth-Hitchcock Medical Center,
One Medical Center Drive, Lebanon, NH 03756, USA
E-mail: Joseph.Rosen@dartmouth.edu

Abstract: Healthcare situations are ever increasingly complex: team performance can easily deteriorate when medical procedures are delivered by teams composed of individuals having different intentions. In fact, medical errors resulting in catastrophic outcomes are often due to the conflicting goals, plans, or intentions among those individuals who make up teams. To improve patient safety, we propose a computational framework to model and simulate the healthcare professional's decision-making processes. We also provide a methodology to evaluate team performance by analysing gaps among individuals whose goals are deduced from their perceptions and observations through intent inferencing. In particular, we focus on the dynamic changes in the healthcare professionals' decision-making processes when the patient condition is changing over time, while accounting for the various healthcare providers' individual differences. Understanding, analysing and aiding individuals to make better decisions for improving patient safety by providing a state-of-the-art computational approach is our ultimate research goal.

Keywords: Bayesian knowledge modelling; healthcare practices; healthcare team; intent inferencing; clinical decision making; gap analysis; medical error.

Reference to this paper should be made as follows: Santos, E., Kim, K.J., Yu, F., Li, D. and Rosen, J. (2013) 'Bayesian knowledge modelling for healthcare practices', *Int. J. Simulation and Process Modelling*, Vol. 8, No. 1, pp.52–65.

Biographical notes: Eugene Santos, Jr. received his BS ('85) in Mathematics and Computer Science from Youngstown State University, a M.S. ('86) in Mathematics (specializing in Numerical Analysis) from Youngstown State University, as well as ScM ('88) and PhD ('92) degrees in Computer Science from Brown University. He is currently Professor of Engineering in the Thayer School of Engineering at Dartmouth College, Hanover, NH. His areas of research interest include artificial intelligence, intent inferencing, social and cultural modelling, computational social science, automated reasoning, decision science, adversarial reasoning, user modelling, natural language processing, probabilistic reasoning, and knowledge engineering, verification and validation, protein folding, virtual reality, and active user interfaces. He has served on many major conference program committees from intelligent agents to evolutionary computing. He is currently Editor-in-Chief for the IEEE Transactions Cybernetics, an associate editor for the International Journal of Image and Graphics, and is also on the editorial advisor board for System and Information Sciences Notes and on the editorial boards for Journal of Intelligent Information Systems and Journal of Experimental and Theoretical Artificial Intelligence. He is a Fellow of the IEEE.

Keum Joo Kim received her BS ('93) in Computer Science and Engineering from Ewha Womans University, and MS ('95) in Computer Engineering from Ewha Womans University, Seoul, South Korea. She has worked for LG Central Institute Technology as research scientist before completing PhD ('09) in Computer Engineering from the Thayer School of Engineering at Dartmouth College. She is currently a research associate at the Thayer School of Engineering at Dartmouth College, Hanover, NH. Her research interest includes artificial intelligence, probabilistic reasoning, global optimization, protein folding, and computational modelling of human behaviours. She has served as a member of program committee or reviewer for many professional conferences including IEEE International Conference of Social Computing, Journal of Intelligent Information Systems, IEEE

Congress on Evolutionary Computation, IEEE Transactions on Systems, Man, and Cybernetics: Part B, etc.

Fei Yu (GSM'07) received the BS in Computer Science from the Hong Kong Polytechnic University, Hong Kong, China in 2007. She is currently a PhD candidate in computer engineering at the Thayer Engineering School, Dartmouth College. She has published papers in Web Intelligence and Intelligent Agent Technology (WI/IAT) conference, User Modelling Personalisation and Adaptation (UMAP) conference, and EUROSIM Conference. She has also served as a reviewer for the IEEE Transactions on Systems, Man and Cybernetics: Part C, *Journal of Intelligent Information System*, etc. Her research interest includes intent and cultural modelling, information retrieval, and text summarisation.

Deqing Li received the BS ('07) in Electronic and Information Engineering from the Hong Kong Polytechnic University, Hong Kong, China. She is currently working toward the PhD degree in Computer Engineering at the Thayer Engineering School, Dartmouth College. She has published papers in the Proceedings of SPIE, the Proceedings of the User Modelling, Adaptation, and Personalisation, the Proceedings of the 2008 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology, the Proceedings of the IEEE Conference on Systems Man and Cybernetics and the IEEE Transactions on Systems, Man, and Cybernetics: Part A, and a book chapter in the E-Government Diffusion, Policy, and Impact: Advanced Issues and Practices. Her research interest is in decision theory, intent modelling, and related applications.

Joseph Rosen is a Professor of Surgery at DHMC in the division of Plastic Surgery and an adjunct associate Professor at the Thayer School of Engineering. His interests span from biomedical engineering to biological warfare. For the past 15 years, he has acted as a consultant for the defense department. He has chaired a panel to review how we respond to blast injuries in the battlefield and how we can improve the medical response and treatment. Presently, he is part of a consortium evaluating how regenerative medicine and transplantation can be used to restore wounded warriors to functional independence. He is also the chair of an ad hoc committee for virtual reality and training for ACAPS. Additionally, he has been involved in relief work internationally for the past 30 years - most recently in Vietnam where he and his team treat children with congenital and traumatic deformities.

1 Introduction

Dynamic decision making arises in many situations including military (Visser, 2010), financial (Merigo and Gil-Lafuente, 2010), sports (Johnson, 2006), and medical and other emergencies (Harding, 2004). When faced with these situations, humans—especially those under stress—can make inappropriate or unfavourable decisions, resulting in irreversible and even catastrophic damage. In particular, healthcare professionals confront tremendous challenges in trying to make the right decisions at the right time due to the high complexity, great uncertainty, intensive time pressure and severe risk inherent in healthcare systems. For example, the complexity intensifies when

a the medical procedure and equipment are complicated,

b healthcare professionals from different departments are needed to work together for a particular treatment,

c an error rooted in one part of the healthcare system is propagated into another part of the system and

d the patient's status is changing dramatically (Taib et al., 2011).

The uncertainty grows over clinical information transferred among the multiple individuals responsible for the same patient's care when they are separated by time, space or organisation. For instance, the diurnal distribution of errors follows the nurses' daily shifts (Donchin et al., 2003). Consequently, this impacts team performance because individuals would interpret identical factual information differently and make varying decisions based on personal traits or self-interests. These discrepancies among individuals working as a team can lead to medical errors and adverse events, causing critical harm to patients. Therefore, it is worth investigating methodologies to measure and reduce the gaps among individual healthcare professionals. In addition, we are interested in how personal bias impacts the gap when patient status is changing dynamically.

Medical errors are planned activities that fail to achieve their original goal (Reason, 2000). These errors do not occur by chance and are not specific to a certain group of people classified by gender, profession, age or experience (Taib et al., 2011). Although some of them are known to be preventable, they still lead to a significant number of adverse events, resulting in severe injuries and deaths of patients. A study conducted with 74,485 patient records has reported that the median incidence of in-hospital adverse events was 9.2%. Out of these adverse events, 43.5% were found to be preventable, whereas 7.4% of them led to deaths (Varies et al., 2008).

The well-known causes of these errors are human mistakes, failure of medical equipment and technology and systemic flaws. Human errors cannot be fully prevented, but they do not lead to harm if the healthcare system is robust or error tolerant. However, healthcare systems sometimes have flaws in their organisational processes and trigger errors regardless of individuals performing clinical actions (Reason, 2000). Strategies to fix these system include the use of computational technologies, simplifying and standardising surgical protocols (Lansac et al., 2008), moving report systems from traditional handwriting to computerised documentation (Beach & Sions, 2011), minimising the number of handoffs in a system (Maughan et al., 2011), decentralising health information systems and decision-making processes (Xiao et al., 2010), developing clinical guidelines (Isern et al., 2011) and increasing communications in multidisciplinary teams (Deering et al., 2011). For understanding and aiding humans at avoiding actions vulnerable to errors, tools to investigate and analyse human decision-making processes have been employed, including Markov chain analyses (Brothers et al., 2004), game theory (Wout and Sanfey, 2011), Bayesian inference (Pibouleau and Chevret, 2011), interactive decision trees (Turner, 2009), stochastic optimal matches (Kiesler and Auerbach, 2006), reinforcement learning (Yechiam et al., 2010), case-based reasoning (Ocampo et al., 2011) and fuzzy cognitive maps (Stylios et al., 2008). For medical equipment failure, medical institutions have developed special policies to ensure the safe and correct functioning of medical devices as well as to train and educate healthcare professionals in proper usage of medical machines. In addition, human-machine interactions have been explored through computational simulations (Mudumbai et al., 2010).

Teams are essential for patient safety, though it is individuals who perform clinical actions. Most medical procedures are delivered by teams rather than individuals. For training healthcare teams, policies used for commercial and military aviation, such as Crew resource management (CRM) (Sundar et al., 2007) for focusing skills of flight crews, have been adapted, since both fields are similar in that the primary cause of many accidents is identified as human error. CRM has been the foundation of many programmes supported by the US Department of Defense (DoD), taking an active role in improving the team performance of healthcare professionals assigned to different military treatment facilities (MTFs) to improve patient safety. One of the main goals of the DoD has been the development, implementation and integration of team training throughout the military health system (MHS), where team training has had a long history of success (Alonso et al., 2006). In such high-risk environments, any individual behaviour has the potential to result in the loss of multiple human lives or incur substantial costs. With regards to team behaviour, communication has been identified as a major source of team errors. For example, communication breakdown was reported to cause 20% of adverse events inside an anesthesiology department (Jeffcott and Mackenzie, 2008). To improve communication for effective team performance, we focus on gap analysis through modelling and simulating individual healthcare professionals in this paper.

Team performance has been studied through clinical surveys, direct observation and technology-based analysis of real medical treatments (Jeffcott and Mackenzie, 2008). Clinical survey is the simplest way to analyse teams, commonly based on interviews or self-reports, but has limitations; it hardly captures the complexity of team behaviours in healthcare settings. This is due to the fact that an individual's self perception may not match his or her behaviour as observed by others (Andersen et al., 2010). Direct observation can be the most useful tool to identify recurrent or interrelated factors in communication within teams delivering medical procedures (Zimmermann et al., 1994). Using technologies such as video or audio capture is particularly useful in collecting real-time data and is essential for reviewing and examining high-risk surgical procedures for evaluating team performance (Mackenzie and Xiao, 2003). However, this is time consuming and requires significant effort. Unlike these studies, which are based on static information, we focus on the dynamic nature of team performance, which changes depending on individual healthcare professionals adjusting their decisions appropriately according to changes in patient status over time, as well as those healthcare professionals' personal preferences.

Previously, we had primarily applied our computational framework to model and simulate static instances, where patient condition was fixed during the time period under consideration (Santos et al., 2012b). In that study, we modelled general and plastic surgeons' decision-making processes and simulated medical error situations caused by an individual surgeon's misunderstanding of another surgeon's intent in delivering patient care, where the general surgeon had performed subcutaneous mastectomy, but had been advised to do simple mastectomy by the plastic surgeon. The miscommunication between two surgeons caused the patient to lose her natural nipple, which was different from what the patient had consented to at the beginning of the surgery. In more recent efforts (Santos et al., 2012a), we modelled and analysed a potential wrong-site surgery, which included a pre-operative nurse's misunderstanding a patient's tattoo as a surgical site marking. In that study, we analysed team performance by comparing gaps among individual team members, including an ophthalmologist, an anesthesiologist and an OR nurse and used it to recognise potential medical errors for a particular team. However, we only considered preoperative patient condition in this case, which does not fully represent the dynamic nature of real healthcare situations.

In this paper, we consider the challenges that arise when the patient condition changes over time, which requires that the surgeons' decisions must be adjusted accordingly. Therefore, we present a new methodology for dealing with this situation. To this end, we employ a knowledge fusion algorithm (Santos et al., 2011) designed to aggregate knowledge from multiple sources as a strategy for handling changes in patient conditions over time. In addition, the gaps among individual healthcare professionals' intents are analysed to estimate team performance, which would contribute to improving patient safety by providing appropriate warnings and feedbacks to individuals for communicating better with their co-workers. Ultimately, we hope this study assists individuals to make the right decision at the right time by fully understanding given situations, including their co-workers' intents for improving patient safety and healthcare quality.

This paper is organised as follows: our theoretical framework is founded on Bayesian knowledge bases (BKBs). As such, we will first describe them, as well as the fusion algorithm, in detail in the following section. Next, we will introduce the idea of surgical intent modelling and gap analysis as a fundamental framework to model and simulate healthcare practices. After that, we will describe a post-op panniculectomy case with a few variations and present our empirical protocols as well as the results obtained. Finally, we will end this paper with our conclusions and discussion of future directions.

2 Background

In general, individual team members are expected to perform their tasks with a continual understanding of surrounding situations that include other team members. Decisions are supposed to be based on the evidence available to those individuals, which is incomplete and uncertain in many cases. Therefore, it is natural for individuals to interpret those facts according to their own judgments. Furthermore, they sometimes anticipate the actions to be taken by other team members in line with their understanding of the behaviours of others. To model and simulate individuals' decision-making processes, it is necessary to deal with all of these facts associated with the decisions made through a computational framework. To this end, in this section, we review three fundamental components of our research:

a modelling an individual's clinical decision-making processes,

b aggregating new information into existing models while properly managing potential inconsistencies and

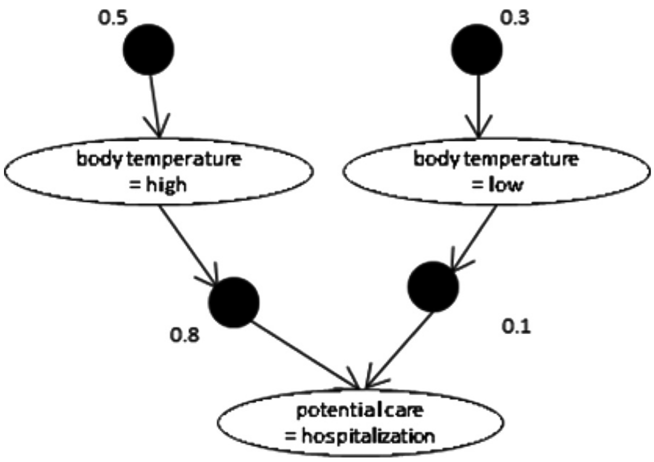
c inferring intentions of individual team members from the information observed, perceived and acknowledged by those individuals.

2.1 Bayesian knowledge bases (BKBs)

The knowledge relevant to clinical decisions can be described by BKBs (Santos, 2001; Santos and Santos, 1999). BKBs are an alternative to BNs (Bayesian networks), since BNs fail to handle cyclical conditions, cannot operate well unless they have a complete probability distribution and cannot be fused together consistently (Pearl, 1988). BKBs allow for fine-grained dependent relationships among pieces of knowledge in a simple, probabilistically sound "if-then" format. BKBs are also founded on the fact that knowledge is incomplete and captures only the information that is known, without making any forced assumptions about the remaining knowledge. At the heart of BKBs is the ability to explain the reasoning/decision-making that takes place.

The graphs depicting BKBs are composed of nodes and arcs, where the arcs denote causal relationships between knowledge while the content of the relationships is enclosed in the nodes. The nodes can be classified into two types: I-nodes and S-nodes. An I-node represents the states of random variables (i.e., how random variables are instantiated) while an S-node represents a specific rule associated with the information represented by two connected I-nodes. Therefore, a probability distribution is attached to S-nodes in general, as shown in Figure 1, where I-nodes are white and S-nodes are black. For instance, the knowledge that "if body temperature is high, then a surgeon determines hospitalisation as a potential care with the probability of 0.8" is encoded through two I-nodes and one S-node in Figure 1.

Figure 1 BKB fragment



BKBs introduce a more compact representation of knowledge than BNs by accommodating incomplete knowledge. This further enables BKBs to perform reasoning with lower computational complexity on average. Reasoning in BKBs can be performed in two ways; belief revision and belief updating. Belief revision computes the posterior probability of an event happening when the evidence is observed, where an event can be described by a world composed of a set of random variables instantiated accordingly. Through the chain rule, the joint probability of a world can be written as

$$P(X) = \prod_{i=1}^{m} P(A_i = a_i \mid A_i = a_{i+1}, \ldots, A_m = a_m)$$

where $A_i = a_i$ represents the i^{th} I-node in the world and m represents the total number of random variables in the world. Belief updating seeks the posterior probability of a single random variable having relevant instantiation to evidence given, according to Bayes' Theorem. Therefore, it is natural to result in tiny probability values from belief revision, since the values become smaller as more random variables are associated with the inference, which is the case of surgical intent inferencing due to the complexity of clinical decision-making processes. BKBs have been extensively studied with highly efficient algorithms for reasoning (Rosen et al, 2004).

2.2 Bayesian knowledge fusion

The information represented in BKBs must be updated accordingly over time, whenever there is any change. When the patient's condition is represented by BKBs, an algorithm to integrate the change of patient condition into existing BKBs is necessary. Originally, the fusion algorithm was devised to aggregate information provided by multiple experts while preserving the probabilistic consistency (Santoset al., 2009) (Santos et al., 2011). The algorithm to aggregate multiple BKBs cannot be straightforward, since the probabilities inside each fragment can become inconsistent when simply merged together. Here, a fragment means a single BKB to be fused. Therefore, a careful design strategy has been devised to handle potential disagreement among multiple fragments constructed from different sources (i.e., experts) in such a way that two special nodes are added to original BKBs when fused: the source node and the reliability index. Source nodes indicate which knowledge information comes from which fragment when fused, while the reliability index denotes the trustworthiness of the knowledge contained in a particular fragment. With these additional nodes, the inference process on the fused BKB can be realised and provide an explanation for evidence observed while keeping all of the probabilistic information contained in the BKBs consistent. The following is the fusion algorithm mentioned above.

BAYESIAN-KNOWLEDGE-FUSION

Let F be an empty BKB.
For each fragment Ki to be fused
Generate reliability index r(σ_i),
where σ_irepresents the source of i^th fragment
For all s-nodes q∈S_i
Let α be an I-node supported by a rule q
Create the source I-node for q with reliability
r(σ_i) pertinent to α
Add K_i into F.
Consolidate I-nodes containing the same information
across K_0 to K_i
For all source I-nodes, normalize the weight of supporting
s-nodes
(sum of weights supporting a random variable must not
exceed 1)

where K={K_1,K_2,...,Kn } represents a set of n BKFs
(Bayesian Knowledge Fragments),
A more formal representation of the algorithm can be found
in (Santos, Wilkinson, & Santos, 2011).

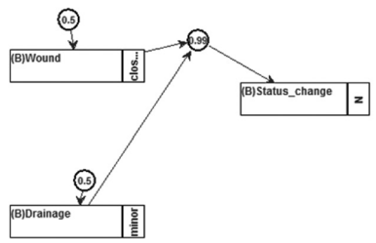
We apply the algorithm to deal with dynamic situations in healthcare practices where updated information on patient condition must be accounted for constantly and added to existing knowledge bases. For example, on Date 1, the patient's vital sign is stable and the patient status is not changed. As days go by, the patient starts to show high body temperature, abnormal respiratory rate, open wounds and major drainage, which results in a higher chance of abnormal vital sign and major status change. The new information is fused into the BKB of each healthcare team member as it occurs. An example of BKB fusion is shown in Figure 2. The two fragments in Figure 2(a) and Figure 2(b) respectively represent the patient condition on Date 1, when his wound was closed and drainage was minor and on Date 2, when major drainage was observed. These two fragments are merged into a bigger fragment in Figure 2(c), which represents all the information we have about the patient up to Date 2. In Figure 2(c), each S-node is parameterised with a source node indicating which fragment it comes from and currently equal reliabilities are assigned to the fragments. While the common I-nodes such as Wound=closed are merged, all S-nodes as well as the source nodes remain separated. During the inferencing of the fused fragment, the I-nodes representing patient conditions ((*B*)*Wound=closed* and (*B*)*Drainage=major*) instead of source nodes are set as evidence, such that all fragments that were fused earlier still contribute to the computation, if any. Therefore, the joint probability of the world in which *Status_change=N* becomes *P*((*B*)*Wound=closed*|*src_w=2*)* *P*(*src_w=2*)**P*((*B*)*Drainage=major*|*src_d=2*)**P*(*src_d=2*)**P*((*B*)*Status_change=N*| (*B*)*Wound=closed,* (*B*)*Drainage=major, src_sc=2*) **P*(*src_sc=2*) = 0.5* 0.5* 0.5* 0.5* 0.3* 0.5= 0.0094. In contrast, the world in which *Status_change=slight,* whose probability is 0.0156, is more likely to happen.

2.3 Intent inference

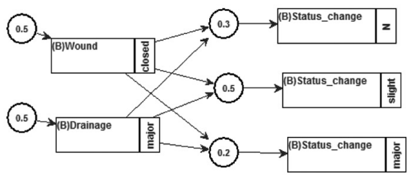
Healthcare team members' decision-making processes can be simulated through individual intent inferencing based on BKBs. Intent can be defined as a combination of goals that are being pursued by individuals, beliefs that support the goals and actions that achieve the goals. In other words, the intent can be deduced by considering these components. We typically construct a behavioural model by optimising individuals' behavioural patterns. Thus, we collect data through observation of individuals' actions and environments and deliver the data to the model.

BKBs have been applied successfully in various domains, such as adversary intent inferencing and war-gaming, in which human intent was inferred through reasoning with BKBs (Pioch et al., 2009) (Santos et al., 2008) (Santos E. Jr. et al., 2007). The instantiation of random variables is represented by i-nodes, which are classified into the four types: axioms, beliefs, goals and actions. These are essential components associated with human intent. Axioms (denoted by (*X*)) represent what a person believes about himself; beliefs (denoted by (*B*)) represent what a person believes about others (including other people and surrounding situations); goals (denoted by (*G*)) represent what results a person wants to achieve; and actions (denoted by (*A*)) represent what a person will do to realise his goal. Axioms and beliefs may influence themselves or each other and both can contribute to goals (mostly sub-goals) and actions (Santos and Zhao, 2006) (Santos, 2003). Taking Figure 2(b) as an example of an intent model, the surgeon's evaluation of the patient's status depends on the surgeon's belief about the wound and drainage situations of the patient. If the patient's wound is closed and her drainage is minor, it is more likely that there is a slight change in her status. In addition to this, intent inferencing can be used for other purposes as well: description of personal insights, prediction of future events and diagnosis of current outcomes. Ultimately, it can assess earlier predictions by contrasting them with current outcomes and help enhance predicting accuracy by providing an explanation of current outcomes.

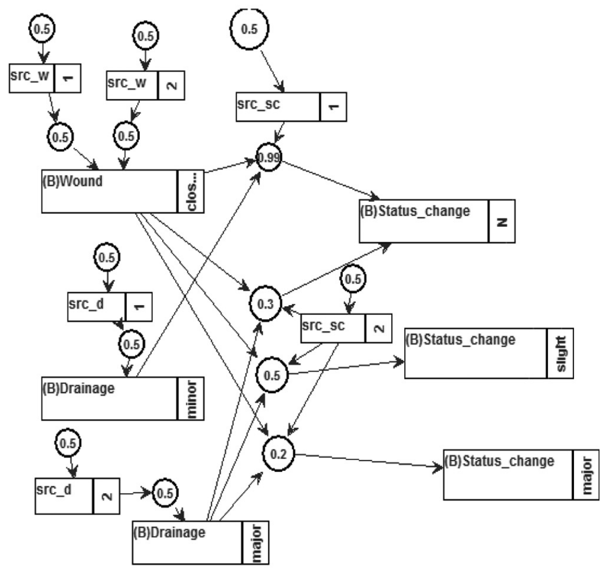
Figure 2 BKB fusion. (a) BKB fragment of patient condition on Date 1, (b) BKB fragment of patient condition on Date 2, (c) fused BKB of patient condition



(a)



(b)



(c)

3 Evaluating team performance

In addition to individual intent modelling and inferencing, we address the collective intent of individuals in teams. Teams play a fundamental role in healthcare practices and their performances are crucial to patient safety. To ensure patient safety, teams must be well coordinated and communication among members must be constantly strong. As a part of a computational methodology to model and simulate dynamic changes in healthcare practices, we use gap analysis as a way to evaluate the organisational intent towards improving team performance. With this approach, we can simulate medical cases and analyse team performance.

3.1 Surgical intent modelling

Surgical intent modelling was proposed to model and simulate the clinical decision-making processes of healthcare professionals. Through this, we aim to improve the healthcare team members' understanding of surrounding environments and other team members' intents (Santos et al., 2012B). Considering the fact that healthcare services involve multiple operations and a wide range of people who must make discrete efforts to accomplish their common goals, tailoring intent models for each healthcare team member is necessary. In particular, surgeons' intent models are supposed to be the most sophisticated, since they have both the most responsibility and the greatest authority at the same time in clinical decision making. Surgical intent models are naturally expected to include the entire process of healthcare service from diagnosing to discharging the patient. However, it would be an intractable process to try to encompass every fine detail of the entire process. As such, we currently select the most relevant elements with the appropriate level of detail when building the models, as shown in Figure 3. A surgeon is supposed to make a pre-decision based on patient condition and self-interests. The pre-decision is confirmed or modified to post-decision depending on the surgeon's competency, which is inferred from his personal experience, history of malpractice and complexity of the procedure to be taken up. Depending on the procedure chosen, the most probable action to take can be anticipated in reasoning through BKBs. In particular, the elements we choose for the intent models of surgeons are beliefs about the condition of the patient, axioms about the surgeon's own capability in performing the medical procedure, goals regarding choice of procedures and actions that are taken to fulfil the procedure. In addition, individual differences are implemented as axioms in our current study, since surgeons' clinical decisions can vary depending on their professional and personal traits. For instance, surgeons with high financial pressure and self-interest often choose medical treatment that is not the best for the patient's health.

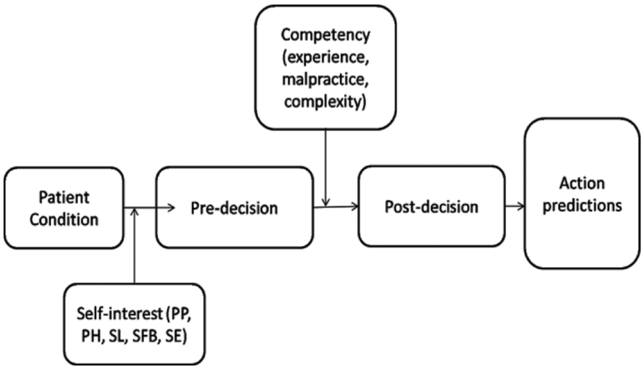
3.2 Individual differences

It is necessary to understand individual differences and similarities for modelling an individual's decision-making processes in healthcare practices. We classify individual differences as either professional or personal and assume both of these influence individual competence in performing medical procedures.

3.2.1 Professional differences

Individuals are different due to their educational background, individual experience, history of malpractice, complexity of procedures to take up during patient care, etc. As a consequence, their roles in the clinical decision-making processes and in delivering healthcare services are varied. For instance, surgeons have the greatest authority in clinical decision-making processes and make overall decisions associated with patient health, while nurses have more limited authority to manage patient care and make decisions relevant to wound care and pain management.

Figure 3 Skeleton of surgical intent model



3.2.2 *Personal differences*

Individuals with the same professional background can be varied in their personalities, some of which change over time very slowly while others are transient and do not last long. For example, extremely fatigued individuals do not remain in the same state for a long time, since the level of fatigue can change relatively quickly. On the other hand, the best-interest of individuals is more stable, though changes can occur over time. As sources of best-interest of individuals, patient health (PH), patient preference (PP), surgeon's liability (SL), surgeon's financial benefits (SFB) and surgeon's ego (SE) are considered, as shown in Figure 3.

3.3 *Gap analysis*

A medical situation is composed of various individuals and medical devices; medical errors occur when any of these elements does not function appropriately. In medical studies, gap analysis has been used as a way to assess individuals' self-appraisal in communication (Calhoun et al., 2010). In our research, we use gap analysis to evaluate the performance of a team delivering healthcare services. Based on the probabilistic knowledge representation system used for our research, we compute gap values by comparing probability distributions of individual team members belonging to the same team. Since we believe individuals' intents are well coordinated with the collective intent of the team in an effective team, we consider the team with the smallest gap value as the safest team with respect to medical errors. However, when some individuals make decisions conflicting with others and the collective intent of the team, this leads to deterioration in team performance. By comparing gap values obtained from different teams under the same situation, we can identify which team is more vulnerable to medical errors than others. The formulation to compute gap values can be described as

$$g(x) = \sum_{i=1}^{n} \sum_{j=1}^{n} | P(i) - P(j) |$$

where $g(x)$ denotes the gap value of team x composed of n individual members in an arbitrary situation. $P(i)$ denotes the likelihood of the world of an individual i, while $P(j)$ represents that of another individual j in the same situation. The gap value can be computed and interpreted in various ways, but we interpret the gap value as a measure of team performance to deliver healthcare service in a safe and secure manner. Thus, a team having a large gap means that individual team members have a significant discrepancy and the team performs badly.

4 Case description and experimental design

This section describes our validation processes dealing with both static and dynamic situations associated with a patient having a circumferential panniculectomy.

4.1 *Case description*

The case pertains to a middle-aged female who had a circumferential panniculectomy performed in an OSC (outpatient surgical centre) by a team including a general surgeon, a plastic surgeon and some nurses. The general surgeon was in charge of a hernia repair using mesh work and the plastic surgeon took care of the rest of the surgery. During the pre-op, the scrub nurse prepped the anterior side of the patient. After completing the anterior portion of the surgery (both the hernia and the panniculectomy), the patient was turned onto the prone position. In this position, the back was prepped and then the panniculectomy was completed, which may raise the risk of infection. A Foley catheter, which is commonly inserted at the beginning of the prep, was done in the middle of the operation prior to turning the patient over in this case. Either of the two: the timing for the prep or the placement of the Foley may have led to increase the risk of infection, since the Foley is placed at the beginning of the case and then a circumferential prep is done in general.

The patient was discharged and went home on the day of the surgery. A visiting nurse took care of the patient on a daily basis. After a few days, the visiting nurse reported that the incision came open and began to drain. At the same time, the patient complained of increasing pain from the wound. The general surgeon suggested admitting the patient to the hospital when this was reported first, but the plastic surgeon insisted on home care for a few more days. The disagreement between the general surgeon and the plastic surgeon was never resolved. A little over a week later, the two surgeons examined the patient separately on the same day, but still disagreed on the admission of the patient to the hospital. One day after two weeks, another plastic surgeon took over the case since the original plastic surgeon was out of town. The new plastic surgeon decided to admit the patient immediately and pursued a follow-up procedure. By that time, the patient had already experienced a lot of pain, high temperature and drainage from the wound. During the follow-up procedure, it was confirmed that the patient had an infection, which was resolved with further surgery and antibiotics. The original plastic surgeon should have admitted the patient immediately after the wound opened.

4.2 Selection of simulation points

For validating the applicability of our approach to the case, we selected five critical time points within two weeks after the patient had the panniculectomy operation and was discharged from OSC. We simplified this case because our framework is based on a discrete representation of information and the patient condition did not change so dramatically that we needed to model each actual day. As shown in Table 1, the patient condition worsened from Date 1 to Date 4 and recovered on Date 5 after both surgeons (general surgeon and the new plastic surgeon) agreed on readmitting the patient to hospital ("HOME" denotes the surgeon's decision to discharge the patient from OSC and take care of her at home, while "HOSP" represents the surgeon's decision to readmit the patient to the hospital).

4.3 Design of five cases representing personal differences

To validate our approach, we modelled five possible medical situations, where the major differences were surgeons' best-interests. In each case, we assumed a healthcare team composed of four individuals: general surgeon, plastic surgeon, visiting nurse and patient. For the panniculectomy case, we speculated on the role of the plastic surgeon in delivering the healthcare service and varied his best-interest by setting evidence differently while keeping other members' best-interest fixed. While varying the plastic surgeon's best-interest, we addressed five categories: patient preference, patient health, surgeon liability, surgeon's financial benefit and surgeon's ego, as shown in Figure 3. If the plastic surgeon considers a patient's preference as his first priority, he will make a decision that conforms to the patient's desires. If a surgeon considers a patient's health to be the highest concern, he makes a decision that can improve a patient's health most. When surgeons seek to reduce liability as their primary interest, they make decisions that help reduce their future personal risks in case any adverse incident happens. Pursuing the surgeon's financial benefit as a primary interest refers to a situation in which the surgeon makes a decision to maximise his individual or organisational income. Sometimes, a surgeon may be too anxious about trying out a new clinical procedure he/she has invented and put the highest priority on his/her ego by delivering it without full validation. In a real situation, a surgeon tends to pursue a mixture of these five best-interests rather than any particular one. Thus, we hypothesise five possible cases, in each of which individual's best-interest is mixed with different types of best-interest, as described by the weights inside the parentheses. The weights that are not specified explicitly are set at 0%. Except for the plastic surgeon, we assume the best-interest of other team members is patient-health at 100%.

4.3.1 Case 1

The plastic surgeon focuses on both satisfying a patient's preference (refers to his preference on the care he will receive based on his economic situation, physical and mental condition and so forth) and the patient's health during a decision-making process. The weights for the two types of best interests are roughly equivalent (patient preference=100%, patient health=80%).

4.3.2 Case 2

The plastic surgeon considers a patient's health to be the most important factor when making a decision (patient health =100%).

4.3.3 Case 3

The plastic surgeon focuses on reducing his/her liability and improving a patient's health. The weights for these two types

Table 1 Change of patient condition and decisions

Time Points	*Date 1*	*Date 2*	*Date 3*	*Date 4*	*Date 5*
Specific Date	Feb 6th	Feb 8th	Feb 17th	Feb 18th	Feb 23rd
Patient Condition	Body temp = normal	Body temp = normal	Body temp = normal	Body temp = abnormal	Body temp = normal
	Pulse rate = normal	Pulse rate = normal	Pulse rate = normal	Pulse rate = normal	Pulse rate = normal
	Blood pressure = normal	Blood pressure = normal	Blood pressure = normal	Blood pressure = normal	Blood pressure = normal
	Respiratory rate = normal	Respiratory rate = normal	Respiratory rate = normal	Respiratory rate = abnormal	Respiratory rate = normal
	Wound = closed	Wound = closed	Wound = open	Wound = open	Wound = closed
	Drainage = minor	Drainage = major	Drainage = major	Drainage = major	Drainage = major
General Surgeon	HOME	HOSP	HOSP	HOSP	HOSP
Plastic Surgeon	HOME	HOME	HOME	HOME	HOSP

of best-interests are roughly equivalent (patient health=80%, surgeon liability=100%).

4.3.4 Case 4

The plastic surgeon focuses on reducing his/her liability and improving a patient's health. The weight of liability is considerably larger than that of patient health (patient health=50%, surgeon liability=100%).

4.3.5 Case 5

The plastic surgeon has invented a new clinical procedure and is anxious to try it out, with the hope of becoming famous in the field. Probably, he/she overestimates his/her own capability to handle the patient and employs the new procedure, which is not fully tested by other medical professionals. The weight of ego is considerably larger than that of patient health (patient health=50%, surgeon ego=100%).

4.3.6 Experimental validation

We used the BKB fusion algorithm to simulate the dynamic situations in the panniculectomy case. The generic BKBs for two surgeons are similar in most parts of their decision-making processes and have minor differences due to their unique roles. In addition, we consider the visiting nurse and the patient as separate BKBs as well. Even though they are not active decision makers in the patient's care, we assume they both play some roles through providing supplementary information to the surgeons. For the visiting nurse's BKB, the decision associated with the reporting of patient condition to the doctors is inferred. For the patient's BKB, the patient's satisfaction is derived from the outcomes obtained. Those BKBs for nurses and patients are very limited and not sophisticated enough to cover their entire decision-making processes, since this is beyond our current research interests.

To simulate the dynamics of the surgeons' decision-making processes, which is based on the patient condition changing over time, we used the BKB fusion algorithm (Santos et al., 2009). Through the experiments conducted, we validate that BKBs can represent the dynamics in medical decision making when the patient's conditions are changed. The fragments of BKBs, which refer to the input BKBs in the fusion process, are relatively small and contain only partial information representing the information pertinent to changes. For instance, we developed a generic BKB representing a surgeon's decision-making processes at Date 2 by fusing two BKBs: one represents patient condition and the other contains the information consistent during the period, as shown by Figure 4. The left part of Figure 4 represents the patient condition at Date 2, which was obtained by fusing a BKB representing the patient condition at Date 1 and another BKB representing its change at Date 2. The right part of Figure 4 contains the information consistent during the time period. Since we assume that the patient condition is accumulated over time, a generic BKB representing the surgeons' decision-making processes becomes more sophisticated as time goes. As a consequence, the left part of Figure 5 is more complex

Figure 4 Surgical intent model at Date 2

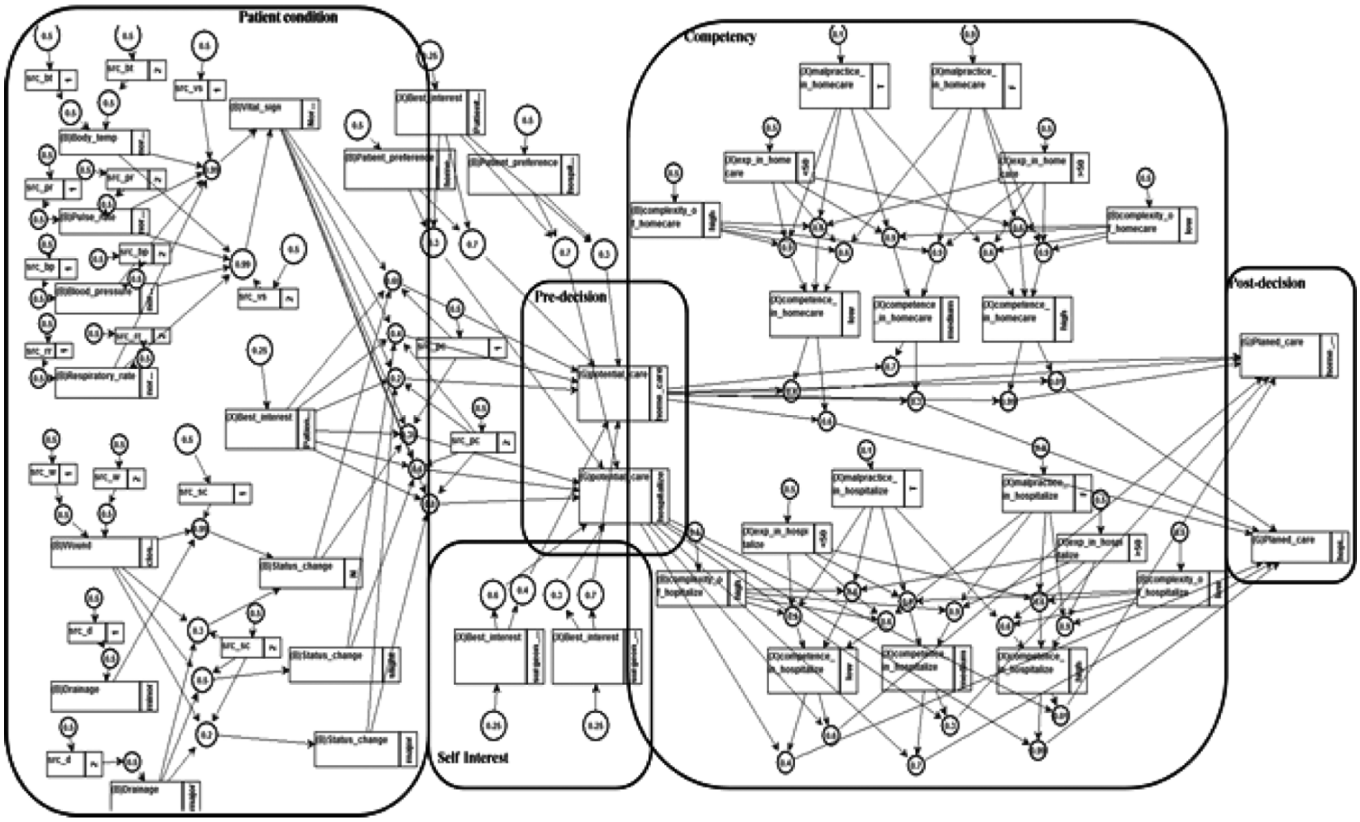
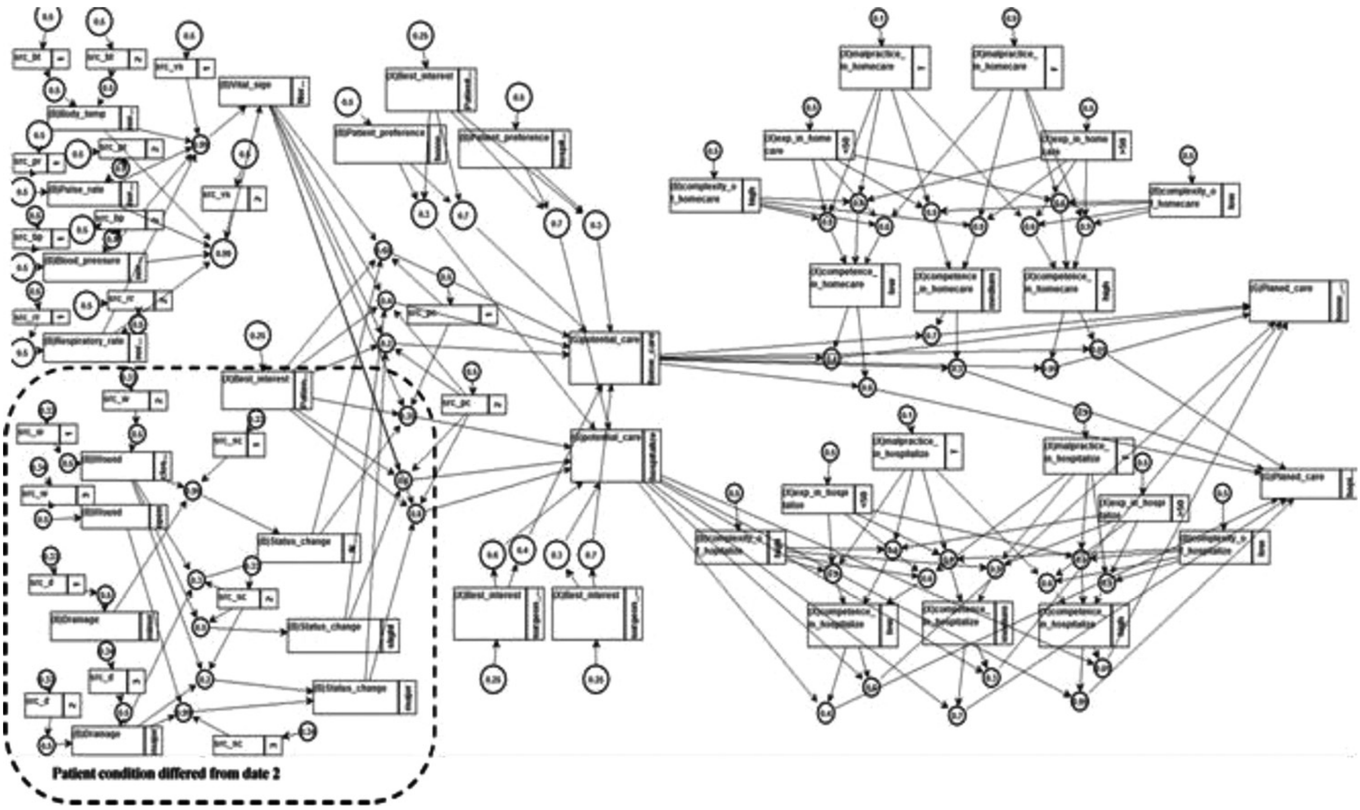


Figure 5 Surgical intent model at Date 3



than that of Figure 4. Their beliefs about patient condition are changed according to the assumption given in Table 1. Since the best-interest of the general surgeon in each case is supposed to be the same (patient-health at 100%), the reasoning model realised for him is the same regardless of the case, although its realisation is different at each date. However, the best-interest of the plastic surgeon in each case is realised differently, according to the design explained in Section 4.3 and this was implemented differently by setting evidence according to the patient condition described in Table 1. Table 2 shows the overall scale of the generic BKBs, including the number of random variables, number of I-nodes, the average connectivity, the number of S-nodes (rules) and the average number of conditions for each rule contained.

With the BKBs specified above, we conducted two sets of experiments to examine whether the BKBs and their fusion approach can provide a true representation of reasoning processes. In static validation, we tested the BKBs on Date 1, with varying professional and personal differences. In dynamic validation, we tested if the fused BKBs accurately represent the changes made in the decision-making processes with regard to the patient condition changes.

4.4 Static validation

The purpose of our static validation is to test if the BKBs constructed to represent individuals in a healthcare team can truly represent a wide range of individuals and their decision-making processes. Since the professional and personal attributes of individuals do not change over a short time period in general, we assume these attributes are static during the time period under our consideration. For example, a surgeon's experience does not change during five time steps or a two-week period. In addition, personal best-interest does not change within a limited time, although it may change over a longer time period (years or decades).

4.4.1 Professional differences vs. error probability

As for professional differences, we addressed individual experience, history of malpractice and complexity. One of our general assumptions is that less experienced individuals make mistakes more frequently than highly experienced individuals. Table 3 represents the results of experiments obtained through the surgeon's BKB. The history of malpractice, experience and complexity are denoted as m, E and C, respectively and the two levels of history of malpractice, experience and complexity are presented as Low (L) and High (H). The "Ratio" in the last column indicates how much bigger the probability of an event happening defined by the 1st rank is, as compared to the probability of an event happening defined by the 2nd rank. Therefore, the 1st rank probability was divided by the 2nd rank probability to get the "Ratio." As shown in Table 3, when the complexity of the procedure is high, the surgeon is highly likely to change his decision from home care to OSC when his level of malpractice and experience is low, since the surgeon would like to ensure patient safety by keeping him and the medical equipment more readily accessible. However, the patient can be taken care of well through home care if the surgeon is highly experienced, but does not cause malpractice frequently, which is shown by the 4th row. If the surgeon has a high malpractice history, he would be more risk-averse and would likely change his decision from HOME to HOSP when the procedure is highly complex, even if he is experienced enough with the procedure, which is shown by the 8th row. The ratios in the first, third and seventh rows are the highest, meaning that the surgeon is very deterministic about his decision. The similarity in the ratios is due to our limited implementation that these three cases all result in high competence.

Table 2 Size of surgeon BKBs over time

Time	*RVS.*	*I-no.*	*CON.*	*S-no.(rules)*
1	20	36	1.64	63
2	29	57	1.67	95
3	29	60	1.65	102
4	29	72	1.69	121
5	29	72	1.69	121

We designed individual surgeon's BKBs in such a way that these three factors (i.e., experience, complexity and prior malpractice) influence individual competence on a specific clinical procedure (i.e., HOME and HOSP), just like the nurse's BKB. However, we consider the patient's BKB differently, since we assume that she judges her satisfaction based on either direct (her own) experience or indirect (other people she is associated with) experience, rather than the complexity or history of malpractice.

4.4.2 Personal differences vs. error probability

As personal differences, we address the best-interest of medical professionals, including surgeons and nurses. Table 4 demonstrates a few examples of how different types of interests influence the final decision when the patient's condition is not changed. As mentioned earlier. PP. PH. SL SFB and SE represent patient preference, patient health, surgeon liability, surgeon financial benefit and surgeon ego respectively, as explained in Section 4.2. Each row represents how a surgeon determines his/her procedure when his/her best-interest is set as evidence. For example, the first row represents how a surgeon determines home care as the best procedure when his best-interest is patient preference.

4.5 Dynamic validation

Based on the static validation. we expanded the simulation into five time periods to validate that the fused BKBs represented the dynamics of the panniculectomy case accurately. To this end, we conducted an additional set of experiments and computed gap values over time for each case we addressed earlier.

4.5.1 Dynamics of potential procedure

In the panniculectomy case, the only source of dynamics is the change of patient condition, such as the wound opening and the drainage and the potential procedure must cope with this change of patient condition. Therefore, we conducted a set of experiments to test if the procedure predicted by inferencing

Table 3 Professional differences vs. error probability

Evidence				*Target (Planned Procedure)*				
Potential Procedure	*M*	*E*	*C*	*1st rank*	*2nd rank*	*1st rank prob.*	*2nd rank prob.*	*Ratio*
Home	L	L	L	HOME	HOSP	1.81E–05	1.83E–07	98.9 0
Home	L	L	H	HOSP	HOME	1.09E–05	7.32E–06	1.49
Home	L	H	L	HOME	HOSP	2.71E–05	2.74E–07	98.9 0
Home	L	H	H	HOME	HOSP	1.92E–05	8.24E–06	2.33
Home	H	L	L	HOME	HOSP	2.13E–06	9.15E–07	2.33
Home	H	L	H	HOSP	HOME	1.83E–06	1.22E–06	1.50
Home	H	H	L	HOME	HOSP	2.01E–06	2.03E–08	99.0 0
Home	H	H	H	HOSP	HOME	1.22E–06	8.14E–07	1.50

Table 4 Personal differences vs. error probability

Evidence	*Target (Planned Procedure)*				
Best-interest	*1st rank*	*2nd rank*	*1st rank prob.*	*2nd rank prob.*	*Ratio*
PP (HOME)	HOME	HOSP	1.30E–03	6.00E–04	2.17
PP (HOSP)	HOSP	HOME	1.30E–03	6.00E–04	2.17
PH	HOME	HOSP	2.50E–03	1.30E–03	1.92
SL	HOME	HOSP	2.70E–03	1.10E–03	2.45
SFB	HOSP	HOME	2.30E–03	1.50E–03	1.53
SE	HOSP	HOME	1.00E–03	3.00E–04	1.17

changes appropriately according to the patient condition. Table 5 shows the results of the experiments obtained by varying the patient condition described in Table 1 and the best-interest of the plastic surgeon according to the design in Section 4.3. The scale of the joint probabilities becomes smaller as the time proceeds, because more information pertinent to patient condition is fused in.

4.5.2 Gap analysis in panniculectomy case

For using gap values as a measure of team performance, we made some basic assumptions regarding individuals' beliefs about others. We assumed that all healthcare professionals' best interests are patient health at 100%. Based on this assumption, we hypothesised that there is no gap among team members if all of them put their best-interests towards patient health at 100%, which was described by case 2 in our study. Another assumption is about comparing probability distributions after reasoning through BKBs. Since comparing probability distributions obtained from BKBs representing different individuals would not make any sense, we set baselines with the probability distributions obtained from BKBs representing individuals having their best-interests towards patient health at 100%, since we believe that those intents are what others expect. To compute the gap of a certain team, we summed up all gap values obtained by comparing one's probability to choose a certain decision with the probability expected by others. Consequently, the team described by case 2 had no gap, as shown by Figure 6, because all team members set their best-interest towards patient health at 100%.

Case 1 describes a team where the plastic surgeon's best interest is divided into patient preference and health. In this case, he/she insisted on readmitting the patient to the hospital constantly from Date 1. At first, we examined the most probable decision made by that plastic surgeon at Date 1, which was "HOSP", as shown in Table 5. Since this is the most probable decision of that plastic surgeon at that time, but not the decision expected by others, we compared it with the probabilistic distribution expected by others with the same evidence given. For instance, the gap (5.10 E-07) shown in Figure 6. was obtained by comparing two probability distributions; one represents the probability expected by others (2.49 E-08) and the other represents the probability of that plastic surgeon's choosing "HOME" (i.e., 1.98 E-06) at Date 1. Although we compared the probabilities of the nurse and the patient as well, only the probabilities determined by the plastic surgeon made a difference here, since we set the best-interests of the other individuals towards patient health at 100%, as explained in Section 4.2. Although the surgeon's motivation is not ideal, his/her decision turns out to be good for the patient from Date 2, since the patient condition gets worse and she needs to be hospitalised again.

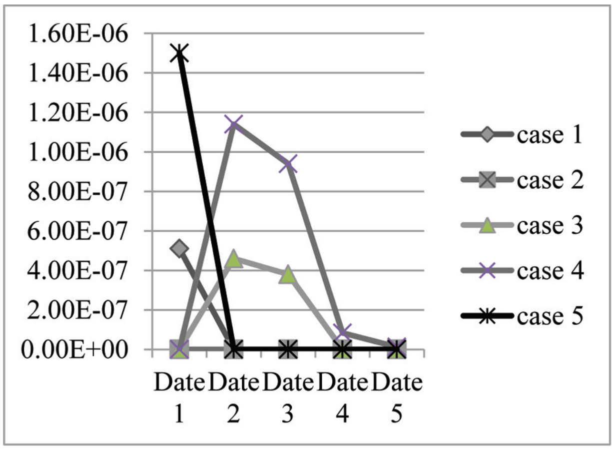
In case 3, the plastic surgeon insisted on home care, since he cared about his liability more than patient health. However, when the patient condition got worse, he changed his decision to readmit the patient to the hospital at Date 4. The decisions made by case 4 were not the right (ideal) decisions at Date 2 and Date 3, as shown in Table 4, so the gap values were computed accordingly. Case 4 is a more severe case with respect to the patient's safety, since this plastic surgeon was more biased towards his/her liability than patient health and insisted on home care despite the patient's pain. The gap value became the biggest at Date 4, since the decisions made are far from the right decisions, except at Date 1. The decreasing gap value supported our assumption that the plastic surgeon would become sceptical of his decision because the patient condition worsened, as provided by the evidence. Case 5 is similar to case 1, since the plastic surgeon decided to perform his own clinical procedure and wanted to keep the patient in the hospital. Although the general conjecture of the gap value is similar to case 1, the values are different from those of case 1, since the probabilities obtained depend on the best-interests of the plastic surgeons.

Table 5 Dynamics of potential care

		Target (Potential Procedure)				
Case	*Time*	*1st rank*	*2nd rank*	*1st rank prob.*	*2nd rank prob.*	*Ratio*
1	1	HOSP	HOME	6.70E–06	1.98E–06	1.35
	2	HOSP	HOME	1.32E–06	6.04E–07	2.19
	3	HOSP	HOME	8.23E–07	3.52E–07	2.34
	4	HOSP	HOME	2.22E–08	8.40E–09	2.64
	5	HOSP	HOME	1.49E–08	6.62E–09	2.25
2	1	HOME	HOSP	2.49E–06	1.33E–06	1.87
	2	HOSP	HOME	2.27E–06	1.51E–06	1.50
	3	HOSP	HOME	1.88E–06	4.70E–07	4.00
	4	HOSP	HOME	5.54E–08	7.24E–09	7.65
	5	HOSP	HOME	2.49E–08	1.65E–08	1.51
3	1	HOME	HOSP	2.68E–06	1.14E–06	2.35
	2	HOME	HOSP	2.64E–06	1.81E–06	1.46
	3	HOME	HOSP	1.65E–06	1.50E–06	1.10
	4	HOSP	HOME	4.44E–08	3.92E–08	1.13
	5	HOSP	HOME	2.49E–08	1.65E–08	1.51
4	1	HOME	HOSP	2.68E–06	1.14E–06	2.35
	2	HOME	HOSP	2.64E–06	1.13E–06	2.34
	3	HOME	HOSP	1.65E–06	9.40E–07	1.76
	4	HOME	HOSP	1.96E–07	1.39E–07	1.42
	5	HOME	HOSP	2.99E–08	1.28E–08	2.34
5	1	HOSP	HOME	1.34E–06	9.90E–07	1.35
	2	HOSP	HOME	1.32E–06	6.04E–07	2.19
	3	HOSP	HOME	8.23E–07	3.52E–07	2.34
	4	HOSP	HOME	2.22E–08	8.40E–09	2.64
	5	HOSP	HOME	1.49E–08	6.62E–09	2.25

The biggest gap was obtained from case 5 at Date 1, as shown in Figure 6. Considering communication breakdown among team members in healthcare practices, the team's performance would deteriorate most when the plastic surgeon was very arrogant and insisted on his/her opinion, regardless of other co-workers. The small gap obtained from case 1 supports our belief that considering patient preference more than patient health would be less harmful than the egoistic plastic surgeon. However, this offset can be adjusted by designers who build up individual BKBs. As shown by the experiments conducted, our computational framework has enough capability of representing clinical decision-making processes, including individuals' professional and personal characteristics.

Figure 6 Gap analysis with five cases (see online version for colours)



5 Conclusion and future works

Our study provides a computational methodology to improve patient safety and care quality through evaluation of team performance by computing gaps among individuals whose intents are inferred from Bayesian reasoning. In particular, we focus on the personal and professional differences of individuals in making clinical decisions over time. For professional differences, we address the impact of individual experience, history of malpractice and the complexity of the medical procedures under consideration. For personal differences, we focus on the best-interests of the individual healthcare professionals, including patient health, patient preference, surgeon's liability, financial benefits and ego as sources of best-interest. By integrating gap analysis into surgical intent inferencing, we enhanced our system of modelling and simulating to help healthcare professionals understand other team members better and promote team performance consequently.

There are several things to do in the future. First, we need to extend our current framework to cover other team members' perspectives better. For instance, we defined five types of best-interest from the surgeon's view and built BKBs for all healthcare team members, including the nurse and the patient. The BKBs representing the nurse and patient are limited in representing their best-interests and their impact on decision-making processes. Therefore, we need to address how much knowledge and what types of decisions are relevant to other team members as well as to team performance. Second, individual differences need further investigation. It is hard to identify the boundary conditions of the gap indicating potential harm, since it is true that some gaps do not lead to any real damage, while others always result in catastrophes. Most likely, the gap is hierarchical, depending on the size and properties accounted for. Furthermore, using the gap as a sole measure of team performance can be misleading, since teams can become vulnerable to errors without a noticeable gap. For instance, a team composed of individuals, all of whom have the same best-interest towards their own financial benefits at 100%, may not have any gap, indicating vulnerability to medical errors, though the team is far from the ideal for patient safety.

Acknowledgments

The work was supported in part by grants from the Office of Naval Research and Air Force Office of Scientific Research. A preliminary version of this work can be found in Santos et al. (2011).

References

Alonso, A., Baker, D.P., Holtzman, A., Day, R., King, H., Toomey, L. et al. (2006) 'Reducing medical error in the Military Health System: How can team training help?', *Human Resource Management Review*, Vol. 16, No. 3, pp.396–415.

Andersen, P.O., Jensen, M.K., Lippert, A. and Ostergaard, D. (2010) 'Identifying non-technical skills and barriers for improvement of teamwork in cardiac arrest teams', *Resuscitation*, Vol. 81, No. 6, pp.695–702.

Beach, M.J. and Sions, J.A. (2011) 'Surviving OR Computerization', *AORN Journal*, Vol. 93, No. 2, pp.226–241.

Brothers, T.E., Cox, M.H., Robinson, J.G., Elliott, B.M. and Nietert, P. (2004) 'Prospective decision analysis modelling indicates that clinical decisions in vascular surgery often fail to maximize patient expected unility', *Journal of Surgical Research,* Vol. 120, No. 2, pp.278–287.

Deering, S., Johnston, L.C. and Colacchio, K. (2011) 'Multidisciplinary teamwork and communication training', *Seminars in Perinatology*, Vol. 35, No. 2, pp.89–96.

Donchin, Y., Gopher, D., Olin, M., Badihi, Y., Biesky, M., Sprung, C.L. et al. (2003) 'A look into the nature and causes of human errors in the intensive care unit', *Quality & Safety Health Care*, Vol. 12, pp.143–148.

Harding, T.P. (2004) 'Psychiatric disability and clinical decision making: The impact of judgement error and bias', *Clinical Psychology Review*, Vol. 24, No. 6, pp.707–729.

Isern, D., Sanchez, D. and Moreno, A. (2011) 'Ontology-driven execution of clinical guidelines', *Computer Methods and Programs in Biomedicine,* Vol. 107, No. 2, pp.122–139.

Jeffcott, S.A. and Mackenzie, C.F. (2008) 'Measuring team performance in healthcare: Review of research and implications for patient safety', *Journal of Critical Care*, Vol. 23, No. 2, pp.188–196.

Johnson, J.G. (2006) 'Cognitive modelling of decision making in sports', *Psychology of Sports and Exercise,* Vol. 7, No. 6, pp.631–652.

Kiesler, D.J. and Auerbach, S.M. (2006) 'Review: Optimal matches of patient preferences for information decision-making and interpersonal behavior: Evidence, models and interventions', *Patient Education and Counseling*, Vol. 61, No. 3, pp.319–341.

Lansac, E., Centa, I.D., Raoux, F., Attar. N.A. Acar. C., Joudinaud, T. et al. (2008) 'A lesional classification to standardize surgical management of aortic insufficiency towards valve repair', *European Journal of Cardio-thoracic Surgery*, Vol. 33, No. 5, pp.872–880.

Mackenzie, C.F. and Xiao, Y. (2003) 'Video techniques and data compared with observation in emergency trauma care', *BMJ Quality & Safety in Health Care*, Vol. 12, No. 2, pp.ii51–ii57.

Maughan, B.C., Lei, L. and Cydulka, R.K. (2011) 'ED handoffs: observed practices and communication errors', *American Journal of Emergency Medicine*, Vol. 29, No. 5, pp.502–511.

Merigo, J.M. and Gil-Lafuente, A.M. (2010) 'New decision-making techniques and their application in the selection of financial products', *Information Sciences*, Vol. 180, No. 11, pp.2085–2094.

Mudumbai, S., Fanning, R., Howard, S., Davies, M. and Gaba, D. (2010) 'Use of medical simulation to explore equipment failures and Human-Machine interactions in anesthesia machine pipeline supply crossover', *Society for Technology in Anesthesia*, Vol. 110, No. 5, pp.110–1292.

Ocampo, E., Maceiras, M., Herrera, S., Maurente, C. and Rodriguez, D. (2011) 'Comparing Bayesian inference and case-based reasoning as support techniques in the diagnosis of Acute Bacterial Meningitis', *Expert Systems with Applications*, Vol. 38, No. 8, pp.10343–10354.

Pearl, J. (1988) '*Probabilistic reasoning in intelligent systems: networks of plausible inference*', San Francisco: Morgan Kaufmann.

Pibouleau, L. and Chevret, S. (2011) 'Bayesian statistical method was underused despite its advantages in the assessment of implantable medical devices', *Journal of Clinical Epidemiology*, Vol. 64, No. 3, pp.270–279.

Pioch, N., Melhuish, J., Seidel, A., Santos, E.J. and Li, D. (2009) 'Adversarial intent modelling using embedded simulation and temporal Bayesian knowledge bases', *SPIE Defense and Security Symposium*, Vol. 7348, pp.1–12, Orlando. FL.

Reason, J. (2000) 'Human error: models and management', *British Medical Journal: Education and Debate*, Vol. 320, pp.768–770.

Rosen, T., Shimony, S. and Santos, E. Jr. (2004) 'Reasoning with BKBs – Algorithms and Complexity', *Annals of Mathematics and Artificial Intelligence*, Vol. 40, Nos. 3–4, pp.403–425.

Santos, E. Jr. and Zhao, Q. (2006) 'Adversarial models for opponent intent inferencing. In Kott, A. McEneaney, W. *Adversarial Reasoning: Computational Approaches to Reading the Opponents Mind* (pp.1–22). Boca Raton: Chapman & Hall/CRC.

Santos, E. Jr. (2001) 'Verification and validation of Bayesian knowledge-bases', *Data & Knowledge Engineering*, Vol. 37, No. 3, pp.307–329.

Santos, E. Jr. (2003) 'A cognitive architecture for adversary intent inferencing: Knowledge structure and computation', *SPIE 17th Annual International Symposium on Aerospace/Defense Sensing and Controls AeroSense.* Orlando. FL.

Santos, E. Jr. and Santos, E.S. (1999) 'A framework for building knowledge-based under uncertainty', *Journal of Experimental and Theoretical Artificial Intelligence*, Vol. 11, pp.265–286.

Santos, E. Jr., Kim, K.J., Yu, F., Li, D., Arbogast. P., Jacob, E.A. et al. (2011) 'Modelling and simulating dynamic healthcare practices', *International Defense and Homeland Security Simulation Workshop*, Rome, Italy.

Santos, E. Jr., McQueary, B. and Krause, L. (2008) 'Modelling adversarial intent for interactive simulation and gaming: The fused intent system', *SPIE: Defense and Security Symposium' 6965*, Orlando, FL.

Santos, E. Jr., Wilkinson, J. and Santos, E. (2009) 'Bayesian knowledge fusion', *22nd International FLAIRS Conference.* AAAI Press.

Santos. E. Jr., Wilkinson, J. and Santos, E.E. (2011) 'Fusing multiple Bayesian knowledge sources', *International Journal of Approximate Reasoning*, Vol. 52, No. 7, pp.935–947.

Stylios, C.D., Georgopoulos, V.C., Malandraki, G.A. and Chouliara, S. (2008) 'Fuzzy cognitive map architectures for medical decision support systems', *Applied Soft Computing*, Vol. 8, No. 3, pp.1243–1251.

Sundar, E., Sundar, S., Pawlowski, J., Blum, R., Feinstein, D. and Pratt, S. (2007) 'Crew resource management and team training', *Anesthesiology Clinics*, Vol. 25, No. 2, pp.283–300.

Taib, I.A., McIntosh, A.S., Caponecchia, C. and Baysari, M.T. (2011) 'A review of medical error taxonomies: A human factors perspective', *Safety Science*, Vol. 49, No. 5, pp.607–615.

Turner, K.J. (2009) 'Abstraction and analysis of clinical guidance trees', *Journal of Biomedical Informatics*, Vol. 42, No. 2, pp.237–250.

Varies, E.N., Ramrattan, M.A., Smorenburg, S.M., Gouma, D.J. and Boermeester, M.A. (2008) 'The incidence and nature of in-hospital adverse events: a systematic review', *Quality and Safety in Health Care*, Vol. 17, No. 3, pp.216–223.

Visser, M. (2010) 'Configurations of human resource practices and battlefield performance: A comparison of two armies', *Human Resource Management Review*, Vol. 20, No. 4, pp.340–349.

Wout, M. and Sanfey, A.G. (2011) 'Interactive decision-making in people with schizotypal traits: A game theory approach', *Psychiatry Research*, Vol. 185, Nos. 1–2, pp.92–96.

Xiao, L. Hu. B. Croitoru. M. Lewis. P. and Dasmahapatra. S. (2010) 'A knowledgeable security model for distributed health information systems', *Computers & Security*, Vol. 29, No. 3, pp.331–349.

Yechiam, E., Arshavsky, O., Shamay-Tsoory, S.G., Yaniv, S. and Aharon, J. (2010) 'Adapted to explore: Reinforcement learning in Autistic Spectrum Conditions', *Brain and Cognition*, Vol. 72, No. 2, pp.317–324.

Zimmermann, J., Rousseau, D., Duffy, J., Devers, K., Gillies, R., Wagner, D. et al. (1994). 'Intensive care at two teaching hospitals: an organizational case study', *American Journal of Critical Care*, Vol. 3, No. 2, pp.129–138.