Using a Bayesian Belief Network Model to Categorize Length of Stay for Radical Prostatectomy Patients

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Acknowledgment

Research described in this paper was supported by the NSERC-CHRP grant. It was conducted when Szymon Wilk was a post-doctoral fellow at the MET Research Group, University of Ottawa.
The authors would like to thank the anonymous reviewers for their helpful suggestions that improved this paper.

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Abstract

A clinical pathway implements best medical practices and represents sequencing and timing of interventions by clinicians for a particular clinical presentation. We used a Bayesian belief network (BBN) to model a clinical pathway for radical prostatectomy and to categorize patient's length of stay (LOS) as being met or delayed given the patient's outcomes and activities. A BBN model constructed from historical data collected as part of a retrospective chart study represents probabilistic dependencies between specific events from the pathway and identifies events directly affecting LOS. Preliminary evaluation of a BBN model on an independent test sample of patients' data shows that model reliably categorizes LOS for the second and third day after the surgery (with overall accuracy of 82% and 84% respectively).

Keywords

Clinical pathway, length of stay, radical prostatectomy, Bayesian belief network, clinical decision support

1. Introduction

A clinical pathway (also called critical pathway, care map, or integrated plan of care) describes the sequencing and timing of interventions by physicians, nurses and other healthcare professionals, designed to minimize delays, improve resource utilizations and enhance the quality of tertiary care. Clinical pathways have been accepted in hospitals and various healthcare organizations in many countries as a tool that facilitates the management and delivery of quality clinical care.

A clinical pathway "amalgamates all the anticipated elements of care and treatment of all members of the multidisciplinary team, for a patient of a particular case-type or grouping within an agreed time frame, for the achievement of agreed outcomes" [1]. It usually consists of four essential components: a timeline, patient activities, patient outcomes, and the variance record. The variance record documents all outcome and activity deviations from the pathway. Such a record can later be used to revise and modify a pathway.

It is argued that managing a patient according to a clinical pathway should result in more effective care. This argument is true provided that a patient's progress as described by outcomes and clinical team activities does not deviate significantly from the pathway, while in a tertiary care practice such deviations occur [2]. Development of the clinical pathways is described in the literature, while the impact of the actual outcomes and activities on patient's length of stay (LOS) is less reported.

Research on clinical pathways mostly deals with representing them in a formal way [3, 4] by documenting, collecting and representing variances [5, 6], and developing decision support tools that would supplement a pathway with a predictor of LOS [7, 8]. Widely adopted methodologies to model clinical pathways and the clinical guidelines they implement [9] include PERT/CPM models [3], Petri nets, skeletal plans and decision rules in the Arden syntax (see [4] for a review). The methodologies for using variance records allow tracking variances associated with a clinical pathway [5, 6], but are usually limited to variance frequencies, while their impact on LOS is not evaluated [5]. Finally, predictors of LOS are often implemented with neural network models; thus they may be difficult to comprehend by the patient management teams, although they may have acceptable predictive accuracy [7, 8].

In the research described in this paper we developed a theoretical model of a clinical pathway that addresses the interrelated character of the activities and outcomes in the pathway and can be used to assess their impact on patient's LOS. We implemented the theoretical model using a clinical pathway developed and used at The Ottawa Hospital – Civic Campus for management of radical prostatectomy (RPP). The RPP timeline covers the surgery day, four days after it, and subsequent visits to the urology clinic. The RPP describes approved practice guidelines that specify how to manage patients after the surgery in order to discharge them after four days (or earlier if possible). In other words the RPP is used at The Ottawa Hospital – Civic Campus to manage routine or typical case mix that has reasonable chance to be discharged as per RPP guidelines. Difficult radical prostatectomy patients receive specialized post-surgical care and the RPP is not followed due to unlikely event of maintaining LOS. However, the number of such cases (i.e., those who are not managed according to the RPP) is relatively small. Thus, the patient management team is using the RPP as a standardized management tool as opposed to a personalized diagnostic tool used to evaluate severity of patient's conditions in order to derive at revised prognosis.

Considering the nature of the decision problem and the characteristics of a pathway, we used a Bayesian belief network (BBN) as the theoretical decision model to predict the impact of the activities and outcomes on LOS (we will use the term BBN-RPP model hereafter while referring to this implementation). Specifically, the BBN-RPP model allows for re-evaluating the probabilities of LOS being met or delayed.

The BBN methodology was selected for several reasons. First, evaluating the impact of observed outcomes and activities on probability of maintaining or delaying LOS on the basis of current observations is a typical conditional-type probability question. A BBN model is designed to answer such a question. Second, the clinical pathway represents a sequence of events (patient outcomes and activities) in time and the relationships among them. Therefore, it is possible to view the pathway as a probabilistic process with conditional probabilities of the events that can be assessed from past data. The events on the pathway are interdependent and form a network structure that can be represented by a BBN. Moreover, a BBN is well suited to represent events as variables with sets of possible values and their assigned probabilities [10]. Finally, unlike a neural network, a BBN provides a comprehensive and readable representation of a clinical pathway that can be verified and examined by physicians and other patient management team members.

The process of developing the BBN-RPP model involved several steps. First, we identified the variables describing events in the RPP. Then, we collected the data required for developing the model from the retrospective chart study, and constructed the model using this data. Finally, we conducted a validation test to verify the predictive accuracy of the BBN-RPP model using new patients' data.

The BBN-RPP model was implemented in the MET environment [11] as the MET-MPM (Mobile Pathway Monitor) application – a decision support tool for categorizing LOS given a patient's outcomes and activities. MET is a decision support environment for developing and deploying point-of-care applications available *anytime and anywhere*, running on various mobile devices (e.g., handheld or tablet computers) and supporting diversified clinical problems (including triage, management and access to clinical information). In the past we used the MET environment to implement several clinical applications, mainly for triaging various presentations of acute pain (abdominal pain [12] and scrotal pain [13]). Some of them were successfully tested in clinical practice [14], further validating our decision support methodology.

2. Methods

2.1. Retrospective chart study

The data collection was conducted at The Ottawa Hospital - Civic Campus (Ottawa, Ontario, Canada), which belongs to The Ottawa Hospital group. It is a teaching hospital affiliated with the University of Ottawa and it provides health care services on a tertiary-level and specialty care to the residents of Eastern Ontario. The hospital handles 70,000 surgical cases, 120,000 emergency visits and 770,000 outpatient visits a year (2004 data). For a retrospective study we used charts of cancer patients managed by different surgical teams for the radical prostatectomy during the period 2002 to 2003. As epidemiological studies have not shown differences in recovery patterns after a radical prostatectomy between Canadian, U.S., and European populations it is reasonable to conclude that our sample is representative of other populations.

The RPP timeline covers the surgery day, four days after it, and subsequent visits to the urology clinic. We focused on the period after the surgery and considered three time windows, referring to the first, second and third day (from 00:00 to 24:00) of the patient's stay in the hospital ward after the surgery and denoted them as post-op day 1, 2 and 3 respectively. We did not consider the day of surgery because of completely different management regime, and post-op day 4 because it is a discharge day according to the pathway. In order to obtain a complete clinical picture for each patient included in the study, we integrated data recorded in the RPP with information from the Discharge Summary, Integrated Progress Notes, and Variance Tracking Records that form standard information components included in a patient's file. All of the expected patient's outcomes listed in the clinical pathway (e.g., urine output, wound outcome, etc.) were represented as variables. This list was further expanded to include variables representing some non-outcome related activities (e.g., nutrition with RPP, ambulation with RPP). LOS was defined as a dependent variable and it indicated whether the expected length of hospital stay was met (was shorter or equal to 4 post-op days as suggested in the pathway) or delayed (was longer than 4 post-op days). Theoretically it is possible to predict exact LOS in days instead of categorizing it as being met or delayed. However, in practice most of the patients are discharged on post-op day 4 or 5 (there are very few patients discharged on 6 day or later), thus a binary categorization of values of LOS results in more reliable decision model.

Table 1 presents all variables considered in the retrospective study together with their values and time windows of occurrence (indicated by "+" symbol for appropriate time window). This binding of variables to specific time windows (post-op days) allowed us to capture time dependency of events in the RPP by sequencing the variables in the BBN model. The majority of variables were observed in all time windows (e.g., vital signs). However, some variables were limited to specific post-op days (e.g., psychological condition was evaluated on post-op day 1 only). There were a few variables that had values common for all post-op days, and a few that had day-specific values (e.g., a normal value of the respiratory function might occur on post-op day 1, 2 and 3, while mild on post-op day 1 only, as indicated by "+" in appropriate time window column in Table 1). Variables having only one value for a specific time window were excluded from the analysis for that day (e.g., respiratory function for post-op day 2 and 3). This limited the number of all variables included in the BBN model to 35 (including the LOS variable).

Insert Table 1 here

Reducing chances for faulty input data asks for an involvement of a domain expert in data transcription, especially if data comes from a retrospective chart study. In many instances, availability of such an expert can constitute a bottleneck in model development process. In a study described here data transcribed from patients' files had to be preprocessed by a urology specialist. The preprocessing included translation of information recorded on charts as text notes to specific values (e.g., a note describing vital signs was translated into one of two possible values -- normal or abnormal). Moreover, numerical information was discretized according to the norms defined by a specialist. For example, the pain score for pain at rest was transformed into one of three discrete values – no pain (recorded score equal to 0), mild pain (recorded score between 1 and 3) and medium pain (recorded score between 4 and 7).

2.2. Foundations of a BBN model

In this section we present the basic theory behind a BBN model that was described in detail in [10, 15] among others. A BBN denoted by $B=(G,P)$ is represented by a directed acyclic graph $G=(X,A)$ with a set of nodes $X=\{x_1,x_2,\ldots,x_n\}$ representing stochastic variables taking a finite set of values, and a set of arcs $A\in X\times X$ representing direct dependencies between the associated variables. The strength of these dependencies is quantified by conditional probabilities. A joint probability distribution P is defined on the stochastic variables that can be factorized according to the topology of the graph as follows: $P(x_1,x_2,\ldots,x_n)=\prod_{i=1}^{n}P(x_i|par(x_i))$ where $par(x_i)$ is parent of the node x_i. This implies that $P(x_1,x_2,\ldots,x_n)$ can be defined in terms of local probability tables $P(x_i|par(x_i))$ by assuming the variable x_i to be conditionally independent of all its predecessors given the parents $par(x_i)$ [16]. Such a formulation allows evaluating conditional probabilities being subject to some earlier observations, providing that there is a path in a network linking the variables in question.

In order to develop a BBN, it is necessary to know the precedence relationships in a network, the events and their occurrences, and the conditional probabilities associated with the values of variables representing these events. There are several ways to acquire this information. One is to develop the BBN model from the subjective assessment elicited from a domain expert. Another is to estimate the model from historical data. This latter approach was used to develop the BBN-RPP model. The motivation for such an approach is as follows:

1. In the RPP, the relationships between the events are complicated, which makes it difficult to develop manually the cause-effect graph.
2. Conditional probabilities can be obtained either from extensive interviews with the experts – a method not feasible in most practical applications – or automatically. We decided on automatic acquisition and conditional probabilities were estimated from data using the maximum likelihood method.

We used the K2 algorithm [15] to develop the BBN-RPP model from a retrospective data set. K2 constructs a BBN model from a set of cases D described by a set of ordered discrete variables $X=\{x_1,x_2,\ldots,x_n\}$. It uses a greedy search method to build the structure of a BBN, and it works in a loop over all variables that become nodes in the network, initially assuming that a node has no parents. Then it incrementally adds a parent that gives the highest increase of the probability of the resulting network. If it is impossible to increase the posterior probability of the network or the maximum number of parents a node in a network may have is reached, the algorithm stops resulting in a BBN that maximizes $P(B,D)$ – the posterior probability of a network B on a database D.

Once a BBN model is constructed, it can be used to make bi-directional inferences. There are many effective procedures to make inferences using a BBN model [16, 17]. They all operate on the same underlying probability distribution and therefore the results – the required conditional probabilities – are the same.

2.3. Evaluation of a BBN model

In order to evaluate the quality of the BBN-RPP model, we conducted an experiment that verified its predictive capabilities and classification accuracy. In this experiment we used an independent sample of patients' charts that were selected following the protocol used earlier in the retrospective study described in Section 2.1.

Data from these new charts were used as input to the BBN-RPP model, and the outcome with the highest probability (met or delayed LOS,) was considered as a recommendation to be compared with the gold standard (verified LOS recorded on a patient's chart).

In order to perform a thorough validation and verify the ability of the BBN-RPP model to categorize LOS early in the management process, we used a three-step validation procedure. In the first step, we used data from post-op day 1 as an input to the model; in the second step we used data from post-op day 1 and 2; and in the third step we used data from all three days. These steps correspond to using the model on the first, second and third post-op day respectively.

The classical measure of the performance of a decision model is *accuracy of classification*, defined here as a percentage ratio of the correctly classified charts to all classified charts. We used this measure when testing the BBN-RPP model on the independent sample to evaluate its overall performance and the performance for specific decision classes.

3. Results

3.1. Data

A set of 75 charts was selected and values were transcribed to form a learning data set (see Table 2 for a description). The set included a complete description for each patient's chart (values of all necessary variables were recorded), with a well balanced distribution between LOS classes (55% of patients coming from the met LOS class, and the remaining 45% from the delayed LOS class).

Insert Table 2 here

The learning set satisfied all requirements of the K2 algorithm; namely all variables were discrete and did not have missing values, all cases were independent, and variables were ordered according to the time sequence outlined in the RPP by binding specific variables to specific post-op days.

3.2. BBN-RPP model structure

The BBN-RPP model takes patient outcomes and activities as inputs and as output provides conditional probabilities of LOS being met or delayed. The model also provides a graphical visualization of the relationships between the variables representing events in the pathway. From the structure of the BBN-RPP model (Figure 1) it can be seen that the variables (see nodes that are directly linked by arcs to LOS node and are highlighted in Figure 1) immediately affecting LOS are:

- The type of patient's nutrition (liquid or solid) in post-op day 2 (NutriW2).
- The amount of drainage from the Jackson-Pratt wound drain in post-op day 3 (Jp3).

Moreover, the model's structure clearly underlines time dependencies between events – variables are constrained to depend only on their predecessors as specified in the RPP timeline, e.g., variables for post-op day 2 depend only on variables recorded on post-op day 1 and 2 (NutriW2 depends on Psycho1 and Vs2), and not on those for post-op day 3.

Insert Figure 1 here

The BBN-RPP model can be used not only to categorize LOS given values of observed variables, but also to evaluate the impact of observed variables on the patient's future conditions and LOS. For example, Tables 3 and 4 present results of evaluating the impact of two variables directly affecting LOS on the conditional probabilities of LOS being met or delayed. This analysis can be expanded to include any linked pair of variables in the BBN model and thus verify how the specific patient's outcomes and activities affect his future condition.

Insert Table 3 here

Insert Table 4 here

3.3. Evaluation of the BBN-RPP model

The BBN-RPP model was evaluated on a testing set transcribed retrospectively from 50 new charts. The testing set included a higher proportion of charts with met LOS (66%) than the learning set (see Table 5).

Insert Table 5 here

The results of the evaluation are presented in Table 6.

Insert Table 6 here

They show that the BBN-RPP model reliably categorizes LOS on post-op day 2 and 3 and that in general, it is more accurate in categorizing patients' to met LOS class. Such model's behavior follows intuition – patients discharged according to the pathway usually do not have complications, and their progression through the pathway follows a pattern that is easier to describe and capture by the BBN-RPP model. On the other hand, patients who stay longer than planned may suffer from a variety of complicating conditions that are difficult to capture in the model. Although the overall classification on post-op day 1 is relatively high (74%), the model overestimates the met LOS class, misclassifying many charts of patients with delayed LOS. On post-op day 2 the predictive power of the BBN-RPP model improves – the accuracy for the delayed LOS class increases from 24% to 65%, and it further improves on post-op day 3, reaching 71%. Interestingly, the accuracy for the met LOS class is relatively stable – it decreases after post-op day 1 (it was 100% for that day) to 91% on both post-op days 2 and 3. It is consistent with an intuition – the more information about a patient's outcomes and activities becomes available, the more accurately the model works. The results reported here may differ for different centers, but they demonstrate significant potential of the proposed modeling methodology for evaluating causal inferences in the RPP.

4. Conclusions

Research described in this paper used a retrospective chart study to develop the BBN-RPP model representing a clinical pathway. We applied this model to predict the revised probability for LOS being met or delayed. The structure of the BBN-RPP model and all conditional probabilities were obtained from data using automatic learning. The performance of the model was tested on an independent sample of chart data and the results demonstrated that the model very well describes probabilistic inferences.

Following consultations with urology specialists, we were able to conclude that the BBN-RPP model supports an understanding of the process of patient care by providing new information for evaluating the impact of events on a patient's progression according to the RPP. Unlike in conventional approaches where such evaluation is based on experience of members of a clinical team, here the information coming from the BBN-RPP model is objective and observer-independent as it is elicited using historical data. Additional advantages of using the BBN-RPP model include ability to identify events that are directly associated with LOS, and also an opportunity to re-evaluate patient's management considering revised conditional probabilities of the events from the RPP providing new information about patient's condition.

The BBN-RPP model was implemented as the MET-MPM application within the MET environment. In a tertiary care a tool like MET-MPM should give a clinical management team new insight into the patient's LOS given the current observations. Since LOS is one of the most important proxies for resource utilization in a hospital, the determination of intervening events in a pathway and evaluation of their chances of occurrence should support more effective utilization of resources required to manage patient's recovery after a surgery.

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Table 1: Variables in the RPP

Code	Name	Values	Descriptions or examples	Post-op day 1	2	3
Psycho	Patient psychological condition	abnormal	e.g. Patient's anxiety	+		
		normal	Patient can understand and is compliant	+		
Vs	Vital signs	abnormal	e.g. The pulse rate of the patient is abnormal	+	+	+
		normal	Vital signs of the patient are normal	+	+	+
Temp	Temperature	abnormal	Patient's temperature is abnormal		+	+
		normal	Patient's temperature is normal		+	+
ActW	Ambulation with the RPP	no	Patient does not ambulate	+	+	+
		ambulate	Patient does (progressive) ambulation	+	+	+
NutriW	Nutrition with the RPP	fluid	Patient drinks fluid	+	+	+
		regular	Patient takes regular foods		+	+
NutriO	Nutrition outcome	vomit	Patient vomits	+	+	+
		nausea	Patient feels nausea	+	+	+
		normal	None of the above	+	+	+
PainR	Pain at rest	medium	The verbal pain score at rest of the patient is between 4-7	+	+	+
		mild	The verbal pain score at rest of the patient is between 1-3	+	+	+
		nopain	Patient has no pain at rest (score 0)	+	+	+
Resp	Respiratory function	mild	e.g. Crackle, difficult to breath	+		
		normal	The respiratory function of the patient is normal	+	+	+
Jp	JP (Jackson Pratt wound drainage system) output	large	The amount of JP output is large	+	+	+
		medium	The amount of JP output is medium	+	+	+
		small	The amount of JP output is small	+	+	+
		d/c	JP is discontinued		+	+
Hema	Evidence of hematuria	yes	Patient has evidence of hematuria	+	+	+
		bt	Patient has blood-tinged	+	+	+
		no	Patient has no evidence of hematuria	+	+	+
UrineO	Urine output	inadequate	The amount of urine output is inadequate	+	+	+
		adequate	The amount of urine output is adequate	+	+	+
BowelS	Bowel sounds outcome	absent	The bowel sound is absent	+	+	
		present	The bowel sound is present	+	+	
PainM	Mobility outcome	medium	The verbal pain score with mobility of the patient is between 4-7	+	+	+
		mild	The verbal pain score with mobility of the patient is between 1-3	+	+	+
		nopain	Patient has no pain with mobility (score 0)	+	+	+
Wound	Wound outcome	medium	Patient's incision has severe infection		+	+
		mild	Patient's incision has mild infection		+	+
		normal	Patient's incision has no evidence of redness, swelling, rash, dehiscence		+	+
LOS	Length of patient's stay	delayed	Patient is discharged after post-op day 4			
		met	Patient is discharged on or before post-op day 4			

Table 2: Learning data set

	# of charts	% of charts
Met LOS	41	54.7
Delayed LOS	34	45.3
Total	75	100.0

Table 3: Evaluation of the impact of the nutrition in the post-op day 2 (NutriW2) on LOS

	Probability of LOS	
NutriW2	Met	Delayed
Fluid	0.265	0.735
Regular	0.684	0.316

Table 4: Evaluation of the impact of the JP output in the post-op day 3 (JP3) on LOS

	Probability of LOS	
JP3	Met	Delayed
Large	0.181	0.819
Medium	0.325	0.675
Small	0.216	0.784
D/c	0.677	0.323

Table 5: Testing data set

	# of charts	% of charts
Met LOS	33	66.0
Delayed LOS	17	34.0
Total	50	100.0

Table 6: Results of evaluation of the BBN-RPP model

Accuracy	Post-op day 1	Post-op day 2	Post-op day 3
Met LOS	100.0%	90.9%	90.9%
Delayed LOS	23.5%	64.7%	70.6%
Overall	74.0%	82.0%	84.0%

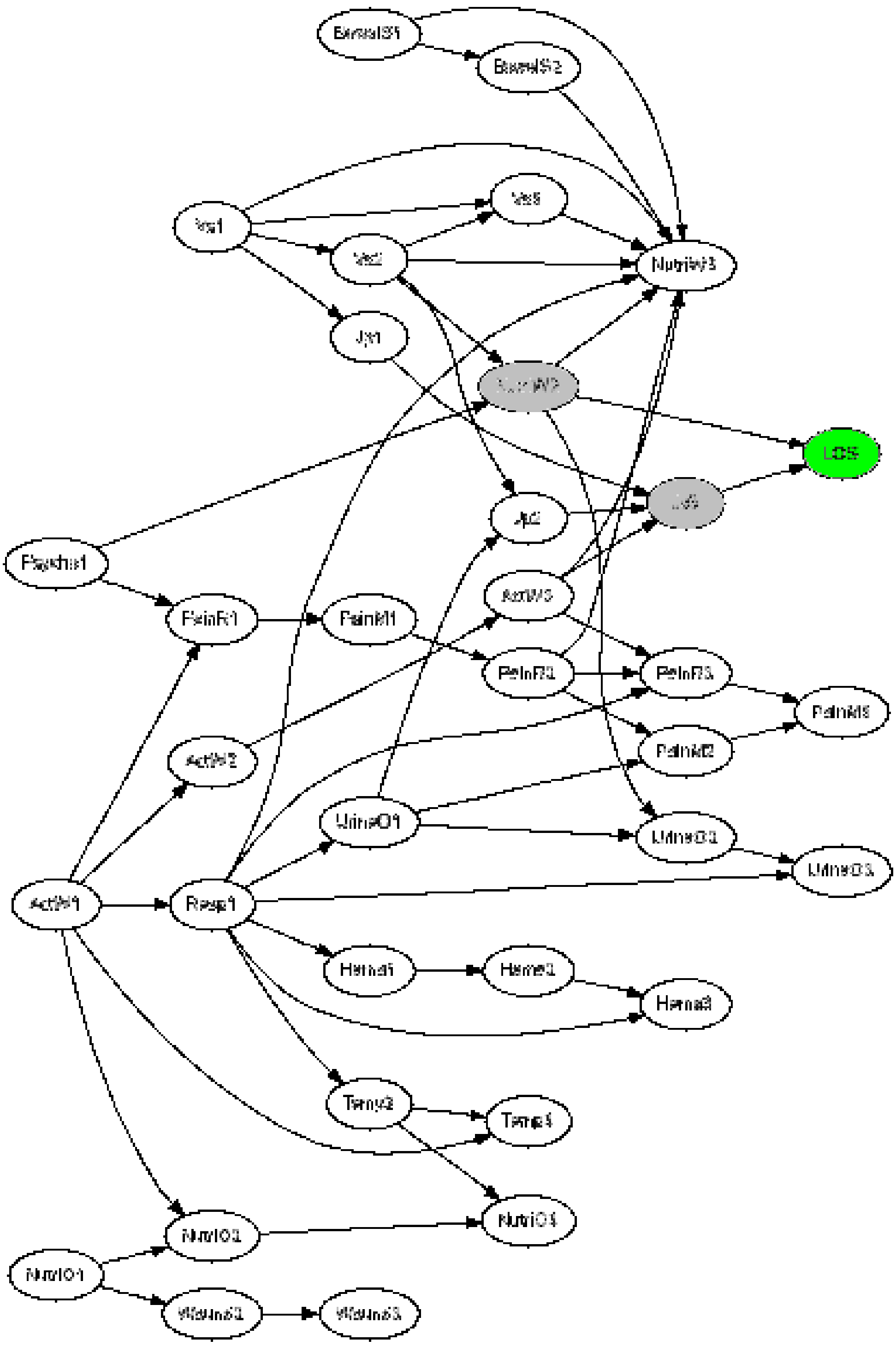

Figure 1. Network structure of the BBN-RPP model