



Université d'Ottawa • University of Ottawa



# Université d'Ottawa - University of Ottawa

FACULTÉ DES ÉTUDES SUPÉRIEURES  
ET POSTDOCTORALES

FACULTY OF GRADUATE AND  
POSTDOCTORAL STUDIES

Mingmei LI

AUTEUR DE LA THÈSE - AUTHOR OF THESIS

M. Sc. (Systems Science)

GRADE - DEGREE

Systems Science

FACULTÉ, ÉCOLE, DÉPARTEMENT - FACULTY, SCHOOL, DEPARTMENT

TITRE DE LA THÈSE - TITLE OF THE THESIS

Application of Bayesian belief network model to evaluate variances in clinical  
caremap : radical prostatectomy case study

W. Michalowski

DIRECTEUR DE LA THÈSE - THESIS SUPERVISOR

CO-DIRECTEUR DE LA THÈSE - THESIS CO-SUPERVISOR

EXAMINATEURS DE LA THÈSE - THESIS EXAMINERS

D. Lane

H. Viktor

J.-M. De Koninck, Ph.D.

LE DOYEN DE LA FACULTÉ DES ÉTUDES  
SUPÉRIEURES ET POSTDOCTORALES

DEAN OF THE FACULTY OF GRADUATE  
AND POSTDOCTORAL STUDIES

**Application of the Bayesian Belief Network Model  
to Evaluate Variances in a Clinical Caremap:  
Radical Prostatectomy Case Study**

A thesis submitted to The School of Graduate Studies and  
Research

in partial fulfillment of the degree of

Master of Science

Mingmei Li

Systems Science

University of Ottawa

Ottawa, Ontario, Canada, K1N 6N5

2004

© Mingmei Li, Ottawa, Canada, 2004



Library and  
Archives Canada

Bibliothèque et  
Archives Canada

Published Heritage  
Branch

Direction du  
Patrimoine de l'édition

395 Wellington Street  
Ottawa ON K1A 0N4  
Canada

395, rue Wellington  
Ottawa ON K1A 0N4  
Canada

*Your file* *Votre référence*

*ISBN: 0-494-01528-4*

*Our file* *Notre référence*

*ISBN: 0-494-01528-4*

#### NOTICE:

The author has granted a non-exclusive license allowing Library and Archives Canada to reproduce, publish, archive, preserve, conserve, communicate to the public by telecommunication or on the Internet, loan, distribute and sell theses worldwide, for commercial or non-commercial purposes, in microform, paper, electronic and/or any other formats.

The author retains copyright ownership and moral rights in this thesis. Neither the thesis nor substantial extracts from it may be printed or otherwise reproduced without the author's permission.

#### AVIS:

L'auteur a accordé une licence non exclusive permettant à la Bibliothèque et Archives Canada de reproduire, publier, archiver, sauvegarder, conserver, transmettre au public par télécommunication ou par l'Internet, prêter, distribuer et vendre des thèses partout dans le monde, à des fins commerciales ou autres, sur support microforme, papier, électronique et/ou autres formats.

L'auteur conserve la propriété du droit d'auteur et des droits moraux qui protègent cette thèse. Ni la thèse ni des extraits substantiels de celle-ci ne doivent être imprimés ou autrement reproduits sans son autorisation.

---

In compliance with the Canadian Privacy Act some supporting forms may have been removed from this thesis.

Conformément à la loi canadienne sur la protection de la vie privée, quelques formulaires secondaires ont été enlevés de cette thèse.

While these forms may be included in the document page count, their removal does not represent any loss of content from the thesis.

Bien que ces formulaires aient inclus dans la pagination, il n'y aura aucun contenu manquant.

  
**Canada**

## **Abstract**

A clinical caremap is a cost-effective tool for clinical process improvement that has been accepted in hospitals and various healthcare organizations in many countries. However, compared to the literature describing the initial development of the clinical caremaps, the evaluation of the impact of the variances in the caremap pathway on the patient's expected outcomes and the patient's length of stay (LOS) remains relatively less analyzed. In this research, we deal with the issue of variances in the clinical caremap by building a Bayesian belief network named BBN\_RPC to model the radical prostatectomy caremap. The BBN\_RPC model provides insight into probabilistic dependencies that exist among the activities (variables) in the caremap. We then use the BBN\_RPC model to analyze possible variances and to make inferences. The results show that most of the activities in the caremap are related with each other and to some extent linked with the patient's length of stay (LOS), whereas different activities have different weights on the LOS. Using radical prostatectomy patients' data from a retrospective chart study conducted at the Ottawa Civic Hospital, we have applied the BBN\_RPC model to predict a patient's future conditions and the LOS, based on the current observations. Predictive accuracy of the BBN\_RPC model was evaluated by cross validation tests, which showed the accuracy for predicting the patient's LOS, given the patient's observations during the first two post-op days, is at approximately 94 % level.

**Keywords:** Caremap, Bayesian belief network, Variance, Radical Prostatectomy, Length of stay, Clinical pathway

## **Acknowledgements**

I would like to thank my supervisor, Professor Wojtek Michalowski, for his advice and comments on my work, and his suggestions that helped to improve this thesis. I would like to thank Dr. Anthony Thijssen from The Ottawa Hospital, Civic Campus, for organizing the retrospective chart study and help in interpretation of clinical results.

Many thanks go to my parents, my husband and my friends, for their unfailing support and encouragement.

## Contents

<b>Abstract .....</b>	<b>2</b>
<b>Acknowledgements .....</b>	<b>3</b>
<b>List of Tables.....</b>	<b>6</b>
<b>List of Figures .....</b>	<b>7</b>
<b>List of Acronyms.....</b>	<b>8</b>
<b>List of Symbols .....</b>	<b>9</b>
<b>1 Introduction.....</b>	<b>11</b>
1.1 Motivation of the Study .....	11
1.2 Objective of the Study.....	13
1.3 Significance of the Research .....	14
1.4 Thesis outline .....	15
<b>2 Review of the Literature .....</b>	<b>16</b>
2.1 Description of the Provincial Health Care System .....	16
2.2 Caremap Development and Analysis.....	17
2.3 Factors Affecting the LOS.....	19
2.4 Why Bayesian Belief Networks was Chosen for Our Study .....	20
<b>3 Methodology .....</b>	<b>22</b>
3.1 Bayes' Theorem and Beliefs.....	22
3.2 Bayesian Belief Networks .....	23
3.3 Bayesian Learning: Acquiring a BBN from Data .....	26
<b>4 Application of the BBN Model: Modelling Radical Prostatectomy</b>	
<b>Caremap.....</b>	<b>30</b>
4.1 Components of the RPC.....	30
4.2 Development of a BBN Model for the RPC.....	32
4.3 Performance Evaluation .....	39
<b>5 Inferences and Analysis using the BBN_RPC Model .....</b>	<b>43</b>
5.1 Factors Associated with the LOS in the BBN_RPC Model .....	43

5.2	Inference in the BBN_RPC Model .....	44
5.3	Analysis of Variances .....	49
<b>6</b>	<b>Conclusion and Future Work.....</b>	<b>56</b>
6.1	Summary and Conclusions.....	56
6.2	Future work.....	57
	<b>References.....</b>	<b>58</b>
	<b>Appendix A: The Radical Prostatectomy Caremap.....</b>	<b>61</b>
	<b>Appendix B: The K2 Method .....</b>	<b>68</b>
	<b>Appendix C: Tables .....</b>	<b>70</b>

## List of Tables

Table 1: Variables in the RPC .....	70
Table 2: A Form for Transcribing Patients' Data from Charts .....	73
Table 3: A Training Dataset for Developing the BBN_RPC Model.....	74
Table 4: Out-of-sample Data Used for the BBN_RPC Model Performance Evaluation.....	82
Table 5: Conditional Probabilities Associated with Each Variable in the BBN_RPC Model.....	86
Table 6: Probabilities of Each Variable in the BBN_RPC Model .....	92
Table 7: Probabilities of Outcomes on Post-op Day 3 for a "Good Case" patient p1.....	93
Table 8: Posterior Probabilities for Patient's LOS given Each Event.....	94

## List of Figures

Figure 4.1	The General Caremap.....	31
Figure 4.2	The Structure of the BBN_RPC Model.....	40
Figure 4.3	Cross Validation Test.....	41
Figure 4.4	Results of 10-fold Cross Validation Test.....	41
Figure 5.1	Distribution of Patients' Chances of Meeting the LOS given the Current Conditions .....	48
Figure 5.2	Posterior Probability of the Patient's LOS for Event e1 and e2 .....	50
Figure 5.3	Posterior Probability of the Patient's LOS given Each Event .....	51
Figure 5.4	Finding the Most Probable Cause of Variance e83 .....	54

## List of Acronyms

Initials	Meanings
LOS	Length of patient's stay in the hospital
BBN	Bayesian belief network
RPC	Radical prostatectomy caremap
BBN_RPC	Bayesian belief networks model of radical prostatectomy caremap

## List of Symbols

Symbols	Meanings
$P$	Probability distribution.
$S$	An arbitrary belief-network structure containing all the variables
$P(S)$	Prior probability of $S$
$D$	A set of data
$P(D)$	The probability of $D$ being correct
$P(D   S)$	The probability of $D$ being correct, given the correctness of the structure $S$
$P(S   D)$	Posterior probability of the structure $S$ A conditional probability of the structure $S$ given the data $D$
$E$	The average accuracy of the model
$t$	Time $T = \{t   t = 1, \dots, \tau\}$ ; $t = \tau$ : discharge time.
$X_i^t$	The $i^{\text{th}}$ patient's activity or patient's outcome at time $t$
$C$	The constant prior probability $P(S)$ for each $S$
$pa(i)$	The parents of the $i^{\text{th}}$ node
$N_{ij}$	The number of cases in the database in which the parent of

	the $i^{\text{th}}$ variable has its value $j$ .
$N_{ijk}$	The number of cases in the database in which the value of the $i^{\text{th}}$ variable is $k$ , and its parent value is $j$
$r_i$	The number of values for the $i^{\text{th}}$ variable
$n$	$n$ variables
$m$	$m$ parent variables of the variable

# 1 Introduction

## 1.1 Motivation of the Study

Hospital funding in Ontario is done through the Ministry of Health and Long Term Care. Up to now, it has been very difficult to control the overall growth in health care costs [1]. In order to achieve a sustainable level of quality of care within the health care system on the one hand, at a reasonable cost on the other, many reforms in the hospital system are necessary. One way of reducing hospital costs is by reducing inpatient's length of stay (LOS). In fact, cost of the LOS is often used to measure hospital efficiency, and it is also considered to be a reasonable proxy of resource utilization [1]. One way of controlling the LOS is to develop and introduce unified patient's management procedures within a hospital for the same presentation. This is accomplished by creating a so-called caremap.

The caremap explicitly lists the care process (e.g., intervention, assessment, and nutrition) and the expected patient's outcomes sequentially over the course of hospitalization. It is supposed to be followed by the patient's management team (e.g., physicians, nurses). By mapping usual interventions and outcomes, the patient's management team is capable of following a pre-defined path that results in streamlined care and improved efficiency. Use of a caremap should also diminish the impact of individual physician management practices on the LOS because the patient is managed by a team, each responsible for his/her own task, instead of by the individual care provider. However, in many cases the caremap cannot be followed adequately because of different reasons such as patient complications, and patient mental problems [2]. That is, some patients will encounter problems in the course of their hospitalisation, causing variation in the interventions and outcomes. Variances are the unexpected events that are different from what is predicted on the

clinical caremap, and might be negative or positive. A negative variance that occurs early in the pathway may affect the timing of subsequent activities, causing a cascading effect through the rest of the care delivery process, thus affecting the LOS [3]. Therefore, analysis of variation is an essential part of developing the clinical caremap. It provides useful and accurate information on the frequency and causes of variations in patient care and it also encourages members of the patient's management team to continuously redefine the caremaps to reflect current "best practices".

Previous studies [2] [4] have reported on how to document, collect and report variances in accordance with developing the clinical caremap. However, the primary issue not addressed so far involves a comprehensive analysis of the design of the relationships among the elements in the caremap and how the variance in realization of some of the activities will affect the LOS. In particular, the following issues still have to be addressed:

1. Most studies have only focused on how to design and develop the caremap using a multidisciplinary team that meets regularly and includes nurses, physicians, therapists, and pharmacists among its members [2]. However, this is only the first step toward improving clinical processes. The impact of the variances in the caremap on expected patient's outcomes and the patient's length of stay remains relatively less known compared to the literature describing the initial development of pathways.
2. Some case reports have been published on variance analysis and reporting [3] [4] [5]. However, none of these reports has shown the relationships between the use of pathway variances and patient's outcomes, whereas such relationships are very important issues in evaluating variances. Moreover, none of them quantified the impact of variance in the clinical caremap on the patient's LOS.

Since evaluating the variances is a very important step in developing the caremap, we believe that it is very valuable to find a qualitative approach to evaluate the

impact of deviations from a caremap on the future condition of the patient and ultimately on the LOS. Therefore, our research question is how to evaluate impact of the deviations from the clinical caremap occur on the patient's LOS and the patient's expected outcomes?

## 1.2 Objective of the Study

In this research, we will study the impact of negative variances in a caremap on the LOS. Specifically, we will try to determine how the occurrence of a specific condition impacts the chances of maintaining the predicted LOS.

In order to achieve this objective, the Bayesian Belief Network (BBN) has been selected to model a specific caremap because activities comprising a caremap can be described as a probabilistic process with conditional probabilities that are dependent on each other and form a network. In our research, we use the radical prostatectomy caremap (RPC) as a case study for the description and the evaluation of the BBN model. The RPC was created and is used in the Ottawa Civic Hospital (see Appendix A for description).

The research described in this thesis was conducted following these two phases:

- a) Development of the BBN model for a radical prostatectomy caremap:
  - Establishment of a set of random variables in the caremap and establishment of the relationship between them.
  - Computation of the conditional probability that provide the relationship between one variable and its immediate parent variables.
- b) Application of this model to evaluate the impact of the current negative deviations of a new patient's caremap on the patient's future condition and on the patient's LOS.

## 1.3 Significance of the Research

### 1.3.1 Empirical Significance

Attracting almost one third of the costs of all health care spending in Canada, hospitals represent the largest category of expenditures on health care. Therefore, improving hospital operations can provide an important source of savings. Within hospitals' expenditures, costs of inpatients' stay play the most important role. One of the main factors influencing this cost is the LOS, and specifically deviations from the best practices. Introduction of the caremaps to manage inpatients' stay was supposed to help in controlling this expenditure, with the argument that great savings can be realized by reducing the LOS in such a way. However, if the caremap cannot be followed adequately, it will influence the LOS negatively and the positive impact of following the best practices can be significantly diminished. The problem faced by the management team is to know in advance the patient's probable outcome and the patient's LOS given certain events that prevent them from following a caremap as planned; if they knew these things, they could determine how to manage the patient efficiently. Thus, studying the impact of negative deviation from the caremap on the LOS is a very important issue for effective patient management.

### 1.3.2 Theoretical Significance

The theoretical significance for this study lies in the demonstration how a novel methodology such as a BBN can be used to model a caremap and evaluate the impact of compliance with prescribed activities on the patient's LOS. First, we identified a specific clinical case – a prostate cancer and associated radical prostatectomy caremap, which was used to define variables required by the BBN model for the RPC (BBN\_RPC). Then, data required for model development were collected from the retrospective chart study, and a model was developed using these data. In addition, we used out-of-sample data to evaluate the predictive accuracy of the BBN\_RPC model. Moreover, we successfully applied the

BBN\_RPC model to evaluate the impact of negative variances in the caremap on the patient's expected outcomes and the LOS.

## 1.4 Thesis outline

The thesis is organized into six sections. Section 1 introduces the motivation and objective of our research and Section 2 reviews the relevant literature. Section 3 provides justification for the methodology and Section 4 applies the proposed methodology to the development of the BBN model for the radical prostatectomy caremap. Section 5 presents the inferences from the caremap model and Section 6 draws the conclusions and summarizes the topics for further investigation.

## **2 Review of the Literature**

In this section, we briefly review the relevant literature that has been grouped into the following four main areas:

- Description of the provincial health care system
- Caremap development and analysis
- Factors affecting the LOS
- Why Bayesian Belief Networks was chosen for our study

### **2.1 Description of the Provincial Health Care System**

Management and delivery of health care is a provincial responsibility with the provincial governments being responsible for allocating the budgets to hospitals, continuing care services, public health services, etc. Hospitals are usually incorporated under a provincial statute. In addition, hospitals are non-profit, and provincially registered corporate entities [6].

The current health care system faces a dilemma. On one hand, with the multidimensional pressures on provincial government budgets such as the increase of an aging population, the implementation of new technologies, and the growth of public expectations etc., the pace of health care spending is increasing faster than inflation. In the long term, the provincial health care system is faced with a fiscally sustainable challenge [6]. On the other hand, one of the major categories of all health care spending is hospital expenditure. The current situation of many hospitals is that they are involved in increasing operating losses and deteriorating working capitals, that is, hospitals are experiencing greater difficulties in meeting day-to-day needs. For example, the vast majority of paid inpatient nursing time (78.5 out of every 100 hours) for direct care of inpatients has been increased. Total

staff time (60.3 out of every 100 hours) on patient care activities has also been increased [7].

One of the attempts to control costs of inpatient care is to reduce the average length of hospital stay without hurting patient care. The inpatient's length of stay after surgery appears to be one of the main components of this cost [1]. If the LOS could be reduced, there would be a great saving in hospital costs. A report from the Ontario Hospital Association [8] states that operating cost pressures have greatly increased in recent years, and this report points out that more emphasis on the LOS reduction could have substantially reduced the hospital's operating costs and occupancy levels. Research published during the past year addressed ways to reduce the length of inpatients stay [9] [10]. The implementation of a clinical caremap is an attempt to introduce "best clinical practice" so that the hospital stays within prescribed LOS – which in turn is determined on a basis of province-wide best practices in a given clinical presentation and "adopted" in the hospital considering its type (teaching, tertiary, community, etc.). Therefore, the implementation of caremaps has a positive impact on managing the LOS. Hudson [10] reports that the Alamance Regional Medical Center decreased the LOS of those patients by over 3% where clinical caremaps were used, while the volume of patients managed that way increased. Chang [11] reports that implementing the caremap can decrease the LOS significantly in patients who underwent either a transurethral prostatectomy or an inguinal herniorrhaphy. Moreover, the caremap promotes quality patient care by incorporating existing standards, practice guidelines, and research findings, and by providing a mechanism to monitor quality care based on patient's outcomes. Hofmann [4] points out that the complication rate of patients undergoing coronary artery bypass graft procedures after following the caremap has decreased from 16.6% to 5% in Mount Clemens General Hospital.

## 2.2 Caremap Development and Analysis

The caremap (also called *clinical pathways*, *care management*, or *care planning*) is a "multidisciplinary plan of best clinical practice for specified groups of patients

with a particular diagnosis that aids the coordination and delivery of high quality care” [2]. It consists of four essential components: a timeline, categories of care processes (e.g., assessment, treatment, activity, etc.), patient’s outcome criteria, and the variance record. As a patient-oriented, cost-effective care management system, the caremap is increasingly being used [2]. However, in many cases, the caremap can not be followed closely because of patients’ subjective personal problems, or problems caused by the hospital system, etc. Therefore, many researchers suggest that the caremap should be flexible enough to allow for certain discrepancies and needs to be developed to suit different circumstances [2] [12]. Ignatavicius et al. [2] give examples of developing alternative caremaps such as developing two caremaps when the patient is suffering two diseases (e.g., a patient suffers from both diabetic and hypoglycaemia disease). Additionally, Lin et al. [12] have developed the flexible hemodialysis care process to predict possible paths for an admitted patient.

Despite the intent to define the essential components of care, there still are variations in how care will be delivered and how patients will respond. Luttman et al. [3] point out that patient’s outcomes do not always follow the relevant caremap. Process variances will occur when the patient is not progressing at the standard rate through the caremap. Furthermore, these variances can be positive or negative. Positive variances occur when the patient progresses towards projected outcomes earlier than expected. Negative variance occurs when the patient fails to meet projected outcomes; either there is a delay in meeting the outcomes, or there is a need for additional interventions previously unplanned. At the same time, they designed a statistical model that has been developed to improve cardiac clinical process, based on the concepts of the PERT/CPM method. But in their research, only a few critical variances were monitored. Hofmann [4] presented a methodology where nurses write variances on a variance-tracking tool attached to the pathway. Nurses follow up on these variances and address them during each shift. Thereafter, the tracking tool is sent to the quality management department or its equivalent for analysis and reporting. However, only the frequency of the

general variances according to critical path categories was listed in his research. None of the above research addresses the issues of to what extent the variance will affect the LOS.

As improvements in the quality of care are achieved through continuously redefining the caremap to reflect current best practices, variance analysis is a very important audit tool. Any negative variances might influence the patient's conditions; ultimately, they might influence the patient's LOS. Therefore, how to efficiently evaluate the impact of negative variances in the clinical caremap in terms of LOS is an important subject to consider during the development of a caremap.

In this research, we are not going to develop a new caremap. Because care processes involve complex interactions between many people and departments, it can take a multidisciplinary team several weeks to develop a single pathway [2]. In fact, we model the specific caremap using the BBN model, thus obtaining the relationships between activities in the care process and the effect of these relationships on the LOS. Ultimately, we apply this model to study the impact of negative variances in a radical prostatectomy caremap on the activities, including the LOS.

### 2.3 Factors Affecting the LOS

In terms of LOS, much research has been done on what kind of factors would affect the LOS once the patients are admitted into the hospital. For example, Gardner et al. [13] have done research on the surgical and postoperative factors affecting the LOS after a radical prostatectomy. They conducted a retrospective chart study and discovered 22 factors impacting the LOS. In another research study [14], the relationship between the patient's admission attributes and the LOS in the geriatric hospitals was analyzed and the distribution of the LOS was determined given a set of values for selected admission attributes. It was reported that both patient's admission factors and some surgical and postoperative factors influence the LOS.

Marshall et al. [15] offer a conditional phase-type model to predict the distribution of the LOS.

Although the above studies demonstrated the importance of individual attributes for the LOS, they did not deal with a clinical caremap directly.

## 2.4 Why Bayesian Belief Networks was Chosen for Our Study

Studying the impact of variances in the caremap on the patients' future conditions on the basis of current observations is a typical conditional-type probability question. Conditional probability describes changes of an isolated event subject to prior knowledge. Occurrence of a specific event (i.e. patient's condition or action) may be in that sense considered as prior knowledge. However, the caremap consists of complex processes that capture many events and relationships between them. Therefore, development of a simple Bayes' model is not feasible. What is required is a model based on Bayes' concept but allowing the representation of a chain of probabilistic events that are related with each other.

To represent the complex causal relationships and probabilistic semantics between numerous variables, three techniques including decision trees, artificial neural networks and Bayesian Belief Networks (BBN) are usually used [12].

Bayesian Belief Networks have the distinguishing characteristics compared to decision trees and artificial neural networks [16].

- a) Nodes in BBNs represent propositions with well-defined semantics and well-defined probabilistic relationships to other propositions. Units in neural networks, on the other hand, typically do not represent specific propositions. Even if they did, the calculations carried by the network do not treat propositions in any semantically meaningful way.
- b) Variables in BBNs have two dimensions – the range of values for the proposition, and the probability assigned to each of those values. The outputs of a neural network can be viewed as either the probability of a

Boolean variable, or an exact value for a continuous variable, but neural networks cannot handle both probabilities and multi-valued variables simultaneously.

- c) BBNs can easily represent inter-dependencies or independencies between variables. However, the decision tree technique can't and also it may not prevent a minority of special cases from being ignored.

The BBN model has been widely applied to deal with process tasks such as diagnosis [12] [14] [16], fault analysis, machine learning [17], etc. For example, Marshall et al. [14] successfully use the BBN to model the relationships between the patient's admission attributes and the LOS in the geriatric hospitals, and the distribution of the LOS was determined given a set of values for selected admission attributes.

In addition, the caremap is a patient focused tool, and the purpose of all the care activities is to improve patient's conditions in time. That is, there are paths linking the patient's conditions and care activities in the caremap. They represent a sequence of events in time and relationships among them, thus making it possible to consider a caremap as network. The BBN was originally designed to model similar network structures.

As we described in section 2.1, implementing the caremap can reduce the LOS. If the caremap cannot be followed, it will influence patient's LOS negatively. That is, we will not achieve the cost-effective purpose of the caremap activities. Therefore, studying the impact of deviations from implementing the caremap on the LOS is a very important issue. If the patient's management team can determine in advance the likely outcome and duration of the patient's stay, they can make better decisions about how to manage the patient in the next steps of the care process. Our approach to dealing with this issue is described in greater detail in the following sections.

### 3 Methodology

As stated in Section 1, the research encompasses several issues, including modeling the caremap, making a prediction or explanation, and evaluating the model. In this section, we first describe rationale behind selecting the BBN to model the specific caremap. Then, we give the basic concepts of the Bayes' Theorem and the BBN model. Finally, we discuss the important aspects of developing a BBN model and using the BBN model to make inferences.

#### 3.1 Bayes' Theorem and Beliefs

##### 1. Bayes' Theorem

Bayesian model provides the formalism for reasoning about conditional probability of an event subject to some prior probability.

The Bayes' theorem states that:  $P(B_i|A) = \frac{P(A|B_i)P(B_i)}{\sum_{i=1,\dots,n} P(A|B_i)P(B_i)}$  where A, B are

events.  $B = \{B_i|i = 1,\dots,n\}$  is a set of exhaustive and mutually exclusive sub-events.

Suppose we are interested in  $B_i$  and begin with a prior probability  $P(B_i)$ , representing our belief about  $B_i$  before observing any relevant evidence. Suppose we then observe A. Then we need to revise our belief of  $B_i$ , that is,  $P(B_i|A)$ , which is called a posterior probability. The posterior probability can be obtained by

multiplying the prior probability  $P(B_i)$  by the ratio  $\frac{P(A|B_i)}{\sum_i P(A|B_i)P(B_i)}$ . The BBN

model uses the Bayes' theorem as the basic concept for making such inferences. Therefore, Bayes' method has the ability to incorporate prior information into the

inferential process so that inference is a continuous, dynamic process in which new information is used to revise the current knowledge.

## 2. Probability and Belief

Russell et al. [16] reported, “In the objectivist view, probabilities are real aspects of the universe rather than being just descriptions of an observer’s degree of belief. However, the subjectivist describes probabilities as a way of characterizing an agent’s beliefs”. Lauritzen and Spiegelhalter [18] and Pearl [19], the innovators of the BBN model, are subjective Bayesians. They interpreted the probability in the networks as degrees of belief. So, a BBN is defined in term of belief instead of probability.

## 3.2 Bayesian Belief Networks

A Bayesian belief network  $B = (G, P)$  is represented by a directed acyclic graph<sup>[1]</sup>  $G = (X(G), A(G))$  with a set of nodes  $X(G) = \{X_1, X_2, \dots, X_n\}$  representing stochastic variables taking a finite set of values and a set of arcs  $A(G) \in X(G) \times X(G)$  signifying the existence of direct dependencies between the linked variables, and the strength of these dependencies is quantified by conditional probabilities. A joint probability distribution  $P$  is defined on the stochastic variables that can be factorised according to the topology of the graph as follows:

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^n P(X_i | pa(X_i)) \text{ Where } pa(X_i) \text{ is the parent of the node } X_i.$$

It means that  $P(X_1, X_2, \dots, X_n)$  can be defined in terms of local probability tables  $P(X_i | pa(X_i))$  by assuming the variable  $X_i$  to be conditionally independent of all predecessors of  $X_i$  given the parents  $pa(X_i)$  [18]. The above allows the evaluating of conditional probabilities being subject to some earlier observations, providing that there is a path in a network linking the variables in question.

---

<sup>1</sup> Acyclic graph: a graph has no directed cycles.

### 3.2.1 Components of the BBN Model

According to the above descriptions, we can describe the components of the BBN model as follows:

Time set:  $T = \{t \mid t = 1, \dots, \tau\}$  which generally refers to the time the event occurred.

Time is discrete.

State set:  $X = \{X_i^t \mid i = 1, \dots, n; t = 1, \dots, \tau\}$  This generally refers to a set of variables that represent the status of the events. Each variable can take a finite set of values.

$t \sim$  Time  $t \in T$

$X_i^t \sim$  The  $i^{\text{th}}$  stochastic variable.

$X_i^t = j \sim$  The value of the  $i^{\text{th}}$  variable equals  $j$  at time  $t$ . Each value of a variable represents the instance at which a certain event may occur.

$\Theta^t \sim \Theta^t = \{\theta_i^t : P(X_i^t \mid pa(X_i^t)) \rightarrow [0,1] \mid i = 1, \dots, n\}$  denotes the set of prior probability assessment functions associated with the belief network before observations are obtained.

### 3.2.2 Problem Solving: Inference

Once the BBN model is constructed, it can be used to make inferences about the events and the inferences are bi-directional. In order to give a general idea of how to make such inferences using a BBN model, we briefly describe the brute force solution [16] that computes the joint probability distribution over its variables according to the constructed BBN. That is, given the joint probability distribution, all possible inference queries can be answered by summing  $P(X_1, X_2, \dots, X_n)$  over all events entailed by the query events [18] [19] [20]. For example, if we have a simple BBN with the structure  $X_1 \rightarrow X_2 \rightarrow X_3 \rightarrow X_4$ , we want to know  $P(X_4 \mid X_1)$  (it is also called causal inferences). From the rules of probability we have

$$P(X_4 | X_1) = \frac{\sum_{X_2, X_3} P(X_1, X_2, X_3, X_4)}{P(X_1)} \quad (a)$$

Where  $P(X_1, X_2, X_3, X_4)$  is the joint probability which is determined from the BBN. Therefore, given the network structure as described above, (a) becomes

$$P(X_4 | X_1) = \frac{\sum_{X_2, X_3} P(X_1, X_2, X_3, X_4)}{P(X_1)} = \frac{P(X_1) \sum_{X_2} P(X_2 | X_1) \sum_{X_3} P(X_3 | X_2) P(X_4 | X_3)}{P(X_1)}$$

Similarly, if we want to know  $P(X_1 | X_4)$  (it is also called diagnostic inferences), we have

$$P(X_1 | X_4) = \frac{\sum_{X_2, X_3} P(X_1, X_2, X_3, X_4)}{\sum_{X_1, X_2, X_3} P(X_1, X_2, X_3, X_4)} = \frac{P(X_1) \sum_{X_2} P(X_2 | X_1) \sum_{X_3} P(X_3 | X_2) P(X_4 | X_3)}{\sum_{X_1} P(X_1) \sum_{X_2} P(X_2 | X_1) P(X_1) \sum_{X_3} P(X_3 | X_2) P(X_4 | X_3)}$$

That is, using conditional independence of the BBN, we can often reduce the dimensionality of the problem by rewriting the sums over multiple variables as the product of sums over a single variable.

There are many other effective procedures [18] [19] for computing arbitrary conditional probability distributions. For example, node deletion and edge reversal has been discovered to produce a small network representing a marginal of the original distribution, thus yielding the required conditional probabilities almost directly [19]. Another approach is to transform the original Bayesian network into a decomposable model that is more suitable for computations [18]. It is difficult to give general principles for determining which methods are most suitable for a particular situation. They all operate on the same underlying probability distribution and therefore the results - the required conditional probabilities - are the same. However, discussion and evaluation of these different approaches is beyond the scope of this research.

### 3.3 Bayesian Learning: Acquiring a BBN from Data

The process of building a BBN model is often the key step in developing BBN representation of a real-world problem. There are several ways to develop the BBN for an application domain. One way is to develop the BBN from the subjective assessment elicited by some domain experts. For example, the notion of cause and effect is typically used to develop the BBN [16] [18] [19]. Generally speaking, to develop a BBN for a given set of variables, we establish parent-child relationships between them, with parent being a direct cause and child being an immediate effect. This method is widely used in some applications such as diagnosing problems [18] [19], or troubleshooting problems [16], in which the relationship of cause and effect is easily found based on expert knowledge. However, any BBN built in this way is only tentative, and ought to be subject to revision in the light of further data. There are many situations in which the appropriate domain expertise is not initially available, so that right from the beginning we need look into data to suggest what qualitative modelling assumptions might be appropriate.

Moreover, the clinical caremap with many variables and the relationships among variables is so complex that it is rather difficult to simply develop the cause-effect graph structure. What we need is to establish the dependency of the LOS on a subset of the elements in the caremap in order to form a BBN. Therefore, we use another method called learning structure from data to develop the BBN for our knowledge domain. The goal of this method is to find the most probable belief-network structure from various possible structures.

Based on the Bayes' Theorem, Bayesian learning, which constitutes a probabilistic view of learning, is an efficient learning method. The underlying assumption is that there is a set of structures for a BBN model, each having a certain probability of being correct. Receiving new information from the database changes the probabilities of each structure. For instance, an observation might contradict a

structure, or strengthen the belief in it. The aim is to be able to find a structure with the highest probability of being correct, given a specific set of data.

As we know, with the number of nodes (variables), the number of possible structures grows exponentially. The following equation [17] is derived to explain the number of possible belief-network structures that contain  $n$  nodes:

$$f(n) = \sum_{i=1}^n (-1)^{i+1} \binom{n}{i} 2^{i(n-i)} f(n-i)$$

where  $n$  denote the number of nodes (variables).

For  $n=2$ , the number of possible structures is 3; for  $n=7$  in our example, there are millions of possible structures. Thus, an exhaustive enumeration of all network structures is not feasible and the following assumptions and constraints are introduced, in order to reduce the complexity for determining the most probable structure of a BBN:

Constraint 1: The order of variables can greatly reduce the number of possible structures.

Constraint 2: Prior probability of each possible structure of the BBN is the same before we observe the data  $D$ .

Assumption 1: The variables in the database are discrete.

Assumption 2: Patient cases occur independently, given a belief-network model.

Assumption 3: There are no cases that have variables with missing data.

Assumption 4: Before we observe database  $D$ , we assume that the numerical probabilities in the BBN are uniform in the interval  $[0, 1]$ .

In this situation, we obtain the following objective function in terms of the variable and its immediate parent variables. (For proof of equation (1), see [17].)

Objective function used for the structure selection

$$MAX_S [P(S|D)] = C \prod_{i=1}^n MAX_{pa(i)} \left[ \prod_{j=1}^m \frac{(r_i - 1)!}{(N_{ij} + r_i - 1)!} \prod_{k=1}^{r_i} N_{ijk} ! \right] \quad (1)$$

- $D$  denotes database.
- $S$  denotes an arbitrary belief-network structure containing all the variables in the database.
- $P(S|D)$  denotes a conditional probability of the structure  $S$  given the data  $D$ .
- $C$  denotes the constant prior probability  $P(S)$  for each  $S$ .
- $pa(i)$  denotes the parents of the  $i^{th}$  variable.
- $N_{ijk}$  denotes the number of cases in the database in which the value of the  $i^{th}$  variable is  $k$ , and its parent value is  $j$ .
- $N_{ij}$  denotes the number of cases in the database in which the parent variable of the  $i^{th}$  variable has its value  $j$ .  $N_{ij} = \sum_{k=1}^{r_i} N_{ijk}$
- $r_i$  denotes the number of values for the  $i^{th}$  variable.
- $n$  denotes  $n$  variables.
- $m$  denotes  $m$  parent variables of the variable.

The above objective function, along with four assumptions and two constraints are used to develop a BBN in our research.

From equation (1), we see that the determination of the most likely belief-network structure has an exponential time complexity and sometime it is even computationally infeasible. In our research, a polynomial-time heuristic algorithm called K2 method [17] is chosen to solve the above function, which is more efficient than exhaustive enumeration. The description of K2 method has provided in Appendix B.

So far, we have introduced the basis of the BBN model, and we also describe how to use a Bayesian approach to learn the qualitative and quantitative dependency

relationships among a set of discrete variables. In the next section, we will describe development of the BBN to represent the radical prostatectomy caremap.

## 4 Application of the BBN Model: Modelling Radical Prostatectomy Caremap

In this section we describe the details of modelling the radical prostatectomy caremap (RPC). The aim is to validate the abstract design principles of BBN model by developing the specific BBN\_RPC model that describes the relationships between elements in the caremap, and to get further insight into the performance aspects of the model.

The research leading towards development of the BBN\_RPC model could be divided into four phases, namely, understanding the RPC, developing a BBN to model the RPC, evaluating the model, and applying the model to study the impact on the patient's future conditions given current observations. The first three phases are described in this section.

### 4.1 Components of the RPC

In general, a caremap consists of the following elements [21], as partially illustrated in Figure 4.1.

- (1) Time line: the first row in Figure 4.1 indicates the period of time spanning from the admission day to the day of discharge.
- (2) Critical path: shows the usual basic care such as medications, assessment, etc. The left column in Figure 4.1 lists critical paths. We will refer to these elements as “actions”.
- (3) Patient outcomes: shows the usual expected patient's physical conditions, for example, such as “walks full length of hallway x 2 independently”.

(4) Patient progress corresponds with the caremap: shows whether care and outcomes are congruent with the pathway or whether there are variances. This is recorded in the bottom section in Figure 4.1.

**Figure 4.1 The General Caremap**

Post-op Day 2		Date:      yy      mm      dd
<b>Critical Path</b>		<b>Patient Outcomes</b>
<b>Medications</b>		<b>Pain Control</b>
<b>Assessments/Treatments</b>		Demonstrates progressive ADL related to adequate pain control
<b>Activity</b>		<b>Mobility</b>
Progressive ambulation – independent		Walks full length of hallway x 2 independently
...		...
Patient progress corresponds with clinical pathway: D <input type="checkbox"/> Yes <input type="checkbox"/> No                      NTV – circle above, VC _____ Signature: _____                      Time _____		

Source: The Ottawa Hospital, 2001

The clinical caremap specifies the actions that should be taken and the expected patient’s conditions that should be achieved at a given time. It also identifies when the patient should leave the hospital and what criteria should be met upon discharge. If the expected criteria are not achieved at the expected time, the variances will be recorded in the section of the caremap entitled “Patient progress corresponds with clinical pathways”. In the following paragraph, we describe variances in greater detail.

**Variances**

During the implementation of the RPC, there still are variations in how care will be delivered and how patients will respond. Negative variance is the activity in the caremap that does not occur at all, or does not occur on the scheduled time. For example, if the patient does not take the regular food on Post-op day 2, it constitutes a variance because according to the caremap, the patient is supposed to take regular food on this day.

In general, variances observed for patients on the RPC are classified under the following categories: system variance, clinician / caregiver variance, and patient variance [2][22]. All these variances might ultimately affect the patient's outcomes and the discharge time. However, if we were to focus on these three categories, the amount of variance data collected would be huge. Besides, the clinical caremap identifies when the patient should leave the hospital, which depends on the patient's actions and the patient's outcomes. Therefore, in this research, we consider only those variances that occurred in area of the patient's actions and the patient's outcomes that are deemed to be important for the management of the patients on the RPC and that may affect the quality of care. If all these variances are followed up and analyzed, the RPC can be incrementally developed and the efficiency of implementing the RPC should be also improved.

The caremap for the RPC designed and used in the Ottawa Civic hospital is given in Appendix A. A care of every patient admitted to the Civic campus of The Ottawa Hospital for prostate surgery follows this caremap

## 4.2 Development of a BBN Model for the RPC

Development of the BBN\_RPC model involves:

- Step 1: Defining variables in the RPC.
- Step 2: Collecting data.
- Step 3: Creating a BBN\_RPC model.

### 4.2.1 Definition of Variables

In the BBN, each variable is a group of mutually exclusive events. Each value of a variable represents the instance at which a certain event may occur. Here we describe what variables in the RPC are and how we define values for the variables.

#### 1. Variables in the RPC

We classified variables according to the categories identified in the RPC case (elements of the left hand and right hand columns of the caremap) because the elements in these categories generally reflect the procedure of the patient care. Moreover, clinical staff is already familiar with these standardised elements in the RPC. These categories are: activity, nutrition, patient teaching, pain, respiratory function, elimination, and mobility. Each category is valid only for the time frame specified in the pathway, so we include time period in the variables' definition; it begins at the time of post-surgery and ends at the time of discharge.

In the BBN\_RPC model, variables correspond to “actions” or “patient’s outcomes” from the caremap. All of the expected “patient’s outcomes” listed in the caremap (e. g. patient teaching, respiratory function, etc.) are represented as variables. However, only those actions are considered as variables, which directly depend on the previous patient’s outcomes. For example, in the clinical caremap of Appendix A, there is an action called “Indwelling urethral catheter on Post-op day 2”, which will not be considered as a variable because this event is related to the patient’s management team rather than being directly related to the patient’s outcome on Post-op day 1. On the other hand, the action called “patient walking on Post-op day 2” will be considered as a variable because it is directly dependent on the patient’s activity outcome of the previous day. Thus only the two categories in the actions named “activity” and “nutrition” are selected as the variables.

Therefore, the selected set of variables associated with the patient’s actions and the patient’s outcomes is used in the BBN\_RPC model that generally represents the RPC. Each of these variables is in fact linked to the time period of the caremap.

## 2. Values of variables

In order to construct the BBN model, the variables are defined to have discrete values. In the RPC case, first, we consider the expected result of the patient’s action or outcome as one of the values of this variable. Second, we list all the possible deviations of this variable from the real patients’ charts, and consider them as other

values of this variable. It will be demonstrated later that such an approach provides a very efficient way to evaluate the patient's variances. For example, the variable "the amount of urine output on Post-op day 1" is supposed to be adequate (0.5 ml/kg/h) in the RPC. Therefore, one of value of this variable is *adequate*. Besides, when we look into the patients' charts, we found some patients have *inadequate* urine output. Hence, this deviation is considered as another value of this variable. To further explain it, we give another example; "pain score" is used to evaluate the variable "Mobility outcome on Post-op day 1". If the verbal pain score is recorded as 0, we assign the value "*nopain*" to this variable. If the pain score for the mobility of the patient falls between 4 and 7 on Post-op day 1, the value "*medium*" will be assigned to this variable. If the pain score is between 1 and 3 on Post-op day 1, we assign the value "*mild*". Thus, this variable has three values "*medium*" "*mild*" or "*nopain*". The value "*medium*" reflects a negative variance because the patient pain score should be at most *mild* on this day.

In addition, all continuous variables need to be discretized. For example, the variable "the duration of stay" is a continuous variable with certain distribution. However, the RPC specifies the expect LOS, so we are interested in if the LOS is delayed or not when the variances occur. Therefore, this variable can be discretized as *meeting the LOS* and *delayed LOS*.

Following the process described above we identified the variables from the RPC (see Table 1 in Appendix C for detailed description of the variables and their values). The first column of Table 1 lists the chronological order of the variables. In the caremap, the order of the variables is determined according to the time sequence. The events are labelled in the sixth column of Table 1 in Appendix C for further analysis of variances.

#### **4.2.2 Data Collection and Sample Identification**

The data collection was conducted at the Ottawa Civic Hospital which is an acute care teaching hospital in Ottawa. A set of patients' charts managed by different

teams during the period 2002 to 2003 for the RPC was randomly selected from the RP patient information database.

Analysis of the RPC has identified the variables of information gathered from patients with the prostate cancer. However, not every patient's information is recorded in the clinical caremap by clinicians and nurses. To collect all the information relevant with pre-defined variables, we first need to integrate the following charts together to gather data: "discharge summary", "integrated progress notes", "variance tracking records", and "clinical pathway". The patient information was transcribed and put into the format presented in Table 2.

Then, the patient information was validated with the help of clinicians and nurses. To ensure that the transcribed data are meaningful, all ambiguities were resolved by consulting with the clinicians. In order to generate accurate BBN structure for the RP patients, the data accuracy is very important. By consulting the clinician and nurses, we pre-processed the data in the following manner: (1) missing values were evaluated by consulting the clinician and nurses and possibly filled using secondary data sources, and (2) deleting the records with too many missing values. Hence no missing values were included in the data set in this study. The values recorded for our stay represent the average patient's condition in a day (between 00.00 to 24:00). Finally, each patient data was entered into the aggregated table using Microsoft EXCEL.

In our research, considering more cases above 125 probably would strengthen the robustness of the BBN\_RPC model. However, number of evaluated charts was a function of availability and a time frame for the research. Additional constraining factor was a fact that the hospital started to use the RPC only since 2002.

In this study, all the variances and clinical data for 125 patients were collected retrospectively through review of clinical notes and the pathway documents, which included in Table 3 and Table 4. The 75 cases included in Table 3 were used as

input to the K2 algorithm to create the dependency structure for the BBN\_RPC model and to calculate its conditional probability. The remaining 50 cases included in Table 4 were used to evaluate the performance of the BBN\_RPC model. The column headings of these two tables are in the form of a series of data vectors such as UrineO1 (“Urine output at the Post-op day 1”), UrineO2 (“Urine output at the Post-op day 2”), etc., each describing either the patient’s activity or the patient’s outcome in the specified period of time. The first column of these two tables identifies a patient case. Each case corresponds to a value assignment for each of the variables.

#### **4.2.3 Developing a BBN\_RPC Model**

After defining the variables, we define the relationships between variables. In this research we used “the learning from data” approach to create the BBN\_RPC model. The rationale for such an approach is as follows:

1. In the RPC, the pathology, the relationships between patient outcomes and patient activities are complicated, which makes it difficult to find the cause-effect graph structure manually. This would also require experts who have complete knowledge of the domain – a condition that is not necessary when using the learning approach.
2. Conditional probabilities can be obtained either from the extensive interviews with the experts – a method not feasible in most practical applications, or automatically. We decided for the learning method and conditional probabilities were obtained from data using the Maximum likelihood method.
3. Continuous update of the BBN\_RPC model as new data becomes available is an important aspect while modeling the caremap. A BBN built by the learning approach is easier to maintain and upgrade because only new variables need to be considered instead of consulting the relevant experts to reconsider the domain. Moreover, a BBN constructed manually still needs to be validated and updated further using new patients’ data.

The Bayesian learning and the K2 method [17] were used to develop a BBN\_RPC model from an aggregated data set. Here, we first describe the data set for the RPC case.

A set of variables is selected according to patient actions and outcomes listed in the RPC, and it is represented as  $\{X_i^t | i = 1, \dots, n; t = 1, \dots, \tau\}$ , where

$t$  denotes the time in discrete days in the RPC, (in days).

$t=1$  denotes “Post-op Day 1”<sup>[2]</sup>

$t=2$  denotes “Post-op Day 2”

$t=3$  denotes “Post-op Day3”

$X_i^t$  denotes the  $i^{th}$  activity or outcome of the patient at time  $t$ ;

$i=1$  denotes “Patient Psychological Condition”

$i=2$  denotes “Vital Signs”

$i=3$  denotes “Temperature”

$i=4$  denotes “Activity with the RPC”

$i=5$  denotes “Nutrition with the RPC”

$i=6$  denotes “Nutrition Outcome”

$i=7$  denotes “Pain at rest”

$i=8$  denotes “Respiratory Function”

$i=9$  denotes “JP output”<sup>[3]</sup>

$i=10$  denotes “Evidence of Hematuria”

$i=11$  denotes “Urine Output”

$i=12$  denotes “Bowel Sounds outcome”

$i=13$  denotes “Mobility outcome”

$i=14$  denotes “Wound outcome”

---

<sup>2</sup> “Post-op Day 1” means that the patient stays in the ward from 00:00 to 24:00 in the first day after the operation, etc.

<sup>3</sup> JP denotes Jackson Pratt wound drainage system that is used to help healing by draining fluid from the wound.

$i=15$  denotes “Length of patient stay”

Based on the clinical judgement and the RPC, we decided to remove 7 redundant variables of the total 45 variables, as described below:

1. For the variables  $X_1^1$ ,  $X_1^2$ , and  $X_1^3$ , only  $X_1^1$  needs to be considered because “Patient psychological condition ( $i=1$ )” is a comparatively stable condition; so considering this patient state in time 1 is enough.
2. For the variables  $X_{12}^1$ ,  $X_{12}^2$ , and  $X_{12}^3$ , only  $X_{12}^1$  and  $X_{12}^2$  need to be considered because “Bowel sounds outcome ( $i=12$ )” is listed in the Post-op day 1 and Post-op day 2, and it is not listed in the Post-op day 3, so we do not need to consider this patient state in time 3.
3. Also, for the variables  $X_3^1$ ,  $X_3^2$ ,  $X_3^3$ ,  $X_{14}^1$ ,  $X_{14}^2$ , and  $X_{14}^3$ , only  $X_3^2$ ,  $X_3^3$ ,  $X_{14}^2$ , and  $X_{14}^3$  need to be considered because “Temperature ( $i=3$ )”, and “Wound outcome ( $i=14$ )” are only listed in the last two post-op days in the RPC.
4. Finally, for the variables  $X_{15}^1$ ,  $X_{15}^2$  and  $X_{15}^3$ , only  $X_{15}^3$  needs to be considered because “Length of stay ( $i=15$ )” is only listed in the last day of the RPC.

The resulting set of 38 variables has been ordered according to the patient’s actions and outcomes in the specified period of time of the RPC. The complete set is illustrated in Table 1 in Appendix C.

All of the variables have been evaluated using mutually independent events according to the certain splitting criteria mentioned outlined in Section 4.2.1. Thus, the data set using for developing the BBN\_RPC model consists of 75 patient cases (See Table 3 in Appendix C); each of the patient cases is actually an assignment of a value to each variable.

A dataset developed in such a way satisfies the requirements of the K2 method, namely:

1. All variables are discrete.
2. All patient cases are independent.
3. There are no cases with missing data.
4. Variables are ordered according to the time sequence outlined in the RPC.
5. Before obtaining observation of data, we assume that the numerical probabilities to place in the belief network are uniform in the interval [0, 1].
6. Before learning a BBN\_RPC model from data, we assume that all the possible structures are equally likely.

A computer program that integrates Bayesian learning and the K2 algorithm called Bayesware Discover 1.0 <sup>[4]</sup> was used to develop a BBN\_RPC model from the data. The training set containing 75 patients' cases was used as an input into the program and the BBN\_RPC was developed as the most probable network given the data.

The formalism used to represent the BBN\_RPC model is described in Figure 4.2, showing the structure of the network, and in Table 5 in Appendix C, showing the conditional probabilities for the variable and its immediate parents. Additionally, the frequency of each event is given in Table 6. From the structure of the BBN\_RPC model, one can notice that there are still some isolated variables, indicating that there is no evidence coming from the analysis of training set (75 cases) that these isolated variables have relationship with other variables. For example,

The BBN\_RPC model created from data was evaluated using the 50 out-of-sample cases of Table 4. This evaluation is described in the next section.

### 4.3 Performance Evaluation

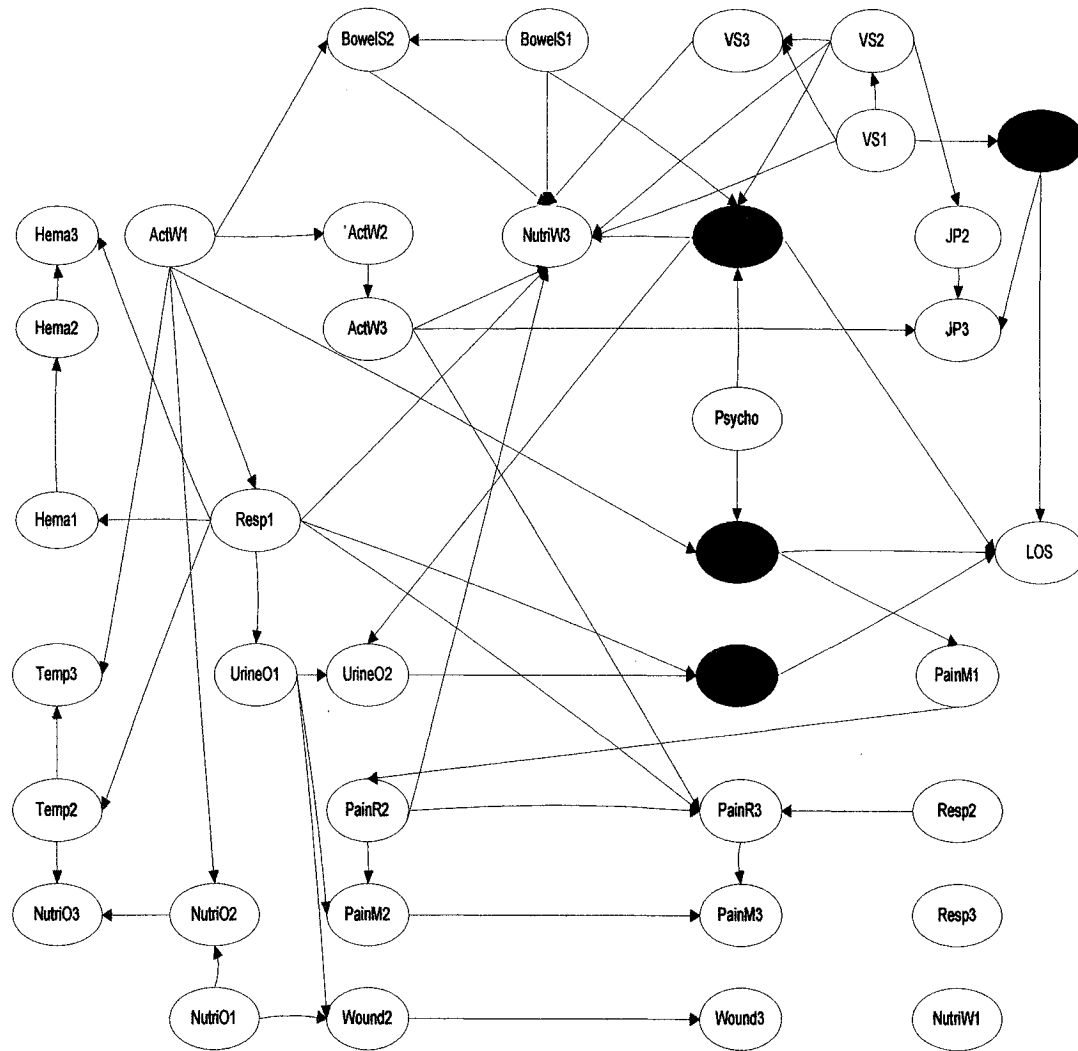
In order to evaluate the predictive accuracy of the BBN\_RPC model, we used k-fold cross validation test that is very efficient method to check how well a model

---

<sup>4</sup> Bayesware Discover 1.0: Software can be downloaded from [www.bayesware.com](http://www.bayesware.com), 2000.

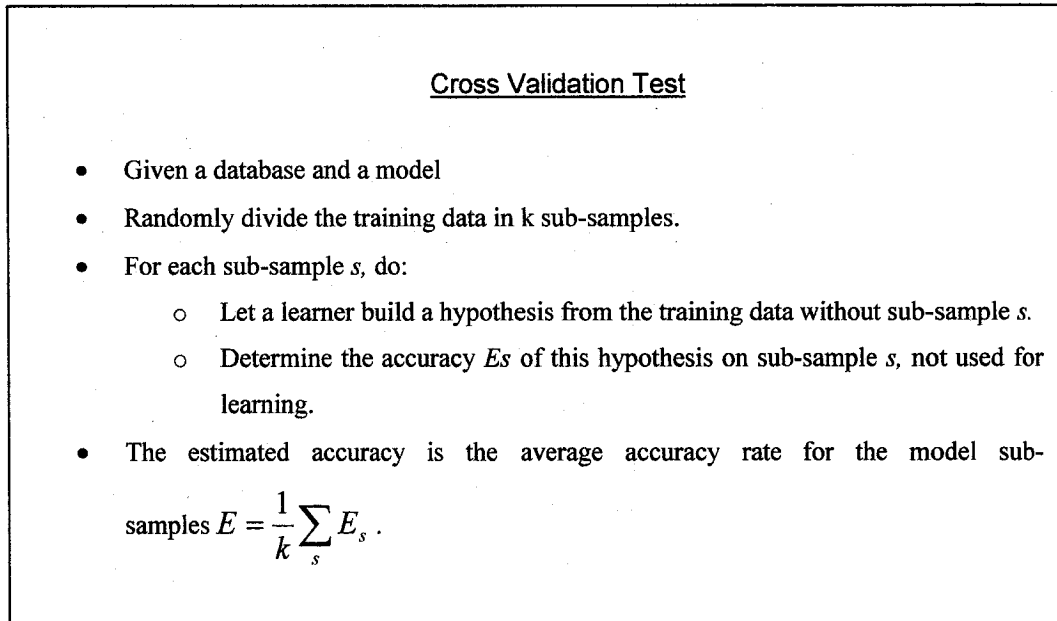
generalizes to new data. Steps associated with the cross validation test are described in Figure 4.3.

**Figure 4.2 The Structure of the BBN\_RPC Model**



Note: The nodes of the BBN\_RPC are a set of random variables that describe the care procedure for the radical prostatectomy patients. A set of directed links connects pairs of nodes. The parents of a node are all those nodes that have arrows pointing to it. Each node has a conditional probability table associated with it (see Table 5), which quantifies the effects that the parents have on the node.

**Figure 4.3 Cross Validation Test**

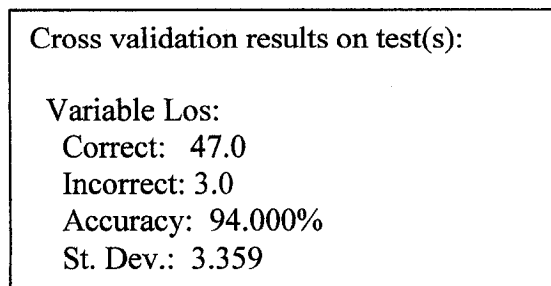


Source: <http://www-2.cs.cmu.edu/~schneide/tut5/node42.html>.

In general when  $k$  is bigger, the accuracy of the model will be higher. For efficiency, we choose  $k=10$  in this study. The data set we used to estimate the accuracy of the BBN\_RPC model is given in Table 4 where 50 patient cases are included.

The result is in Figure 4.4, showing that the average accuracy for predicting the LOS given the observed patient's conditions during Post-op day 1 and Post-op day 2 is approximately 94% level. This results shows that the model fits the new data well.

**Figure 4.4 Results of 10-fold Cross Validation Test**



In this section we described the development of the BBN\_RPC model. In the next section, we will use this model to evaluate the impact of negative variances in the RPC on the patient's LOS.

## 5 Inferences and Analysis using the BBN\_RPC Model

The BBN\_RPC model can be used for the following types of analysis on the evaluation of the caremap. First, from the BBN\_RPC model, we can find factors that affect the LOS directly, and then we will show that this impact can be quantified in terms of revised probability of meeting the LOS. Finally, we will apply this model to analyze the variances and their impact on the patient's future conditions and the LOS.

### 5.1 Factors Associated with the LOS in the BBN\_RPC Model

One of the advantages of the BBN\_RPC model is that it provides a graphical visualization allowing recognizing the possible relationships existing among the elements in the caremap in a very intuitive and easy way. Thus, we can easily observe the factors affecting the LOS from the structure of the BBN\_RPC model.

The structure of the BBN\_RPC model shows that four variables named "PainR1 (the patient's verbal pain at rest on Post-op day 1)," "NutriW2 (the type of food the patient took on Post-op day 2)," "Jp1 (the amount of JP on Post-op day 1)," and "UrineO3 (the amount of the patient's urine output on Post-op day 3)" directly affect the patient's LOS. The nodes associated with these four variables are highlighted in green in Fig 4.2. The strength of the relationship between the variables and the LOS variable is shown in Table 5 in Appendix C, where node number 38 is the LOS variable, and its parent nodes are the above four variables. That is, given the values of the parent variables, the distribution of the variable LOS can be determined.

Other variables are conditionally independent of the patient's LOS providing that we are given the value of these four variables.

## 5.2 Inference in the BBN\_RPC Model

We can use the BBN\_RPC model to perform probabilistic inference, such as calculating the distribution of the patient's future condition given the current observations. According to the comparison of the probabilities of the patient's future conditions, we can induce most likely future events.

Here, we are going to illustrate possible use of the BBN\_RPC model for evaluating the variance by considering three hypothetical cases that were abstracted from the different groups of patients. Assuming the patient conditions during Post-op day 1 and Post-op day 2 are given, we could infer the patient future conditions on Post-op day 3 and the LOS by calculating the posterior probability.

These three patient cases are taken from real patients' data and were not included in the training set used to develop the BBN\_RPC model. These cases are: (1) Good Case, where patient was able to follow the caremap during the first two Post-op days almost without deviations, (2) Medium Case, where patient had some negative variances during the first two Post-op days, and (3) Worse Case, where patient had some severe variances from the caremap during the first two Post-op days. The patient conditions of these three cases during the first two Post-op days are described as follows.

### **Good Case : patient p1**

Patient's conditions before Post-op day 3: The male patient had a radical retropubic prostatectomy and pelvic lymphadenectomy procedure on April 4<sup>th</sup>. His operation went very well without intraoperative complications. After surgery, he was transported to a hospital room. During Post-op day 1 and Post-op day 2, the

patient's actions and outcomes were summarized as follows (with variances identified in *italics*):

1. He had normal comprehension.
2. His vital signs were normal.
3. His temperature was normal.
4. He ambulated with assistant for a while.
5. His diet type smoothly changed from fluid to regular food.
6. He was not nausea and he did not vomit.
7. His pain severity at rest was between 0-3.
8. His respiratory functions were normal.
9. The amount of JP was small.
10. On the Post-op day 1, he did not have evidence of hematuria. However, on the Post-op day 2, he had *blood-tinged* urine output.
11. His urine outputs are adequate.
12. His bowel sounds are present.
13. His pain severity with mobility is between 0-3.
14. His wounds or incisions looked normal.

**Medium case : patient p2**

Patient's conditions before Post-op day 3: The male patient had a radical retropubic prostatectomy procedure on September 5<sup>th</sup>. His operation went very well without intraoperative complications. After surgery, he was transported to a hospital room. During Post-op day 1 and Post-op day2, the patient's actions and outcomes were summarized as follows (with variances identified in *italics*):

1. He had normal comprehension.
2. His vital signs were normal.
3. His temperature was normal.
4. He ambulated with assistant for a while.
5. His diet type was fluid on the Post-op day 1. However, his diet type was still *fluid* on the Post-op day 2.
6. He was not nauseous and he did not vomit.

7. His pain severity at rest was 0.
8. His respiratory functions were normal.
9. The amount of JP was small.
10. He did not have any evidence of hematuria.
11. His urine outputs were adequate.
12. His bowel sound was *absent* before Post-op day 3.
13. His pain severity with mobility was 0.
14. His wounds or incisions looked normal.

**Worse Case: patient p3**

Patient's conditions before Post-op day 3: The male patient had a radical retropubic prostatectomy procedure on April 2nd. He had been catheter dependent now for essentially 22 months during which time his urinary bladder had been in a state of dysfunction. After surgery, he was transported to a hospital room. During Post-op day 1 and Post-op day 2, the patient's actions and outcomes were summarized as follows (with variances identified in *italics*):

1. He had normal comprehension.
2. His pulse rhythm was *irregular* on the Post-op day 1; his pulse rhythm was regular on the Post-op day 2.
3. His temperature was normal.
4. He did not *ambulate* on the Post-op day 1, and he also did not *ambulate progressively* on the Post-op day 2.
5. His diet type was fluid on the Post-op day 1. However, his diet type was still *fluid* on the Post-op day 2.
6. He was not nauseated and he did not vomit.
7. His pain severity at rest was between 0-3.
8. His respiratory functions were normal.
9. The amount of JP was small.
10. He did have *blood-tinged* urine output on the Post-op day 1, he did not have any evidence of hematuria on the Post-op day 2.

11. In the presence of a suprapubic cystostomy, this allows the physiological reproducing of urinary bladder filling and storage with intermittent variable time clamping of the suprapubic cystostomy. Therefore, his urine outputs recorded as *abnormal* on the Post-op day1 and Post-op day2.
12. His bowel sounds were absent.
13. His pain severity with mobility was between 0-3.
14. His wounds or incisions looked normal.

### **BBN RPC model application to evaluate three cases**

All the above patients' information can be regarded as new evidences and used as input into the BBN\_RPC model. By using Bayesian inference software (i.e. MSBNX or Bayesware Discover), we can calculate the posterior probability of patient's actions and outcomes on the Post-op day 3, and the distribution of the patient's LOS. In Figure 5.1, we illustrate the distributions of the LOS given the current conditions of each patient.

#### **Analysis:**

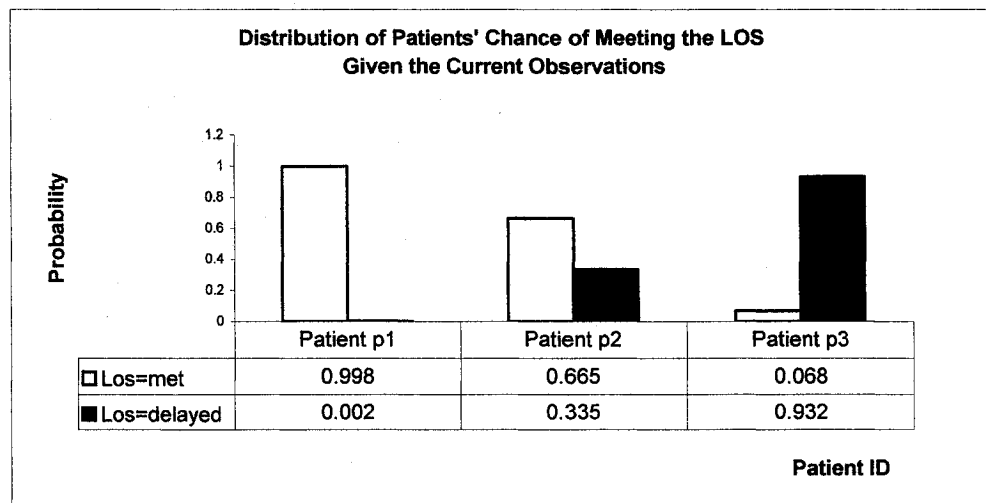
Patient p1 for the Good Case: Application of the BBN\_RPC model for this patient tells us that providing patient's condition during Post-op day 1 and Post-op day 2 is as described, the chance that the LOS will be delayed is 0.2%, implying that there is 99.8% chance of discharging a patient as planned in the caremap. Similarly, the posterior probability of patient actions and outcomes on Post-op day 3 is calculated and included in Table 7 in Appendix C, which allows us to check how a specific patient's conditions (in this case, conditions during the first two post-op days) affects chances of occurrence of the activities that follow these days.

Patient p2 for the Medium Case: This is a patient with some complications encountered during Post-op day 1 and Post-op day 2. Entering the patient data

to the BBN\_RPC model results in the information, that there is 33.5% chance of delaying the LOS.

Patient p3 for the Worse Case: The worse case patient had more pronounced complications/deviations from the caremap, as observed during Post-op day 1 and Post-op day 2. Thus his chances of delaying LOS are very high at 93.2%.

**Figure 5.1 Distribution of Patients' Chances of Meeting the LOS given the Current Conditions**



Note: The white column illustrates the posterior probability of meeting the LOS given the current observations of each patient. The black column illustrates the posterior probability of delaying the LOS given the current observations of each patient.

The first row of the data table is the patient identification. The data in the second row denotes the probability of meeting the LOS given the current observations of each patient. The data in the third row denotes the probability of delaying the LOS given the current observations of each patient.

**Conclusion**

Using retrospective data, it is possible to compare the predictive capability of the BBN\_RPC model versus actual discharge date. The results of such a comparison are given in the table below for each of these three cases. Analysis of this table shows that the prediction of the patient's LOS is quite accurate. For example, the patient in the Worse Case was supposed to be discharged on Post-op day 3 after being admitted into the hospital and undergoing radical prostatectomy. Given his

observations during the first Post-op day, the BBN\_RPC model predicted that he will be discharged after Post-op day 3. In his hospital chart, actual discharge date was on Post-op day 4. Therefore, the accuracy of prediction of a discharge date by the BBN\_RPC model is verified by the actual discharge date.

Case	Prediction of discharge date by the BBN_RPC model	Actual discharge date from the chart
Good Case p1	On or before Post-op day 3	On Post-op day 2
Medium Case p2	On or before Post-op day 3	On Post-op day 3
Worse Case p3	After Post-op day 3	On Post-op day 4

Note: This table is for comparisons of predicted date of discharge and actual date of discharge

### 5.3 Analysis of Variances

The BBN\_RPC model can be applied to evaluate the impact of negative variances on the patient's future conditions. Analysis of variances provides valuable and accurate information on the frequency and causes of variations in patient care.

In this section, for notational simplicity, the values of variables are called events. That is, an event is in fact an instance of a variable.

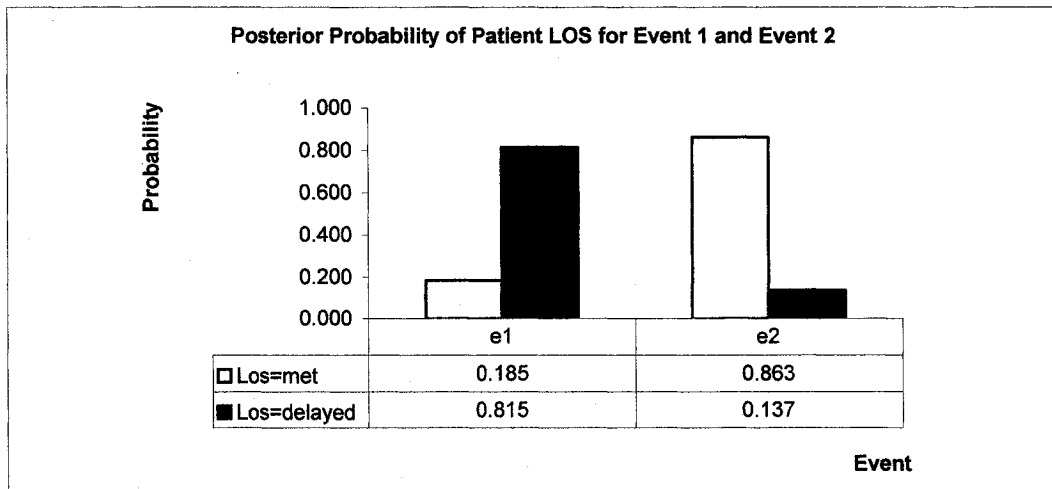
#### 5.3.1 Effects of Variances on the LOS

As we described in the section 4.2.1, variables consist of mutually independent events. Variances are considered as instances of variables and are included in these events. Therefore, in order to describe how each variance affects the LOS, we calculate the posterior probability of the LOS given each event. According to the order of variables in Table 1, we gave each value of a variable a symbol in the sixth column of this table. For example, the first value of the first variable named "Psycho" is *abnormal* which means the patient has abnormal psychological condition. We labelled it as event *e1*. The second value of the same variable is

*normal* which means the patient has normal psychological condition. We labelled it as event  $e2$ . Similarly, the first value of the second variable in Table 1 was labelled  $e3$ , and so on.

We use a simple example to describe the effect of variances on the patient's LOS. The variable named "Psycho (the patient's psychological condition or understanding)" has two values. The first value is event  $e1$  ("the patient has abnormal understanding"), which is a deviation. The second value is event  $e2$  ("the patient has normal understanding"), which is the expected patient's outcome in the caremap. If we input " $Psycho = e2$ " into the BBN\_RPC model, then the chance of " $LOS = met$ " is 0.863. If we input " $Psycho = e1$ ", the posterior probability of " $LOS = met$ " is 0.185. Therefore, we conclude that if the deviation  $e1$  occurs, the chance of the patient's being discharged on schedule has decreased from 0.863 to 0.185 (see Figure 5.2).

**Figure 5.2 Posterior Probability of the Patient's LOS for Event  $e1$  and  $e2$**



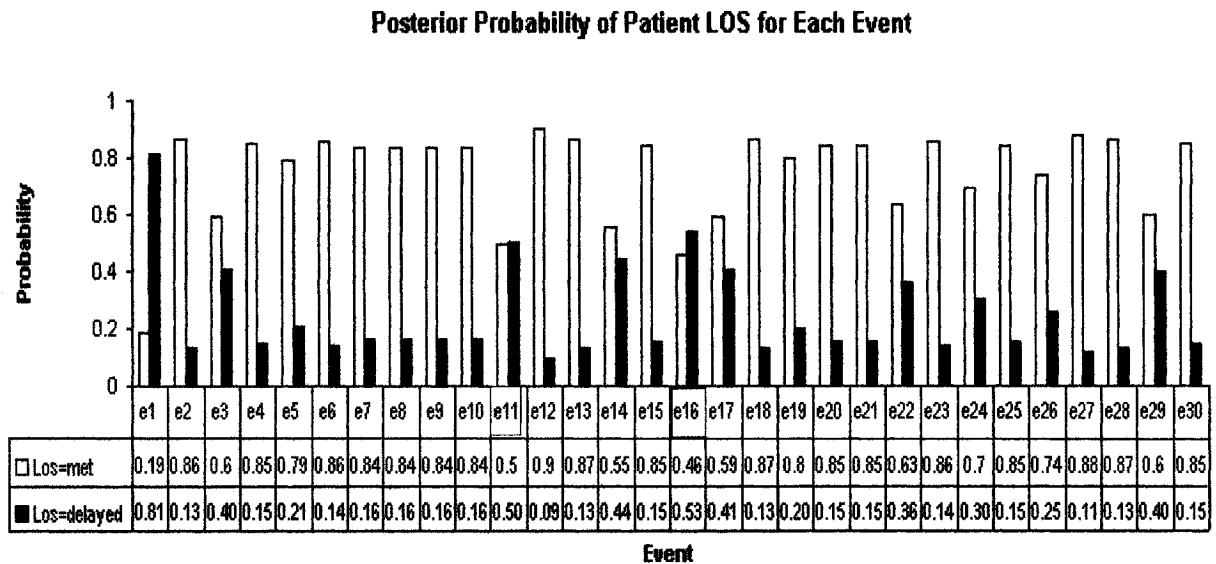
Note: The white column illustrates the posterior probability of meeting the LOS given the observed event. The black column illustrates the posterior probability of delaying the LOS given each event. The first row of the data table is the event. The data in the second row of the data table denotes the probability of meeting the LOS given each event. The data in the third row denotes the probability of delaying the LOS given each event.

Event  $e1$  denotes that patient has abnormal understanding; event  $e2$  denotes that patient has normal understanding.

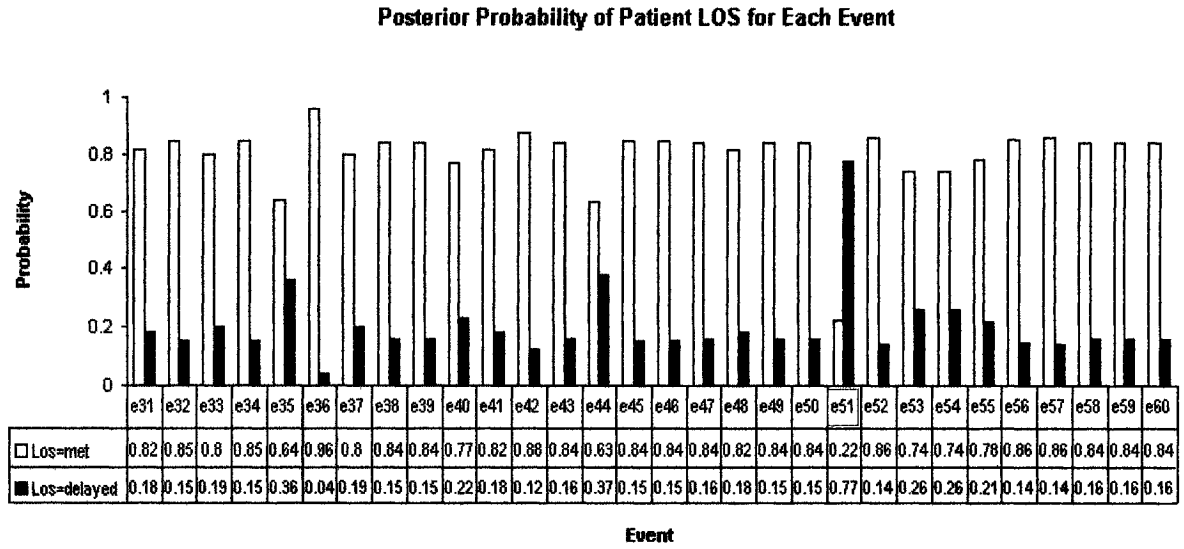
Then, we calculated all the posterior probabilities of the LOS for every instance of each variable and included them in the Table 8 in Appendix C. At the same time, we illustrate them in Figure 5.3 where we can easily identify each event's effect on the patient's LOS.

If there is a deviation from the RPC, the chance of the patient's future conditions meeting the caremap requirement will be decreased. We quantify these impacts so that we can know to what extent it has been decreased and whether it will affect the patient's LOS or not. Moreover, we can conclude that a few variances in the RPC have a great effect on the LOS such as event *e1* (the psychological condition of the patient is abnormal), event *e11* (the patient's pain score at rest at the Post-op day1 is 4-7), event *e16* (the amount of JP at post -op day 1 is large), event *e51* and *e83* (the amount of the patient's urine output is inadequate) because the posterior probabilities of meeting the LOS is no more than 0.5 with each variance represented by these events. These five events are highlighted in red in Figure 5.3.

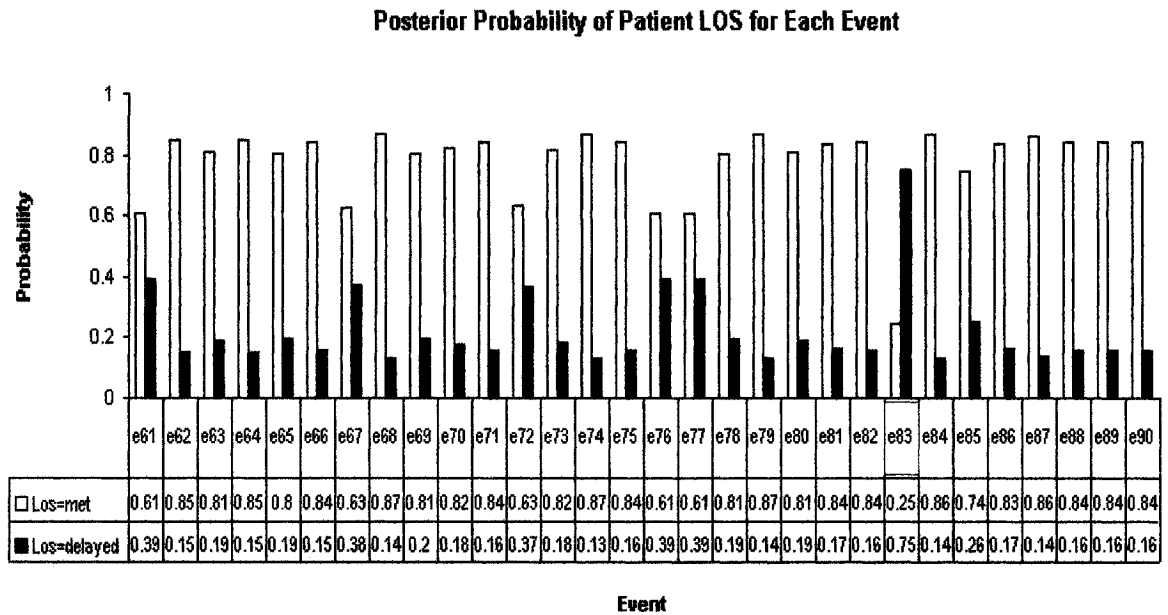
**Figure 5.3 Posterior Probability of the Patient's LOS given Each Event**



**Figure 5.3 (continued):**



**Figure 5.3 (continued):**

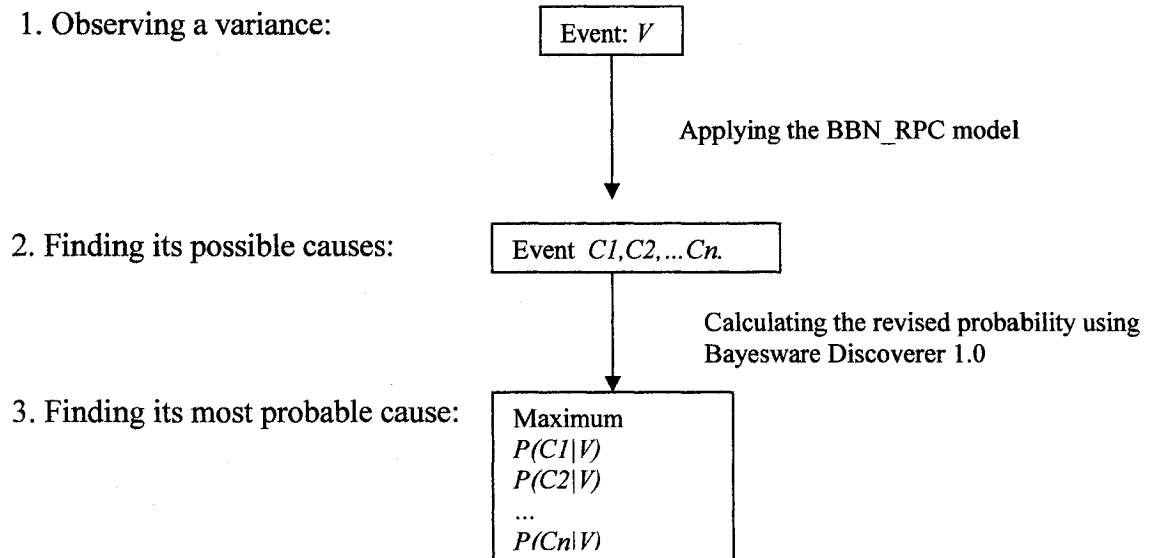


Note: The white column illustrates the posterior probability of meeting the LOS given the observed event. The black column illustrates the posterior probability of delaying the LOS given each event. The first row of the data table denotes the event. The data in the second row of the data table denotes the probability of meeting the LOS given each event. The data in the third row describes the probability of delaying the LOS given each event.

### 5.3.2 Causes of Variances

Since we know that some variances have a significant effect on the LOS, we would like to control them in advance. Therefore, the analysis of causes of the variances is another important issue. The BBN\_RPC model can be used to evaluate the most probable cause of the given variance. That is, we can help the patient's management team find the possible patient's conditions in a previous stage, which caused this variance.

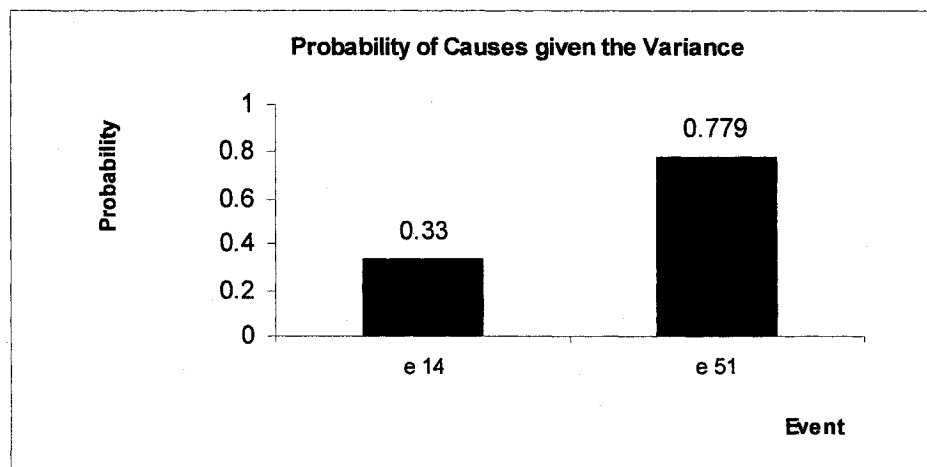
The procedure for finding the most probable cause of a variance is illustrated as follows:



For instance, the variable named “UrineO3” (the patient’s urine output on Post-op day 3) is one of the key factors affecting the LOS. Therefore, given the variance in this patient’s outcome (i.e. the patient’s urine output is inadequate on Post-op day 3); we can find the probable cause of this variance. The process of finding the most possible cause of this variance is as follows:

1. Observing a variance: the patient's urine output is inadequate on Post-op day 3. This event is grouped into the variable named "UrineO3" which has two possible values (i.e. two possible events)  $e84$  (the urine output is adequate on Post-op day 3) and  $e83$  (the urine output is inadequate on Post-op day 3). In this example, event  $e83$  is observed.
2. Finding the possible causes: from the BBN\_RPC model, we see that the variable "UrineO3" has two parent variables "UrineO2" and "Resp1". "UrineO2" likewise includes two events:  $e52$  and  $e51$ : the latter is a deviation because the patient was supposed to have adequate urine output on Post-op day 2. Lastly, "Resp1" includes two events:  $e15$  and  $e14$ : the latter is a deviation (the patient's respiratory function was mildly abnormal on Post-op day 1). Hence, we can induce either event  $e14$  or event  $e51$  as the cause of the variance  $e83$ . That is, events ( $e14$  and  $e51$ ) are the two possible causes for the variance  $e83$ .
3. Finding the most probable cause: we calculate the posterior probability of  $P(e51|e83)$  being 0.779 and  $P(e14|e83)$  being 0.330. Then, we conclude that the event  $e51$  is the most probable cause because the chance of event  $e51$  is bigger than that of event  $e14$  when the patient ends up in event  $e83$ . That is, event  $e51$  is more likely to occur given the event  $e83$ . The result is illustrated in Figure 5.4.

**Figure 5.4 Finding the Most Probable Cause of Variance e83**



Note: Event e14 denotes that the patient has a mild abnormal respiratory function on Post-op day 1; event e51 denotes that the patient has inadequate urine output on Post-op day 2. The black column illustrates the posterior probability of each event given the observed event e83. Event e83 denotes that the patient has inadequate urine output on Post-op day 3.

As described above, the BBN\_RPC model provides information on factors affecting the LOS, the frequency of variances, and causes of variances. Having such an information (that wasn't available before), the patient management team can focus on the critical factors and the key variances and continuously redefine the caremap to reflect current "best practices." Moreover, estimation of compliance with the caremap for a admitted patient can help the management team to know in advance the patient's probable outcomes including the LOS, and help them to adjust the activities included in a caremap in order to provide the best care while at the same time maintaining LOS. .

Clinical evaluation of the results produced by the BBN\_RPC model was very favourable. Dr. Thijssen who was consultant in this research was especially impressed with a manner the BBN\_RPC handled "three cases" that were taken from the charts to evaluate "normal", "a problematic" and a "difficult" patients. He stated that the model produced recommendations that were very much in line with clinical acumen and that such analysis has significant practical potentials.

## 6 Conclusion and Future Work

### 6.1 Summary and Conclusions

This research used a retrospective data for patients who underwent the radical prostatectomy to illustrate the potential of using a BBN for modeling the clinical caremap. We applied the BBN\_RPC model to evaluate how different deviations from a caremap affected the LOS. To construct the BBN\_RPC model, firstly we identified relevant variables from the patients' charts including the RPC, and we grouped mutually independent events into variables. Secondly, we used Bayesware Discover software to obtain the most probable structure of network and the conditional probabilities for the nodes (variables). Moreover, we used out-of-sample data to test the predictive accuracy of the BBN\_RPC model. The BBN\_RPC model provided both an understanding of the process of patient care, and an evaluation of the impact of negative variances. The results of this research may be summarized as follows:

1. Use of a BBN to model a caremap allows to intuitively identifying the factors associated with the LOS from the graphical structure of this model.
2. By computing the probabilities in the network, we could use the BBN\_RPC model to assess the conditions of patients throughout their stay in the hospital, given the current observations.
3. We provided the means to quantify the impact of negative variances on the patients' future conditions and the patients' LOS. In addition, we were able to identify these variances that have the most effect on the LOS.

In conclusion, this is the first research to use a BBN to model the clinical pathway and it proved that a BBN is useful methodology in modelling the caremap and evaluating the impact of variances, thus providing a patient's management team with insight into patient's future conditions given the current observations. Since

the LOS is one of the most important proxies of the hospital resource utilization, the determination of pertinent factors and the evaluation of variances would support patient's management.

## 6.2 Future work

Use of the BBN required discrete or categorical data instead of continuous distribution so that all variables need to be evaluated by suitable categories. Further work could expand the current BBN modeling methodology to take account of a continuous data especially with regards to patient's length of stay that should increase the accuracy of evaluation of patient's outcomes. Moreover another learning method with less assumptions than K2 (discussed in Section 3.4) might present better opportunities for learning network structure from data.

## References

1. Ontario Hospital Association. The Change Foundation and CIBC Releases Financial Review on the State of Hospital Finances in Ontario. <http://www.oha.com>, 1998.
2. Ignatavicius, D.D., & Hausman, K.A. *Clinical Pathways for Collaborative Practice*. W.B. Saunders, Philadelphia, 1995.
3. Luttman, R.J., & Laffel, G.L., & Pearson, S.D. Using PERT/CPM To Design and Improve Clinical Processes. *Quality Management in Health Care*. Pp13-28, Vol. 3, 1995.
4. Hofmann, P.A. Critical Path Method: An Important Tool for Coordinating Clinical Care. *Journal on Quality Improvement*. Pp235-246, Vol. 19, 1993.
5. Schriefer, J. Managing Critical Pathway Variances. *Journal on Quality Improvement*. Pp30-42, Vol. 3, 1995.
6. Armstrong, P., & Armstrong, H., & Fegan, C. *Universal Healthcare*, the New Press, New York, 1998.
7. Begin, M. *Health Services Organization and Policy*. HAH6260 course notes, University of Ottawa, Ottawa, 2002.
8. Hay Group. Operational Review and Clinical Audit of the Ottawa Hospital. 2001. <http://www.ottawahospital.on.ca/about/reports/opsrevfin2001.pdf>
9. Cavan, D.A., & Hamiton, P., & Everett J., & Kerr, D. Reducing Hospital Inpatient Length of Stay for Patients with Diabetes. *Diabetic Medicine*, Pp162-164, Vol.18, 2001.

10. Hudson, C. Alamance Regional Medical Center Reduces Medicare denials, Length of Stay Integrating Care Management Services with Premier. <http://www.premierinc.com/all/informatics/success/alamance.pdf>
11. <http://www.bmido.com/pathway.htm>
12. Lin, F.R., & Chiu, C.H., & Wu, S.C. Using Bayesian Networks for Discovering Temporal-State Transition Patterns in Hemodialysis. The 35<sup>th</sup> Hawaii International Conference on System Science, Pp153-160, Vol. 6, IEEE, 2002.  
[csdl.computer.org/comp/proceedings/hicss/2002/1435/06/14350153.pdf](http://csdl.computer.org/comp/proceedings/hicss/2002/1435/06/14350153.pdf)
13. Gardner, T.A., & Bissonette, E.A., & Petroni, G.R., & McClain, R., & Sokoloff, M.H., & Theodorescu, D. Surgical and Postoperative Factors Affecting Length of Hospital Stay after Radical Prostatectomy. *American Cancer Society*, Pp424-430, Vol.89, 2000.
14. Marshall, A.H., & McClean, S.I., & Shapcott, C.M., & Hastie, I.R., & Millard, P.H. Developing a Bayesian Belief Network for the Management of Geriatric Hospital Care. *Health Care Management Science*, Pp25-43, Vol.4, 2001.
15. Marshall, A.H., & McClean, S.I., & Shapcott, C.M., & Millard, P.H. Modelling Patient Duration of Stay to Facilitate Resource Management of Geriatric Hospital, *Health Care Management Science*, Pp 249-255, Vol. 4, 2002.
16. Russell, S., & Norvig, P. *Artificial Intelligence: A Modern Approach*. Prentice-Hall Inc., New Jersey, 1995.

17. Cooper, G.F., & Herskovits, E. A Bayesian Method for the Induction of Probabilistic Networks from Data. *Machine Learning*, Pp309-347, Vol. 9, 1992.
18. Cowell, R.G., & Dawid, A.P., & Lauritzen, S.L., & Spiegelhalter, D.J. *Probabilistic Networks and Expert Systems*. Springer Verlag. New York, 1999.
19. Pearl, J. *Probabilistic Reasoning in Intelligent System: Networks of Plausible Inference*. Morgan Kaufmann Publishers, Inc., San Mateo, California, 1988.
20. Murphy, K.P. A Brief Introduction to Graphical Models and Bayesian Networks, 2003 <http://www.ai.mit.edu/~murphyk/Bayes/bnintro.html>
21. The Ottawa Hospital. Clinical Pathway Manual. *Ottawa Hospital*, 2001.
22. Cheah, J. Clinical Pathways – An Evaluation of its Impact on the Quality of Care in an Acute Care General Hospital in Singapore. *Journal of Singapore Medicine*, Pp335-346, Vol. 41, 2000.

## **Appendix A: The Radical Prostatectomy Caremap**

The Radical Prostatectomy Caremap (RPC) was designed and is used in The Ottawa Hospital - Civic campus for the patients diagnosed with a prostate cancer and who were admitted to the hospital for radical prostatectomy. It describes the basic plan of care and expected patient outcomes according to a specified timeframes. It is divided into several sections such as:

- “Critical Path” that shows the usual basic care.
- “Patient Outcomes” that shows usual expected patient outcomes.
- “Patient Progress Corresponds with Clinical Pathway” that shows whether care and outcomes are congruent with the pathway or whether there are variances.

PAU	Day of Surgery Pre-op SDA / SDCU
Date: yy mm dd	Date: yy mm dd
Critical Path	Critical Path
<p><b>Assessment &amp; teaching per PAU standards and procedure specific education material</b></p> <p><b>Tests</b> CBC Na, K, Cl, Creatinine, Glucose Type and Screen Urine C&amp;S</p> <p><b>Additional testing if required per PAU standards</b> <input checked="" type="checkbox"/> <b>If done</b>  <input type="checkbox"/> PTT / INR                      <input type="checkbox"/> ECG                      <input type="checkbox"/> Chest X-ray</p> <p><b>Additional Orders</b> Measure for TED stockings Ensure patient has Urology Bowel Prep prescription</p> <p><b>Discharge Planning</b> Discuss expected length of stay Initiate Discharge Preparation Clinical Pathway</p>	<p><b>Assessment &amp; teaching per Same Day Admission standards and procedure specific education material.</b></p> <p>Additional testing if required per Same Day Admission standards <input checked="" type="checkbox"/> <b>If done</b></p> <p>Glucose meter: for diabetic patient PTT / INR: for patient normally taking warfarin (Coumadin) - Unless normal result obtained after warfarin discontinued per pre-op instructions Electrolytes: for dialysis dependant patient CBC if autologous blood donor</p> <p><b>Additional Orders</b> IV N/S @ 50 ml/hr (or D5W if diabetic) Apply TED stockings Rofecoxib 50 mg PO with sips on arrival to SDA or 2 hours pre-op (Civic Campus)</p> <p><b>Antibiotics:</b> <i>If No history of allergy to penicillin or to other beta-lactam antibiotics;</i> or <i>History of non-life threatening reaction to penicillin or other beta-lactam antibiotics (eg rash, diarrhea, stomach upset)</i></p> <p>IV Cefazolin: 1g, 1 h pre-op Or If patient has a history of life threatening reaction (hypotension, bronchospasm, urticaria, angioedema) to penicillin or other beta-lactam antibiotics</p> <p><b>IV Vancomycin 1g, 1 hour pre-op</b></p> <p><b>Send with chart to OR:</b> Heparin 5000u SC</p>
<p><b>Patient Outcomes</b></p> <p><b>Patient / Family Teaching</b> Understands pre-op instructions including bowel prep Understands usual post-op course, plan for pain management, and usual self care measures to prevent post-op complications – per patient education booklet</p> <p><b>Discharge Planning</b> Understands usual length of stay Appropriate discharge plan in place or if no suitable discharge plan in place - social work has been consulted</p>	<p><b>Patient Outcomes</b></p> <p><b>Patient / Family Teaching</b> Compliant with pre-op instructions Understands usual events/ expectations of operative day Understands usual post-op course, plan for pain management, and usual self care measures to prevent post-op complications – per patient education booklet</p>
<p>Patient Progress corresponds with clinical pathway <input type="checkbox"/> Yes <input type="checkbox"/> No                      NTV – circle above, VC _____ Signature: _____ Time: _____</p>	<p>Patient Progress corresponds with clinical pathway <input type="checkbox"/> Yes <input type="checkbox"/> No                      NTV – circle above, VC _____ Signature: _____ Time: _____</p>

VC Variance Codes      187 Mobility outcome Day 2 not achieved  
 NTV Non tracked variance      492 Not discharged by end of pathway - Continued need for acute care  
 Off Ordered off pathway      510 Not discharged by end of pathway - Non-medical reason

Radical Prostatectomy 03-01-21

Day of Surgery Post-op PACU	
Date: yy mm dd	
Critical Path	Patient Outcomes
<b>O<sub>2</sub> sat monitoring and O<sub>2</sub> administration per PACU protocol</b>  <b>VS. assessment, treatment, and teaching per PACU standards</b>  Additional Orders Bedrest TED stockings Pneumatic compression stockings until discharge from PACU Indwelling urethral catheter <i>Record urine output &amp; assess catheter drainage q1h (clots, excessive bleeding)</i> Jackson Pratt NPO to clear fluids as tolerated May transfer to ward when PACU criteria for transfer are achieved	Urine output adequate (minimum 0.5 ml/kg/h) Achieves PACU criteria for transfer to ward
<b>Patient progress corresponds with clinical pathway:</b> <b>D</b> <input type="checkbox"/> Yes <input type="checkbox"/> No      NTV – circle above, VC _____ Signature: _____ Time _____ <b>E</b> <input type="checkbox"/> Yes <input type="checkbox"/> No      NTV – circle above, VC _____ Signature: _____ Time _____ <b>N</b> <input type="checkbox"/> Yes <input type="checkbox"/> No      NTV – circle above, VC _____ Signature: _____ Time _____	
<b>D : 8 - 12 h day shift / E : evening shift , if applicable / N : 8 - 12 h night shift</b>	

**VC Variance Codes**      **187** Mobility outcome Day 2 not achieved  
**NTV Non tracked variance**      **492** Not discharged by end of pathway - Continued need for acute care  
**Off Ordered off pathway**      **510** Not discharged by end of pathway - Non-medical reason

Day of Surgery Post-op - Ward	
Date: yy mm dd	
Critical Path	Patient Outcomes
<p><b>Assessments/Treatments</b>            VS q 4 h x 24h &amp; pm , SpO<sub>2</sub> q12h            Intake &amp; Output q4h x 24h            Analgesia assessment as per APS Assessment Protocol            TED stockings            Monitor dressing change if draining            Jackson Pratt            Systems assessment, Respiratory, GU, GI q 12h &amp; pm</p> <p><b>Activity</b>            Bed rest            Dangle x 1 minimum</p> <p><b>Nutrition</b>            Full Fluids</p> <p><b>Elimination</b>            Indwelling urethral catheter</p> <p><b>Patient Teaching</b>            Reinforce            -deep breathing &amp; coughing            -leg exercises            -wound splinting            -pain management            -diet</p> <p><b>Discharge Planning</b>            Per Discharge Preparation clinical pathway</p>	<p><b>Patient Teaching</b>            Demonstrates wound splinting            Compliant with activity</p> <p><b>Pain</b>            Pain score mild at rest to moderate with activity            Verbalizes adequate pain control</p> <p><b>Respiratory Function</b>            Respiratory rate, rhythm, and effort are stable (RR &gt; 8 &lt; 20 at rest)            SpO<sub>2</sub> within limits of titration protocol            Level of sedation: easily arousable            Effective Deep Breathing and Coughing            No new evidence of crackles, wheezes, bronchial breath sounds</p> <p><b>Elimination</b>            Notify surgeon if JP output is greater than ½ urine output q4h            Urine output adequate ( 0.5 ml/kg/h ) when trended over 4h</p> <p><b>Mobility</b>            Tolerates dangle x 1 at bedside</p>
<p><b>Patient progress corresponds with clinical pathway:</b></p> <p>D <input type="checkbox"/> Yes <input type="checkbox"/> No      NTV – circle above, VC _____ Signature: _____ Time _____</p> <p>E <input type="checkbox"/> Yes <input type="checkbox"/> No      NTV – circle above, VC _____ Signature: _____ Time _____</p> <p>N <input type="checkbox"/> Yes <input type="checkbox"/> No      NTV – circle above, VC _____ Signature: _____ Time _____</p>	
<p><b>D : 8 - 12 h day shift / E : evening shift , if applicable / N : 8 - 12 h night shift</b></p>	

VC Variance Codes      187 Mobility outcome Day 2 not achieved  
 NTV Non tracked variance      492 Not discharged by end of pathway - Continued need for acute care  
 Off Ordered off pathway      510 Not discharged by end of pathway - Non-medical reason

Post-op Day 1	
Date:   yy       mm       dd	
<b>Critical Path</b>	<b>Patient Outcomes</b>
<p><b>Assessments/Treatments</b>                  VS q4h until 24h post-op then q12h, SpO<sub>2</sub> q12h                  Intake &amp; Output q4h until 24h post-op then q12h                  Analgesia assessment as per APS Assessment Protocol                  TED stockings                  Monitor dressing - change dressing if draining                  Jackson Pratt                  Systems assessment, Respiratory, GU, GI q 12h &amp; prn</p> <p><b>Activity</b>                  Chair x 3                  Ambulate for short walk with minimal assistance                  Progressive ambulation throughout the day (with minimal assistance <math>\square</math> independent as tolerated)</p> <p><b>Nutrition</b>                  Diet as ordered</p> <p><b>Elimination</b>                  Indwelling urethral catheter</p> <p><b>Patient Teaching</b>                  Reinforce                  -deep breathing &amp; coughing                  -wound splinting                  -pain management                  diet                  activity                  Review                  -catheter care &amp; drainage system</p> <p><b>Discharge Planning</b>                  Per Discharge Preparation clinical pathway                  Review discharge plans with patient / family</p>	<p><b>Patient Teaching</b>                  Independent with wound splinting                  Understands progression of activity                  Understands progression of diet                  Understands catheter care and drainage system</p> <p><b>Pain</b>                  Pain score mild at rest to moderate with activity                  Demonstrates progressive activity related to adequate pain control</p> <p><b>Respiratory Function</b>                  Respiratory rate, rhythm, and effort are stable (RR &gt; 8 &lt;20 at rest)                  SpO<sub>2</sub> within limits of titration protocol                  Effective Deep Breathing and Coughing                  Level of sedation easily arousable                  No new evidence of crackles, wheezes, bronchial breath sounds</p> <p><b>Elimination</b>                  Notify surgeon if Jackson Pratt output is greater than ½ urine output via urethral catheter q4h                  Bowel sounds present                  Urine output adequate ( 0.5 ml/kg/h ) when trended over 4h</p> <p><b>Mobility</b>                  Tolerates activity as planned</p>
<b>Patient progress corresponds with clinical pathway:</b>	
<b>D</b> <input type="checkbox"/> Yes <input type="checkbox"/> No	NTV – circle above, VC _____ Signature: _____ Time _____
<b>E</b> <input type="checkbox"/> Yes <input type="checkbox"/> No	NTV – circle above, VC _____ Signature: _____ Time _____
<b>N</b> <input type="checkbox"/> Yes <input type="checkbox"/> No	NTV – circle above, VC _____ Signature: _____ Time _____
<b>D : 8 - 12 h day shift / E : evening shift , if applicable / N : 8 - 12 h night shift</b>	

Post-op Day 2	
Date: yy mm dd	
<b>Critical Path</b>	<b>Patient Outcomes</b>
<p><b>Medications</b> Convert IV to saline lock if drinking well</p> <p><b>Assessments/Treatments</b> VS &amp; SpO<sub>2</sub> q12h Intake &amp; Output q12 TED stockings Remove dressing – open to air Jackson Pratt Systems assessment: Respiratory, GU, GI q shift &amp; prn</p> <p><b>Activity</b> Progressive ambulation - independent</p> <p><b>Nutrition</b> Diet as ordered</p> <p><b>Elimination</b> Indwelling urethral catheter</p> <p><b>Patient Teaching</b> Per patient education booklet Reinforce -activity -catheter care &amp; drainage system Review -discharge instructions</p> <p><b>Discharge Planning</b> Per Discharge Preparation clinical pathway Confirm discharge plans with patient / family</p>	<p><b>Patient Teaching</b> Demonstrates ability to manage catheter care and drainage system Understands discharge plans and discharge care -wound care -activity -pain</p> <p><b>Pain</b> Requests analgesia as needed Demonstrates progressive ADL related to adequate pain control</p> <p><b>Respiratory Function</b> Respiratory rate, rhythm, and effort are stable (RR &gt; 8 &lt;20 at rest) SpO<sub>2</sub> within limits of titration protocol No new evidence of crackles, wheezes, bronchial breath sounds</p> <p><b>Elimination</b> Jackson Pratt drainage &lt; ½ volume of urine output from urethral catheter in 24 h Bowel sounds present Urine output adequate ( 0.5 ml/kg/h ) when trended over 4h</p> <p><b>Mobility</b> Walks full length of hallway x 2 independently</p> <p><b>Wound</b> Temp within normal range No evidence of wound redness, swelling, drainage or dehiscence</p>
<b>Patient progress corresponds with clinical pathway:</b>	
D <input type="checkbox"/> Yes <input type="checkbox"/> No	NTV – circle above, VC _____ Signature: _____ Time _____
E <input type="checkbox"/> Yes <input type="checkbox"/> No	NTV – circle above, VC _____ Signature: _____ Time _____
N <input type="checkbox"/> Yes <input type="checkbox"/> No	NTV – circle above, VC _____ Signature: _____ Time _____
<b>D : 8 - 12 h day shift / E : evening shift , if applicable / N : 8 - 12 h night shift</b>	

<b>Post-op Day 3 Discharge Day</b> <b>Date:</b> yy        mm        dd	
<b>Critical Path</b> <b>Assessments/Treatments</b> VS Remove saline lock Monitor incision Urine output D/C TED stockings D/C Jackson Pratt drain if amount < 50 ml previous 24 hours. Apply dry dressing over site. Notify Urology service if criteria for removal of JP not met. Discharge with clips if present  <b>Activity</b> AAT  <b>Nutrition</b> Diet as ordered  <b>Elimination</b> Indwelling urethral catheter  <b>Patient Teaching</b> Reinforce discharge instructions  <b>Discharge Planning</b> Discharge if discharge criteria achieved If unable to discharge today: If unable to discharge but acute care no longer required - verify if patient should be designated as ALC. If yes – initiate ALC form. Document appropriate variance code Complete Discharge Documentation section of Discharge Preparation clinical pathway	<b>Patient Outcomes</b> <b>Discharge Criteria met:</b> <b>Understands:</b> Discharge instructions per patient education booklet Signs of wound complication that should be reported to MD Follow-up appointment Care of Jackson Pratt if applicable Adequate pain control with oral analgesia No evidence of respiratory impairment Passing flatus Tolerating regular diet Adequate urine output Adequate mobility - progressing toward baseline No evidence of wound complication
<b>Patient progress corresponds with clinical pathway:</b> <b>D</b> <input type="checkbox"/> Yes <input type="checkbox"/> No        NTV – circle above, VC _____ Signature: _____ Time _____ <b>E</b> <input type="checkbox"/> Yes <input type="checkbox"/> No        NTV – circle above, VC _____ Signature: _____ Time _____ <b>N</b> <input type="checkbox"/> Yes <input type="checkbox"/> No        NTV – circle above, VC _____ Signature: _____ Time _____	
<b>D : 8 - 12 h day shift / E : evening shift , if applicable / N : 8 - 12 h night shift</b>	

## Appendix B: The K2 Method

This appendix is extracted from the materials in Reference [17].

Cooper and Herskovits proposed a heuristic search algorithm called the K2 method for locating a BBN that maximizes the probability of the probable BBN structure given the data.

The main idea of this method is to begin with a node has no parents, and to add incrementally the parent whose addition most increases the probability of the resulting structure. When the addition of no single parent can increase the probability, adding parents to the node is stopped. For node  $i$ , the following function can be used to compute the probability of the resulting structure.

$$g(i, pa(i)) = \prod_{j=1}^m \frac{(r_i - 1)!!}{(N_{ij} + r_i - 1)!} \prod_{k=1}^{r_i} N_{ijk} !$$

The heuristic search algorithm K2 method can be expressed in the following flowchart, in which:

*i*: *ith node.*

*n*: *the total number of nodes.*

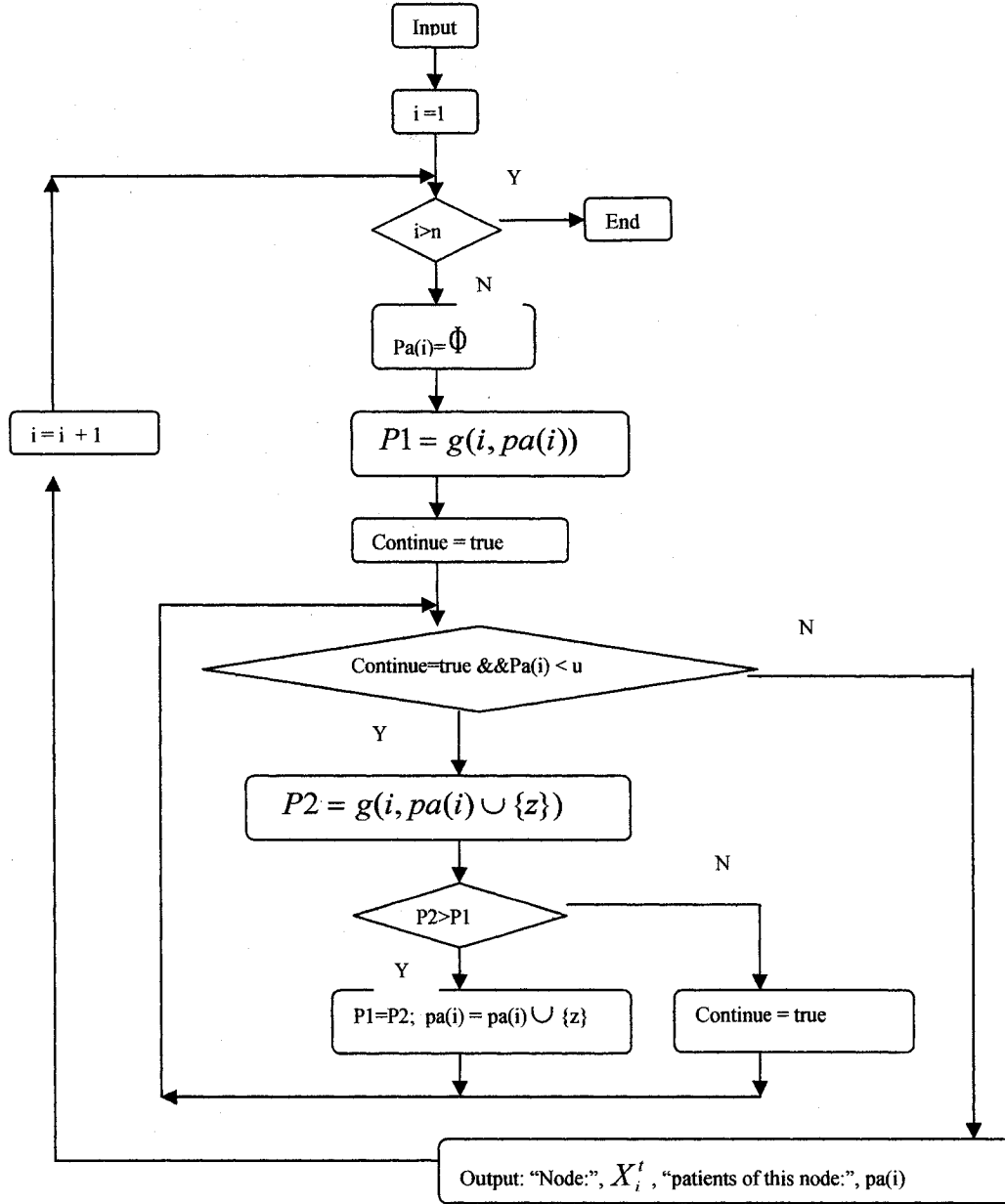
*Pa(i)*: *the parent nodes of the ith node.*

*u*: *the upper bound on the number of parents a node may have.*

*z*: *the nodes that precede ith node in the ordering.*

Input: *A set of  $n$  nodes, an ordering on the nodes, an upper bound  $u$  on the number of parents a node may have, and a database  $D$  containing  $N$  cases.*

Output: *For each node, it prints out the parents of the node.*



This flowchart illustrates the heuristic search algorithm. A training dataset containing a set of  $n$  variables, an ordering on the variables, *are the* inputs into the algorithm. The output of this algorithm is the variable and its immediate parent variables.

## Appendix C: Tables

**Table 1: Variables in the RPC**

N o.	Variable	Variable Name	Categories	Descriptions or Examples	Event
1	$x_1^1$	Psycho	abnormal	e.g., Patient's anxiety;	e1
			normal	Patient can understand and is compliant	e2
2	$x_2^1$	Vs1	abnormal	e.g., The pulse rate of the patient is abnormal on Post-op day 1	e3
			normal	Vital signs of the patient are normal on Post-op day 1	e4
3	$x_3^1$	ActW1	no	Patient does not ambulate on Post-op day 1	e5
			ambulate	Patient does ambulate on Post-op day 1	e6
4	$x_4^1$	NutriW1	Fluid	Patient drinks fluid on Post-op day 1	e7
5	$x_5^1$	NutriO1	vomit	Patient vomits on Post-op day 1	e8
			nausea	Patient feels nausea on Post-op day 1	e9
			normal	None of the above	e10
6	$x_6^1$	PainR1	medium	The verbal pain score at rest of the patient is between 4-7 on Post-op day 1	e11
			mild	The verbal pain score at rest of the patient is between 1-3 on Post-op day 1	e12
			nopain	Patient has no pain at rest on Post-op day 1	e13
7	$x_7^1$	Resp1	mild	e.g., Crackle, difficult to breath on Post-op day 1	e14
			normal	The respiratory function of the patient is normal on Post-op day 1	e15
8	$x_8^1$	Jp1	large	The amount of JP is large on Post-op day 1	e16
			medium	The amount of JP is medium on Post-op day 1	e17
			small	The amount of JP is small on Post-op day 1	e18
9	$x_9^1$	Hema1	yes	Patient has evidence of hematuria on Post-op day 1	e19
			Bt	Patient has blood-tinged on Post-op day 1	e20
			no	Patient has no evidence of hematuria on Post-op day 1	e21
10	$x_{10}^1$	UrineO1	inadequate	The amount of Urine is inadequate on Post-op day 1	e22
			adequate	The amount of Urine is adequate on Post-op day 1	e23
11	$x_{11}^1$	BowelS1	absent	The bowel sound is absent on Post-op day 1	e24
			present	The bowel sound is present on Post-op day 1	e25
12	$x_{12}^1$	PainM1	Medium	The verbal pain score with mobility of the patient is between 4-7 on Post-op day 1	e26
			Mild	The verbal pain score with mobility of the patient is between 1-3 on Post-op day 1	e27
			Nopain	Patient has no pain with mobility on Post-op day 1	e28
13	$x_2^2$	Vs2	Abnormal	e.g., The pulse rate of the patient is abnormal on Post-op day 2	e29
			Normal	Vital signs of the patient are normal on Post-op day 2	e30
14	$x_3^2$	Temp2	Abnormal	Patient's temperature is abnormal on Post-op day 2	e31
			Normal	Patient's temperature is normal on Post-op day 2	e32
15	$x_4^2$	ActW2	No	Patient does not ambulate on Post-op day 2	e33
			Ambulate+	Patient does progressive ambulation on Post-op day 2	e34
16	$x_5^2$	NutriW2	Fluid	Patient drinks fluid on Post-op day 2	e35
			regular	Patient have regular foods on Post-op day 2	e36

**Table 1 (continued):**

N o.	Variable	Variable Name	Categories	Descriptions or Examples	Event
17	$x_6^2$	NutriO2	vomit	Patient vomits on Post-op day 2	e37
			nausea	Patient feels nausea on Post-op day 2	e38
			normal	The nutrition outcome of the patient is normal on Post-op day 2	e39
18	$x_7^2$	PainR2	medium	The verbal pain score at rest of the patient is between 4-7 on Post-op day 2	e40
			mild	The verbal pain score at rest of the patient is between 1-3 on Post-op day 2	e41
			nopain	Patient has no pain at rest on Post-op day 2	e42
19	$x_8^2$	Resp2	normal	The respiratory function of the patient is normal on Post-op day 2	e43
20	$x_9^2$	Jp2	large	The amount of JP is large on Post-op day 2	e44
			medium	The amount of JP is medium on Post-op day 2	e45
			small	The amount of JP is small on Post-op day 2	e46
			d/c	JP is discontinued on Post-op day 2	e47
21	$x_{10}^2$	Hema2	yes	Patient has evidence of hematuria on Post-op day 2	e48
			Bt	Patient has blood-tinged on Post-op day 2	e49
			no	Patient has no evidence of hematuria on Post-op day 2	e50
22	$x_{11}^2$	UrineO2	inadequate	The amount of Urine is inadequate on Post-op day 2	e51
			adequate	The amount of Urine is adequate on Post-op day 2	e52
23	$x_{12}^2$	BowelS2	absent	The bowel sound is absent on Post-op day 2	e53
			present	The bowel sound is present on Post-op day 2	e54
24	$x_{13}^2$	PainM2	medium	The verbal pain score with mobility of the patient is between 4-7 on Post-op day 2	e55
			mild	The verbal pain score with mobility of the patient is between 1-3 on Post-op day 2	e56
			nopain	Patient has no pain with mobility on Post-op day 2	e57
25	$x_{14}^2$	Wound2	medium	Patient's incision has severe infection on Post-op day 2	e58
			mild	Patient's incision has mild infection on Post-op day 2	e59
			normal	Patient's incision has no evidence of redness, swelling, rash, dehiscence on Post-op day 2	e60
26	$x_2^3$	Vs3	abnormal	e.g., The pulse rate of the patient is abnormal on Post-op day 3	e61
			normal	Vital signs of the patient are normal on Post-op day 3	e62
27	$x_3^3$	Temp3	abnormal	Patient's temperature is abnormal on Post-op day 3	e63
			normal	Patient's temperature is normal on Post-op day 3	e64
28	$x_4^3$	ActW3	no	Patient does not ambulate on Post-op day 3	e65
			ambulate+	Patient does progressive ambulation on Post-op day 3	e66
29	$x_5^3$	NutriW3	fluid	Patient drinks fluid on Post-op day 3	e67
			regular	Patient have regular foods on Post-op day 3	e68
30	$x_6^3$	NutriO3	vomit	Patient vomits on Post-op day 3	e69
			nausea	Patient feels nausea on Post-op day 3	e70
			normal	The nutrition outcome of the patient is normal on Post-op day 3	e71

**Table 1 (continued):**

N o.	Variable	Variable Name	Categories	Descriptions or Examples	Event
31	$X_7^3$	PainR3	medium	The verbal pain score at rest of the patient is between 4-7 on Post-op day 3	e72
			mild	The verbal pain score at rest of the patient is between 1-3 on Post-op day 3	e73
			nopain	Patient has no pain at rest on Post-op day 3	e74
32	$X_8^3$	Resp3	normal	The respiratory function of the patient is normal on Post-op day 3	e75
33	$X_9^3$	Jp3	large	The amount of JP is large on Post-op day 3	e76
			medium	The amount of JP is medium on Post-op day 3	e77
			small	The amount of JP is small on Post-op day 3	e78
			d/c	JP is discontinued on Post-op day 3	e79
34	$X_{10}^3$	Hema3	yes	Patient has evidence of hematuria on Post-op day 3	e80
			Bt	Patient has blood-tinged on Post-op day 3	e81
			no	Patient has no evidence of hematuria on Post-op day 3	e82
35	$X_{11}^3$	UrineO3	inadequate	The amount of Urine is inadequate on Post-op day 3	e83
			adequate	The amount of Urine is adequate on Post-op day 3	e84
36	$X_{13}^3$	PainM3	medium	The verbal pain score with mobility of the patient is between 4-7 on Post-op day 3	e85
			mild	The verbal pain score with mobility of the patient is between 1-3 on Post-op day 3	e86
			nopain	Patient has no pain with mobility on Post-op day 3	e87
37	$X_{14}^3$	Wound3	medium	Patient's incision has severe infection on Post-op day 3	e88
			mild	Patient's incision has mild infection on Post-op day 3	e89
			normal	Patient's incision has no evidence of redness, swelling, rash, dehiscence on Post-op day 3	e90
38	$X_{15}^3$	LOS	delayed	Patient is discharged after Post-op day 3	e91
			met	Patient is discharged on or before Post-op day 3	e92

**Table 2: A Form for Transcribing Patients' Data from Charts**

The table below illustrates how charts' data was transcribed. It contains the information for a radical prostatectomy patient who followed the caremap. The data in the grey area are not considered because there are not parts of a caremap.

Patient ID:

Date:

	Post-op 1	Post-op 2	Post-op 3
Psychology	normal		
VS	normal	normal	Normal
Temp	normal	normal	Normal
ActDoneW	A	A+	AAT
NutriW	fluid	regular	Regular
NutriOut	normal	normal	Normal
VASR	nopain	nopain	Nopain
RespFun	normal	normal	Normal
JP	small	small	d/c
Hematuria	no	no	No
UrineOut	adequate	adequate	Adequate
BowelSound	faint	faint	
MobAchiW	nopain	nopain	Nopain
Wound	normal	normal	Normal
Discharge			yes

**Table 3: A Training Dataset for Developing the BBN\_RPC Model**

The table contains information on 75 that was used to develop the BBN\_RPC model. The first column identifies a patient case. The column headings describe either the patient's activity or the patient's outcome.

#	Variables and their values								
	Psycho	Vs1	Actw1	Nutriw 1	Nutrio1	Painr1	Resp1	Jp1	He- ma1
1	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Medium	Bt
2	Normal	Normal	Ambulate	Fluid	Vomit	Nopain	Normal	Small	No
3	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Medium	No
4	Normal	Normal	No	Fluid	Normal	Medium	Normal	Small	No
5	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
6	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Y
7	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
8	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	Bt
9	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
10	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
11	Abnormal	Normal	Ambulate	Fluid	Normal	Medium	Normal	Small	Bt
12	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	Bt
13	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
14	Normal	Normal	No	Fluid	Normal	Mild	Normal	Small	Bt
15	Normal	Normal	Ambulate	Fluid	Nausea	Nopain	Normal	Small	Bt
16	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
17	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
18	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	Bt
19	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
20	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	Bt
21	Normal	Normal	Ambulate	Fluid	Normal	Medium	Normal	Small	Bt
22	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
23	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
24	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
25	Normal	Normal	Ambulate	Fluid	Nausea	Nopain	Normal	Small	No
26	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
27	Normal	Normal	No	Fluid	Normal	Mild	Normal	Small	Bt
28	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
29	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
30	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
31	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
32	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
33	Normal	Normal	No	Fluid	Normal	Mild	Normal	Small	No
34	Abnormal	Normal	No	Fluid	Normal	Medium	Normal	Small	No
35	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
36	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
37	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	Y
38	Normal	Normal	No	Fluid	Normal	Mild	Normal	Small	No
39	Normal	Normal	No	Fluid	Normal	Nopain	Normal	Small	No
40	Normal	Normal	No	Fluid	Normal	Medium	Normal	Small	No
41	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
42	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
43	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
44	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
45	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
46	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
47	Normal	Normal	No	Fluid	Normal	Medium	Normal	Medium	Bt
48	Normal	Normal	No	Fluid	Normal	Mild	Normal	Small	Y
49	Normal	Abnormal	No	Fluid	Normal	Medium	Normal	Large	Bt
50	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No

**Table 3 (continued):**

#	Variables and their values								
	Psycho	Vs1	Actw1	Nutriw 1	Nutrio1	Painr1	Resp1	Jp1	He- ma1
51	Normal	Normal	No	Fluid	Normal	Mild	Normal	Small	Bt
52	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
53	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
54	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
55	Normal	Abnormal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Y
56	Normal	Normal	No	Fluid	Normal	Mild	Mild	Small	Y
57	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
58	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
59	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
60	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
61	Normal	Normal	No	Fluid	Normal	Mild	Normal	Small	Bt
62	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
63	Normal	Normal	Ambulate	Fluid	Nausea	Nopain	Normal	Medium	Bt
64	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	Bt
65	Normal	Normal	No	Fluid	Nausea	Mild	Normal	Small	Y
66	Normal	Normal	No	Fluid	Normal	Nopain	Normal	Small	Y
67	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Medium	No
68	Normal	Normal	No	Fluid	Normal	Medium	Normal	Small	No
69	Normal	Normal	No	Fluid	Normal	Nopain	Normal	Small	No
70	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	Bt
71	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
72	Normal	Normal	No	Fluid	Nausea	Nopain	Normal	Small	Bt
73	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
74	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
75	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No

**Table 3 (continued):**

#	Variables and their values								
	Urineo1	Bowels 1	Painm1	Vs2	Temp2	Actw2	Nutriw2	Nutrio 2	Painr2
1	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
2	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
3	Adequate	Present	Medium	Normal	Normal	Ambulate+	Regular	Normal	Medium
4	Adequate	Present	Medium	Normal	Normal	No	Regular	Normal	Medium
5	Adequate	Present	Mild	Normal	Normal	Ambulate+	Fluid	Normal	Mild
6	Adequate	Present	Medium	Normal	Abnormal	Ambulate+	Fluid	Normal	Mild
7	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Mild
8	Adequate	Present	Mild	Normal	Normal	Ambulate+	Fluid	Normal	Nopain
9	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
10	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
11	Adequate	Present	Medium	Normal	Normal	Ambulate+	Fluid	Normal	Medium
12	Adequate	Present	Medium	Normal	Normal	Ambulate+	Regular	Normal	Mild
13	Adequate	Present	Mild	Normal	Abnormal	Ambulate+	Regular	Normal	Mild
14	Adequate	Present	Medium	Normal	Normal	Ambulate+	Fluid	Normal	Mild
15	Adequate	Present	Mild	Normal	Normal	Ambulate+	Fluid	Nausea	Mild
16	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Mild
17	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
18	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
19	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
20	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Mild
21	Adequate	Present	Medium	Normal	Normal	Ambulate+	Regular	Normal	Medium
22	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
23	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Mild
24	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
25	Inadequate	Present	Nopain	Normal	Normal	Ambulate+	Fluid	Nausea	Nopain
26	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Fluid	Normal	Nopain
27	Adequate	Present	Medium	Normal	Normal	No	Regular	Normal	Mild
28	Adequate	Present	Medium	Normal	Normal	Ambulate+	Regular	Normal	Mild
29	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
30	Adequate	Present	Mild	Normal	Normal	Ambulate+	Fluid	Normal	Nopain
31	Inadequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
32	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
33	Adequate	Present	Medium	Normal	Normal	No	Fluid	Normal	Mild
34	Adequate	Present	Medium	Normal	Normal	Ambulate+	Fluid	Normal	Mild
35	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
36	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
37	Adequate	Present	Mild	Normal	Normal	Ambulate+	Fluid	Normal	Nopain
38	Adequate	Present	Mild	Normal	Normal	Ambulate+	Fluid	Normal	Nopain
39	Adequate	Present	Mild	Normal	Normal	No	Regular	Normal	Nopain
40	Adequate	Present	Medium	Normal	Normal	Ambulate+	Regular	Nausea	Mild
41	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Mild
42	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
43	Adequate	Present	Medium	Normal	Abnormal	Ambulate+	Fluid	Normal	Mild
44	Adequate	Present	Mild	Normal	Normal	Ambulate+	Fluid	Normal	Mild
45	Adequate	Present	Medium	Normal	Abnormal	Ambulate+	Regular	Normal	Mild
46	Adequate	Present	Mild	Normal	Normal	Ambulate+	Fluid	Normal	Nopain
47	Adequate	Present	Medium	Normal	Normal	Ambulate+	Fluid	Normal	Mild
48	Adequate	Absent	Medium	Normal	Normal	Ambulate+	Fluid	Normal	Mild
49	Adequate	Present	Medium	Abnormal	Abnormal	No	Fluid	Normal	Medium
50	Adequate	Present	Medium	Normal	Normal	Ambulate+	Fluid	Normal	Mild

**Table 3 (continued):**

#	Variables and their values								
	Urino1	Bowels 1	Pain1	Vs2	Temp2	Actw2	Nutriw2	Nutrio 2	Painr2
51	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Mild
52	Adequate	Present	Mild	Normal	Abnormal	No	Fluid	Normal	Mild
53	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
54	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Fluid	Normal	Nopain
55	Inadequate	Present	Nopain	Abnormal	Normal	Ambulate+	Fluid	Normal	Nopain
56	Inadequate	Present	Medium	Normal	Abnormal	Ambulate+	Fluid	Normal	Mild
57	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
58	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
59	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
60	Adequate	Present	Mild	Normal	Abnormal	Ambulate+	Fluid	Normal	Mild
61	Adequate	Present	Mild	Normal	Normal	No	Regular	Normal	Medium
62	Inadequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
63	Adequate	Present	Mild	Normal	Abnormal	Ambulate+	Fluid	Nausea	Nopain
64	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Mild
65	Adequate	Present	Medium	Normal	Abnormal	Ambulate+	Regular	Normal	Mild
66	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
67	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Mild
68	Adequate	Present	Medium	Normal	Normal	Ambulate+	Regular	Normal	Mild
69	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
70	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Mild
71	Adequate	Present	Mild	Normal	Abnormal	Ambulate+	Regular	Normal	Nopain
72	Adequate	Present	Mild	Normal	Abnormal	Ambulate+	Regular	Vomit	Nopain
73	Adequate	Absent	Nopain	Normal	Normal	Ambulate+	Fluid	Normal	Nopain
74	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
75	Adequate	Absent	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain

**Table 3 (continued):**

#	Variables and their values									
	Resp2	Jp2	Hema2	Urineo2	Bowels 2	Painm2	Wound2	Vs3	Temp3	Actw3
1	Normal	D/C	Bt	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
2	Normal	D/C	No	Adequate	Present	Mild	Mild	Normal	Normal	Ambulate++
3	Normal	Small	No	Adequate	Present	Medium	Normal	Normal	Normal	Ambulate++
4	Normal	Small	No	Adequate	Present	Medium	Normal	Normal	Normal	Ambulate++
5	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
6	Normal	Small	Y	Adequate	Present	Mild	Medium	Normal	Abnormal	Ambulate++
7	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
8	Normal	Small	Bt	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
9	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
10	Normal	Small	Bt	Adequate	Present	Mild	Mild	Normal	Normal	Ambulate++
11	Normal	Small	Bt	Adequate	Present	Medium	Normal	Normal	Normal	Ambulate++
12	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
13	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
14	Normal	Small	No	Adequate	Present	Medium	Normal	Normal	Normal	Ambulate++
15	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
16	Normal	Small	Y	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
17	Normal	Small	Bt	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
18	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
19	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
20	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
21	Normal	Small	Bt	Adequate	Present	Medium	Normal	Normal	Normal	Ambulate++
22	Normal	Small	Bt	Adequate	Present	Mild	Mild	Normal	Normal	Ambulate++
23	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
24	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
25	Normal	Small	No	Inadequate	Present	Nopain	Mild	Normal	Normal	Ambulate++
26	Normal	Medium	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
27	Normal	Small	Bt	Adequate	Present	Medium	Normal	Normal	Normal	Ambulate++
28	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
29	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
30	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
31	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
32	Normal	Small	Bt	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
33	Normal	Small	Bt	Adequate	Present	Medium	Mild	Normal	Normal	No
34	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
35	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
36	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
37	Normal	Small	Y	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
38	Normal	Small	Y	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
39	Normal	Small	No	Adequate	Present	Nopain	Mild	Normal	Normal	No
40	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
41	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
42	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
43	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Abnormal	Ambulate++
44	Normal	Small	Y	Adequate	Present	Medium	Normal	Normal	Normal	Ambulate++
45	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Abnormal	Ambulate++
46	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Abnormal	Ambulate++
47	Normal	Small	Bt	Adequate	Present	Medium	Normal	Normal	Abnormal	Ambulate++
48	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Abnormal	Ambulate++
49	Normal	Large	Bt	Adequate	Present	Medium	Normal	Abnormal	Abnormal	No
50	Normal	Small	No	Adequate	Present	Medium	Normal	Normal	Normal	Ambulate++

**Table 3 (continued):**

#	Variables and their values									
	Resp2	Jp2	Hema2	Urineo2	Bowels 2	Painm2	Wound2	Vs3	Temp3	Actw3
51	Normal	D/C	Bt	Adequate	Present	Mild	Normal	Normal	Abnormal	Ambulate++
52	Normal	Small	Bt	Adequate	Present	Mild	Mild	Normal	Normal	Ambulate++
53	Normal	Small	Bt	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
54	Normal	Medium	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
55	Normal	Small	No	Inadequate	Present	Nopain	Normal	Abnormal	Normal	Ambulate++
56	Normal	Medium	Y	Inadequate	Present	Medium	Normal	Normal	Abnormal	Ambulate++
57	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
58	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
59	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
60	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Abnormal	Ambulate++
61	Normal	Small	No	Adequate	Present	Medium	Normal	Normal	Normal	Ambulate++
62	Normal	Medium	Bt	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
63	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
64	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
65	Normal	Small	Bt	Adequate	Present	Medium	Mild	Normal	Abnormal	Ambulate++
66	Normal	Small	Y	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
67	Normal	Medium	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
68	Normal	Small	No	Adequate	Present	Medium	Normal	Normal	Normal	Ambulate++
69	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
70	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
71	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Abnormal	Ambulate++
72	Normal	Small	Bt	Adequate	Present	Mild	Mild	Normal	Abnormal	Ambulate++
73	Normal	Small	No	Adequate	Absent	Nopain	Normal	Normal	Normal	Ambulate++
74	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
75	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++

**Table 3 (continued):**

#	Variables and their values									
	Nutriw3	Nutrio3	Painr3	Resp3	Jp3	He ma3	Urineo3	Painm3	Wound3	LOS
1	Regular	Normal	Nopain	Normal	D/C	Bt	Adequate	Nopain	Normal	Met
2	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
3	Regular	Normal	Mild	Normal	Small	No	Adequate	Mild	Normal	Delayed
4	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Met
5	Regular	Normal	Mild	Normal	D/C	Bt	Adequate	Mild	Normal	Delayed
6	Regular	Normal	Mild	Normal	Small	Y	Adequate	Mild	Medium	Delayed
7	Regular	Normal	Nopain	Normal	Small	Bt	Adequate	Mild	Mild	Met
8	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
9	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
10	Regular	Normal	Nopain	Normal	D/C	Bt	Adequate	Nopain	Normal	Met
11	Fluid	Normal	Mild	Normal	D/C	Bt	Adequate	Mild	Normal	Delayed
12	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
13	Regular	Normal	Mild	Normal	Small	Bt	Adequate	Mild	Normal	Delayed
14	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Met
15	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Delayed
16	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
17	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
18	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Met
19	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
20	Regular	Normal	Mild	Normal	D/C	Bt	Adequate	Mild	Normal	Met
21	Regular	Normal	Mild	Normal	D/C	Bt	Adequate	Mild	Normal	Met
22	Regular	Normal	Nopain	Normal	D/C	Bt	Adequate	Mild	Mild	Delayed
23	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Met
24	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
25	Regular	Normal	Nopain	Normal	Small	No	Inadequate	Nopain	Normal	Delayed
26	Regular	Normal	Nopain	Normal	Small	No	Adequate	Mild	Normal	Delayed
27	Regular	Normal	Mild	Normal	Small	Bt	Adequate	Medium	Normal	Delayed
28	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Met
29	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
30	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
31	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
32	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
33	Fluid	Normal	Mild	Normal	Small	Bt	Adequate	Mild	Normal	Delayed
34	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Delayed
35	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
36	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
37	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Mild	Normal	Met
38	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Mild	Normal	Met
39	Regular	Normal	Mild	Normal	Small	No	Adequate	Mild	Mild	Delayed
40	Regular	Normal	Mild	Normal	Small	No	Adequate	Mild	Normal	Met
41	Regular	Normal	Nopain	Normal	D/C	Bt	Adequate	Mild	Normal	Delayed
42	Regular	Normal	Nopain	Normal	D/C	Bt	Adequate	Mild	Normal	Met
43	Regular	Normal	Nopain	Normal	Small	Bt	Adequate	Nopain	Normal	Delayed
44	Regular	Normal	Mild	Normal	Small	Y	Adequate	Mild	Normal	Delayed
45	Regular	Normal	Mild	Normal	D/C	Bt	Adequate	Mild	Normal	Delayed
46	Regular	Normal	Nopain	Normal	D/C	Bt	Adequate	Mild	Normal	Delayed
47	Regular	Normal	Mild	Normal	Small	Bt	Adequate	Mild	Normal	Delayed
48	Fluid	Normal	Mild	Normal	D/C	Bt	Adequate	Mild	Normal	Delayed
49	Fluid	Normal	Medium	Normal	Large	Bt	Adequate	Medium	Normal	Delayed
50	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Met

**Table 3 (continued):**

#	Variables and their values									
	Nutriw3	Nutrio3	Painr3	Resp3	Jp3	Hema3	Urineo3	Painm3	Wound3	LOS
51	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Delayed
52	Regular	Normal	Mild	Normal	D/C	Bt	Adequate	Mild	Mild	Delayed
53	Regular	Normal	Nopain	Normal	D/C	Bt	Adequate	Nopain	Normal	Met
54	Regular	Normal	Nopain	Normal	Small	No	Adequate	Nopain	Normal	Delayed
55	Fluid	Normal	Nopain	Normal	D/C	No	Inadequate	Nopain	Normal	Delayed
56	Fluid	Normal	Medium	Normal	Small	Bt	Inadequate	Medium	Normal	Delayed
57	Regular	Normal	Nopain	Normal	Small	No	Adequate	Mild	Normal	Met
58	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
59	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
60	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Delayed
61	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Delayed
62	Regular	Normal	Nopain	Normal	Small	No	Adequate	Nopain	Normal	Delayed
63	Regular	Nausea	Nopain	Normal	Small	No	Adequate	Mild	Normal	Delayed
64	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Met
65	Regular	Normal	Mild	Normal	D/C	No	Adequate	Medium	Mild	Delayed
66	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Mild	Normal	Met
67	Regular	Normal	Mild	Normal	Medium	No	Adequate	Mild	Normal	Delayed
68	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
69	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Mild	Normal	Met
70	Regular	Normal	Nopain	Normal	D/C	Bt	Adequate	Nopain	Normal	Met
71	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
72	Regular	Vomit	Nopain	Normal	Small	Bt	Adequate	Mild	Normal	Delayed
73	Fluid	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Delayed
74	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
75	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Mild	Normal	Met

**Table 4: Out-of-sample Data Used for the BBN\_RPC Model Performance Evaluation**

#	Variables and their values								
	Psycho	Vs1	Actw1	Nutriw1	Nutrio1	Painr1	Resp1	Jp1	He-mal
76	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
77	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
78	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
79	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
80	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Large	No
81	Normal	Normal	Ambulate	Fluid	Nausea	Medium	Normal	Small	Bt
82	Normal	Normal	No	Fluid	Normal	Mild	Normal	Small	Bt
83	Normal	Normal	No	Fluid	Normal	Mild	Normal	Small	No
84	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
85	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
86	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
87	Normal	Normal	No	Fluid	Normal	Mild	Normal	Small	Bt
88	Normal	Normal	Ambulate	Fluid	Normal	Medium	Normal	Small	Bt
89	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
90	Normal	Normal	Ambulate	Fluid	Normal	Mild	Mild	Small	No
91	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
92	Normal	Normal	No	Fluid	Normal	Mild	Normal	Small	Bt
93	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
94	Normal	Normal	No	Fluid	Normal	Nopain	Normal	Small	Bt
95	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
96	Normal	Normal	No	Fluid	Normal	Mild	Normal	Small	No
97	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
98	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
99	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
100	Normal	Abnormal	No	Fluid	Normal	Mild	Normal	Small	No
101	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
102	Normal	Normal	No	Fluid	Normal	Mild	Normal	Small	Bt
103	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
104	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
105	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
106	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Medium	No
107	Normal	Normal	No	Fluid	Normal	Mild	Normal	Small	No
108	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
109	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
110	Normal	Normal	No	Fluid	Normal	Mild	Normal	Small	Bt
111	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
112	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
113	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
114	Normal	Normal	Ambulate	Fluid	Normal	Mild	Normal	Small	No
115	Normal	Normal	No	Fluid	Normal	Nopain	Normal	Small	No
116	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
117	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	Bt
118	Normal	Normal	No	Fluid	Normal	Mild	Normal	Small	No
119	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
120	Normal	Normal	No	Fluid	Normal	Nopain	Normal	Small	No
121	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
122	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No
123	Normal	Normal	No	Fluid	Normal	Nopain	Normal	Small	No
124	Normal	Normal	Ambulate	Fluid	Normal	Medium	Normal	Small	No
125	Normal	Normal	Ambulate	Fluid	Normal	Nopain	Normal	Small	No

**Table 4 (continued):**

#	Variables and their values								
	Urineo1	Bowels 1	Painm1	Vs2	Temp2	Actw2	Nutriw2	Nutrio 2	Painr2
76	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Mild
77	Adequate	Present	Mild	Normal	Normal	Ambulate+	Fluid	Normal	Mild
78	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Mild
79	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
80	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
81	Adequate	Present	Medium	Normal	Normal	Ambulate+	Fluid	Normal	Mild
82	Adequate	Present	Medium	Normal	Normal	Ambulate+	Regular	Normal	Medium
83	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Mild
84	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
85	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
86	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Nausea	Nopain
87	Inadequate	Present	Medium	Normal	Normal	Ambulate+	Regular	Normal	Nopain
88	Adequate	Present	Medium	Normal	Normal	Ambulate+	Regular	Normal	Mild
89	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
90	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
91	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
92	Adequate	Present	Medium	Normal	Abnormal	Ambulate+	Fluid	Normal	Mild
93	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Mild
94	Adequate	Present	Nopain	Normal	Abnormal	Ambulate+	Fluid	Normal	Nopain
95	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
96	Adequate	Present	Medium	Normal	Normal	Ambulate+	Regular	Normal	Mild
97	Adequate	Present	Mild	Normal	Normal	No	Fluid	Normal	Mild
98	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
99	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
100	Inadequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Mild
101	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
102	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
103	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Mild
104	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Mild
105	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
106	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Medium
107	Adequate	Present	Mild	Normal	Abnormal	Ambulate+	Fluid	Normal	Nopain
108	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
109	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Fluid	Normal	Nopain
110	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
111	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
112	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
113	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Mild
114	Adequate	Present	Mild	Normal	Normal	Ambulate+	Fluid	Normal	Mild
115	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
116	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
117	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
118	Adequate	Present	Mild	Normal	Normal	Ambulate+	Fluid	Normal	Mild
119	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
120	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
121	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain
122	Adequate	Present	Medium	Normal	Normal	Ambulate+	Fluid	Normal	Mild
123	Adequate	Present	Mild	Normal	Normal	Ambulate+	Regular	Normal	Nopain
124	Adequate	Present	Medium	Normal	Normal	Ambulate+	Fluid	Normal	Mild
125	Adequate	Present	Nopain	Normal	Normal	Ambulate+	Regular	Normal	Nopain

**Table 4 (continued):**

#	Variables and their values									
	Resp2	Jp2	He ma2	Urineo2	Bowels 2	Painm2	Wound2	Vs3	Temp3	Actw3
76	Normal	Medium	Bt	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
77	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
78	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
79	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
80	Normal	Large	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
81	Normal	Small	Bt	Adequate	Present	Medium	Normal	Normal	Normal	Ambulate++
82	Normal	Small	Bt	Adequate	Present	Medium	Mild	Normal	Normal	Ambulate++
83	Normal	Small	No	Adequate	Present	Mild	Mild	Normal	Normal	Ambulate++
84	Normal	Small	Bt	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
85	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
86	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Abnormal	Ambulate++
87	Normal	Small	Bt	Adequate	Present	Medium	Mild	Normal	Normal	Ambulate++
88	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
89	Normal	D/C	Bt	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
90	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
91	Normal	D/C	Bt	Adequate	Present	Nopain	Mild	Normal	Normal	Ambulate++
92	Normal	Small	Bt	Adequate	Present	Medium	Normal	Normal	Abnormal	Ambulate++
93	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
94	Normal	Small	Bt	Adequate	Present	Nopain	Mild	Normal	Normal	Ambulate++
95	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
96	Normal	Small	No	Adequate	Present	Medium	Normal	Normal	Normal	Ambulate++
97	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
98	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
99	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
100	Normal	Small	Bt	Inadequate	Present	Mild	Normal	Normal	Normal	No
101	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
102	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
103	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
104	Normal	Small	Bt	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
105	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
106	Normal	Medium	No	Adequate	Present	Medium	Normal	Normal	Normal	Ambulate++
107	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
108	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
109	Normal	Small	Bt	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
110	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
111	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
112	Normal	Small	No	Adequate	Present	Mild	Mild	Normal	Normal	Ambulate++
113	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
114	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
115	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
116	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
117	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
118	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
119	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
120	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
121	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++
122	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
123	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
124	Normal	Small	No	Adequate	Present	Mild	Normal	Normal	Normal	Ambulate++
125	Normal	Small	No	Adequate	Present	Nopain	Normal	Normal	Normal	Ambulate++

**Table 4 (continued):**

#	Variables and their values									
	Nutriw3	Nutrio3	Painr3	Resp3	Jp3	He ma3	Urineo3	Painm3	Wound3	LOS
76	Regular	Normal	Mild	Normal	Sma ll	No	Adequate	Mild	Normal	Delayed
77	Regular	Normal	Nopain	Normal	D/C	Bt	Adequate	Nopain	Normal	Delayed
78	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
79	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
80	Regular	Normal	Nopain	Normal	Med ium	No	Adequate	Mild	Normal	Delayed
81	Regular	Normal	Mild	Normal	D/C	Bt	Adequate	Mild	Normal	Delayed
82	Regular	Normal	Mild	Normal	D/C	Bt	Adequate	Medium	Mild	Delayed
83	Regular	Normal	Nopain	Normal	D/C	Bt	Adequate	Nopain	Normal	Delayed
84	Regular	Normal	Nopain	Normal	D/C	Bt	Adequate	Nopain	Normal	Met
85	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
86	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Delayed
87	Regular	Normal	Mild	Normal	D/C	Bt	Adequate	Mild	Mild	Delayed
88	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Mild	Met
89	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
90	Regular	Normal	Nopain	Normal	Sma ll	Bt	Adequate	Mild	Normal	Delayed
91	Regular	Normal	Nopain	Normal	D/C	Bt	Adequate	Nopain	Normal	Met
92	Regular	Normal	Mild	Normal	D/C	Bt	Adequate	Mild	Normal	Delayed
93	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
94	Regular	Normal	Nopain	Normal	D/C	Bt	Adequate	Nopain	Mild	Met
95	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Mild	Normal	Met
96	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Met
97	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Delayed
98	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
99	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
100	Fluid	Normal	Mild	Normal	D/C	No	Inadequat e	Mild	Normal	Delayed
101	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
102	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
103	Regular	Normal	Nopain	Normal	D/C	Bt	Adequate	Nopain	Normal	Met
104	Regular	Normal	Mild	Normal	D/C	Bt	Adequate	Mild	Normal	Met
105	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Mild	Normal	Met
106	Regular	Normal	Medium	Normal	Med ium	No	Adequate	Medium	Normal	Delayed
107	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
108	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
109	Regular	Normal	Nopain	Normal	D/C	Bt	Adequate	Nopain	Normal	Met
110	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
111	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
112	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Mild	Normal	Met
113	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Met
114	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Delayed
115	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
116	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
117	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
118	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Delayed
119	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
120	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Mild	Normal	Met
121	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	Met
122	Regular	Normal	Mild	Normal	D/C	No	Adequate	Mild	Normal	Delayed
123	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Mild	Normal	Met
124	Fluid	Normal	Nopain	Normal	D/C	No	Adequate	Mild	Normal	Delayed
125	Regular	Normal	Nopain	Normal	D/C	No	Adequate	Nopain	Normal	met

**Table 5: Conditional Probabilities Associated with Each Variable in the BBN\_RPC Model**

Parent Nodes	Node1: <b>Psycho</b>	
N/A	abnormal	normal
	0.033	0.967

Parent Nodes	Node2: <b>Vs1</b>	
N/A	abnormal	normal
	0.033	0.967

Parent Nodes	Node3: <b>ActW1</b>	
N/A	no	ambulate
	0.257	0.743

Parent Nodes	Node4: <b>NutriW1</b>	
N/A	Fluid	
	1.000	

Parent Nodes	Node7: <b>Resp1</b>	
<b>ActW1</b>	mild	normal
no	0.064	0.936
ambulate	0.004	0.996

Parent Nodes	Node10: <b>UrineO1</b>	
<b>Resp1</b>	inadequate	adequate
mild	0.833	0.167
normal	0.057	0.943

Parent Nodes	Node11: <b>BowelS1</b>	
N/A	absent	present
	0.033	0.967

Parent Nodes	Node13: <b>Vs2</b>	
<b>Vs1</b>	abnormal	normal
abnormal	0.900	0.100
normal	0.003	0.997

Parent Nodes	Node14: <b>Temp2</b>	
<b>Resp1</b>	abnormal	normal
mild	0.833	0.167
normal	0.151	0.849

Parent Nodes	Node15: <b>ActW2</b>	
<b>ActW1</b>	no	ambulate+
no	0.321	0.679
ambulate	0.022	0.978

Parent Nodes	Node5: <b>NutriO1</b>		
N/A	vomit	nausea	normal
	0.018	0.070	0.912

Parent Nodes	Node8: <b>JP1</b>		
<b>Vs1</b>	large	medium	small
abnormal	0.467	0.067	0.467
normal	0.002	0.070	0.927

Parent Nodes	Node9: <b>Hema1</b>		
<b>Resp1</b>	Y	Bt	No
mild	0.778	0.111	0.111
normal	0.083	0.445	0.472

Parent Nodes	Node12: <b>PainM1</b>		
<b>PainR1</b>	medium	mild	nopain
medium	0.973	0.013	0.013
mild	0.379	0.617	0.004
nopain	0.055	0.525	0.420

Parent Nodes	Node18: <b>PainR2</b>		
<b>PainM1</b>	medium	mild	nopain
medium	0.240	0.775	0.005
mild	0.029	0.446	0.525
nopain	0.007	0.007	0.986

Parent Nodes	Node21: <b>Hema2</b>		
<b>Hema1</b>	Y	Bt	no
Y	0.561	0.288	0.152
Bt	0.033	0.843	0.123
no	0.060	0.116	0.824

Parent Nodes	Node22: <b>UrineO2</b>		
<b>NutriW2</b>	<b>UrineO1</b>	inadequate	adequate
regular	inadequate	0.056	0.944
regular	adequate	0.003	0.997
fluid	inadequate	0.962	0.038
fluid	adequate	0.005	0.995

**Table 5 (continued):**

Parent Nodes		Node6: PainR1		
ActW1	Psycho	medium	mild	nopain
no	abnormal	0.867	0.067	0.067
no	normal	0.279	0.498	0.224
ambulate	abnormal	0.867	0.067	0.067
ambulate	normal	0.020	0.363	0.617

Parent Nodes			Node16: NutriW2	
Psycho	BowelS1	Vs2	fluid	Regular
abnormal	present	abnormal	0.500	0.500
abnormal	present	normal	0.029	0.971
abnormal	absent	abnormal	0.500	0.500
abnormal	absent	normal	0.500	0.500
normal	present	abnormal	0.029	0.971
normal	present	normal	0.695	0.305
normal	absent	abnormal	0.500	0.500
normal	absent	normal	0.029	0.971

Parent Nodes		Node17: NutriO2		
ActW1	NutriO1	nausea	vomit	Normal
no	vomit	0.333	0.333	0.333
no	nausea	0.026	0.487	0.487
no	normal	0.061	0.003	0.935
ambulate	vomit	0.048	0.048	0.905
ambulate	nausea	0.965	0.018	0.018
ambulate	normal	0.001	0.001	0.998

Parent Nodes		Node20: JP2		
Vs2	large	d/c	medium	Small
abnormal	0.450	0.050	0.050	0.450
normal	0.002	0.043	0.097	0.859

Parent Nodes		Node24: PainM2		
UrineO1	PainR2	medium	mild	Nopain
Inadequate	medium	0.333	0.333	0.333
Inadequate	mild	0.905	0.048	0.048
Inadequate	nopain	0.013	0.013	0.973
adequate	medium	0.982	0.009	0.009
adequate	mild	0.250	0.748	0.002
adequate	nopain	0.002	0.499	0.499

**Table 5 (continued):**

Parent Nodes		Node34: Hema3		
Resp1	Hema2	Y	Bt	no
Mild	Y	0.048	0.905	0.048
Mild	Bt	0.333	0.333	0.333
mild	no	0.333	0.333	0.333
normal	Y	0.333	0.333	0.333
normal	Bt	0.002	0.675	0.324
normal	no	0.002	0.002	0.997

Parent Nodes		Node36: PainM3		
PainM2	PainR3	medium	mild	Normal
medium	medium	0.965	0.018	0.018
medium	mild	0.168	0.829	0.003
medium	normal	0.033	0.033	0.933
mild	medium	0.333	0.333	0.333
mild	mild	0.002	0.996	0.002
mild	normal	0.002	0.570	0.428
normal	medium	0.333	0.333	0.333
normal	mild	0.033	0.933	0.033
normal	normal	0.002	0.002	0.996

Parent Nodes		Node30: NutriO3		
Temp2	NutriO2	nausea	vomit	Normal
abnormal	nausea	0.905	0.048	0.048
abnormal	vomit	0.048	0.905	0.048
abnormal	normal	0.005	0.005	0.989
normal	nausea	0.018	0.018	0.965
normal	vomit	0.333	0.333	0.333
normal	normal	0.001	0.001	0.998

Parent Nodes		Node23: BowelS2	
ActW1	BowelS1	present	absent
no	absent	0.900	0.100
no	present	0.993	0.007
ambulate	absent	0.100	0.900
ambulate	present	0.998	0.002

**Table 5 (continued): Conditional Probability for Each Variable in the BBN\_RPC**

Parent Nodes				Node31: PainR3		
Resp2	ActW3	Resp1	PainR2	medium	mild	normal
normal	No	mild	medium	0.333	0.333	0.333
normal	no	mild	mild	0.333	0.333	0.333
normal	no	mild	nopain	0.333	0.333	0.333
normal	no	normal	medium	0.949	0.026	0.026
normal	no	normal	mild	0.026	0.949	0.026
normal	no	normal	nopain	0.026	0.949	0.026
normal	ambulate++	mild	medium	0.333	0.333	0.333
normal	ambulate++	mild	mild	0.949	0.026	0.026
normal	ambulate++	mild	nopain	0.333	0.333	0.333
normal	ambulate++	normal	medium	0.005	0.989	0.005
normal	ambulate++	normal	mild	0.001	0.773	0.226
normal	ambulate++	normal	nopain	0.001	0.029	0.970

Parent Nodes			Node33: Jp3			
ActW3	Jp1	Jp2	large	medium	Small	d/c
no	large	large	0.970	0.010	0.010	0.010
no	large	d/c	0.250	0.250	0.250	0.250
no	large	medium	0.250	0.250	0.250	0.250
no	large	small	0.250	0.250	0.250	0.250
no	medium	large	0.250	0.250	0.250	0.250
no	medium	d/c	0.250	0.250	0.250	0.250
no	medium	medium	0.250	0.250	0.250	0.250
no	medium	small	0.250	0.250	0.250	0.250
no	small	large	0.250	0.250	0.250	0.250
no	small	d/c	0.250	0.250	0.250	0.250
no	small	medium	0.250	0.250	0.250	0.250
no	small	small	0.005	0.005	0.985	0.005
ambulate++	large	large	0.250	0.250	0.250	0.250
ambulate++	large	d/c	0.250	0.250	0.250	0.250
ambulate++	large	medium	0.250	0.250	0.250	0.250
ambulate++	large	small	0.250	0.250	0.250	0.250
ambulate++	medium	large	0.250	0.250	0.250	0.250
ambulate++	medium	d/c	0.010	0.010	0.010	0.970
ambulate++	medium	medium	0.010	0.970	0.010	0.010
ambulate++	medium	small	0.003	0.003	0.990	0.003
ambulate++	small	large	0.250	0.250	0.250	0.250
ambulate++	small	d/c	0.005	0.005	0.005	0.985
ambulate++	small	medium	0.002	0.002	0.995	0.002
ambulate++	small	small	0.000	0.000	0.153	0.847

**Table 5 (continued): Conditional Probability for Each Variable in the BBN\_RPC**

Parent Nodes				Node38: LOS	
UrineO3	PainR1	Jp1	NutriW2	Delayed	Met
inadequate	medium	large	regular	0.500	0.500
inadequate	medium	large	fluid	0.500	0.500
inadequate	medium	medium	regular	0.500	0.500
inadequate	medium	medium	fluid	0.500	0.500
inadequate	medium	small	regular	0.500	0.500
inadequate	medium	small	fluid	0.500	0.500
inadequate	mild	large	regular	0.500	0.500
inadequate	mild	large	fluid	0.500	0.500
inadequate	mild	medium	regular	0.500	0.500
inadequate	mild	medium	fluid	0.500	0.500
inadequate	mild	small	regular	0.500	0.500
inadequate	mild	small	fluid	0.986	0.014
inadequate	nopain	large	regular	0.500	0.500
inadequate	nopain	large	fluid	0.500	0.500
inadequate	nopain	medium	regular	0.500	0.500
inadequate	nopain	medium	fluid	0.500	0.500
inadequate	nopain	small	regular	0.500	0.500
inadequate	nopain	small	fluid	0.993	0.007
adequate	medium	large	regular	0.500	0.500
adequate	medium	large	fluid	0.986	0.014
adequate	medium	medium	regular	0.500	0.500
adequate	medium	medium	fluid	0.986	0.014
adequate	medium	small	regular	0.003	0.997
adequate	medium	small	fluid	0.993	0.007
adequate	mild	large	regular	5.000	0.500
adequate	mild	large	fluid	0.500	0.500
adequate	mild	medium	regular	0.993	0.007
adequate	mild	medium	fluid	0.500	0.500
adequate	mild	small	regular	0.001	0.999
adequate	mild	small	fluid	0.001	0.999
adequate	nopain	large	regular	0.500	0.500
adequate	nopain	large	fluid	0.500	0.500
adequate	nopain	medium	regular	0.014	0.986
adequate	nopain	medium	fluid	0.014	0.986
adequate	nopain	small	regular	0.001	0.999
adequate	nopain	small	fluid	0.334	0.666

**Table 5 (continued):**

Parent Nodes			Node28: ActW3	
ActW2	no	ambulate+		
no	0.433	0.567		
ambulate	0.004	0.997		

Parent Nodes		Node32: Resp3	
N/A	normal		
	1.000		

Parent Nodes		Node19: Resp2	
N/A	normal		
	1.000		

Parent Nodes			Node35: UrineO3	
UrineO2	abnormal	normal		
abnormal	0.900	0.100		
normal	0.500	0.500		
abnormal	0.944	0.056		
normal	0.002	0.998		

Parent Nodes				Node25: Wound2		
NutriO1	medium	mild	normal			
Vomit	0.083	0.833	0.083			
Nausea	0.021	0.583	0.396			
Normal	0.016	0.074	0.910			

Parent Nodes		Node26: Vs3	
Vs1	Vs2	abnormal	normal
abnormal	Abnormal	0.944	0.056
abnormal	Normal	0.500	0.500
Normal	Abnormal	0.500	0.500
Normal	Normal	0.002	0.998

Parent Nodes		Node27: Temp3	
ActW1	Temp2	abnormal	normal
No	Abnormal	0.971	0.029
No	Normal	0.205	0.795
ambulate	Abnormal	0.621	0.379
ambulate	Normal	0.023	0.977

Parent Nodes				Node37: Wound3		
Wound2	medium	mild	normal			
medium	0.833	0.083	0.083			
mild	0.012	0.440	0.548			
normal	0.002	0.017	0.981			

Parent Nodes									Node29: NutriW3	
Vs1	Vs2	BowelS2	PainR2	ActW3	Resp1	Vs3	Bowel1	NutriW2	fluid	regular
abnormal	abnormal	present	medium	no	Mild	abnormal	present	fluid	0.500	0.500
...	...	...	mild	...	...	...	...	...	...	...
			...						0.500	0.500
normal	normal	absent	nopain	ambulate++	normal	normal	absent	regular	0.500	0.500

Note: Here we did not include a whole table of the conditional probabilities for node 29 in the BBN\_RPC because this table consists of the 768 rows and all the conditional probabilities are the same.

**Table 6: Probabilities of Each Variable in the BBN\_RPC Model**

No.	variable	value	Probability (75 cases)	No.	variable	value	Probability (75 cases)
1	Psycho	abnormal	0.033	21	Hema2	yes	0.096
		normal	0.967			Bt	0.452
2	Vs1	abnormal	0.033			no	0.452
		normal	0.967	22	UrineO2	inadequate	0.031
3	ActW1	no	0.257			adequate	0.969
		ambulate	0.743	23	BowelS2	absent	0.026
4	NutriW1	Fluid	1.000			present	0.974
		5	NutriO1	vomit	0.018	24	PainM2
nausea	0.070			mild	0.531		
normal	0.912			nopain	0.258		
6	PainR1	medium	0.112	25	Wound2	medium	0.018
		mild	0.387			mild	0.123
		nopain	0.501			normal	0.860
7	Resp1	mild	0.020	26	Vs3	abnormal	0.033
		normal	0.980			normal	0.967
8	Jp1	large	0.018	27	Temp3	abnormal	0.177
		medium	0.070			normal	0.823
		small	0.912	28	ActW3	no	0.046
9	Hema1	yes	0.096			ambulate+	0.954
		Bt	0.439	29	NutriW3	fluid	0.895
		no	0.465			regular	0.105
10	UrineO1	inadequate	0.072	30	NutriO3	vomit	0.009
		adequate	0.928			nausea	0.016
11	BowelS1	absent	0.033			normal	0.975
		present	0.967	31	PainR3	medium	0.019
12	PainM1	medium	0.283			mild	0.444
		mild	0.503			nopain	0.537
		nopain	0.214	32	Resp3	normal	1.000
13	Vs2	abnormal	0.033			33	Jp3
		normal	0.967	medium	0.016		
14	Temp2	abnormal	0.164	small	0.297		
		normal	0.836	d/c	0.677		
15	ActW2	no	0.099	34	Hema3	yes	0.035
		ambulate+	0.901			Bt	0.314
16	NutriW2	fluid	0.367			no	0.652
		regular	0.633	35	UrineO3	inadequate	0.038
17	NutriO2	vomit	0.013			adequate	0.962
		nausea	0.068	36	PainM3	medium	0.046
		normal	0.919			mild	0.572
18	PainR2	medium	0.084			nopain	0.382
		mild	0.440	37	Wound3	medium	0.018
		nopain	0.476			mild	0.070
19	Resp2	normal	1.000			normal	0.912
		20	Jp2	large	0.016	38	LOS
medium	0.095			met	0.840		
small	0.845						
d/c	0.043						

**Table 7: Probabilities of Outcomes on Post-op Day 3 for a “Good Case” patient p1**

No.	Variable Name	Categories	Posterior Probability
26	Vs3	abnormal	0.002
		normal	0.998
27	Temp3	abnormal	0.023
		normal	0.977
28	ActW3	no	0.004
		ambulate++	0.996
29	NutriW3	fluid	0.500
		regular	0.500
30	NutriO3	vomit	0.001
		nausea	0.001
		normal	0.998
31	PainR3	medium	0.001
		mild	0.774
		nopain	0.225
32	Resp3	Normal	1.000
33	Jp3	Large	0.000
		Medium	0.000
		Small	0.156
		d/c	0.844
34	Hema3	Yes	0.002
		Bt	0.675
		No	0.324
35	UrineO3	inadequate	0.002
		Adequate	0.998
36	PainM3	Medium	0.002
		Mild	0.898
		Nopain	0.098
37	Wound3	Medium	0.0021
		Mild	0.017
		Normal	0.981
38	LOS	Delayed	0.002
		Met	0.998

**Table 8: Posterior Probabilities for Patient's LOS given Each Event**

No.	Variable name	Categories	PosteriorProbability for patientLOS (met,delayed)		Event
1	Psycho	abnormal	0.185	0.815	e1
		normal	0.863	0.137	e2
2	Vs1	abnormal	0.595	0.405	e3
		normal	0.849	0.151	e4
3	ActW1	no	0.79	0.210	e5
		ambulate	0.858	0.142	e6
4	NutriW1	Fluid	0.84	0.160	e7
5	NutriO1	vomit	0.84	0.160	e8
		nausea	0.84	0.160	e9
		normal	0.84	0.160	e10
6	PainR1	medium	0.497	0.503	e11
		mild	0.904	0.096	e12
		nopain	0.868	0.132	e13
7	Resp1	mild	0.552	0.448	e14
		normal	0.846	0.154	e15
8	Jp1	large	0.462	0.538	e16
		medium	0.59	0.410	e17
		small	0.867	0.133	e18
9	Hema1	yes	0.799	0.201	e19
		Bt	0.845	0.155	e20
		no	0.845	0.155	e21
10	UrineO1	inadequate	0.634	0.366	e22
		adequate	0.856	0.144	e23
11	BowelS1	absent	0.695	0.305	e24
		present	0.845	0.155	e25
12	PainM1	medium	0.744	0.256	e26
		mild	0.884	0.116	e27
		nopain	0.865	0.135	e28
13	Vs2	abnormal	0.598	0.402	e29
		normal	0.849	0.151	e30
14	Temp2	abnormal	0.817	0.183	e31
		normal	0.845	0.155	e32
15	ActW2	no	0.801	0.199	e33
		ambulate+	0.845	0.155	e34
16	NutriW2	fluid	0.638	0.362	e35
		regular	0.957	0.043	e36

**Table 8 (continued):**

No.	Variable name	Categories	PosteriorProbability		Event
			for patient'sLOS (met,delayed)		
17	NutriO2	vomit	0.801	0.199	e37
		nausea	0.841	0.159	e38
		normal	0.841	0.159	e39
18	PainR2	medium	0.771	0.229	e40
		mild	0.816	0.184	e41
		nopain	0.875	0.125	e42
19	Resp2	normal	0.84	0.160	e43
20	Jp2	large	0.632	0.377	e44
		medium	0.844	0.156	e45
		Small	0.844	0.156	e46
		d/c	0.839	0.161	e47
21	Hema2	yes	0.819	0.181	e48
		Bt	0.842	0.158	e49
		no	0.843	0.157	e50
22	UrineO2	inadequate	0.222	0.778	e51
		adequate	0.86	0.140	e52
23	BowelS2	absent	0.737	0.263	e53
		present	0.737	0.263	e54
24	PainM2	medium	0.783	0.217	e55
		mild	0.855	0.145	e56
		nopain	0.857	0.143	e57
25	Wound2	medium	0.84	0.160	e58
		mild	0.84	0.160	e59
		normal	0.84	0.160	e60
26	Vs3	abnormal	0.61	0.390	e61
		normal	0.848	0.152	e62
27	Temp3	abnormal	0.809	0.191	e63
		normal	0.847	0.153	e64
28	ActW3	no	0.804	0.196	e65
		ambulate++	0.842	0.158	e66
29	NutriW3	fluid	0.625	0.375	e67
		regular	0.865	0.135	e68
30	NutriO3	vomit	0.805	0.195	e69
		nausea	0.82	0.18	e70
		normal	0.841	0.159	e71

**Table 8 (continued):**

No.	Variable name	Categories	PosteriorProbability for patientLOS (met,delayed)		Event
31	PainR3	medium	0.632	0.368	e72
		mild	0.816	0.184	e73
		nopain	0.868	0.132	e74
32	Resp3	normal	0.84	0.16	e75
33	Jp3	large	0.607	0.393	e76
		medium	0.606	0.394	e77
		small	0.806	0.194	e78
		d/c	0.865	0.135	e79
34	Hema3	yes	0.812	0.188	e80
		Bt	0.835	0.165	e81
		no	0.844	0.156	e82
35	UrineO3	inadequate	0.246	0.754	e83
		adequate	0.864	0.136	e84
36	PainM3	medium	0.744	0.256	e85
		mild	0.833	0.167	e86
		nopain	0.862	0.138	e87
37	Wound3	medium	0.84	0.16	e88
		mild	0.84	0.16	e89
		normal	0.84	0.16	e90