

A Bayesian decision support model for assessment of endodontic treatment outcome

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Objective. This article presents a decision support model that describes the mutual relationships among multiple variables for assessment of the outcome of endodontic treatment.

Study design. The model was built on the data-driven Bayesian network (BN) methodology. Randomized controlled trials of nonsurgical endodontic treatment from January 1966 through August 2007 were chosen to be our data source. The total sample size in the included studies was 8783 cases. The structure and conditional probability distributions of the BN were learned from the data using Necessary Path Condition algorithm and Expectation-Maximization learning algorithm respectively.

Results. Receiver operating characteristic curve analysis showed that the model was highly accurate in predicting the endodontic treatment outcome; the area under the curve (AUC) was 0.902. The predictions generated by the model are in line with majority consensus predictions of the endodontists. In the cases where the endodontists' predictions were uncertainty, the proposed model predicted them more accurately.

Conclusion. A decision support model can be constructed from clinical trails to successfully predict endodontic treatment outcome. (*Oral Surg Oral Med Oral Pathol Oral Radiol Endod* 2008;xx:xxx)

Optimal dental treatment planning requires an accurate assessment of the outcome of any required endodontic treatment. Relevant knowledge on the outcome of endodontic treatment is key to clinical decision making, particularly when endodontic treatment is weighed against tooth extraction and replacement. Endodontic treatment outcome is a multifactorial event. Numerous studies have examined the potential association between various factors and the outcome of endodontic treatment, e.g., presence of periapical lesion and number of visits,¹ type of sealer,² or type of coronal restoration³; this does not allow several independent variables to be considered simultaneously.

Clinical decision-support models are designed to provide expert support for health professionals making clinical decisions. The models use embedded clinical knowledge to help clinicians analyze patient data and make decisions regarding diagnosis, prevention, and

treatment. Prognostic models in particular have become important instruments for prediction purposes that help clinicians and patients to make treatment choices. Given a set of patient-specific parameters (e.g., preoperative findings, treatment modalities), they predict the future occurrence of the treatment outcome.⁴ In the context of apical periodontitis, this term applies to the chances of healing. During the estimation of treatment prognosis, the clinicians were not very certain about the point estimates that they provided given limited number of observations. The resulting need to deal with uncertainty and multiple variables, we present a decision support model that describes the mutual relationships among variables that come into play on the endodontic treatment outcome.

Clinical decision-support models must rely on knowledge that originates from a variety of sources. In early models, knowledge acquired directly from medical experts was encoded in the form of rules that were triggered and chained according to an embedded inference engine.⁵ There have been extensive developments in statistical and machine-learning research in the past few decades. These advances have coincided with improvement in data quality and quantity from the implementation of large repository of clinical data. Increased availability of data has allowed further development of several models that can detect patterns in biomedical data and generalize well to previously unseen cases. Clinical decision support models that use statistical or machine learning techniques are now available in virtually every medical specialty.^{6,7}

This research was funded by National Electronic and Computer Technology Grant number NT-B-22-MS-14-50-04.

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Received for publication Feb 15, 2008; returned for revision Apr 6, 2008; accepted for publication May 6, 2008.

1079-2104/\$ - see front matter

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doi:10.1016/j.tripleo.2008.05.011

In this study, we describe a novel approach that uses the information from high-level clinical trials to help understand the causal relationships of multiple variables. We report on the data-driven Bayesian network (BN) probabilistic model for predicting the outcome of endodontic treatment focusing on effect of multiple variables. A Bayesian network (or a belief network) represents domain knowledge qualitatively by the use of graphical diagrams with nodes and arrows that represent variables and the relationships among the variables.⁸ Quantitatively, the degree of dependency is expressed by probabilistic terms. Since the introduction of BNs in the 1980s, a large number of applications have been developed in different medical domains, e.g., supporting diagnosis⁹ and therapy selection.¹⁰ The advantages of using BNs to model causal relationships among multiple variables include the following: (1) They can be used to predict a target variable, e.g., treatment outcome, in the face of uncertainty when any subset of the modeled variables is missing. (2) A causal relationship can be represented by an arc between 2 nodes and the conditional probabilities of one node conditioned on its parents. This provides a model that is intuitive to clinicians and that can be used to generate explanations. (3) Properly designed BNs can provide a valid output when any subset of the modeled variables is present.

There are many ways of acquiring the structure and parameters of a BN¹¹ (i.e., the nodes and arcs, and the conditional probabilities). The methods can be categorized into the following: (1) All human-composed: human experts provide the nodes, the arcs, and the conditional probabilities. As the complexity of the network increases, it can become very demanding of expert time. (2) Human-composed structure and machine-learned parameters learned from data: human experts provide the causal relationships, the network structure is designed using this information, and the parameters can be learned from data. (3) All machine-learned: using one of the available Bayesian network structure learning algorithms, the network structure can be learned from data as well as the parameters. Because the purpose of this study was to incorporate the evidence being reported in clinical trials to construct the BN model, the third strategy was chosen to compose the entire model.

The overall goal of this BN prognostic model was to assist clinicians to understand causal relationships of multiple factors affecting the outcome of endodontic treatment and to facilitate decision making on predicting the success of endodontic treatment for optimal treatment planning. We have designed an experiment in which we prepared clinical data sets from high-level clinical trials. We then applied BN learning algorithms

to these data sets to develop a model for predicting the success of endodontic treatment. Finally, we tested the accuracy of the model with the validating data sets and used the model to predict the outcome of endodontic treatment in the patients.

MATERIAL AND METHODS

We have designed an experiment in which we prepared clinical data sets from clinical trials. The study was conducted using data extracted from the retrospective studies on nonsurgical endodontic treatment outcome. The modeling process began with the identification of variables for use in the prediction algorithms. The authors referred to the retrieved articles and textbooks in endodontics supplemented with authors' experiences gained from endodontic practice and training, and composed a list of related variables. The retrieved articles were then explored to find data elements corresponding to listed variables. One data element represented one case (tooth) attached with labeled variables. The data were stored as separate data sets; the data sets were used to train the decision-support model (training data) and to evaluate the model's performance (validating data). We applied BN learning algorithms to the training data sets to develop a model for predicting the success of endodontic treatment. Finally, we tested the accuracy of the model with the validating data sets and implemented the model to predict the outcome of endodontic treatment in the patients (Fig. 1).

Data retrieval and preparation

MEDLINE, EMBASE, and the Cochrane Library served as our primary computerized data source. A search strategy (adapted from Torabinejad et al.¹¹) was developed to identify English language articles dealing with success and failure of nonsurgical root canal therapy from January 1966 through August 2007. Text words describing different endodontic treatments and phrases related to the success and failure of nonsurgical root canal therapy were used to allow for a broader capture of literature.

The abstracts of all retrieved articles were reviewed for inclusion based on the following criteria:

1. Success and failure, such as periapical healing or persistence of a lesion;
2. The success rate of endodontics in a specified population followed over time.

Articles that simply described a clinical technique or studies that did not have a follow-up of 1 year after the initial treatment were excluded. Articles that addressed short-term success and failure, such as presence or absence of pain, were also excluded from the search body.

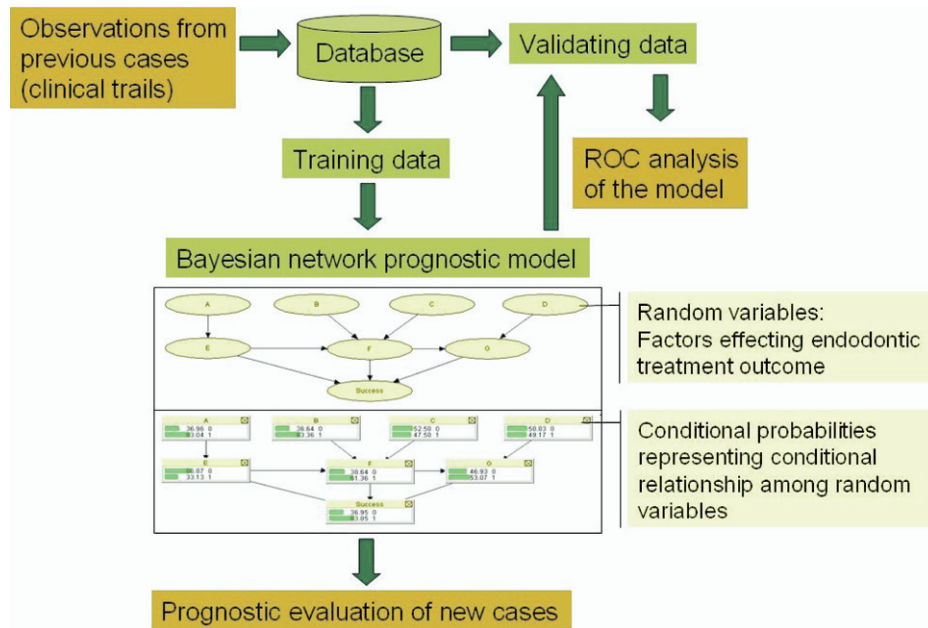


Fig. 1. The process of data preparation and analysis, from the data source to model performance testing.

The articles on the final list were read thoroughly. Level of evidence including randomized controlled trials and cohort studies were chosen to be our data source. An assessment using the CONSORT guidelines¹² was used for these studies. Two authors (S. Sangsuratham and N.R.) independently reviewed the full-text articles included in the final set and verified by the first author (S. Suebnukarn). For each article, variables affecting the endodontic treatment outcomes were identified. One data element recorded all variable states (e.g., nonvital tooth, absence of periapical lesion, 1-visit root canal treatment) of 1 patient.

Bayesian network

We have chosen to use Bayesian networks as the underlying model for the decision-support model. The ability of BNs to model uncertainty and causal relationships among variables makes them an attractive tool in a number of medical applications.^{13,14} In a BN, each variable is modeled as a node and the causal relationship between 2 variables may be represented as a directed arc. For each node, a conditional probability table is supplied that represents the probabilities of each values of this node, given the conditions of its parents (i.e., all the nodes that have arcs pointed to this node) (Fig. 2).

There are 2 kinds of learning in building the BN. Structural learning is the process where the system learns the dependencies between the variables that lie in the data. Parametric learning fills in the parameters

(conditional probability tables) describing the strength of the dependencies in the learned structure.

Structural learning. The algorithm used to learn the structure of the network was the Necessary Path Condition (NPC) algorithm.¹⁵ The NPC algorithm belongs to the class of constraint-based learning algorithms. The basic idea of these algorithms is to derive a set of conditional independence and dependence statements by statistical tests. The algorithm performs the following steps:

- Statistical tests for conditional independence are performed for all pairs of variables (except the pairs for which a structural constraint has been specified).
- An undirected link is added between each pair of variables for which no conditional independences were found. The resulting undirected graph is referred to as the skeleton of the learned structure.
- Colliders are then identified, ensuring that no directed cycles occur. (A collider is a pair of links directed such that they meet in a node.) For example, if we find that A and B are dependent, B and C are dependent, but A and C are conditionally independent given S, not containing B, then this can be represented by the structure $A \rightarrow B \leftarrow C$.
- Finally, directions are enforced for those links whose direction can be derived from the conditional independences found and the colliders identified.

Parametric learning. An Expectation-Maximization (EM) algorithm¹⁶ was used to find maximum likelihood



Fig. 2. (A) A simple Bayesian network. Each arc indicates a causal relationship. (B) Conditional probability table of treatment outcome. Because the node treatment outcome has 2 parents—pulp vitality and quality of root canal filling, this table contains probabilities of treatment outcome values, given the condition of pulp vitality and quality of root canal filling.

estimates of parameters in a BN model. EM alternated between performing an expectation (E) step, which computed an expectation of the likelihood by including the latent variables as if they were observed, and a maximization (M) step, which computed the maximum likelihood estimates of the parameters by maximizing the expected likelihood found on the E step. The parameters found in the M step were then used to begin another E step, and the process was repeated.

Evaluation of the models

To evaluate the accuracy of the BN model, stratified 10-fold cross-validation was employed. Data elements were split into 10 approximately equal partitions using random sampling to ensure that each variable was properly represented in every partition. Each one (1/10) was used in turn for testing while the remainder (9/10) was used for training the structure and parameter of the BN model. The whole procedure was repeated 10 times resulting in 10 candidate BN models.

A standard approach to estimating the accuracy of a probabilistic model is the area under the receiver operating characteristic curve (ROC).¹⁷ We used this metric to evaluate the accuracy of each BN. Receiver operating characteristic curves plot sensitivity (true positive ratio) by 1-specificity (true negative ratio), for a series of thresholds established by posterior probabilities of the variables from each BN model (the plotted points on the graph). These thresholds provide information regarding the model characteristics that can be used to determine the relative usefulness of the model and the specific threshold that maximizes the desired characteristics (emphasizing either the sensitivity or specificity of the BN model). The area under the curve (AUC) represents an overall measurement of performance of the decision-support model, with 1.0 a perfect test and 0.5 representing a model with no discriminating capacity.

During each iteration, a BN was trained using the training data set and tested using the validating data set. An AUC was calculated for each iteration. The AUCs from these iterations were used to compare the accuracy of the models produced from the different data sets. We chose the model that gives the highest AUC for the comparison with clinicians' predictions.

We randomly selected 30 teeth that had undergone nonsurgical root canal treatment from routine clinical care, which had complete information regarding the preoperative, operative, and 6- and 12-month follow-up examination. Ten of these teeth were considered success, 10 teeth were considered uncertainty, and the other 10 teeth were considered failure based on the 12-month follow-up information. All teeth were evaluated by the first author (S. Suebnukarn) using criteria adopted from Strindberg.¹⁸ In a multirrooted tooth, the clinical periapical diagnosis of the tooth was based on the condition of the most severely affected root.

We recruited 3 endodontists from the faculty at Thammasat University Dental School who had at least 5 years of experience in practicing endodontics after training. The 3 endodontists were each asked to predict the treatment outcome of each tooth at the time of (stage 1) diagnosis and treatment planning, (stage 2) immediately after filling the root canal, and (stage 3) 6-month follow-up examination. Upon the diagnosis and treatment planning, only the information on vitality and preoperative radiograph were given. All information except the restoration was given on the evaluation immediately after filling the root canal. At the 6-month follow-up examination, all information was given. All radiographs were viewed by each evaluator under standardized conditions using a magnifying ($\times 2$) viewer. This gave us a total of 90 data points for each stage to compare to the BN model predictions.

The similar information presented to the endodontists was entered to the BN model. The model was updated and the result of the treatment outcome node that gave highest probability was chosen. The clinical and radiographic information upon the 12-month follow-up examination was used as “gold standard.” The area under the ROC was used to measure an overall accuracy of the endodontists and BN model in predicting the treatment outcome. To test the statistical significance of the agreement between the endodontists and BN model, we used the Kappa statistic, which is commonly used to determine the degree of agreement between 2 alternative testing procedures. Kendall’s W coefficient of concordance was used to summarize the agreement among endodontists.

RESULTS

We retrieved data elements of 8783 cases from 29 articles. Of the 29 clinical “success and failure” studies, there were 16 randomized controlled trials^{1,2,19-32} and 13 cohort studies.³³⁻⁴⁵ The variables selected as input for BN modeling were chosen based on data availability from 29 articles. Table I summarizes the variables and their states extracted from the included articles.

The database contained 19 variables affecting the root canal treatment outcome from 8783 cases extracted from 29 articles (Fig. 3). Most previous studies have used various criteria to determine “success.” The only way to evaluate the outcome from different studies is to approximate the findings of one study with another. The endodontic treatment outcomes (column P) were classified into 3 categories adopted from Strindberg¹⁸: 0 = failure, 1 = uncertainty, 2 = success. For those studies where the periapical index (PAI) score was used, PAI scores 3, 4, and 5 were treated as failure, 2 as uncertainty, and 1 as success. The details for other variables’ states are displayed in Table I. Note that some variables could not be identified from the article. Each row in Fig. 3 represents 1 tooth. The value of missing data was left empty (N/A). The data element with its empty cells was fed to the training algorithms, which managed missing data using the EM algorithms.¹⁶

Prognostic Bayesian network

Fig. 4 shows the structure along with the conditional probability distribution (Fig. 5) of the BN that was built up using one training data set. Note that the learning algorithm was not able to derive the direction of all the links from data because of low dependencies between those variables, and thus some links did not appear. Each node contains a conditional probability table (CPT) that quantifies probabilistic relationships among variables. The CPT specifies the probability of the child

Table I. The availability of variables and states extracted from the included articles

Variables	States
Operator	0 = Specialist 1 = General Practitioner 2 = Postgraduate Student 3 = Undergraduate Student
Tooth vitality	0 = Nonvital 1 = Vital
Presence of periapical lesion	0 = No 1 = Yes
Irrigation type	0 = NaOCl 1 = NaOCl + H ₂ O ₂ 2 = NaOCl + EDTA 3 = NaOCl + Sodium thiosulfate 4 = NSS 5 = EDTA + Savlon
Medication	0 = No medication 1 = Ca(OH) ₂ 2 = CMCP 3 = Ledermix
Number of visits	0 = Multiple visits 1 = Single visit
Culture result	0 = Negative 1 = Positive
Obturation technique	0 = Thermoplasticized injection 1 = Cold lateral condensation 2 = Warm lateral condensation 3 = Vertical condensation 4 = Lateral condensation + Thermoplasticized injection 5 = Lateral condensation + Vertical condensation 6 = Vertical condensation + thermoplasticized injection
Sealer	0 = No sealer 1 = Epoxy resin 2 = Chloroform gutta-percha 3 = ZOE + Ca(OH) ₂ 4 = Ca(OH) ₂ based 5 = Silicone based 6 = ZOE based 7 = Resin chloroform
Root canal filling level	0 = Flush (0-2 mm from apex) 1 = Under (< 2 mm from apex) 2 = Over (> 2 mm from apex)
Coronal restoration	0 = Temporary filling 1 = Filling 2 = Crown 3 = Prefabricated post 4 = Casting post 5 = No
Treatment outcome	0 = Failure 1 = Uncertainty 2 = Success

node being observed conditioned on whether the parent nodes are observed. The node bars display normalized conditional probabilities compatible with the given state and condition on the evidence, normalized to have a maximum value of 100.

	Operator	Vitality	Apical lesi	Irrigation	Cleaning	Medication	Visit	Culture	Filling mat	Filling Tec	Filling leve	Sealer	Broken ins	Restoratio	Coronal se	Outcome
8773	0	0	1	0	1	0	0	0	3	1	0	6	0	1	1	2
8774	0	1	0	0	1	0	0	N/A	3	1	0	6	0	1	1	2
8775	1	0	0	2	1	0	0	N/A	3	1	1	6	N/A	2	N/A	2
8776	2	0	1	2	1	0	1	N/A	3	1	1	6	N/A	1	N/A	1
8777	3	1	0	0	2	0	0	N/A	3	1	0	6	N/A	3	N/A	1
8778	0	0	1	2	2	3	1	N/A	3	1	0	6	N/A	4	N/A	1
8779	0	0	1	2	1	0	0	0	3	1	2	6	1	N/A	N/A	1
8780	1	1	0	2	2	3	0	N/A	3	1	0	6	0	N/A	1	1
8781	1	0	1	4	1	3	1	N/A	3	1	0	6	N/A	N/A	1	0
8782	0	0	1	2	1	3	0	N/A	3	1	0	6	N/A	N/A	N/A	0
8783	3	1	0	0	2	0	0	N/A	3	1	0	6	N/A	3	N/A	1

Fig. 3. Part of the database used to learn the structure and parameters of the BN network.

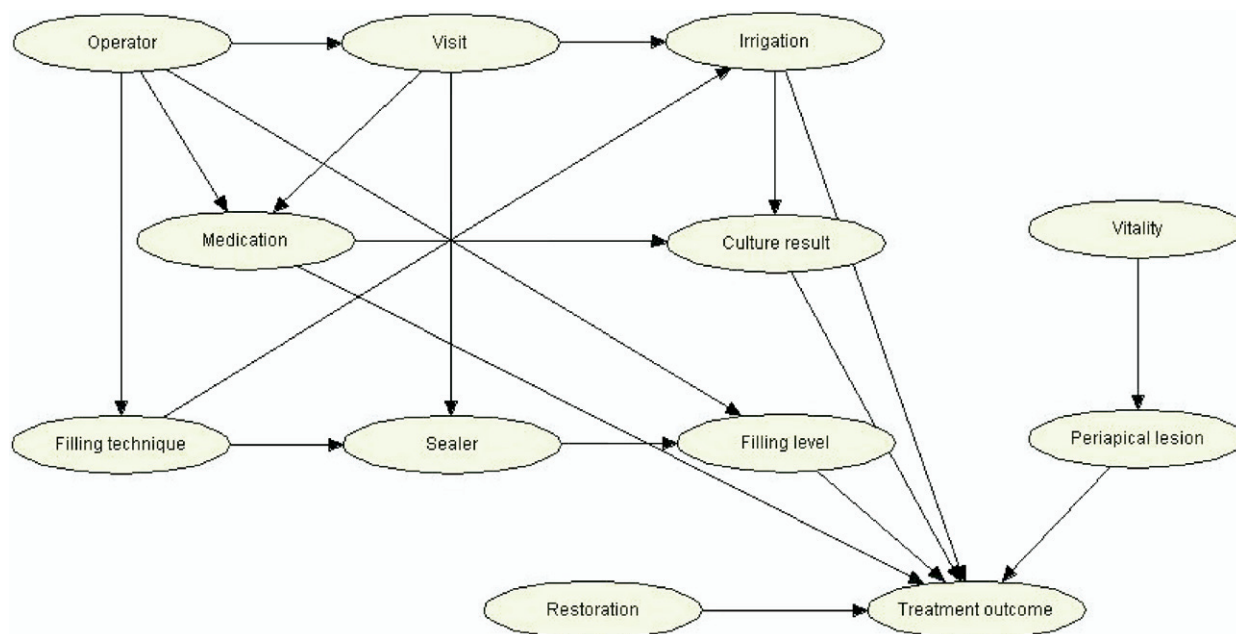


Fig. 4. A BN representing the possible relationships among factors influencing endodontic treatment outcomes. Each arc indicates a causal relationship.

Prognostic scenario analysis

Because of the statistical dependencies between prognostic variables, the scenario cannot be assessed by determining the most likely values for each of the prognostic variables separately. It is often natural to take related events that are about to occur. For instance, the root canal treatment was carried out by the specialist, the tooth had no periapical lesion, the root canal filling level was at the anatomical root apex, and the crown was placed. Fig. 6 shows a screen dump illustrating the propagation algorithm using probabilistic inference with BN after observing the evidence of the above scenario; absence of periapical lesion, flush root canal filling level, crown, and specialist. The posterior probability that the treatment outcome was a success was 0.9435, changing from 0.6547 of the initial state in Fig. 5. The intermediate nodes give some explanation

of the findings: the culture result was negative because of the likelihood of using sodium hypochlorite irrigation ($P = .6859$) and calcium hydroxide medication ($P = .6638$). There was likely to be no difference between performing multiple- ($P = .4321$) or single-visit ($P = .5679$) endodontics, providing the operator was a specialist ($P = 1.000$) and the treatment outcome was a success ($P = .9435$).

Model validation

The AUCs were the result of 10 iterations of 10-fold cross-validation for training/testing of each data set, as well as the implementation of the model to predict the treatment outcome of the patients. Receiver operating characteristic (ROC) curve analysis showed that the model was highly accurate in predicting the endodontic treatment outcome. Among the validation sets, AUC

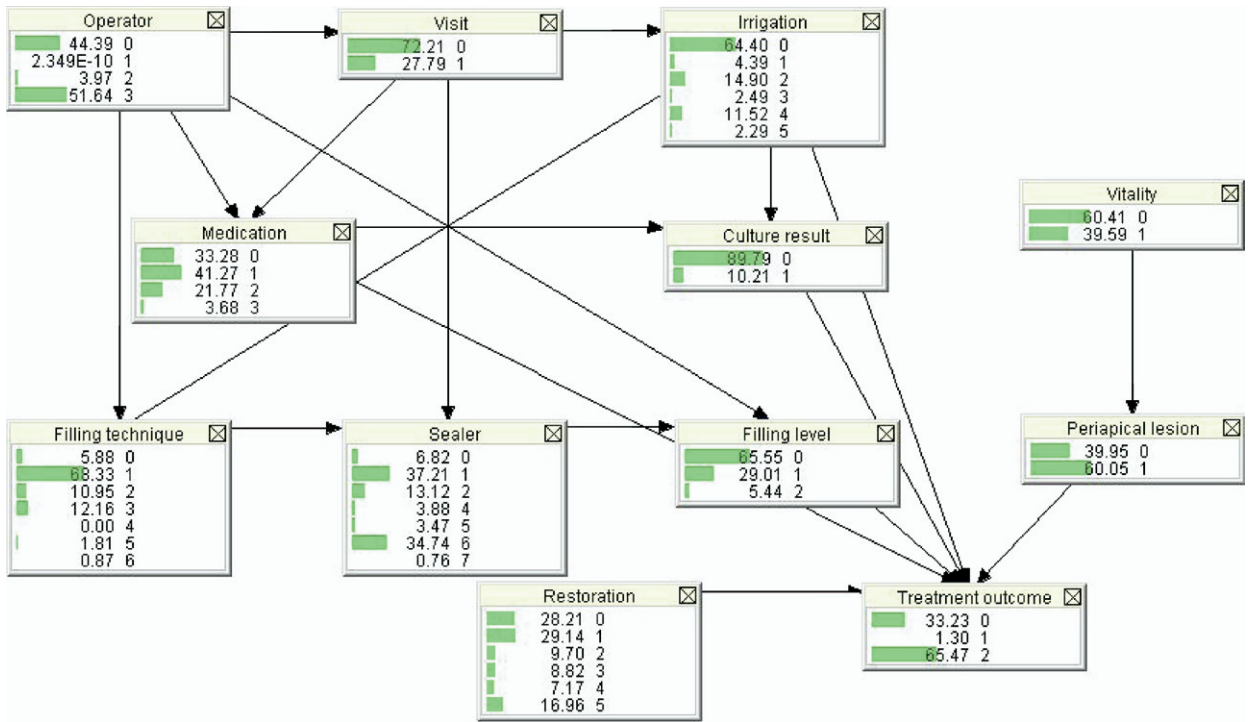


Fig. 5. Conditional probability distribution on all nodes after learning.

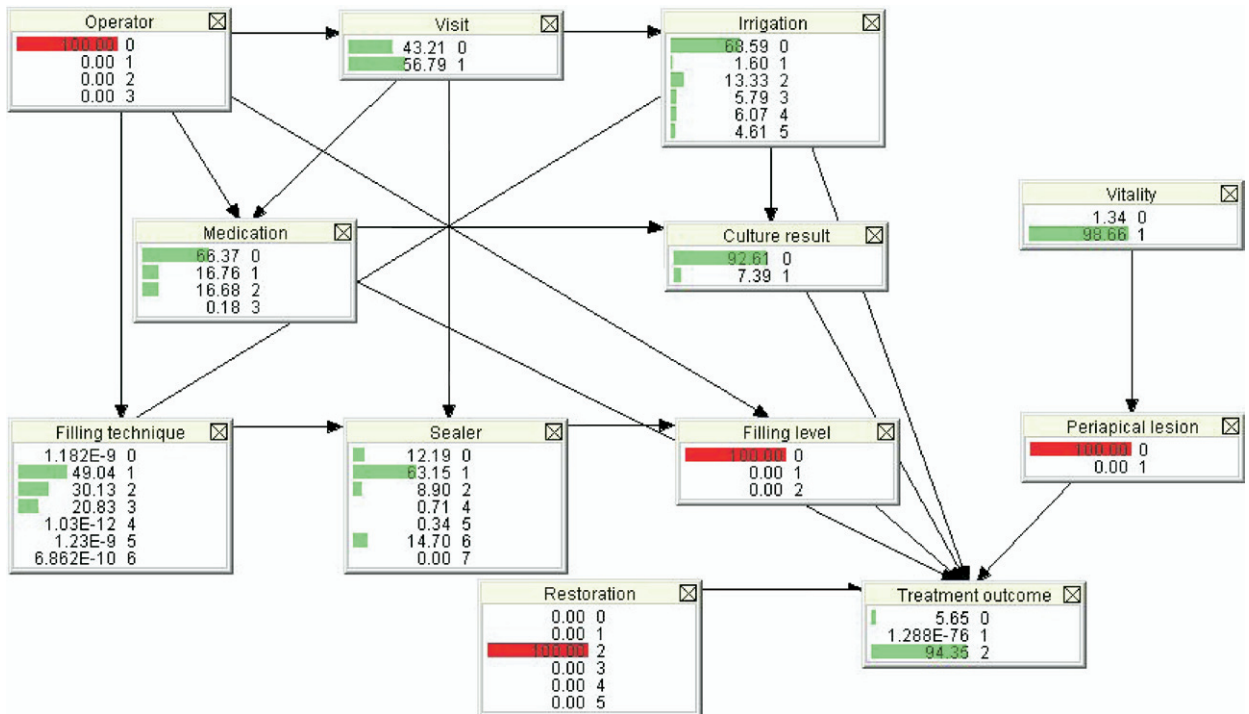


Fig. 6. Conditional probability distribution on all nodes after entering evidence; absence of periapical lesion, flush root canal filling level, crown, and specialist. Note that the posterior probability of endodontic success changed from 0.6547 to 0.9435.

Table II. Results comparing the endodontists and BN model-making predictions

Evaluator	Stage	Prediction (%)	12-month follow-up outcome			Area under ROC
			Success	Uncertainty	Failure	
Endodontist	1	Success	33.33	15.00	0	0.807
		Uncertainty	66.67	70.00	20.00	
		Failure	0	15.00	80.00	
	2	Success	43.33	20.00	0	0.872
		Uncertainty	56.67	76.67	16.67	
		Failure	0	3.33	83.33	
	3	Success	63.33	10.0	0	0.893
		Uncertainty	36.67	80.00	16.67	
		Failure	0	10.00	83.33	
BN model	1	Success	63.33	20.00	0	0.888
		Uncertainty	36.67	70.00	20.00	
		Failure	0	10.00	80.00	
	2	Success	70.00	13.33	0	0.910
		Uncertainty	30.00	80.00	13.33	
		Failure	0	6.67	86.67	
	3	Success	86.67	10.00	0	0.921
		Uncertainty	13.33	80.00	10.00	
		Failure	0	10.00	90.00	

was 0.902. AUC of the Naïve model that gave every node equal probabilities equaled to 0.50 representing a model with no discriminating capacity.

Accuracy in predicting endodontic treatment outcome

Table II shows the percentage of endodontists and the BN model predicting various outcomes for each 12-month follow-up evaluation. For example, the fourth column indicates that in the success cases, the endodontists predicted that 33.33% of them were success, and 66.67% of them were uncertainty on the diagnosis and treatment planning stage. In the same stage, the BN model predicted that 40% of the success teeth were also success, and 60% of them were uncertainty. Overall, the predictions were more accurate when the evaluators (endodontists and BN model) received more information on stages 2 and 3. On average, 53.33% and 26.67% of the success teeth were predicted as uncertainty by the endodontists and BN model respectively. In the failure cases, 17.78% and 14.44% were predicted as uncertainty by the endodontists and BN model respectively. As shown from the table, the AUCs for the BN model were slightly higher than the endodontists in predicting the treatment outcome. By comparing the performance for each stage, there were no statistically significant differences between the AUCs for the endodontists and BN model.

Overall, there was a high degree of agreement between the predictions given by the endodontists and by the BN model (kappa index = 0.793). There was a high degree of agreement among the predictions of the three

endodontists with Kendall's W coefficient of concordance among endodontists predictions = 0.870. Our results indicate that the predictions generated by the BN model are in line with the majority consensus predictions of the endodontists. In the cases where the endodontists' predictions were uncertainty, the BN model predicted them more accurately.

DISCUSSION

Over the past 80 years, an extensive volume of studies has been focused on the prognosis of the outcome of endodontic therapy. Cumulatively, the authors of these studies have recorded, grouped, and analyzed data from thousands of treated cases. Two major reviews had summarized the state-of-the-art knowledge at different times – Strindberg¹⁸ reviewed studies reported in the first half of the 20th century, and Friedman⁴⁶ reviewed studies reported from 1956 up to 1997. From those comprehensive reviews it has become obvious that the data pertaining to the prognosis of apical periodontitis after endodontic therapy is inconsistent and largely variable. Apparently, the wealth of available information is somewhat confused by the lack of standardization among the studies, with respect to material composition, treatment procedures, and methodology. Furthermore, certain clinical procedures performed in specific studies may no longer be relevant to the current practice of endodontics.

There has been a growing international interest in the development of measures to help ensure that practice decision making is better informed by the results of relevant and reliable research. With evidence-based

dentistry in mind, this study presented the prognostic BN for the assessment of endodontic treatment outcome that was built on the BN methodology and introduced a dedicated procedure for BN learning from high-level retrospective studies. According to evidence-based medical and dental practice, randomized controlled trials (RCTs) are high in the hierarchy of quality of evidence⁴⁷ because they can establish the most convincing causal relationship compared with other types of clinical studies, e.g., cohort, case-control, and cross-sectional survey. However the results of article searching of the outcome of endodontic treatment from 1966 to 2007 yielded only 16 RCTs, thus we included high-quality cohort studies to be our data source. Based on the results of these, it appeared that a few high-level studies had been published in the past 4 decades related to the success and failure of nonsurgical root canal therapy. Many factors, such as quality of root canal filling, inaccessible of apical constriction did not appear in the included articles. Other factors, although appeared, indicated low statistical power that can not be related to the other factors as learned by BN algorithms, e.g., tooth type, quality of coronal seal, type of root canal treatment.

Prognostic models are usually induced from historical data by applying supervised data analysis methods such as multivariate logistic regression analysis or tree induction.⁴⁸ This approach has 3 limitations. First, supervised data analysis methods apply attribute selection before inducing a model, often removing many attributes that are deemed relevant for prognosis by users of the model (e.g., clinicians). Second, the resulting models regard prognosis to be a one-time activity at a predefined time. In reality, however, expectations with respect to a patient's future may regularly change as new information becomes available during a treatment process. And third, the models impose fixed roles of predictor (independent variable, input) and outcome variable (dependent variable, output) to the attributes involved. This approach ignores the dynamic nature of care processes, where today's outcome helps to predict what will happen tomorrow.

Recent advances in machine learning, data mining, and intelligent data analysis have resulted in increased utility of their methods to derive medical decision-support models from the data.^{13,14} When we started building a prognostic model for assessment of endodontic treatment outcome, we were confronted with a domain influenced by multiple variables. Moreover, prediction of the treatment outcome was usually uncertain given incomplete information of variables in the domain. We have chosen to use Bayesian networks as the underlying model for the prognostic model. The ability of BNs to model uncertainty and causal relation-

ships among variables makes them an attractive tool in a number of medical applications. While the BN model is an imperfect representation of the real world, it offers a representation of causal relationships among a set of specific domain's variables.¹¹ In our context it gives a picture of the influence of multiple factors on the endodontic treatment outcome. The initial status of our BN model learned from the data sets (Fig. 5) provides the conditional probability distribution of all variables affecting the treatment outcome. In fact it allows for the comparison of the effect of different factors on the prognosis of the treatment. For example, by evaluating the effectiveness of intracanal medicaments used in the management of apical periodontitis (the apical lesion is fixed to "presence"), we found that calcium hydroxide yields the highest probability of the success of the treatment outcome. This finding was in line with the meta-analysis conducted by Law and Messer.⁴⁹ Considering effectiveness of single-visit versus multiple-visit endodontic treatment of teeth with apical periodontitis, we found that the probability of the success of the treatment outcome was slightly higher in the single-visit treatment, which was similar to the RCTs conducted by Weiger et al.²⁸ and Peters and Weselink.³¹ However, the meta-analysis conducted by Sathorn et al.⁵⁰ yielded no differences. Our BN also gave a similar picture of the influence of the root canal filling level as reported by Kojima et al.⁵¹ where the probability of endodontic treatment success with flush level was the highest followed by overextension and underextension in vital teeth. Although the representation of relationships between nodes using conditional probability tables can be unwieldy, the explicit documentation of the logic and probability structure of the network allows the relationships to be scrutinized and revised with the collection of more data and the accumulation of new evidence.

CONCLUSION

We introduce a new type of BN prognostic model that provides a structured representation of a treatment process by modeling the mutual relationships among variables that come into play in the subsequent stages of the care process and the outcome of endodontic treatment. The BN allows for making predictions at various times during a treatment process, each time using all the available information of the patient concerned. In conclusion, the model was highly accurate in predicting the treatment outcome of the patients. A prognostic scenario analysis of the model was explicitly described. As such, we anticipated the use of BN for prognostic application to support the clinical use of it. The methodology presented in our study can be applied for building the decision-support model in other do-

mains in dentistry such as periodontal treatment or dental implant.

We acknowledge the statistical advice provided by Prof. Richard Madsen from the University of Missouri, and Hugin Expert for letting us use the BN software.

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