# MODELING AND SIMULATING DYNAMIC HEALTHCARE PRACTICES

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**ABSTRACT**

Recent research has been undertaken to reduce medical errors and to prevent adverse events that may result from unsafe and insecure situations in complex healthcare practices. Integration of individuals into teams is one of the most challenging but promising issues in the research. Modeling and simulating the complex, dynamic healthcare practices are useful to train individual team members, and subsequently enhance individual and team competencies to boost team performance. In this paper, we propose a methodology to model and simulate dynamic medical situations in healthcare practices by integrating gap analysis with intent inferencing. In intent inferencing, individuals' goals are deduced from their perceptions and observations, and collective intent of individuals is evaluated through gap analysis. As the vast majority of services in healthcare are delivered by a group of individuals, enabling the individuals to figure out the best decision for the patient beyond existing limitations is expected to improve the quality of care significantly.

Keywords: healthcare team, medical procedure, intent inferencing, decision making, gap analysis

## 1. INTRODUCTION

When a set of planned activities in healthcare practices fails to achieve its original goals, we consider it a medical error. Medical errors have led to a significant number of injuries or patient deaths and have become a topic of much concern (Taib, McIntosh, Caponecchia, & Baysari, 2011). Injuries caused by medical management rather than the underlying disease of the patient are identified as adverse events (Bucknall, 2010). Medical errors and adverse events are not rare outcomes nowadays. It is widely acknowledged that many modern healthcare practices are so complex that they can foster unsafe and insecure conditions for patient care. Of the many causes behind these undesirable events, poor teamwork is a significant contributor. Better integration of individuals into teams and optimization of team performance is a promising strategy to increase the quality of care.

Modeling and simulating the complex, dynamic healthcare practices are important in training healthcare team members, and boosting team performance by enhancing individual and team competencies. An effective team performance can be realized if individual team members have a profound understanding, beyond their own limited perceptions and observations, of surrounding environments and teammates. To realize this, it is necessary to provide sufficient information to healthcare professionals when they need to make critical decisions under diverse requests and conflicting demands. Previously, state of the art computational technologies have been adopted to support safe and secure healthcare practices (Adler-Milstein & Bates, 2010). In the same line of research, we propose a methodology to model and simulate dynamic medical situations in healthcare practices by integrating gap analysis with intent inferencing.

Intent inferencing is a branch of knowledge engineering, in which individuals' goals are deduced from their perceptions and observations. Beyond individuals, collective intent of individuals is addressed by gap analysis in this paper. With the information provided by our computational tool, we hope to enable individuals to make the best decisions for the patient in a given situation

Previously, studies to improve team performance have been conducted through developing measures or indicators of team performance, which were commonly based on clinical surveys, direct observation or video-based analysis of real medical performance (Jeffcott & Mackenzie, 2008). These measures were useful to help train and assess real-life team performance. However, these measures have often overlooked patient conditions, which are dynamically changing over time in real-life healthcare practices, and the fact that individuals (healthcare providers) are likely biased when making decisions in complex situations (Brockopp, Downey, Powers, Vanderveer, & Warden, 2004). Furthermore, the conflict between these individuals during patient management is often the key to deteriorating team performance (Coombs, 2003).

Organizational behaviors can be realized by each individual's discrete efforts to accomplish their roles, plans and goals, while team dynamics depend heavily on all individuals' collaboration, coordination, and communication. Thus, team performance in multidisciplinary practices cannot be measured by simply collecting individuals' movements. Even if we trace all of these behaviors, the available information is still incomplete and insufficient to describe overall team



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performance. Therefore, we employ not only a computational technique to infer individuals' intents from their observables but also a strategic methodology to evaluate collective intent of individuals through integrating gap analysis with intent inferencing.

In our earlier studies (Santos, et al., 2010), we applied our methodology to model and simulate primarily static instances of real-life medical cases in which adverse events occurred due to the lack of communication between surgeons. In this work, we present an advanced methodology to model and simulate more dynamic situations over longer periods of time in real-life healthcare practices. Through the simulation, we address the impact of differences between individuals in making clinical decisions by investigating a post-op panniculectomy case, in which two surgeons made conflicting decisions for the same patient.

In the next section, we will describe BKBs and other background studies. Then we will introduce our idea to measure team performance with gap analysis. After that, we will present a real-life post-op panniculectomy case and show how we simulate the case with our methodology. Finally, we will end this paper with a conclusion and future directions for this research.

## 2. BACKGROUND

To ensure patient safety in real-life healthcare practices, individual team members must perform their roles and tasks with continual understanding of dynamic situations and of other team members. In this section, we review three fundamental ideas associated with intent inferencing as a part of our research: (1) representing the information relevant to clinical decision makings, (2) aggregating new information into existing knowledge while properly managing potential inconsistencies, and (3) inferring intents of individual team members from the information observed, perceived and acknowledged by those individuals.

### 2.1. Bayesian Knowledge Bases (BKBs)

The information available in healthcare practices can be represented by BKBs, which are generalizations of Bayesian Networks (BNs) that allow context-specific independence and cyclic relationships among knowledge. BKBs are rule-based probabilistic models to represent knowledge using graphs and probabilistic theory. The graphs are composed of nodes and arcs, where arcs denote causal relationships between knowledge and nodes contain the content of the knowledge. Unlike BNs, there are two types of nodes in BKBs: the i-node, representing a state of a random variables (i.e. how random variables are instantiated) and the s-node, denoting a conditional probability of the causal relationship as shown in Fig 1, where the knowledge that "if body temperature is high, then a surgeon determines hospitalization as a potential care with the probability of 0.8." is contained.

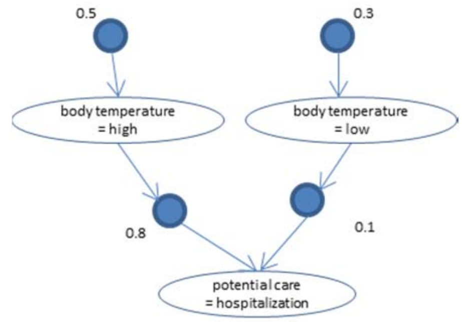

Figure 1: BKB fragment

BKBs are known to be simpler and more concise than BNs in representing knowledge since they can accommodate incomplete knowledge and perform reasoning with less complexity. BKBs have been extensively studied with highly efficient algorithms for reasoning (Rosen, Shimony, & Santos, 2004).

### 2.2. Bayesian Knowledge Fusion

In order to model dynamic changes in healthcare practices, the information represented in BKBs must be updated accordingly. Bayesian knowledge fusion is an algorithm designed to fuse multiple BKBs into a single, large BKB that preserves the information contained in all input sources. Originally, the fusion algorithm was devised to aggregate information provided by multiple experts (E. Santos, J.T. Wilkinson, & Santos, 2009). In order to handle potential disagreement among different experts, two special nodes are added to original BKBs when fused: the source node and the reliability index. Source nodes say which rules in the knowledge base come from which fragments, while the reliability index denotes the trustworthiness of the knowledge contained in the particular fragment. With these additional nodes, the inference process on the fused BKB can consider information from multiple sources and construct an explanation for any evidence observed without violating the basic rules of BKBs.We apply the algorithm to deal with dynamic situations in healthcare practices where updated information of patient condition must be accounted for and added to existing knowledge bases.

### 2.3. Intent inference

Healthcare team members' decision making processes can be simulated through individual intent inferencing based on BKBs. Intent, which can be deduced by individuals' actions, can be defined as a combination of goals that are being pursued by individuals. We typically construct a behavioral model by optimizing individuals' behavioral patterns. Thus, we collect data through observing individuals' actions and environments, and deliver them 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, Melhuish, Seidel, Santos, & Li, 2009) (Santos, McQueary, & Krause, 2008) (Santos, et al., 2007). The instantiation of random


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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 represent what a person believes about himself; beliefs represent what a person believes about others (including other people and surrounding situations); goals represent what results a person wants to achieve; and actions represent what a person will do to realize his goal. Axioms and beliefs may influence themselves or each other, and both can contribute to goals (mostly sub-goals) (E. Santos, 2003).

The intent inferencing can function for three purposes: description of personal insights, prediction of future events and diagnosis of current outcomes. It can describe an insight that motivated individuals and anticipate future actions. In addition, it can assess earlier predictions by contrasting them with current outcomes. It also can provide an explanation of current outcomes.

## 3. EVALUATING TEAM PERFORMANCE

In addition to individual intent inferencing, we address the collective intent of individuals in teams. Teams and their performances are a crucial and integral part of healthcare practices. To ensure patient safety, teams must be well coordinated and communicate well. As a part of a computational methodology to model and simulate dynamic situations in healthcare practices, we use gap analysis as a way to construct a collective intent of a team and integrate it into the surgical intent inferencing. With this integrated approach, we can simulate real-life medical cases and analyze team performance.

### 3.1. Surgical Intent Modeling

Surgical intent modeling 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., 2010). 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. Surgical intent models are naturally expected to include the entire process of healthcare service from diagnosing to discharging the patient. However, it is intractable to encompass every detail of the entire process even if all of them are necessary to infer intentions completely and accurately. Therefore, we select the most relevant elements with the appropriate level of detail when building the models. For example, the elements we choose for 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 fulfill the procedure. In general, surgeons' intent models are the most sophisticated since they have the greatest authority in clinical decision making.

### 3.2. Individual Differences

It is necessary to understand individual differences and similarities for modeling an individual's decision making processes in healthcare practices. We classify individual differences as either professional or personal. Both of these influence individual competence.

#### 3.2.1. Professional Differences

Individuals are different due to their educational background, malpractice experience, complexity of procedures to take during patient care, etc. Therefore, their roles in the clinical decision-making process and in delivering healthcare services are varied. In general, surgeons have the greatest authority in overall clinical decision-making processes, while nurses have more limited authority to manage patient pain.

#### 3.2.2. Personal Differences

Individuals with the same professional background can be very different in their personalities. In general, individual personalities change over time very slowly. However, some attributes 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 self-interest level of individuals is more stable, though changes can occur over time.

### 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 by Calhoun as a way to assess individuals' self-appraisal in communication (Calhoun, Ride, Peterson, & Meyer, 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 which are in conflict 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

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

where $g(x)$ denotes the gap value of team $x$ composed by $n$ individual members in an arbitrary situation, and $P(i)$ denotes the likelihood of the world



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of an individual $i$ 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 low team performance.

## 4. CASE DESCRIPTION

A patient had a circumferential panniculectomy performed by a general surgeon and a plastic surgeon. The general surgeon was in charge of the mesh work and the plastic surgeon was in charge of the rest of the surgery. During the pre-op, the nurse prepped one side of the patient at the beginning and cleaned the other side a while later, rather than clean both sides at once. The Foley catheter, which is commonly implanted at the beginning of the prep, was implanted in the middle of operation in this case.

After the surgery, the patient was discharged and received home care. After a few days, the visiting nurse reported that the drainage came open and the patient had a lot of pain. The general surgeon suggested admitting the patient to the hospital 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. After a few days, 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 pursue a follow-up procedure. By that time, the patient had already experienced a lot of pain in the past few days. During the follow-up procedure, it was confirmed that the wound had been infected. The original plastic surgeon should have admitted the patient immediately after the wound opened.

### 4.1. Panniculectomy Case during 5 days after OR

For modeling and simulating the case dynamically, we shortened the duration of the care from 2 weeks to 5 days after the patient had the panniculectomy operation and was discharged from the hospital. We simplified this case because the patient condition did not change so dramatically that we needed to model each actual day. In addition, we are using a discrete representation of information. As shown in Table 1, we assume the patient condition worsened from Day 1 to Day 4 (as shown by the numbers from -2 to -10) and recovered on Day 5 after both surgeons (general surgeon and the new plastic surgeon) agreed on readmitting the patient to the hospital ("Home" denotes the surgeon's decision to discharge the patient from the hospital and take care of him at home while "Hosp" represents the surgeon's decision to readmit the patient to the hospital).

Table 1: Change of Patient Condition and Surgeons' Decisions

| | Day1 | Day2 | Day3 | Day4 | Day5 |
|---|---|---|---|---|---|
| Patient Status | -2 | -5 | -7 | -10 | -5 |
| General Surgeon | Home | Hosp | Hosp | Hosp | Hosp |
| Plastic Surgeon | Home | Home | Home | Hosp | Hosp |

### 4.2. Possible Cases depending on Personalities

In order to validate our approach, we modeled four possible medical situations, where the major differences were in the surgeons' different types of interests. In each case, we assumed a healthcare team composed of four individuals: general surgeon, plastic surgeon, nurse, and patient. For the panniculectomy case, we speculated on the role of the plastic surgeon in delivering the healthcare service and varied his self-interest while fixing other members' best-interests to patient-health as the highest priority. While varying the plastic surgeon's best-interest, we addressed four categories: patient preference, patient health, surgeon liability, and surgeon cost. If the plastic surgeon considers a patient's preference as his first priority, he will make a decision that conforms to the patient 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 liability in case any incidents happen. Pursuing surgeon cost as a primary interest refers to the situation in which a surgeon makes a decision to maximize his individual or organizational income. In a real situation, a surgeon tends to pursue a mix of these four best-interests rather than only one. Thus, we hypothesize four possible cases, each of which represents a different type of best-interests. Each type of best-interest can contribute to individual's best-interest proportionately and the weights used for each case are presented 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%.

#### 4.2.1. Case 1

A 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 two types of best interests are roughly equivalent (patient preference=100%, patient health=80%).

#### 4.2.2. Case 2:

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



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#### 4.2.3. Case 3:

A plastic surgeon focuses on reducing his/her liability while improving a patient's health. The weights for these two types of best-interests are roughly equivalent (patient health=80%, surgeon liability=100%).

#### 4.2.4. Case 4:

A 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%).

#### 4.2.5. Experimental Results

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 different 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.

In order to simulate the dynamics of the surgeons' decision making processes, which is based on the patient condition that changes over time, we used the BKB fusion algorithm (E. Santos, J.T. Wilkinson, & Santos, 2009). Through the experiments conducted, we validate that BKBs can represent the dynamics in medical decision making when the patient conditions are changed.The fragments of BKBs, which refer to the input BKBs in the fusion process, are relatively small and contain only the information representing the changes through new i-nodes that influence the distribution of pre-existing i-nodes.

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 knowledge and correlations among them. In static validation, we tested the BKBs on Day 1, with varying professional and personal differences. In dynamic validation, we tested if the fused BKBs accurately represent the changes made in decision-making processes with regard to the dynamic patient condition.

### 4.3. 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, surgeons' experience does not change during a 5-day or 2-week period. In addition, personal self-interest does not change within a limited time, although it may change smoothly over a longer time period (years or decades).

#### 4.3.1. Professional Differences vs. Error Probability

As for professional differences, we considered experience, complexity and malpractices. One of our general assumptions is that less experienced individuals make mistakes with a higher probability than highly experienced individuals. Table 2 represents the results of experiments obtained through the surgeon's BKB. In addition, the malpractice, experience and complexity are denoted as M, E and C, respectively and the two levels of malpractice, experience and complexity are presented as Low (L) and High (H). As shown in Table 2, when the complexity of the procedure is high, the surgeon is highly likely to change his decision from home care to hospitalization 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. If the surgeon has a high malpractice history, he would be more risk-averse and would likely change his decision from home care to hospitalization when the procedure is highly complex even if he is experienced enough with the procedure.

Although we confirmed that all individual BKBs follow this tendency, we present here only the experimental results obtained from the general surgeon's BKB.

Table 2: Professional Differences vs. Error Probability

| Evidence | | | | Target (Planned Procedure) | | |
|---|---|---|---|---|---|---|
| Potential Procedure | M | E | C | 1st rank | 2nd rank | 1st rank prob. |
| Home | L | L | L | Home | Hosp | 1.81e-05 |
| Home | L | L | H | Hosp | Home | 1.09e-05 |
| Home | L | H | L | Home | Hosp | 2.71e-05 |
| Home | L | H | H | Home | Hosp | 1.92e-05 |
| Home | H | L | L | Home | Hosp | 2.13e-06 |
| Home | H | L | H | Hosp | Home | 1.83e-06 |
| Home | H | H | L | Home | Hosp | 2.01e-06 |
| Home | H | H | H | Hosp | Home | 1.22e-06 |

#### 4.3.2. Personal Differences vs. Error Probability

As personal differences, we address the self-interest of surgeons and nurses. Table 3 demonstrates a few examples of how different types of interests influence the final decision when the patient's condition is normal. As evidence for best-interest, PP, PH, SL and SC represent patient preference, patient health, surgeon liability and surgeon cost respectively, as explained in



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Section 4.2. Each row represents how a surgeon determines his procedure when his 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, which is home care in this example.

Table 3: Personal Differences vs. Error Probability

| Evidence | Target (Planned Procedure) | | |
|---|---|---|---|
| Best-interest | $1^{st}$ rank | $2^{nd}$ rank | $1^{st}$ rank prob. |
| PP (Home) | Home | Hosp | 0.0013 |
| PP (Hosp) | Hosp | Home | 0.0013 |
| PH | Home | Hosp | 0.0025 |
| SL | Home | Hosp | 0.0027 |
| SC | Hosp | Home | 0.0023 |

### 4.4. Dynamic Validation

Based on the static validation, we expanded the simulation into a 5-day period 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.

#### 4.4.1. Dynamics of Potential Procedure

In the panniculectomy case, the only source of dynamics is the change in patient condition, such as the wound opening and drainage fall. 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 with the BKB changes according to the patient condition, as shown by Table 4.

Table 4: Dynamics of Potential Care

| | | Target (Potential Procedure) | | |
|---|---|---|---|---|
| Case | Day | $1^{st}$ rank | $2^{nd}$ rank | $1^{st}$ rank prob. |
| 1 | 1 | Hosp | Home | 0.00134 |
| | 2 | Hosp | Home | 1.32E-06 |
| | 3 | Hosp | Home | 8.23E-07 |
| | 4 | Hosp | Home | 2.22E-08 |
| | 5 | Hosp | Home | 1.49E-08 |
| 2 | 1 | Home | Hosp | 0.002489 |
| | 2 | Hosp | Home | 2.27E-06 |
| | 3 | Hosp | Home | 1.88E-06 |
| | 4 | Hosp | Home | 5.54E-08 |
| | 5 | Hosp | Home | 2.49E-08 |
| 3 | 1 | Home | Hosp | 0.00268 |
| | 2 | Home | Hosp | 2.64E-06 |
| | 3 | Home | Hosp | 1.65E-06 |
| | 4 | Hosp | Home | 4.44E-08 |
| | 5 | Hosp | Home | 2.49E-08 |
| 4 | 1 | Home | Hosp | 0.00268 |
| | 2 | Home | Hosp | 2.64E-06 |
| | 3 | Home | Hosp | 1.65E-06 |
| | 4 | Home | Hosp | 3.92E-08 |
| | 5 | Home | Hosp | 2.99E-08 |

#### 4.4.2. Gap Analysis in Panniculectomy Case

Gap values were computed using Equation (1) for each case mentioned in Section 4. As shown in Figure 2, we obtained the lowest gap value from case 2 during the 5 days since the both the general and plastic surgeons placed their best-interests towards patient health. In case 1, the plastic surgeon's best interest is set towards patient preference and health, and he insists on readmitting the patient to the hospital from day 1. Although his motivation is not ideal, his decision turns out to be good for the patient health from day 2 since the patient condition gets worse. In case 3, the plastic surgeon insists on home care since he cares about his liability in addition to the patient health. However, since the patient condition gets worse, he changes his decision to readmit the patient to the hospital at day 4. The gap value becomes negligible after the patient was re-hospitalized. Case 4 is a more severe case with respect to the patient safety since this plastic surgeon is more biased to his liability issue and insists on home care until day 5. However, the gap value becomes smaller as time goes on since the plastic surgeon would become skeptical of his decision when the patient condition worsened.

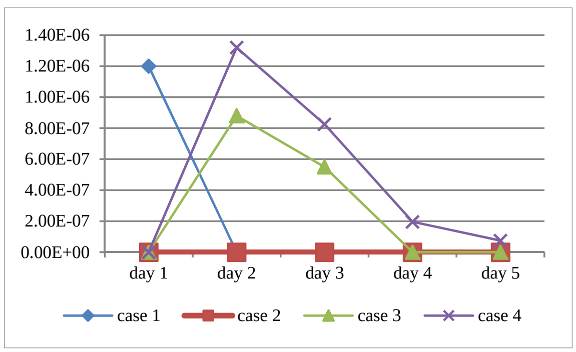


Figure 2: Gap Analysis with four cases

## 5. CONCLUSION AND FUTURE WORKS

In this paper, we proposed a new computational framework to simulate dynamic healthcare practices by employing the Bayesian knowledge fusion method developed to aggregate the information from multiple sources. By modeling and simulating complex real-life situations, we expect to contribute to training healthcare professionals and ensuring patient care. We also



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addressed team performance through gap analysis by integrating gap analysis with individual intent inferencing. Consequently, we hope to supply healthcare practitioners with information of complex situations and help them make the best decision for the patient.

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