Assessing Nursing Home Care Quality Through Bayesian Networks

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Abstract

This article demonstrates how Bayesian networks can be employed as a tool to assess the quality of care in nursing homes. For the data sets analyzed, the proposed model performs comparably to existing quantitative assessment models. In addition, a Bayesian network approach offers several uniques advantages. The structure and parameters of a Bayesian network provide rich insight into the multidimensional aspects of the quality of care. Bayesian networks can be used as a guide in implementing limited resources by identifying information that would be most relevant to an assessment. Finally, Bayesian networks provide a straightforward framework for integrating nursing home care quality research that is conducted in various locations and for various purposes.

Keywords: Nursing Home Quality, Bayesian Networks, Quality Indicators, Nurse Staffing

1 Introduction

Assessing and managing the quality of care in nursing homes has presented a difficult challenge and is a growing concern. Despite calls for reform (Institute of Medicine, 1986), recent reports conclude that the quality of care provided in some facilities still leaves much to be desired (Institute of Medicine, 1996, 2000; Mukamel, Spector, Zinn, Huang, Weimer, and Dozier, 2007; Castle, Engbert, and Liu, 2007). As the United States will encounter an unprecedented number of Americans who require skilled nursing care in the upcoming decades, the need for improved assessment methods has never been more prominent.

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Many studies have explored how various factors such as facility characteristics and ownership, staffing, financial indicators, deficiencies, and clinical quality indicators influence the quality of care in nursing homes. Research also has been conducted to combine these and other factors in an effort to create models that measure the overall quality of care in nursing homes.

The purpose of this article is to demonstrate how Bayesian networks can be employed as a tool to assess the overall quality of care in nursing facilities. When compared to other methods, a Bayesian network approach offers three key advantages. First, the structure and parameters of a Bayesian network provide rich insight into the multidimensional aspects of the quality of care. Second, when used as a classification tool, Bayesian networks clearly identify facilities which could easily move from one quality classification to another. Third, in situations where resources necessary to perform assessments are limited, Bayesian networks can serve as a guide in implementing these resources by identifying information that would be most relevant to an assessment.

The remainder of the article is structured as follows. A literature review of nursing home care quality assessment models is provided in Section 2. Section 3 reviews the core concepts of Bayesian networks. Section 4 demonstrates how Bayesian network models may be created for assessing nursing home care quality. The aforementioned advantages are detailed in Section 5, followed by concluding remarks in Section 6.

2 Nursing Home Care Quality Models

In recent decades numerous models have been developed to assess and manage nursing home care quality. This section is not intended to provide an exhaustive review of such models. Rather, it offers a survey of models, many of which the authors believe to be representative of important advances in this field. For a more extensive review, the reader is referred to Goodson (2005) and Sainfort et al. (1995).

Factors influencing the quality of nursing home care delivery typically fall into one of Donabedian's (1988) three aspects of quality of care assessment: Structure, Process, and Outcome measures (SPO framework). Common structural measures of quality include facility size, occupancy, ownership type, staffing, and percentage of Medicaid and Medicare residents (Harrington et al., 2003). Process measures of nursing home quality describe the process of care provided and encompass actions of the provider in response to the resident and the activities that go on between health professionals and residents (Zimmerman, 2003). Outcome quality measures, on the other hand, measure the results of nursing care processes by measuring whether a resident's condition improves, remains the same, or declines as a result of applied processes (Zimmerman, 2003). Process and outcome measures of quality include both deficiencies and clinical quality indicators (discussed below).

Donabedian's (1988) SPO framework served as the foundation for two notable models. Atchley (1991) modified the framework to include a time dimension. Unruh and Wan (2004), noting the lack of causality among structure, process, and outcomes in models utilizing the SPO framework, constructed a "framework for nursing home quality that links contextual components of quality with structure, structure with process, and process with outcomes, focusing on nursing care quality." The authors suggest further development of the model through structural equation modeling.

A noteworthy non-SPO framework was developed by Rantz et al. (1998, 1999). Their multidimensional theoretical model for nursing home quality is based on focus groups with nursing home staff and residents. Dimensions of quality identified in the model include adequate and caring staff, good communication, a safe and pleasant environment, family involvement, a caring atmosphere, and a home-like environment. The central focuses of the integrated model are residents, families, staff, and community.

Some assessment methods evaluate the quality of care in nursing homes via surveys conducted by outside evaluators. The Observable Indicators of Nursing Home Care Quality Instrument (OIQ), developed by Rantz et al. (2002), measures the overall quality of a nursing facility during a brief on-site visit to a nursing home. The instrument encompasses five dimensions of the quality of care: communication, care, staff, environment, and home and family involvement. Initial validations of the OIQ have been successful and further validation is underway (Rantz et al., 2005). The New York Quality Assessment System also employs surveys conducted by outside evaluators to assess the overall quality of a facility (Ullmann, 1985).

A common method for determining the overall quality of care delivered at a nursing facility is the number of federal deficiencies. When a facility does not comply with federally imposed standards, the facility may be given a deficiency. Deficiencies are best utilized when considering their number, frequency, and severity as illustrated in a study conducted by Chesteen et al. (2005).

The Quality Assessment Index (QAI), developed by Gustafson et al. (1990), employs a hierarchical decomposition process to assess the quality of care. Sainfort et al. (1994) used quality dimensions captured by the QAI in a subsequent study. Their work represents the first model to fully link the structure, processes, and outcomes of care. Using factor analysis to examine the relationship among variables, the researchers identified which of the QAI dimensions were most relevant to a causal model. Path analysis then was employed to examine the relationship among variables and develop a causal model. Patterns of care were then determined through cluster analysis. The authors finish their work by integrating the results of the causal model and the results of the clustering process into a continuous quality improvement framework (Sainfort et al., 1994).

Weech-Maldonado et al. (2003) employ indices to describe the relationship between quality of care and financial performance. In their model, the authors used seven measures of nursing home quality: registered nurse staffing mix, prevalence of physical restraints, prevalence of urethral catheters, pressure ulcer prevalence, incidence or worsening of pressure ulcers, cognitive decline, and mood decline. Two quality indices were formed based on these measures – a process quality index and an outcome quality index. These indices were integrated as part of a larger model using structural equation modeling.

Two studies have utilized clinical quality indicators as predictors of overall nursing home quality. An often employed set of 24 clinical quality indicators (QIs) was developed by researchers at the Center for Health Systems Research and Analysis (CHSRA) at the University of Wisconsin-Madison (CHSRA, 2001). These QIs measure the proportion of residents with the QI condition. Table 1 lists the variables considered in this analysis; classifies them as *structure*, *process*, or *outcome* measures; and specifies their inclusion in our resulting models. The first variable, QOC, is derived from the abovementioned OIQ (Rantz et al., 2005). The next 11 variables constitute structural quality measures often utilized in previous research to evaluate nursing care quality. The remaining portion of Table 1 depicts the 24 CHSRA QIs (CHSRA, 2001). (QI variable names followed by "N" were revised in 1997 since the original development of QIs in the late 1980's (Zimmerman, 2003) and QIs followed by "*" indicate those deemed to be the most sensitive to changes in the overall quality of care (Rantz et al., 2004)). Karon et al. (1999) established the stability of QIs over time by ordering facilities by their QI ranks. The QI rank (or percentile), therefore, provides a relative measure of overall quality within a group of nursing homes.

Instead of employing the QI rank method utilized by Karon et al. (1999), Rantz et al. (2004) and Rantz et al. (2004) classify nursing homes based on their individual QI scores and compare these scores to established QI thresholds (Rantz et al., 2000). The conglomeration of the individual QI ratings yielded an overall classification for the facility – *good*, *average*, or *poor*. Table 2 (where G, A, and P denote the number of QIs in the good, average, and poor ranges, respectively) illustrates the number of QIs within a certain range required to arrive at an overall facility rating.

3 Bayesian Networks

Bayesian networks (BNs) are a multivariate method useful in modeling complex relationships among variables. As it is not the authors' aim to provide a tutorial on BNs, the following discussion is limited to a brief explanation of three key components of BN methodology: structure,

Variable	Description	Assessment Type	Model(s)
QOC	The overall quality of care (QOC) as determined by the total Observable Indicators of Nursing Home Care Quality Instrument (OIQ) score	all	all
BedSz	Number of beds in a facility	structure	BN3,4
Occupancy	Number of beds occupied in a facility	structure	BN3,4,5; Reg
Medicare	Indicates whether or not a facility accepts Medicare residents	structure	BN3
Chain	Indicates whether or not a facility is part of a nursing home chain	structure	BN3,4; Reg
RNhrs	The number of registered nurse hours per resident day	structure	BN3,4; Reg
CNAhrs	The number of certified nurse assistant hours per resident day	structure	BN3,5
Totalhrs	The number of total staff hours per resident day	structure	BN3,4; Reg
Deficiencies	The number of deficiencies issued to a facility	outcome, process	BN4,5; Reg
FP	Indicates for-profit (FP) facilities	structure	BN3,4
NP	Indicates not-for-profit (NP) facilities	structure	BN3,4
GOV	Indicates government (GOV) facilities	structure	BN3,4
QI1N	Prevalence of any injury	outcome	BN1; Reg
QI2*	Prevalence of falls	outcome	BN1,2,4
QI3	Prevalence of behavioral symptoms affecting others	outcome	BN1
QI4N*	Prevalence of diagnosis or symptoms of depression	outcome	BN1,2,4
QI5N*	Prevalence of depression with no treatment	outcome, process	BN1,2,4
QI6*	Use of 9 or more different medications	process	BN1,2,4
QI7N	Onset of cognitive impairment	outcome	BN1
QI8	Prevalence of bladder/bowel incontinence	outcome	BN1
QI9	Prevalence of occasional bladder/bowel incontinence without a toileting plan	outcome, process	BN1
QI10	Prevalence of indwelling catheters	process	BN1
QI11	Prevalence of fecal impaction	outcome	BN1
QI12*	Prevalence of urinary tract infections	outcome	BN1,2,4
QI14*	Prevalence of weight loss	outcome	BN1,2,4
QI15	Prevalence of tube feeding	process	BN1; Reg
QI16*	Prevalence of dehydration	outcome	BN1,2,4
QI17*	Prevalence of bedfast residents	outcome	BN1,2,4,5
QI18*	Incidence of decline in late loss activities of daily living	outcome	BN1,2,4
QI20N	Lack of training / skill practice or ROM for mobility dependent residents	outcome	BN1
QI21N	Prevalence of antipsychotic use, in the absence of psychotic and related conditions	process	BN1; Reg
QI23N	Prevalence of anti-anxiety / hypnotic use	process	BN1
QI24	Prevalence of hypnotic use more than two times in last week	process	BN1
QI26	Prevalence of daily physical restraints	process	BN1,5
QI27	Prevalence of little or no activity	outcome, process	BN1; Reg
QI29*	Prevalence of stage 1-4 pressure ulcers	outcome	BN1,2,4

Table 1: Variable Descriptions, Data Characteristics, and Model Composition

Classification	Criteria
Good	$G \geq 5$ and $(G - P) \geq 2$
Poor	$P \geq 5$ and $(P - G) \geq 5$
Average	$A \geq 15$ and neither Good nor Poor

Table 2: Facility Classification Criteria

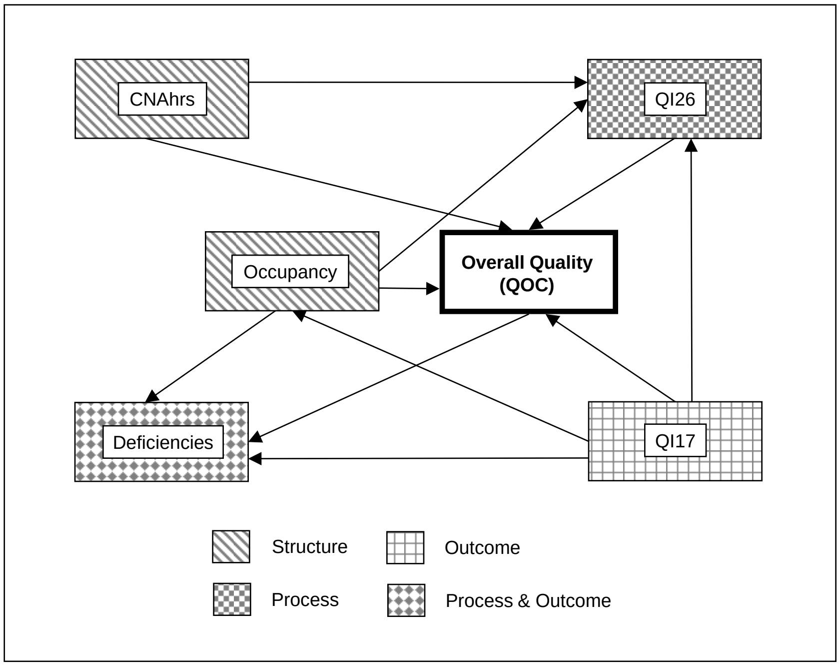

Figure 1: Bayesian Network 5 (BN5)

parameters, and inference.

The structure of a BN is a graph, composed of nodes and edges. The nodes of the graph depict variables (such as the abovementioned measures of quality), each of which may take on certain values (such as a reported value for a QI), while the edges represent influences among the variables. Consider the BN depicted in Figure 1 whose structure suggests that the overall quality of care (QOC) in a nursing home is directly affected by four quality measures: the number of certified nurse assistant hours (CNAhrs), the occupancy rate (Occupancy), the prevalence of bedfast residents (QI17), and the prevalence of daily physical restraints (QI26). The structure of a BN can be developed through judgments of an expert (such as a medical professional providing insights into the quality of care), through structure learning algorithms, or through a combination of the two. For an in-depth discussion of structure learning algorithms, the reader is referred to Geiger and Heckerman (1994), Heckerman et al. (1995), and Bøttcher (2001).

The parameters of a BN provide additional details as to the relationships among variables. Each node in a BN contains a conditional probability table that provides the conditional probability distribution of the node given the various states of its parents. For example, the conditional probability table for QOC in Figure 1 would provide the probability distribution of QOC given every possible configuration of QI26, CNAhrs, Occupancy, and QI17. The ability to quantify relationships among variables influencing the overall quality of care therefore enables BNs to offer new insights to those concerned with quality of care decisions. Similar to the structure of a BN, parameters may be set through expert judgment or determined from data by parameter learning algorithms. For an in-depth discussion of parameter learning algorithms, the reader is referred to Spiegelhalter et al. (1993).

With the structure and parameters of a BN in place, probabilistic inference can be performed within the network. For example, one may obtain estimates of the probability distributions of one or more variables of unknown value given the known values of other nodes in the network. Further details on inference algorithms are given by Pearl (1988), Jensen et al. (1990), Jensen (1996), and Huang and Darwiche (1996).

4 Model Development and Evaluation

4.1 Data and Software

In this section, several BNs for quality of care assessment are developed. As is the case in many modeling studies, the quality of the data was of paramount importance. In this work, the BN structure and parameter learning algorithms required a preexisting overall measure of nursing home care quality with which to build models which would subsequently serve as a method of assessment. Of particular interest to this study was the availability of the overall quality score (labeled QOC in Table 1) as determined by the Observable Indicators of Nursing Home Care Quality Instrument (OIQ) (see Section 2). Research to date indicates that the OIQ provides an excellent, easy-to-use measure of the overall quality of a nursing facility (Rantz et al., 2005). As such, the OIQ score served as the overall measure of nursing home care quality for each nursing home in the analysis. The data analyzed in this study were provided by the University of Missouri-Columbia Sinclair School of Nursing and were gathered as part of a three-year research project funded by the National Institute of Nursing Research of the National Institutes of Health (Rantz et al., 2005). Data collected for each nursing home included the items listed in Table 1. The initial data set of 256 nursing homes was decreased to 234 nursing homes by removing facilities with large amount of missing information and potential OIQ scoring errors. Of these 234 facilities, 20% of the facilities were rated as providing *BelowAverage* care by the OIQ, 60% as providing *Average* care, and 20% as providing *AboveAverage* care according to the rating system employed by Rantz et al. (2005).

In preparation for the models developed in this research, the data set was randomly partitioned into two sets – a learning set ($n = 184$) to be used in determining BN structures and parameters and a validation set ($n = 50$) to be used in validating the BNs. This process was repeated a total of

10 times, resulting in 10 randomly partitioned learning and validation data set pairs. All data sets were proportional to the original data set, with respect to the OIQ score (20% with a BelowAverage OIQ score, 60% with Average, and 20% with AboveAverage).

The BN models created from these data sets were analyzed by two software packages. Deal, a BN software package developed in Denmark by Bøttcher and Dethlefsen (2004), was employed to learn the structures of the BN models. Subsequent parameter learning and inference were conducted in Netica, developed by Norsys Corporation. Structure and parameter learning algorithms employed by these software packages follow the methods of Bøttcher (2001) and Spiegelhalter et al. (1993), respectively.

4.2 Model Creation and Variable Selection

To explore the usefulness of a BN approach to nursing home care quality assessment, five BN models (denoted BN1, BN2, etc.) were created and evaluated. The models were designed to utilize studies conducted by nurse researchers which identify significant indicators of nursing home care quality (see Goodson (2005) for an in-depth discussion of these factors). The last column of Table 1 indicates which variables were included in each of the five BN models. The variables in BN1 include the CHSRA QIs; the variables in BN2 are composed of 10 QIs deemed to be the most sensitive to changes in the overall quality of care (Rantz et al., 2004) (denoted in Table 1 by a * following the variable name); the variables in BN3 are composed of structural measures of quality; the variables in BN4 consist of factors determined by other research to be influential on the overall quality of nursing home care; and BN5 contains variables determined to be significant in a Chi-square test of association (Hogg et al., 2004). In summary, BN1, BN2, BN3, and BN4 include variables determined by previous research to be influential on the overall quality of care while the variables in BN5 are selected based on a quantitative method.

4.3 Evaluation Measures

This section describes the evaluation criteria employed to select the most appropriate BN model with which to evaluate nursing home care quality through a BN framework. By means of the validation data sets, three criteria were utilized to evaluate the five BN models, each of which provides a different perspective as to what associations do or do not exist among the variables in the models and the overall quality of care (QOC). The criteria include *prediction accuracy*, *correlation*, and *ranking accuracy*.

Prediction accuracy indicates how accurately each BN predicted the likelihood of QOC. For each of the 50 facilities in a validation data set, each BN was given knowledge of all variables in the model except for the actual QOC. By means of probabilistic inference schemes for BNs (see Section 3), the probability distribution of QOC was obtained. The state of QOC corresponding to the highest value of the probability distribution was considered to be what the model predicted as the overall quality of care. For example, if the distribution for QOC was determined to be $Pr(\text{QOC} = \mathit{AboveAverage}) = 0.2, Pr(\text{QOC} = \mathit{Average}) = 0.3, Pr(\text{QOC} = \mathit{BelowAverage}) = 0.5$, then the BN predicted the QOC to be BelowAverage for this nursing home. A BN's prediction accuracy is then comprised of a comparison of the model's prediction to the actual QOC (as determined by the OIQ score) for each of the 50 nursing homes in a validation data set.

The correlation measure builds upon the prediction accuracy by further utilizing the probability distribution of QOC. Each nursing home in a validation set is assigned a score of $-1 \times Pr(\text{QOC} = \mathit{BelowAverage}) + 0 \times Pr(\text{QOC} = \mathit{Average}) + 1 \times Pr(\text{QOC} = \mathit{AboveAverage})$. The resulting scores are then correlated (using the Pearson product-moment correlation) with the actual QOC values (the OIQ scores). A higher correlation is indicative of a higher degree of association between the selected variables and the overall quality of care, while a lower correlation implies the converse.

Contrary to the measures described thus far, which are absolute error measures, the ranking accuracy provides a relative measure of accuracy among the 50 facilities in a validation data set. To calculate this measure, facilities are first sorted in ascending order according to the abovementioned score (used to calculate the correlation measure). Recall that each validation data set is proportional to the original data set. Thus, such an ordering (if completely accurate) should result in the first 10 (i.e., 20%) facilities having BelowAverage quality, the next 30 (i.e., 60%) having Average quality, and the remaining 10 (i.e., 20%) having AboveAverage quality. The ranking accuracy compares the order obtained by each model to this completely accurate order. If the actual QOC of one of the first 10 nursing homes is not BelowAverage, the facility is considered to have been misclassified by the model and thus decreases the ranking accuracy. If the actual QOC of one of the next 30 nursing homes is not Average, the facility is also labeled as misclassified. Similarly, if the actual QOC of the remaining 10 nursing homes is not AboveAverage, the facility is considered misclassified. The ranking accuracy for a particular model is then determined by dividing the total number of correctly classified facilities by 50.

Based on the three measures just described, the BN models were compared to the performance of two other popular predictive models. The first is an ordinary least squares regression model where variables were chosen via a stepwise selection procedure. In this regression model, the variables denoted by "Reg" in the last column of Table 1 are employed to predict QOC, the dependent variable. The second model is the QI classification method by Rantz et al. (2004) described in Section 2. Both the regression model and the QI classification scheme were tested using the learning and validation data sets, and the same evaluation criteria were used to evaluate these models.

4.4 Model Evaluation

In comparison to the other BNs, BN1, which includes the 24 CHSRA QIs, incurred the lowest prediction accuracy and posted mediocre performance on the other criteria. BN2, which consisted of QIs determined to be most sensitive in determining nursing home care quality, yielded some improvement, but a more in-depth look at BN2 revealed its inability to distinguish quality of nursing homes. The inclusion of only structural variables in BN3 and factors recommended by other researches in BN4 offered little improvement over previous models. Variables selected by the Chi-square test of association method (BN5) resulted in a marked improvement in correlation and performed as well as or better than the other models on the other criteria.

Performance of the best BN model (BN5), the regression model, and the QI classification model based on the abovementioned criteria is displayed in Table 3. The given accuracy and correlation measures are the average value for the 10 learning and validation data sets. Furthermore, when referencing any accuracy or correlation measures throughout the remainder of this article, such measures represent the average value for the 10 learning and validation sets. Additionally, the differences among prediction accuracy, correlation, and ranking accuracy for all models are statistically significant (as determined by T-tests for the difference among means with 95% significance level).

A comparison of BN5 to the regression model indicates comparable prediction accuracy and better correlation and ranking accuracy of BN5. It is also interesting to note the different variables utilized in each model. More specifically, of the five variables selected by the Chi-square test of association (BN5) and the nine variables chosen via stepwise selection (regression), only two are the same: Occupancy and Deficiencies. Despite this difference, both models perform better than the other models.

In comparison to BN5, the QI classification method has slightly better ranking accuracy, but substantially underperforms BN5 on prediction accuracy. In addition, the QI classification method often predicts a facility with AboveAverage quality as BelowAverage quality and vice-versa. The rate of these totally wrong predictions is 13.5% with the QI classification method, while it rarely happens with BN5. Because BN5 performs better than the other BNs, BN5 is used from this point forward to demonstrate the use of a BN approach to nursing home care quality assessment.

Model	Prediction Accuracy	Correlation	Ranking Accuracy
BN5	0.560	0.364	0.712
Regression	0.568	0.293	0.666
QI Classification	0.460	n/a	0.746

Table 3: Model Performance

5 Advantages of Bayesian Network Approach

This section illustrates three benefits of a BN approach to nursing home care quality assessment. As we demonstrate in this section, Bayesian network assessment provides several advantages not present in existing methods.

5.1 Insights from Model Structure and Parameters

Of the assessment models which provide quantitative feedback (see Section 2), the feedback is limited to a point estimate of a facility's quality. A strength of the BN approach is its ability to provide both qualitative and quantitative insight into the multidimensional makeup of nursing home care quality. The qualitative insight gained from BN5's structure depicts how various factors interact with each other to yield certain levels of nursing home care quality. Further understanding of these interactions is obtained from the quantitative analysis of BN5's parameters. Considered together, the quantitative and qualitative aspects of the BN method of assessment afford a more complete perspective of the quality of care in nursing homes.

The structure of BN5 (depicted in Figure 1) indicates that the overall quality of nursing home care is tightly related to five quality measures: CNAhrs, Occupancy, QI17, QI26, and Deficiencies. The direction of the arc between QOC and Deficiencies implies that the overall quality of care is indicative of the number of deficiencies. This direction of causation makes sense from an evaluation perspective (i.e., the number of deficiencies results from the quality of care provided). Conversely, the arc direction between QOC and the remaining variables implies that they each influence the overall quality. Because the structure of BN5 identifies factors which directly influence the overall quality of nursing home care, significant practical insight is therefore available to nursing home administrators.

Further understanding is obtained through an examination of BN5's parameters. To illustrate how the parameters provide insight into the quality of care, an excerpt from the conditional probability tables of BN5 is presented in Tables 4 and 5. The information provided in Table 4 can be used to examine the relationship between certified nurse assistant staffing levels (CNAhrs) and the

QI17	**CNAhrs**	**Occupancy**	**QI26**	$Pr(\text{QOC} = AboveAverage)$
Good	Good	High	Good	0.674
Good	Average	High	Good	0.250
Good	Poor	High	Good	0.155

Table 4: Conditional Probability Table Excerpt 1

QI17	**CNAhrs**	**Occupancy**	**QI26**	$Pr(\text{QOC} = AboveAverage)$
Poor	Poor	High	Poor	0.150
Poor	Poor	Average	Poor	0.150
Poor	Poor	Low	Poor	0.150

Table 5: Conditional Probability Table Excerpt 2

overall quality of care (QOC). To facilitate this examination, the levels of QI17, Occupancy, and QI26 are held constant while the level of CNAhrs is varied. As shown, the probability that the overall quality of nursing home care is AboveAverage decreases with an increased likelihood of Poor levels of CNAhrs. In other words, the probability of AboveAverage quality of care declines as staffing levels decrease – an important observation for nursing home administrators seeking to improve the overall quality of care.

Table 5 reveals an interesting observation: the occupancy rate has no effect on the overall quality of care when QI17, CNAhrs, and QI26 are at their lowest levels. Therefore, despite a facility's occupancy rate, little or no quality of care improvement can be achieved without first addressing the prevalence of bedfast residents, certified nurse assistant staffing levels, and the prevalence of daily physical restraints. When these factors are held at their middle and upper levels (as opposed to their lower levels in the preceding scenario), the distribution for QOC changes when varying the occupancy rate (not shown in Table 5).

In addition to the insights presented here, further analysis of the structure and parameters of BN5 has yielded valuable information. It is emphasized that administrators should recognize the relative significance of each factor influencing the overall quality of care. Furthermore, attention should not only be given to key factors, but also to closely related factors. In other words, structure and parameter analysis revealed that focusing on only one key factor while ignoring closely related factors may not result in the desired outcome. The BN model thus provides not only an overall quality of care assessment, but also an insightful view of the factors influencing quality of care.

5.2 Classification

Models that attempt to classify nursing homes according to quality of care find it difficult to make accurate classifications. For example, Rantz et al. (2004) classified nursing homes based on their quality indicator (QI) scores and compared them to established QI thresholds (Rantz et al., 2000). The authors discovered, however, that a small change in one or two QIs near the threshold could cause a change in classification. An effective quality assessment model should clearly identify those facilities that could easily move from one classification group to another.

An advantage of employing BNs to assess the quality of care in nursing homes is their ability to provide more transparent classification. In other words, instead of classifying a facility as having *good*, *average*, or *poor* quality, a BN can suggest how *good* or how *poor* the quality is. This is accomplished by considering the entire probability distribution for the overall quality of care (QOC) in a nursing home. Viewed in its entirety, this distribution allows for differentiation among facilities with like classifications.

One method of distinguishing among quality levels within a classification is through cumulative probability. The use of cumulative probability allows one to evaluate the probability that the quality of care is *at least* Average, instead of the probability that the quality of care is *exactly* Average: $Pr(\text{QOC} \geq Average) = Pr(\text{QOC} = Average) + Pr(\text{QOC} = AboveAverage)$.

Table 6 depicts this calculation for 39 nursing homes from a validation data set, all of which were predicted as having Average quality by the proposed model. Recall from Section 4.1 that Average quality encompasses OIQ scores ranging from the 20th to 80th percentiles of nursing homes in this study. Considering that 60% of nursing homes in this study were classified as Average (based on the OIQ score), further insight into the differences among the quality of care delivery in each home would be beneficial to nursing home administrators and consumers.

While the model classifies the facilities in Table 6 as Average, the probability distributions suggest that some of the facilities provide higher quality of care than others. The probability that the quality of care is at least Average ranges from 0.610 to 0.882. Although distinguishing among the quality of care in the nursing homes in Table 6 could be accomplished in a number of ways, consider dividing the range into thirds, as illustrated in Table 6. This differentiation scheme reveals that the 11 facilities with the probability of at least Average quality of care ranging from 0.792 to 0.882 (right most column of Table 6) most likely provide higher quality of care than the 15 facilities with the probability of at least Average quality of care ranging from 0.610 to .700 (left most column of Table 6).

Furthermore, differentiating in this manner may reveal nursing homes with borderline quality of care. In other words, the facilities with high values for the probability of at least Average quality

$Pr(\text{QOC} \geq Average)$		
Bottom Third (0.610 - 0.700)	**Middle Third (0.701 - 0.791)**	**Top Third (0.792 - 0.882)**
0.610	0.707	0.792
0.632	0.714	0.792
0.635	0.714	0.803
0.636	0.714	0.812
0.637	0.727	0.836
0.651	0.727	0.836
0.651	0.729	0.851
0.651	0.745	0.864
0.661	0.751	0.864
0.671	0.751	0.882
0.673	0.786	0.882
0.673	0.786	
0.688	0.789	
0.698		
0.698		

Table 6: Differentiation Among Nursing Homes With Like Classification

of care could be classified as AboveAverage if small improvements were made. Conversely, facilities with lower values for the probability of at least Average quality of care could be classified as BelowAverage if conditions deteriorate. Identification of such borderline cases and distinguishing among the quality of care in nursing homes with like classifications will allow administrators and consumers to more easily identify nursing homes which could quickly move from one classification to another. BNs will thus provide a more informative tool for nursing home classification.

5.3 Assessing with Limited Information

BNs can serve as a guide to assess the quality of care when information collection is limited. In such conditions, *variance reduction factors* suggest which information is most relevant to an assessment. More specifically, variance reduction measures how much the distribution of the overall quality of care (QOC) is influenced by other variables in the BN (Pearl, 1988). An example of how variance reduction can be employed is illustrated with BN5. To make a complete assessment of the overall quality of care with BN5, information is required for four variables: QI26, CNAhrs, QI17,

Variable	Variance Reduction
QI26	7.871
CNAhrs	6.597
QI17	4.636
Occupancy	3.314

Table 7: BN5 Variance Reduction Factors

	$Pr(\text{QOC})$		
	BelowAverage	**Average**	**AboveAverage**
No Information	0.250	0.526	0.224
Partial Assessment	0.154	0.423	0.423

Table 8: Results of Partial Assessment

and Occupancy. The variance reduction factors in Table 7 indicate that information regarding QI26 would be most valuable in making an assessment. As resources permit, additional information could be collected and incorporated into the BN, but such information should be gathered according to the variance reduction factors – the larger the variance reduction, the more valuable the information would be to the assessment.

Consider the case where current resources only permit collection of QI26 and CNAhrs. Table 8 indicates the change in the distribution of QOC given that QI26 is determined to be *Average* and CNAhrs is determined to be *AboveAverage*. Before the partial assessment, QOC was most likely to be Average. Following the partial assessment, QOC is equally likely to be Average or AboveAverage. Moreover, the distribution has shifted away from BelowAverage QOC. Thus, even a partial assessment can yield valuable information. As additional resources become available, the assessment can then be updated.

6 Conclusion and Future Work

It has been demonstrated how Bayesian networks can be used as a tool to assess the quality of care in nursing homes. Such an approach improves upon efforts to date by offering rich qualitative and quantitative insight into the quality of care, by affording a more accurate classification tool, and by assisting in the management of limited resources. In addition, Bayesian networks provide a common framework necessary to combine the efforts of research conducted in various locations and for various purposes. The models developed as part of this research considered both public (structural variables) and private (OIQ scores and QIs) data sources. Employed in this fashion, Bayesian networks will allow research to date to be considered in one unified environment. The functionality of such a framework will be evident by increased collaboration among researchers and by an accelerated pace of investigation into the problem of assessing and improving the quality of care in nursing homes.

Future work with Bayesian networks may provide additional utility when used in conjunction with a larger data set. This would provide more data for structure and parameter learning which may in turn yield a model that provides more in-depth insights into nursing home care quality. Furthermore, a larger data set would allow for more extensive testing of the networks.

In addition to augmenting the data set, future efforts may benefit from considering further measures for the overall quality of care. In this research, the Observable Indicators of Nursing Home Care Quality Instrument (OIQ) (Rantz et al., 2005) was employed for this purpose. While the OIQ has provided valuable insights into the quality of care in nursing homes, other measures may offer further insight and may yield more accurate results. Despite the need for some improvements in future research, the positive implications of assessing the quality of care in nursing homes through a Bayesian network – as illustrated in this analysis – outweigh any limitations or difficulties encountered in this research.

As future work continues to explore a Bayesian network approach to nursing home care quality assessment, not only will the accuracy and content of quality assessments improve, but the ability to advance the quality of care delivery in nursing homes will also increase. As the United States will encounter an unprecedented number of Americans who require skilled nursing care in the upcoming decades, the need for such tools has never been more prominent. An understanding of what affects nursing home care quality will allow administrators to best allocate resources in response to this rising need. Furthermore, such understanding will aid in identifying new and solidifying existing standards of evaluation and will therefore improve the quality of life for a growing segment of America's aging population.

References

Atchley, S. (1991). A time-ordered, systems approach to quality assurance in longterm care. *Journal of Applied Gerontology 10*(1), 19–34.

Bøttcher, S. (2001). Learning bayesian networks with mixed variables. In *Proceedings of the Eighth International Workshop in Artificial Intelligence and Statistics*, pp. 149–156.

Bøttcher, S. and C. Dethlefsen (2004). deal: Learning bayesian networks with mixed variables. R package version 1.2-22.

Castle, N., J. Engbert, and D. Liu (2007). Have nursing home compare quality measure scores changed over time in response to competition? *Quality and Safety in Health Care 16*, 185–191.

Center for Health Systems Research and Analysis (2001). QI definitions. [Online; accessed 12-April-2005; `http://www.chsra.wisc.edu/CHSRA/PIP_ORYX_LTC/QI_Matrix/main.htm`].

Chesteen, S., B. Helgheim, T. Randall, and D. Wardell (2005). Comparing quality of care in non-profit and for-profit nursing homes: a process perspective. *Journal Of Operations Management 23*(2), 229–242.

Donabedian, A. (1988). The quality of care: How can it be assessed? *Journal of the American Medical Association 260*(12), 1743–1748.

Geiger, D. and D. Heckerman (1994). Learning gaussian networks. In *Uncertainty in Artificial Intelligence; Proceedings of the Tenth Conference*.

Goodson, J. (2005). Assessing the quality of care in nursing homes through bayesian belief networks. Master's thesis, University of Missouri-Columbia.

Gustafson, D., F. Sainfort, R. Konigsveld, and D. Zimmerman (1990). Quality assessment index (qai) for measuring nursing home quality. *Health Services Research 25*(1), 97–127.

Harrington, C., J. OMeara, M. Kitchener, L. Simon, and J. Schnelle (2003). Designing a report card for nursing facilities: What information is needed and why. *The Gerontologist 43*(Special Issue II), 47–57.

Heckerman, D., D. Geiger, and D. Chickering (1995). Learning bayesian networks: The combination of knowledge and statistical data. *Machine Learning 20*, 197–243.

Hogg, R., A. Craig, and J. McKean (2004). *Introduction to Mathematical Statistics*. Prentice Hall.

Huang, C. and A. Darwiche (1996). Inference in belief networks: A procedural guide. *International Journal of Approximate Reasoning 15*(3), 225–263.

Institute of Medicine (1986). *Improving the Quality of Care in Nursing Homes*. National Academy Press.

Institute of Medicine (1996). *Nursing staff in hospitals and nursing homes: is it adequate?* National Academy Press.

Institute of Medicine (2000). Improving the quality of long-term care. Technical report.

Jensen, F. (1996). *An Introduction to Bayesian Networks*. London: UCL Press Limited.

Jensen, F., S. Lauritzen, and K. Olesen (1990). Bayesian updating in causal probabilistic networks by local computation. *Computational Statistical Quarterly 4*.

Karon, S., F. Sainfort, and D. Zimmerman (1999). Stability of nursing home quality indicators over time. *Medical Care Research and Review 37*(6), 570–579.

Mukamel, D., W. Spector, J. Zinn, L. Huang, D. Weimer, and A. Dozier (2007). Nursing homes' response to the nursing home compare report card. *Journal of Gerontology: Psychological Sciences 62*, S218–S225.

Pearl, J. (1988). *Probabilistic Reasoning in Intelligent Systems*. San Mateo, CA: Morgan Kaufmann.

Rantz, M., L. Hicks, V. Grando, G. Petroski, R. Madsen, D. Mehr, V. Conn, M. Zwygart-Staffacher, J. Scott, M. Flesner, J. Bostick, R. Porter, and M. Maas (2004). Nursing home quality, cost, staffing, and staff mix. *The Gerontologist 44*(1), 24–38.

Rantz, M., L. Hicks, G. Petroski, R. Madsen, D. Mehr, V. Conn, M. Zwygart-Staffacher, and M. Maas (2004). Stability and sensitivity of nursing home quality indicators. *Journal of Gerontology 59A*(1), 79–82.

Rantz, M., A. Jensdottir, I. Hjaltadottir, H. Gudmundsdottir, J. Gudjonsdottir, B. Brunton, and R. M. (2002). International field test results of the observable indicators of nursing home care quality instrument. *International Nursing Review 49*(4), 234–242.

Rantz, M., D. Mehr, L. Popejoy, M. Zwygart-Stauffacher, L. Hicks, V. Grando, V. Conn, R. Porter, J. Scott, and M. Maas (1998). Nursing home care quality: A multidimensional theoretical model. *Journal of Nursing Care Quality 12*(3), 30–46.

Rantz, M., G. Petroski, R. Madsen, D. Mehr, L. Popejoy, L. Hicks, R. Porter, M. Zwygart-Stauffacher, and V. Grando (2000). Setting thresholds for quality indicators dervied from MDS data for nursing home quality improvement reports: An update. *The Joint Commission Journal on Quality Improvement 26*(2), 101–110.

Rantz, M., M. Zwygart-Stauffacher, and M. Flesner (2005). Advances in measuring quality of care in nursing homes. *Journal of Nursing Care Quality 20*(4), 293–296.

Rantz, M., M. Zwygart-Stauffacher, L. Popejoy, V. Grando, D. Mehr, L. Hicks, V. Conn, D. Wipke-Tevis, R. Porter, J. Bostick, M. Maas, and J. Scott (1999). Nursing home care quality: A multidimensional theoretical model integrating the views of consumers and providers. *Journal of Nursing Care Quality 14*(1), 16–37.

Sainfort, F., J. Ramsay, P. Ferreira, and L. Mezghani (1994). A first step in total quality management of nursing facility care: Development of an empirical model of structure, process and outcome dimensions. *American Journal of Medical Quality 9*(2), 74–86.

Sainfort, F., J. Ramsay, and H. Monato, Jr. (1995). Conceptual and methodological sources of variation in measurement of nursing home quality: An evaluation of 24 models and an empirical study. *Medical Care Research and Review 52*(1), 60–87.

Spiegelhalter, D., A. Dawid, S. Lauritzen, and R. Cowell (1993). Bayesian analysis in expert systems. *Statistical Science 8*(3), 219–283.

Ullmann, S. (1985). The impact of quality on cost in the provision of long-term care. *Inquiry 22*(3), 293–302.

Unruh, L. and T. Wan (2004). A systems framework for evaluating nursing care quality in nursing homes. *Journal of Medical Systems 28*(2), 197–213.

Weech-Maldonado, R., G. Neff, and V. Mor (2003). Does quality of care lead to better financial performance?: The case of the nursing home industry. *Health Care Management Review 28*(3), 201–216.

Zimmerman, D. (2003). Improving nursing home quality of care through outcomes data: the mds quality indicators. *International Journal of Geriatric Psychiatry 18*(3), 250–257.