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**Data Mining to Identify Quality of Care Factors Associated with Liability Claims
and Risk Management Strategies in Florida Nursing Homes**

DISSERTATION

**Presented in Partial Fulfillment of the Requirements for the Degree of
Doctor of Philosophy
Lynn University**

By

Ernande Fortune

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**Data Mining to Identify Quality of Care Factors Associated with Liability Claims
and Risk Management Strategies in Florida Nursing Homes**

Ernande Fortune

Lynn University, 2009

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All praises, honor and glory be to God who made this accomplishment possible. I thank God for the patience, virtue, intelligence, and faith that he gave me throughout this process. I remember it was prior to my father's death at the beginning of January 2000 that he asked me from his hospital bed "Why don't you pursue your doctoral degree?" I replied, "I was at the school today gathering information about that." That was the beginning of my journey. Throughout this process, I have been privileged to meet many special people who have encouraged and prayed for me along the way. I would like to acknowledge Dr. Jeanette Francis, my chair, who has "stepped-up to the plate" to see me through the completion of my journey. I would like to thank the other members of my committee: Dr. Norcio for his knowledge and contribution to my study and Dr. Miller, for being an essential member on my team. Dr. Boisjoly, thank you for listening and for taking the time to read and comment on my dissertation. Additionally, I would like to acknowledge the innumerable contributions of Dr. Joan Scialli throughout this process.

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ABSTRACT

The challenges facing the nursing home industry are increasingly important to the population of the United States. As the population grows older, the number of people that will require services from a nursing home will increase. In today's environment the nursing home business is facing many challenges that will define the future of the industry. Among them is the plaintiff attorney lawsuit against nursing homes, rising liability costs and vulnerability to lawsuits. A reduction in liability claims should allow nursing homes in Florida to remain solvent and stay in business to take care of those who cannot take care of themselves. This demographic shift has to be supported by a vibrant, efficient, and high-quality nursing home system.

The purpose of this study was to examine the influence that quality of care factors and risk management strategies have on liability claims in nursing homes, and to create a risk management model. Four research questions and a hypothesis were tested. The research design was an exploratory and predictive quantitative design using data mining of secondary data. The study analyzed the quality of care factors associated with liability claims and model risk management in order to predict and generate strategies that can decrease claims in Florida nursing homes. The data sets that were used in the study consisted of data from 106 nursing homes from 67 counties in Florida. The study used data mining software application to conduct data mining analysis and create risk management models. The data models developed were used to identify quality of care factors associated with liability claims in Florida nursing homes.

Findings indicated that (a) there was a strong correlation between quality of care indicators and the incidents that led to liability claims; (b) various risk management strategies have been used in Florida, of which the most common seem to be methods for training staff; (c) while various risk management strategies such as training and educating staff do have an effect on the number and severity of lawsuits, they are not necessarily sufficient to decrease nursing homes' exposure to risk substantially; and, (d) the success of the measurements indicated that there are indeed diagnostic tools that can identify areas of risk, but the external factors noted in the answer to the previous question still apply.

The implications and recommendations were essentially that the solution to the problems facing the nursing home industry requires a holistic focus on the legal and financial context of that industry. That holistic focus, in conjunction with efforts to further improve the nursing home industry itself, could help ensure that as millions of Americans begin to retire, they have the necessary resources and infrastructure to support them.

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CHAPTER I

INTRODUCTION TO THE STUDY

Introduction and Background

Liability claims in the nursing home industry continue to be an issue in today's healthcare field. The frequency, cost, and severity of liability claims has risen and the effect of quality and risk management strategies has had mixed effects on these claims. The increase in the numbers of older persons who required long term care services throughout the coming decades due to functional limitations are significant. Therefore, the nursing home industry must be well positioned in the market to attract insurance companies to continue to provide liability coverage for nursing homes in Florida.

The National Institute on Aging reported that one in five Americans were 65 years or older in 2006, amounting to approximately 72 million people. According to the Centers for Medicare and Medicaid Services (CMS) (2003), about 3.5 million people will live in nursing homes in the U.S. during the course of a year. Most researchers have agreed that despite regulatory efforts to improve quality of care in nursing homes, quality continues to be a serious problem (Maas, Kelley, Park, & Specht, 2002). In 1990, The Institute of Medicine's committee for quality review defined quality as the "degree to which health services for individuals and population increase the likelihood of desired health outcomes and are consistent with professional knowledge" (as cited in Kane & Blewett, 1993, p. 93). Dana (2004) defined quality in long-term care as the totality of service features and characteristics that meet or exceed customer needs and expectations (p.1).

According to CMS (2006), since 2000, CMS and states nationwide have made progress in holding nursing homes accountable for meeting health and safety standards and improving care. To attain accountability, CMS (2006) has done the following: (a) revised the survey process on the quality of care and the prevention of abuse and neglect, (b) strengthened enforcement responses to non-compliant nursing homes; (c) provided better information to help consumers make decisions on choosing a nursing home; (d) developed and reported on quality measures, such as the prevalence of pressure ulcers, incontinence, and physical restraints; (e) worked with quality improvement organizations (QIOs) to assist nursing homes in meeting health and safety requirements; and (f) built improved infrastructure for the survey and certification system, such as a new ASPEN Complaints/Incidents Tracking System (ACTS) and the ASPEN Enforcement Manager (AEM) to identify and track needed improvements in the quality of care (p. 1).

In addition, the American Health Care Association developed the Quality First initiative, a quality award program that is criteria-based. This program includes three steps that provide an effective guide for developing a quality improvement initiative and builds on the federal government's Nursing Home Quality Initiative (NHQI) as an internal quality improvement tool (American Health Care Association [AHCA], 2006). There are also other quality programs that focus on the measurement of quality in Florida nursing homes. These include the Advancing Excellence Campaign, the FHCA quality-credentialing program, the Florida Pioneer Network's Culture Change focus, the FMQAI 8th Scope of Work, and the Quality Indicator Survey (QIS) (CMS, 2007). "Collaborating to measure quality of long-term care, report it, support it, and improve it which is the best

path to a high-quality, patient-centered, provider-friendly system that everyone can afford” (CMS, 2007, p. 1).

The Advancing Excellence Campaign is a two-year voluntary program designed to accelerate performance in eight measures of quality, which are meaningful to a broad array of stakeholders (CMS, 2007). The campaign’s goals include four specific clinical measures and four specific process measures: pressure ulcers, restraints, chronic pain, Post-Acute Care (PAC) pain, setting targets, customer satisfaction, staff retention, and consistent staffing. The data for goals five to eight are confidential, unless a facility requests otherwise. However, the first four goals are collected automatically via the Minimum Data Set and are publicly reported on Nursing Home Compare. The Minimum Data Set (MDS) is a clinical foundation for quality care. The MDS, which is an integral aspect of Medicare’s reimbursement system, is the federal tool used to collect data, identify risk factors, support clinical risk evaluation, and create plans to guide services reimbursement system. The MDS also describes the acuity of the resident, reveals the quality measure/quality indicator, and is part of the Quality Indicator Survey process (CMS, 2007).

The Quality Indicator Survey (QIS) is a surveying process used to improve the quality of care in nursing homes. The QIS started a preliminary testing in a staged survey by the University of Colorado between 1992-1997. From 1998-2005, a contract was put in place with CMS to develop the QIS survey process with the University of Colorado, University of Wisconsin, Maverick Systems, Alpine Systems, and to subcontract to RTI. Between 2005-2008, the demonstration and refinement contract was implemented with the University of Colorado. According to CMS (2007), there are four objectives

associated with the QIS process: (1) to improve consistency and accuracy of quality of care and quality of life problem identification through a more structured process, (2) to comprehensively review regulatory areas within current survey resources, (3) to enhance documentation through greater automation to organize survey findings, and (4) to target survey resources on facilities with the largest number of quality concerns (p. 2).

There are two stages in the QIS process and three steps within each stage (CMS, 2006). The two stages include a preliminary investigation of the nursing home practice to ensure compliance with State regulations and to determine the deficient practice. The three steps within each of the stages of the QIS process are sampling, investigation, and synthesis.

Quality of care factors that may be associated with liability claims in long-term health centers are due to both external and internal drivers of loss. External drivers of loss include a plaintiff bar, negative perception of the nursing home industry, negative perception of the nursing center, and juries who are desensitized to the impact of large awards. Internal drivers of loss reported are poor quality of care, resident falls, pressure ulcers, poor documentation, poor relationships between nursing center staff, residents and their families, lack of education of the resident and family on aging and the disease process, staff turnover, and poor employee relations in the nursing center (Stevenson & Studdert, 2003).

Effective risk management education and intervention strategies are necessary to decrease the number of liability claims (Stevens & Bick, 2002). In July 2006, the Florida Agency for Health Care Administration's report to the legislature indicated that between July 1, 2005 and June 30, 2006, the Agency received nursing home Notices of Intent

(NOI) to sue. In 2006, there was an increase of liability claims in Florida. Bourdon and Keefe (2007) reported that even though the frequency of claims continues to increase nationwide, the S.B.1202 tort reform not only reduces severity but also reduces frequency. In fact, Florida, Georgia, Louisiana, Mississippi, Ohio, Texas, and West Virginia had 12.3 claims per 1,000 beds in 2006, a drop from the high of 18.7 claims per 1000 beds in 2001. The average size of a claim for these states also dropped nearly 72% from 1998 to 2006 (p. 1). “Positive effects from other developments, such as stronger defense strategies and the increased use of arbitration, as well as operational changes that focus on quality of care initiatives (e.g., patient safety programs, family education plans, increased staffing ratios, and investment in safer homes and equipment)” would decrease claims (Bourdon & Keefe, 2007, p. 2).

Data mining can be used to effectively detect quality factors associated with liability claims. Data mining is the process of extracting knowledge from large data sets that may be hidden. Hand, Mannila, and Smyth (2001) defined data mining as the “analysis of (often large) observational data sets to find unsuspected relationships and to summarize the data in novel way that are both understandable and useful to the data owner” (p. 1). Through data mining analysis models, patterns are created from the relationships and the summaries formed by the process. Data mining also deals with secondary data collected for purposes other than data mining. This means that the data collection strategy has no correlation with the objectives of data mining. “Data mining is often set in the broader context of knowledge discovery in databases, or KDD. The KDD process involves: selecting the target data, preprocessing the data, transforming them if

necessary, performing data mining to extract patterns and relationships, and then interpreting and assessing the discovered structures” (Hand et al., p. 3).

Purpose

Increased liability claims, divestiture of nursing homes, and the growing senior populations are all factors affecting the nursing home industry. Liability exposure to civil actions brought by residents and their families is a growing reality in the nursing home industry (AON, 2004). Most nursing home providers have been waiting for legislative relief by tort reform or public perceptions to change regarding the intent to file a lawsuit or they choose to stay on the defensive in order to deal with the liability issue (Stevenson & Studdert, 2003). The purpose of this exploratory and predictive (correlational) research study using data mining of a secondary data set was to determine quality of care indicators associated with liability claims in Florida nursing homes, to determine risk management strategies associated with liability claims in Florida, and to create a risk management model to improve quality of care.

Definition of Terms

Independent Variables

Quality of Care Factors in Nursing Homes

Theoretical definition: The quality of care in U.S. nursing homes has been an ongoing issue for the public at large. Quality can be defined as meeting and exceeding the need of a customer. CMS (2006) discussed the action plan for further improvement of nursing home quality in 2007, by mobilizing all available tools and aligning them in a comprehensive strategy. The comprehensive strategy includes:

1. Consumer Awareness and Assistance

2. Survey, Standards, and Enforcement Processes
3. Quality Improvement, which includes restraints, preventable, pressure sores, and culture change.
4. Quality Through Partnerships
5. Value-Based Purchasing

The American Medical Association (AMA) stated that quality of care of a resident “consistently contributes to the improvement or maintenance of quality and/or duration of life” (Weech-Maldonado, Neff & Mor, 2003, p. 202).

Operational definition: Quality of care can be measured by using the Minimum Data Set (MDS) (CMS, 2007). The data generated by the MDS are the discrete data elements that include clinical items of functional dependence and cognitive functioning (CMS, 2007). The MDS instrument collects over 350 discrete data items that create the resident level quality measure and 24 quality indicator reports (Grabowski, Gruber, & Angelelli, 2006). In this study, 24 quality indicators and quality measures are shown as Q1 through QM12 in Appendix B Part 2. The MDS was mandated for administration on all nursing home residents under OBRA 1987 as part on the Resident Assessment Instrument (RAI) (CMS, 2006).

The MDS contains information of residents, activities of daily living (ADLs), behavioral and emotional problems, oral nutritional status, skin condition, treatments, and medications. In this study, the QI generated from the MDS were used as the measurements for quality of care in nursing homes.

Nursing Home Characteristics

Theoretical definition: A nursing home is a place of residence for people who require constant medical care, but at a lower level than a hospital (AHCA, 2007). Usually the residents are older persons, but the term can apply to places of care for people with mental or physical illnesses. According to CMS (2007), a nursing home is characterized by number of beds, type of ownership, and participation in Medicare and/or Medicaid (p. 1).

Operational definition: In this study, a nursing home or skilled nursing facility was characterized by the requirements of the Florida statute 1819 or 1919(a), (b), (c), and (d) of the Act, which would include Medicare and Medicaid eligibility, and certification (AHCA, Long Term Care Survey, 2006). On the quality indicator report, the facility characteristics report includes resident gender, age, payment source, diagnostic characteristics, type of assessment, stability of conditions, and discharge potential (AHCA, Long Term Care Survey, 2006). The characteristics of residents who had an admission, annual or change in status assessment are part of the Minimum Data Set (MDS), which generates the quality indicator report. The characteristics measured are the number of beds, type of ownership and participation in Medicare, Medicaid or both (CMS, 2007). This information was obtained from the nursing home compare link of CMS. Appendix B Part 1 lists the nursing home characteristics measured for this study.

Adverse Incident Outcome

Theoretical definition: Nursing homes are required to monitor the internal actions and events, together with the environment, to provide the safest possible home for the residents (See Appendix G). The risk management program is designed to increase and improve the understanding of how the events that cause harm to residents occur, and

actions that should be taken to prevent those events. According to AON (2006), nursing home adverse incident outcomes include:

1. Death
2. Brain or spinal damage
3. Disfigurement
4. Fracture
5. Limit Function (neurological, physical or sensory)
6. No consent
7. Transfer
8. Adult Abuse
9. Child Abuse
10. Elopement
11. Law Enforcement

Operational definition: The adverse incident outcomes were measured by the AHCA Form 3110-0009, Confidential Nursing Home Initial Adverse Incident Report – 1 Day, and AHCA Form 3110-0010, 3110-0010A, and 3110-0010B, Confidential Nursing Home Complete Adverse Incident Report – 15 Day, which are incorporated by reference when reporting events as stated in Section 400.147, F.S. (See Appendix B, Part 3).

Incidence of Falls

Theoretical definition: An incidence of fall is defined as an occurrence characterized by the failure to maintain an appropriate lying, sitting or standing position, resulting in an abrupt, undesired relocation to the ground. Falls are common and recurrent events in the nursing home population, often resulting from an elder person's inability to

compensate for environmental stresses and his or her underlying disabilities, as well as facility care practices that may be inadequate in reducing the risk of falls (Westmoreland & Baldini, 2005). The following risk factors associated with falling have been identified: sex, age, medication (antipsychotics, antidepressants, or antianxiety drugs), wandering, and loss of balance, chairfast, bedfast, cognitive impairment, co morbidities, bedrails, trunk restraints, activity of daily living (ADL) impairment, urinary incontinence, unsteady gait, and cane/walker use (p. 268). Furthermore, in the elderly nursing home residents, a history of falls is another strong risk factor for incidence of falls. Thus, repeat fallers require comprehensive and individualized preventive interventions (p. 268). Nursing facilities utilize a multifactorial falls risk assessment and management program that consists of three components:

1. A questionnaire to identify risk factors for falls, which can be self-administered or administered by a professional.
2. A thorough medical evaluation (including examination of vision, gait, balance, strength, postural vital signs, medication review, and cognitive and functional status).
3. Follow-up interventions may include a tailored exercise program, environmental modifications, and assistive devices.

Operational definition: Incident reports in nursing homes are routinely kept separate from medical records. Nursing homes usually keep reports and logs, which are presented to surveyors during an inspection. Sources of data collection can be baseline interviews with nursing staff, residents, and significant others, and medical records containing MDS evaluations and hospital discharge summaries. In this study, the MDS

resident level data were used to measure the incidence of falls specific to residents with new fractures on the most recent assessment and the prevalence of falls that were reported to AHCA as adverse.

Risk Management Strategies

Theoretical definition: Risk management is defined in the Florida Statutes 59A-10 Internal Risk Management Program as a “means of identification, investigation, analysis of risks, and the selection of the most and advantageous method of correcting, reducing or elimination of identifiable risks (Florida Statute, 2007, p. 198). According to the AHCA (2004) report to the legislator, a risk management program is designed to increase and improve the understanding of how events that cause harm to residents occur, and actions that should be taken to prevent those events. Nursing homes are required to monitor the internal actions, events, and the environment to provide the safest possible home for the residents.

Operational definition: According to CMS (2006), risk management programs are structured approaches to limit liability risk, which include higher standards of care, quality in nursing homes, and management techniques to minimize exposure. One area of risk management focus since the passing of SB1202 nursing home reform in 2001 is direct care nursing staffing per patient day (ppd). The mandates for nursing home staffing levels are as follows:

1.0 __ppd for RN/LPN

2.3 __ppd for CNA staffing in 2002

2.6 __ppd for CNA staffing in 2003

2.9__ ppd for CNA staffing in 2007 with an average of 2.9 per week with staffing no lower than 2.75 on any day. (See Appendix F- Calculating Staffing for Long Term Care Facilities)

According to Hyer (2007), qualities through the increased regulations are as follows:

1. Zero tolerance for not meeting staffing standards.
2. Providers are required to self-report when they fall below the staffing ppd for 24-hours.
3. A self-imposed moratorium should be initiated on admission for 6 days after 48 hours of not meeting staffing standards.
4. Facilities should post names of direct care staff on duty (i.e. RNs, LPNs, and CNAs) and assignments.
5. Surveyors should review two weeks of staffing and prior 6-month review of staffing to ensure facility compliance. (See Appendix F)

In this study, the facility level data quarterly report that was submitted semi-annually was used to measure risk. It includes staffing ratios, staff turnover, and stability for CNAs, licensed nurses, director of nursing and facility administrator (See Appendix B, Part 5).

Dependent Variable

Liability Claim

Theoretical definition: A liability claim, as defined by AON Risk Consultants (2005), is a demand by an individual or other entity to recover for a loss. The nursing home litigation process for cases allege neglect, abuse, wrongful death, and other offenses against residents in nursing homes (Henry, 2004).

Operational definition: Nursing homes are mandated to report adverse incidents and monthly liability claim form information, considered as a notice of intent (NOI) to sue, to the Agency for Health Care Administration (AHCA). The data are based on individual resident claims per facility. The data are collected by the Agency's Facility Data Analysis Unit (FDAU), and entered into the Florida Regulatory Administration and Enforcement System (FRAES LE) (AHCA, 2006). Therefore, the data for this study were obtained from the Agency's FDAU for the fiscal year 2006.

Frequency of claims is the ratio of the number of claims divided by exposure. *Loss cost* is the cost per exposure of settling and defending claims. *Severity* is the total dollar amount of a claim including indemnity and allocated loss adjustment expense (ALAE). "ALAE are cost in addition to indemnity payments and reserves which are incurred in handling claims" (AON, 2005, p. 69). The *frequency of claims* is measured by the AON as to the number of claims projected for the given time-period divided by the number of occupied beds during that same period. In the AON (2005) report, frequency was presented as the number of claims a year for every 1,000 beds. *Loss cost* was calculated as the ratio of total dollar indemnity and allocated loss adjustment expense (ALAE) to total exposures for a given period of time (AON, 2005). Loss cost were measured in this study by the amount per occupied bed expected to be paid to defend, settle and/or litigate claims arising from incidents occurring during the respective year. In this study, severity was measured by using the average for a given year by dividing the total dollars of losses for all claims incurred in the year by the total number of claims. Therefore, in order to determine frequency, severity, and loss cost, the data included the following for each individual case:

1. Individual claim status
2. Accident date report date
3. Close date
4. Indemnity paid
5. Allocated loss adjustment expense paid
6. Total paid
7. Indemnity incurred
8. Allocated loss adjustment expense incurred
9. Total incurred. (See Appendix B, Part 6).

Data Mining

Theoretical definition: Data mining is the process of extracting knowledge hidden from large data. The PolyAnalyst 6 version software was used to conduct the data mining analysis. According to Megaputer.com, the PolyAnalyst suite is considered the world's most comprehensive and versatile tool. Furthermore, "The Data Mining Package includes PolyAnalyst 6, an industry leading data mining system" (Megaputer, 2007, ¶ 1). PolyAnalyst 6 is a powerful, scalable and easy-to-use data-mining tool.

Operational definition: In this study, data mining was used to analyze large observational data sets from the MDS data that are warehoused by CMS to find unsuspected relationships and to summarize the data in a way that is both understandable and useful to the nursing home industry. Additionally, through the data mining analysis, models or patterns could be created from the relationships and summaries that are formed by the process.

Justification

This study was justified by considering its significance, the scope to which it was a researchable topic and the feasibility of conducting the study. This study was of general interest in the healthcare field in the U.S. Liability claims and risk management are hot topics in the industry today. Although there are many studies on quality improvement, few studies have examined the factors affecting quality of care, risk, and liability in nursing homes. Furthermore, the idea of using data mining to explore and predict new risk management models was of importance since the healthcare industry is still far behind other industries in creating integrated, longitudinal databases that can serve as repositories for data mining (Fickensher, 2005).

Nursing home quality is a multidimensional construct with many quality measures, for example, the MDS quality indicators (Castle & Lowe, 2005). CMS (2006) put in place an action plan for improvement of nursing home quality. CMS and Florida have collaborated to ensure compliance and have held facilities accountable by doing the following:

1. Revised the survey process to focus on the quality and the prevention of abuse and neglect.
2. Strengthened enforcement responses to non-compliant nursing homes.
3. Provided better information to help consumers make decisions on choosing a nursing home.
4. Developed and reported on quality measures, such as the prevalence of pressure ulcers, incontinence, and physical restraints.

5. Worked with quality improvement organizations (QIOs) to assist nursing homes in meeting health and safety requirements.
6. Built improved infrastructure for the survey and certification system, such as a new ASPEN Complaints/Incidents Tracking System (ACTS) and the ASPEN Enforcement Manager (AEM) to identify and track needed improvements in quality of care (CMS, 2006, p. 1).

Burwell, Stevenson, Tell, and Schaefer (2006) stated that insurers and nursing home providers enjoyed a stable market for professional liability insurance in the mid-1990s, however, today, the litigation activity has increased. During this period, insurance carriers left the market and national nursing home chains divested the facilities (Burwell et al.). “The nursing home industry contended that much of the increase in litigation activity was due to frivolous claims not related to negligent care or patient abuse” (Burwell et al., p. 1).

This study was researchable because it asked scientific questions and had variables that could be measured. This study was of significance and was worth examining because it is important to provide quality of care in the nursing home setting while decreasing the risk of liability. At this time, liability claims are causing a crisis in the industry, and it is unknown how critical the situation will get. Furthermore, there are secondary data that are available to conduct the research in a reasonable amount of time and with a reasonable budget. Constructs of the theoretical frameworks were measured and the research followed the procedures to protect the rights of human subjects. This study was beneficial to the research results that identified risk management strategies to decrease claims and improve quality of care in Florida nursing homes.

Delimitations and Scope

1. The geographic area and setting of the sample was limited to nursing homes in Florida.
2. The nursing homes were for-profit corporations not affiliated with a hospital or Continuing Care Retirement Communities (CCRC).
3. The nursing homes must be at least 120-bed capacity.
4. The nursing homes must conduct resident and family council.
5. The nursing homes were listed on the CMS webpage under nursing home compare.
6. The nursing homes are not required to provide permission to participate in the study because the data are available on CMS MDS assessment for nursing homes in Florida through Research Data Assistance Center (ResDAC) on the following site: <http://www.resdac.umn.edu/MDS/Index.asp>.

Chapter I introduced the research study. The introduction discussed liability claims in Florida nursing homes and their effect on the industry as a whole. The purpose of the study was described; the terms were defined theoretically and operationally. The study was justified because it was significant, researchable, and feasible. The delimitations and scope of the study were identified. Chapter II presented the literature review, theoretical framework, and research questions about quality of care factors associated with liability claims and risk management strategies to decrease claims. Chapter III presented the research methods used to answer the questions about quality of care factors associated with liability claims in Florida nursing homes. Chapter III included the design, population, sample, instruments, procedures and ethical aspects,

method of data analysis, and evaluation of the research methods. Chapter IV presented the results of the data analyses that were performed in this study and Chapter V presents a discussion of the findings and interpretations of the data mining results. Furthermore, the limitations and recommendations for future research are discussed.

CHAPTER II

LITERATURE REVIEW, THEORETICAL FRAMEWORK, AND RESEARCH QUESTIONS

The three major sections of this chapter include the literature review, theoretical framework, and research questions. The literature review begins by describing the nursing home center industry's history, characteristics, and quality of service. Furthermore, the literature review discusses quality of care, risk management, liability claims and the method of data mining.

Literature Review

There are many factors associated with liability claims. However, one must make the connection between routine activities (i.e. record review) and lawsuits. Quality is a major factor that is correlated inversely with liability claims in the nursing home industry. There are many factors associated with liability claims that affect quality in the nursing home. Quality can be defined in many different ways based on individual perception. Whether or not quality care is given, it is the perception of the resident or family members that determine whether a liability claim is filed. In the nursing home setting, a good risk management program that is comprehensive, organized and supported by the facility's team is the main building block to quality care.

Most of the findings in the literature on litigation tie quality of care and poor risk management to an increase in frequency, severity, and cost of liability claims (Wright, 2003). Quality improvement and risk management must be the focus of the industry in order to reduce the frequency and severity of claims. Researchers such as Stevenson and Studdert, the AON Actuarial Risk Consultants, and Wright agree that insurance will not

become available throughout many States, for example Florida, until there is certainty in the insurance market (Wright, 2003). The only way to bring certainty to the market is to pass legislation that will reduce the number of claims against nursing homes.

Furthermore, the Agency for Health Care Administration continues to monitor the care quality in nursing centers. No current studies show that claims against nursing homes are on the decline; in fact, the AON Actuary report 2005 shows the contrary.

As the AON 2003 study points out, caps on non-economic damages are the most effective tort reform policy provision for reducing nursing home patient liability claim severity. Nursing homes are committed to providing an affordable yet significant level of financial responsibility as part of legislation that includes these long overdue tort reform measures. Clearly, without new meaningful tort reform, nursing homes and their patients will be left unprotected without affordable insurance. Consequently, the crisis of liability claims will continue to worsen.

The Nursing Home Industry Characteristics

In order to understand current liability issues in the nursing home industry, it is important to review the industry's history. Williamson (1999) reported that in 1997 4% of the 34.1 million older persons in the U.S. received care in 17,176 nursing homes, which provided approximately 1.8 million beds at a cost of \$78.5 billion dollars. "As the baby boomers move into the 65 and older age categories, the number of older persons will double to approximately 70 million, or 20% of the population by 2030" (Williamson, 1999, p. 422). The implication of this fact is that as the older person's population grows, more nursing home resources will be required in order to meet the needs of the population.

The nursing home industry evolved from institutions such as county homes and state mental hospitals that took care of the impoverished older persons (West, Tuch & Goldsmith, 2001). Contemporary nursing home structures include for-profit, non-profit and multi-facility owners. Nursing homes provide long-term care, rehabilitation services (i.e. occupational, physical, and speech therapy), respite care, wound care, Alzheimer's services, and 24-hour nursing services. Many nursing home residents have some form of dementia, and, as a result, are not able to take care of themselves due to cognitive or physical functional decline (Maas et al., 2002). The biggest threat to financial security that retired older persons in the United States face is the high cost of a nursing home care (Clapp, 1996). "More than 40 percent of elders age 60 or over will at some time require expensive nursing home services, either at home or in a nursing home or other housing facility" (Clapp, 1996, p. 46).

Major Payer Mix: Medicare and Medicaid

Medicare is a federal health insurance plan for individuals who are 65 years or older. To qualify, individuals or their spouse must have 40 or more quarters, or 10 years, of Medicare covered employment. Medicare is structured in Part A and Part B coverage. Medicare Part A is a hospital coverage, which covers hospital stays, some hospice, skilled nursing care, and home health care services. Medicare Part B is a medical insurance, which covers physicians' services, outpatient hospital care, physical therapy, diagnostic units, and other services (CMS, 2003). Medicare provides only 100 days of care in a skilled nursing facility per illness for beneficiaries following a minimum of a three-day hospital stay. However, if a nursing home is required for custodial care, the

beneficiary must pay privately or apply for Medicaid to determine eligibility (CMS, 2003).

Medicaid is a federal program that pays for medical assistance for individuals with limited income. To be eligible, individuals must fall under specific categories for which funds are available. Medicaid coverage varies from state to state (CMS, 2003). The basic Medicaid program is important because it is the largest source of state nursing home expenditures. Nursing centers are certified by Medicare and Medicaid and are reimbursed by these agencies for services provided through federal funds. Therefore, nursing centers are required to follow Medicare and Medicaid guidelines when providing quality of care to residents (Kane, Kane, Ladd & Veazie, 1998).

The Office of the Inspector General (OIG) of the U.S. government has independent authority to terminate Medicare and Medicaid provider agreements with nursing homes if the OIG determines that a facility has failed to provide quality of care (Landsberg & Keville, 2001). In order for that to happen, the OIG must be aware of fraudulent billing activities by a facility or other providers, and substandard care must be observed in the course of its fraud investigation. Landsberg and Keville (2001) suggested that nursing homes increasingly were subject to heightened liability for seriously deficient care under state elder abuse and neglect statutes.

In assessing the question of whether Medicare is concerned about quality, a review of literature by Hyman (2003) indicated that there seems to be a large gap between the care people should received and the care people actually receive in nursing homes. A 2000 study by Jencks et al., examined the care provided to Medicare beneficiaries using “24 process-based measures of quality, involving the prevention or

treatment of six medical conditions such as acute myocardial infarction, breast cancer, diabetes, heart failure, pneumonia, and stroke” (as cited in Hyman, 2003, p. 56). The goal for each measure was for 100% of qualifying Medicare beneficiaries to receive the proper intervention. However, the range of quality rates varied widely because the proper intervention depends on the quality measure used in the study. Hyman (2003) stated the structural limitations of quality of care as the reason the Center for Medicare and Medicaid Services (CMS) has not leveraged its market power. For the future, Hyman (2003) suggested that Medicare beneficiaries were more than a little unhappy with this state of affair is true and accurate to the best of my abilities. This article was very important in trying to understand the CMS function in the quality of care issue.

Since Medicare and Medicaid pay a large portion of the cost of nursing home care, increases in liability insurance can lead to greater expenditures by CMS (Wright, 2003, p. 10). Furthermore, Wright (2003) reported that Medicaid pays 49%, Medicare pays 10%, and private sources pay 41% of nursing home charges. As people age, the demand for nursing home services will increase.

AHCA (2007) reviewed nursing home regulatory requirements, reimbursement, quality, and ownership. “The review was limited to the areas of authority for state licensure and Medicaid participation, but provides insight to the current regulatory oversight of Florida nursing homes and examines potential recommendations for change” (AHCA, 2007, p. 2). In Florida, there are 673 licensed nursing homes of which 645 are certified to accept Medicare and Medicaid, 21 are Medicare certified only, six are private pay only and one is inactive. A market research analysis conducted by CMS (2003)

indicated that 16,500 nursing homes were certified to provide Medicare or Medicaid care in the U.S. with approximately 1.8 million total beds.

Approximately 3.5 million Americans live in nursing homes during the course of a year (CMS, 2003). “Medicare classifies about 15,000 nursing homes as skilled nursing facilities. About 85% of Skilled Nursing Facilities (SNFs) are freestanding nursing homes while the other 15% are hospital-based. Three-quarters of freestanding SNFs are operated as for-profit entities, while the majority of hospital-based SNFs are attached to not-for-profit hospitals” (CMS, 2003, p. 5). During 2006-2007, 71% of Florida nursing homes were owned by for-profit entities, and 29% were owned by not-for-profit organizations, including government entities (see Table 2-1 created by the researcher). This is important because the structure of the nursing centers will not exempt the risk of liability claims in the facilities.

Table 2-1

Florida Nursing Homes: Beds, by Type of Ownership, and Notice of Intent

Type of Ownership	Number of Facilities	NH Submitting NOI	Number of Beds	Total # of NOI Submitted
For-profit	477	148	58,982	259
Not-for-profit	184	46	23,458	78
Government	11			
Total	672	194	82,440	337

Note. Data compiled from Centers for Medicare and Medicaid Services 2007

As of April 2002, the trend in the nursing home industry was that many of the largest nursing home chains had divested their facilities and exited from the U.S., because of high insurance costs and aggressive litigation. The decline in total bed count from January 2002 changed from 18.5% to 15.5%.

According to Schaefer and Burwell (2006), Beverly Enterprises, the nation's largest nursing facility operator, sold of its entire Florida operations in January 2002. "Beverly stated that the sale was part of a strategy to divest facilities that accounted for a disproportionately high share of its patient care liability costs" (Schaefer & Burwell, 2006, p. 3). Kindred Healthcare, Inc., the nation's third largest nursing facility operator exited Florida completely in July 2003. Mariner Health Care, Inc., the fourth largest nursing facility operator completed the divestiture of its remaining facilities in Florida in December 2003. In late 2000, National HealthCare Corporation (NHC) divested completely its nursing facility business in Florida. Another top ten nursing facility operator, Extendicare Health Services, Inc., ceased all of its nursing home operations in Florida in January 2001.

Liability issues affect the nursing home industry as a whole, therefore it is necessary to create a quality care environment with effective risk management strategies to decrease claims in nursing homes. This would benefit customers and their families as well as nursing home owners (Stevenson & Studdert, 2003).

A Review of Quality in Nursing Homes

The Omnibus Budget Reconciliation Act of 1987 (OBRA) was the result of an Institute of Medicine (IOM) study which focused on the chronic problem of noncompliance with quality care in nursing facilities since the passage of Medicare and Medicaid (Nursing Home Reform, 1995, p. 1). Prior to OBRA 1987, nursing center regulatory enforcement was relatively lax in the United States. Therefore, IOM made clear recommendations on how CMS could compel nursing centers to achieve compliance with Medicare and Medicaid requirements. The legislation in OBRA (1987)

specifies that a nursing home “must provide services and activities to attain or maintain the highest practicable physical, mental, and psychosocial well-being of each resident in accordance with a written plan of care” (Federal Register, 1996, Rules and Regulations, p. 1). OBRA also states that nursing centers must comply with state and federal requirements for Medicare and Medicaid, and that all centers not in compliance with such requirements may be subject to enforcement action.

The typical consumer is not familiar with the way care and services are delivered in nursing home settings. “The first national experiment in market forces as a regulatory mechanism in healthcare occurred with the growth of the nursing home industry following the passage of the Social Security Act in 1935” (Latimer, 1998, p. 12). Subsequent to the passage of OBRA, government and private sector organizations became increasingly interested in better understanding the quality of care generally provided in the U.S. nursing homes. Bravo, De Wals, Dubois, and Charpentier (1999) conducted an exploratory analysis of the quality of care provided in nursing home centers. Their objective was to identify correlates of the quality of care.

This empirical study provides information about the determinants of quality of care and the interrelationships among quality scores assigned to sample residents. A random sample of 301 residents from 88 facilities in Quebec was selected using a stratified two-stage sampling scheme. This process considered facility size and regulatory status as the stratification factors. Quality was measured with the QUALCARE scale, “a multidimensional instrument comprising of 54 items that assess care in six important areas: environmental, physical, medical management, psychosocial, human rights, and financial” (Bravo, De Wals, Dubois & Charpentier, 1999, p. 4). Interviews of all facility

managers were conducted for descriptive information. Validation studies were conducted on the QUALCARE Scale. Researchers found that the patient variables that correlated with quality of care were gender, socioeconomic status, cognitive functioning, and functional autonomy. Overall reliability was reported as $\alpha=.92$ demonstrating internal consistency reliability of the measurement items.

Bravo et al. (1999) used a hierarchical model to identify factors that affect quality of care given to residents in the nursing home centers. However, the authors state that such an analytical approach requires the investigator to specify how measurement variables influence the distribution of outcomes from one level to the next. They identified four variables that influenced the relationship between cognitive functioning and quality of care. These four are “the number of external collaborators the facility has, the type of training the manager has, the size of the facility, and the age distribution of the clientele” (p. 180). This analytical approach enabled researchers to test the null hypothesis that there was no quality of care variation among nursing home centers.

The result of the one-way ANOVA model with random effects revealed that the presence of cognitive deficits was the strongest correlate of the quality of care provided to a resident. This means that the quality of care residents receive depends on their mental capabilities and varies based on the four factors stated above, and within facilities. The study contains methods that can be employed in subsequent studies dealing with the determinants of quality of care in the nursing home setting. This is a seminal study. It was suggested that future studies should investigate ways to surmount the difficulties of providing care to individuals with diminished mental capabilities. Furthermore, the authors suggest that enhancing caregivers’ knowledge about cognitive deficits and their

skills in meeting the needs of residents with cognitive impairment could be ways to overcome the difficulties of responding to their needs (Bravo et al., p. 187).

McGilton (2002) proposed a model as a mean of enhancing the quality of life of residents in the nursing home setting. No specific models currently explain the development of the relationship among care providers, residents, and care quality outcomes. The purpose of the McGilton study was to propose a model based on an existing theory of the environment by Kayser-Jones (1991) and the relationship theory of Winnicott's 1960 study, and to review the theoretical literature and empirical evidence that supported the elements of the model (as cited in McGilton, 2002). The theories were selected due to the role of the environment of care giving. The model of care proposes that if the provider is reliable, empathetic, and consistent with the nursing home environment, then a positive relationship of quality will develop for the resident (McGilton, 2002). The study provided empirical support for the model. Effective strategies were "continuity of care provider, skills, and knowledge required by care providers, and supportive environment for care providers and secondary outcomes" (McGilton, 2002, p. 16). McGilton (2002) explained the three strategies in the following manner:

1. The continuity of care provider has the acquired skills and knowledge required to enhance interpersonal relationships with patients. For example, reliability and empathy skills are based on dependency and sensitivity in caring for others.
2. Skills and knowledge required by care providers: a consensus among researchers states that positive care provider interactions with residents can have a critical

impact on the development of the relationship between nursing home residents and their caregiver (p. 17).

3. The supportive environment for care providers in the nursing home industry is where the care providers themselves are taken care of. This in turn can cause them to deliver high quality care and facilitate a care provider-resident relationship.

Secondary outcomes are the result of the previous strategies, which are evident by residents feeling less agitated, physical well being, etc. (p. 8).

Limitations reported by the author included methodological shortcomings that hinder the generalizability of findings in continuity of care provider research. Other limitations in the continuity of care provider research included inadequacy of survey instruments, lack of control groups, and small care provider samples. Despite suggested limitations in the continuity of care provider research, the author states that it can lead to positive outcomes, whereby the residents showed “fewer incidences of agitation, an improved affect, an improved physical integrity, and a general increase in well-being. Additionally, it showed a better attitude toward the older persons, less turnover, decreased levels of job-related stress and improved perceptions of the work environment, more certainty about interpreting residents’ behaviors, and closer relationships with residents” (McGilton, 2002, p. 17).

“The reviewed empirical evidence and Kayser-Jones’s (1991) theory suggest that if residents perceive care providers to have effective interactional skills, provide continuity of care, and are supported in their workplace, positive resident and care provider outcomes would ensue” (McGilton, 2002, p. 8). Overall, empirical support for the capacities of the care provider variables (i.e. reliability, empathy, continuity) were

evident in the study, however, the author stated that no intervention incorporating the complete set of theoretical variables were found in the studies. The theoretical variables were not listed in the study.

Data Collection Regarding Quality Care

Clauser and Bierman (2003) explored the rationale for the collection of functional status data in nursing homes that promotes innovative models of care. They examined issues related to data collection for quality improvement and performance measurement at nursing homes as well as for payment. Problems with the current state of functional assessment were highlighted. The first problem identified is that the method of information collection is not well coordinated since the Medicare system provides services in multiple settings and from different providers. For example, in nursing home facilities the Minimum Data Set (MDS) is used. An MDS is a “comprehensive functional status data collection for nursing homes which measures functional, behavioral, social and clinical aspect of the resident care” (Clauser & Bierman, 2003, p. 2). The data are used to create quality indicators (QI) that enable the Centers for Medicare and Medicaid services to flag potential quality problems in specific nursing homes (p. 2).

Home care agencies use the standardized Outcome and Assessment Information Set for home health (OASIS). The OASIS system is used to measure and track outcomes of care in home settings. The data are subsets of information necessary to conduct patient assessment and care planning (Clauser & Bierman, 2003, p. 3). Rehabilitation units in inpatient hospitals use the functional improvement measure. The aspects of assessing functional status for quality and payment were examined. The history of functional assessment was discussed, along with new proposals for classification systems.

Clauser and Bierman (2003) state that CMS has long supported research to develop risk-adjustment methodologies for differences in resources due to health and functional status of patients. Clauser and Bierman (2003) also examined the strengths and weaknesses of existing measures and proposed a method for moving from one system to the next. CMS's ultimate goal is to make payment more equitable and to reduce financial incentives associated with risk selection (Clauser & Bierman, 2003, p. 6). The benefit of the collection of these data is that they provide a wealth of information for future research for liability claims and effective risk management strategies to decrease claims.

Gustafson, Sainfort, Konigsveld, and Zimmerman (1990) developed the Quality Assessment Index (QAI), which is based on the multi-attribute utility (MAU) methodology. The research was an empirical validation of the QAI model that addressed process and structural outcome criteria for measuring nursing home quality (Gustafson et al., 1990). The QAI model of nursing quality measures a "three level process: component, subcomponent, and specific indicator (X_{ij}) level of performance" (Gustafson et al., p. 105) with each having its own level of weight (W) (p. 105). Therefore, the first hierarchical decomposition of quality is composed of components. The second level is disaggregated into subcomponents. In the third level, the specific indicators (X_{ij}) are identified as a measure for each subcomponent.

Nursing home performance on each indicator is converted to a standard utility measurement ($U[X_{ij}]$) between 0 and 100, which represents the relative contribution to the quality assessment (Gustafson et al., 1990). For each component, the score is calculated, summing up the weighted score for each subcomponent (weight of the subcomponent multiplied by the nursing home's performance on the associated

indicator). The weighted sum of the component scores determines the overall score. There were 75 nursing homes in Wisconsin, 18 in New York and 18 in Massachusetts that participated in the validation process. The correlation between the QAI and the number of deficiencies was used to validate the model. The findings revealed a modest relationship between QAI and the number of deficiencies in the nursing homes (Gustafson et al,1990).

The AON Worldwide Actuarial Solutions (2000) is an actuarial analysis of general and professional liability costs in the State of Florida versus the rest of the country. For the 2000 report, only 12 nursing home providers responded, and they represented multi-facility, for-profit operations which primarily provide skilled nursing care. No responses were received from independent or non-profit facilities in Florida. The 2001 Actuarial Solutions study update reported that the cost of liability costs in Florida was significantly higher than in any other state in America. As a result, the insurance market has restricted the capacity to write nursing home insurance in Florida. Furthermore, “insurance companies continue to exit the state and cannot provide coverage when faced with this magnitude of losses, explosion in growth of claims, and extreme unpredictability of results” (Actuarial Solutions, 2001, p. 3). A study by AON Risk Consultants, Inc. (2004) shows that the frequency of claims against Florida’s nursing homes for 2002 and 2003 are higher than the average level of the three years leading up to the tort reform passed in Florida in 2001. The tort reform bills have had little to no effect on reducing claim frequency in Florida. For the 2004 study, AON invited independent single facility operators and large national multi-facility companies

to participate in the study, not all groups responded; therefore, the sample for this study limited external validity of study findings.

Schaefer (2006) conducted a study on recent trends in nursing home liability insurance. An analysis of liability claims filed against nursing home providers was performed to assess the feasibility of linking liability claims data with nursing home quality measures. Interviews were conducted with key stakeholders, which included the providers, insurance brokers, plaintiffs, and defense attorneys. Additionally, a case study of five states was conducted. The states included California, Florida, Georgia, Ohio, and Texas. The quantitative component of the study was limited; therefore, the report was based on qualitative components. According to Schaefer (2006), the limitations were:

1. Data submissions came from large national for-profit chains.
2. Specific data were requested but the providers gave the data maintained internally to manage their liability claims and operated internal risk management programs.
3. Data submissions included internal incidents and events that occurred in the facility.
4. Data submissions included information on estimated liability costs associated with the incident or event, the actual settlement cost, was not available (p. 2).

Liability Issues in Nursing Homes

Why Are Claim Costs High?

The reason that claims are so high is primarily due to negative perceptions of the nursing home industry perpetrated by the media (Johnson & Bunderson, 2002).

Additionally, the mentality that people have of making an easy million and the guilt and fear factors that exist before a resident is admitted to the center tends to alleviate guilt by

lawsuits. The study by Stevenson and Studdert (2003) was an empirical, descriptive study on the rise of nursing home litigation. The purpose was to analyze the relationship between litigation and the quality of nursing home care. The survey sample consisted of 464 attorneys from 43 states (Stevenson & Studdert, 2003). It was a web-based survey with close-ended Likert-like questions, which elicited information from attorneys about nursing home litigation practices such as volume, compensatory value and outcomes of claims (Stevenson & Studdert, 2003). The survey also included questions regarding the alleged injuries and the characteristics of plaintiffs and defendants. The reliability and validity of the survey was reported using an instrument that was pre-tested on a small sample of plaintiffs, defense attorneys, and experts. Results showed an increase in both the number of nursing home claims and the average size of recoveries since. The relationship between litigation and quality were: (a) Litigation diverts resources from resident care; (b) a study of one Florida County facility found no relationship between Online Survey and Certification Assessment and Reporting (OSCAR) deficiencies and lawsuits, and; (c) "The recent rise in nursing home litigation does not appear to track any clearly documented, general deterioration of quality, however, at least part of a discrepancy between litigation and quality trends is likely attributable to plaintiff attorneys gaining ground on a reservoir of substandard care" (Stevenson & Studdert, 2003, p. 4).

Although the study used a large sample of defense and plaintiff attorneys, it did not examine nursing homes and risk factors that validated the increase of litigation in the industry. The study could have been improved if data had also been collected from a nursing home sample. Perhaps the results would have reflected a better understanding of

the scale, dynamics, and outcome of these lawsuits. Limitations reported by Stevenson and Studdert (2003) are that attorneys may have brought professional biases to their survey responses, i.e., they had trouble remembering specific estimates. The authors suggest a future study to identify policy implications for tort reforms, such as caps on damage awards and attorney fees that do not eliminate incentives to deliver high-quality care.

Kapp (2000) describes a paradigm shift away from the traditional highly regulated agency model for nursing homes, which imposes strict regulations on providers. According to Kapp (2000), “tort law allows a service recipient injury to bring a civil malpractice action against a provider seeking money damages for causing the recipient injury (a legal outcome measure) by negligently or intentionally deviating from acceptable professional standards of care under the circumstances (a process measure)” (p. 16). Other researchers contend that this type of solution justifies the assumption that threatened punishment to the nursing facility through liability claims can assure quality care (Kapp, 2000).

Liability issues in nursing homes are recognized as the fastest growing issue nationwide. A review of the literature on nursing homes in Nursing Home Reform (1995) and the Federal Register (1996) revealed that regulatory enforcement would continue to have a positive impact on nursing homes. According to Clapp (1996), the biggest threat to financial security that retired elders face in the United States is the high cost of nursing homes. “More than 40 percent of elders age 60 or over will at some time require expensive long- term care services, either at home or in a nursing home or other housing

facility” (Clapp, 1996, p. 1). Therefore, the risk for liability claims increase with more admissions of residents to nursing homes.

There are many causes of liability claims against nursing homes. Noland (2001) states that fall are a major cause and elopement is the second leading cause of liability claims, in which residents with dementia wander off from the facility exposing himself or herself to injury or death. Finally, a decubitus ulcer is the third leading cause of liability claims. A decubitus ulcer may develop on residents’ skin after lying in one position for an extended period of time (Noland, 2001).

Stephens and Bick (2002) describe a risk assessment and prevention audit pilot project aimed to evaluate the impact of caregiver guideline recommendations designed to reduce pressure ulcers on patients (Stephens & Bick, 2002). The purpose of the project was to determine whether vulnerable patients were more prone to develop pressure ulcers because of their physical being (i.e. mobility) (Stevens & Bick, 2002). A guideline is needed for pressure ulcer risk assessment and prevention because of the “differing risk assessment tools, different patient groups, healthcare settings, and uncertainty regarding how to measure incidence and collate data” (Stephens & Bick, 2002, p. 2). This project collected data on pressure ulcer prevalence, risk assessment, prevention, education, and training in acute and nursing home settings in England and Wales. Analysis of the results at facilities participating in the pilot audit project should increase understanding of the importance of pressure ulcer risk assessment and prevention. These data by Stevens were compared to a second audit and analyzed.

Wright’s (2003) AARP descriptive study provided information regarding nursing home liability insurance. The purpose of the study was to review the nature of and

problems with the cost and availability of nursing home liability insurance, the causes of the problems, and proposed solutions (Wright, 2003). The Weiss Ratings, Inc., an independent insurance company rating agency was used to conduct the study. Weiss Ratings, Inc. contacted a sample of members of the nursing home liability insurance market such as liability insurance companies, brokers, and state regulators. Weiss identified 1,024 insurance companies through its database, of which only 43 wrote nursing home liability insurance. Only six of these companies were willing to participate in the study conducted by Marsh USA Inc., an international risk management and insurance brokering firm, and the Florida Department of Insurance (p.44). “The six respondents to the Weiss survey reported an aggregate 2001 premium of \$400 million, which Weiss estimates to represent approximately 40% of the total market underwriting nursing home liability insurance” (Wright, 2003, p. 44). The results of this study cannot be generalized since there were few respondents to the survey. However, the strength is that the responses of the members of the nursing home liability insurance industry provided an understanding of their attitudes, opinions, and beliefs.

Wright’s (2003) findings regarding the nature and extent of the problems, causes of the problems, and proposed solutions were identified as to the cost and availability of the liability insurance are limited due to the type of participants (i.e. for profit) and demographics. For example, it is more difficult to obtain liability insurance coverage in the south because there is no insurance to be sold. Furthermore, the factors that affect the cost and availability of nursing home liability insurance are (Wright, 2003):

1. Increased litigation
2. Premium cuts during the 1990s

3. Lower returns on investment income
4. More claims and payouts and the perceived variability and unpredictability of claims
5. Losses from claims resulting from the September 11, 2001 terrorist attacks
6. Insurers' business decisions (p. 2).

Proposed solutions:

1. Limits on residents' ability to sue by having tort reforms
2. Improved enforcement of nursing home quality standards
3. Risk management by identifying the risks that could lead to litigation
4. Experience ratings that can rate nursing home insurability and provide a base premium
5. Alternative forms of insurance such as self-insurance, group self-insurance, and joint underwriting agreements (JUAs) and other state-sponsored insurance pools
6. Strengthened regulation of the insurance industry. (p. 37).

Further research is needed "to better understand the effects of the proposed solutions on availability and affordability of nursing home liability insurance, and their effects on quality of care and access to compensation" (Wright, 2003, p. 37).

The market is continuing to change and it is difficult to predict what it will look like in the future. According to Burwell et al. (2006), the following changes have occurred in the market:

1. Most carriers have left the market
2. Limited access to the reinsurance market
3. Surplus line carriers entered the market

4. The terms and conditions of liability insurance coverage changed dramatically
5. Data on the current costs of liability insurance is sporadic
6. Improved underwriting has become increasingly important to profitability
7. Risk management programs are increasingly utilized as a management tool for reducing liability risk
8. Volatility in the nursing home liability insurance market has led to the creation of alternative markets for reducing liability risk. (p. 12).

Social and legal factors have contributed negatively to the increase in the medical professional liability insurance industry in terms of claims frequency and claims severity (Greve, 2002). Sports, salaries, lotteries, and television game show winnings characterize social factors. Legal factors include juries that are more liberal in major metropolitan areas, and plaintiff attorneys who are more sophisticated, well financed, and can afford to accept only cases with high damage value. Frequency is how often claims are asserted; severity is the total cost of resolving malpractice claims (Greve, 2002). Other industry experts suggest that frequency has remained flat or increased modestly (p. 2). “The real problem facing the healthcare industry and its liability insurers in 2002 is severity, given the increasing numbers of large jury awards and settlements” (Greve, 2002, p. 2).

Valledor (2001) contends that risk retention is for predictable losses that are of high frequency and low severity. However, Valledor (2001) suggested that catastrophic losses should be insured or reinsured if available in the insurance market.

Types of Claims-Frequency

AHCA (2006) reported that between July 1, 2005 and June 30, 2006, there were 440 NOI reports submitted to the agency. The top five types of injury reported were

pressure ulcers, falls, abuse, neglect of an adult, and death (AHCA, 2006). Of nursing home claims nationwide, 49% are due to state statutes and 36% are due to common-law causes as the primary legal basis. Stevenson and Studdert (2003) did not designate the remaining 15%. There are 83% of claims in Florida brought under nursing home resident rights statutes (Stevenson & Studdert, 2003). Williams and Bone (2003) describe two primary types of claims being brought against nursing homes: (1) wrongful death or survival claims and; (2) negligent acts. Fiesta (1998) stated that not informing the patient of the circumstances in patient care in a timely manner could make a malpractice case worse.

Number of Claims-Severity

The scale of the litigation was assessed based on attorney surveys. The attorneys surveyed reported 4,700 healthcare claims in the previous twelve months (Stevenson & Studdert, 2003). “More than four-fifths of these claims would recover damages at an average of \$406,000 per claim,” exceeding the average medical malpractice claim total of \$207,000 (p. 1). Burwell et al (2006) compared a study conducted by researchers at Harvard School of Public Health to the AON and ISO studies and the results showed the estimated total of 8,253 claims worth \$2.3 billion in the 12 months prior to the survey as being significantly higher than reported in the AON and ISO study (p. 8). Additionally, “if the total number of estimated claims is divided by the number of total occupied nursing home beds in the U.S. (about 1,620,000) then claim frequency nationwide would equal about 5.1 per 1,000 beds, which is higher than the ISO estimates but considerably lower than the AON estimates” (Burwell et al., p. 8).

Sage (2002) describes a study that examines patient complaints and malpractice litigation involving an academic health center and its affiliated medical group. “Complaints from residents and family are correlated with ‘risk management’ activity, defined as opening case files, incurring investigative or settlement expense in connection with those files, or defending actual lawsuits” (Sage, 2002, p. 3000). The purpose of the study was to examine patient complaints and malpractice litigation involving an academic health center and its affiliated medical group. The value of this study is not just as a litigation cost control device, but it is an awareness aid to improve the medical practice by providing early prevention and a statistically more reliable warning of problems before lawsuits occur (Sage, 2002).

Amount of Claims Loss Cost

Stevenson and Studdert (2003) concluded that compensation payments to plaintiffs in 2001 totaled \$2.3 billion in nursing homes. Of this, \$1.1 billion went to plaintiffs in Florida and the rest of the payments went to plaintiffs in Texas (Stevenson & Studdert, 2003). “The average recovery amount among paid claims to the plaintiffs, whether resolved in or out of court was approximately \$406,000 per claim, nearly twice the level of a typical medical malpractice claim of \$207,000. Plaintiff attorneys nationwide reported a higher level of payment than defense attorneys, but agreed that approximately 17% of payments include punitive damages” (Stevenson & Studdert, 2003, p. 3). Mediation of exposures, which is the loss control aspect of risk treatment, must “exceed traditional hazards to cover legal, procurement, production, markets, partners, and contractual loss potential” (Louisot, 2003, p. 48). Burwell et al (2006) reported that Florida’s S.B. 1202 places a cap on punitive damages at the greater of three

times the compensatory damages or \$1 million, except the cases whereby the defendant was motivated by a financial gain (p. 19). Furthermore, in the cases where the defendant knew the risks that they were placing on the resident, the punitive damages are limited to the greater of four times the compensatory damages or \$4 million (Burwell et al.). There are no caps in cases where the defendant intentionally harmed the claimant. Due to Florida legislation, the recovery of attorney's fees for cases involving death or injury has been eliminated. AON (2005) showed a rapid increase in loss costs in the four-year study that was conducted between 1996 through 2000. Between the period of 2000 and 2004, annual loss costs increased on average by 3%, however, between 1996 and 2004 liability losses increased by over 180% for the providers represented in the study (AON, 2005).

The Insurance Market's Perfect Storm

In order to understand liability claims, it is important to discuss the insurance industry. The National Association of Insurance Commissioner defines nursing home insurance (NAIC) as "any insurance policy or rider advertised, marketed, offered or designed to provide coverage for not less than twelve consecutive months for each covered person" (as cited in Hagen, 1992, p. 70). Factors influencing the availability of insurance in the market for nursing homes may include the rising cost of jury verdicts and settlements, the decline of the stock market, and the September 11 cost effects on reinsurance companies. Burwell et al (2006) reported that the average insurance cost per bed is \$800-\$1,000, and the total size of the market is \$1.4-\$1.7 billion annually (p. 20). Furthermore, they stated that the future of the liability insurance market is dependent on the future of the nursing home litigation.

Williams and Bone (2003) identified four factors as influencing the litigation explosion in nursing homes. The factors were changes in laws concerning resident rights, inadequate state tort reform laws regarding punitive damages, recoverable attorney fees, and public perception of the industry (p. 1). “As a result of these skyrocketing costs, many insurance carriers have left the market completely. Furthermore, those companies that have remained have had to raise premiums and deductibles and scrutinize their book of business, likely choosing not to renew many policies” (Williams & Bone, 2003, p. 1).

AON Risk Consultant defines these key terms: *Loss cost* is the cost per exposure of settling and defending claims. *Loss developments* are the changes in the estimated value of losses attributable to a body of claims, or to a period until all claims are closed. *Loss trend* refers to the change in claim frequency or severity from one period to the next (AON, 2000, p. 41). Kindred Healthcare (2003) inservice estimates that “loss” must meet four criteria before insurance can be purchased: (1) loss must be predictable; one must be able to estimate accurately future losses, (2) loss must be measurable; one must be able to tell when a loss has occurred and place a value on it, (3) loss must be accidental, loss cannot be inevitable, and (4) loss cannot be catastrophic, or unlikely to affect a large percentage of exposure units at the same time.

A case study by Horwitz and Brennan (1995) examined the pros and cons of Florida’s program abandoning tort liability in favor of no-fault injury compensation. As the insurance market is examined, it is evident that the insurance industry crisis is not a new issue. According to Horwitz and Brennan (1995), Florida has been facing a crisis in medical malpractice liability since the 1970s. “Between 1970 and 1975 more than twenty medical malpractice insurers canceled their coverage of Florida physicians, and by the

mid-1980's the state's largest malpractice insurer ceased doing business there altogether" (Horwitz & Brennan, 1995, p. 164). Furthermore, other observers believe that "contractions in secondary insurance markets, which had nothing to do with medical care, affected malpractice markets because of the particularly risky nature of markets" (Horwitz & Brennan, 1995, p. 165). A secondary insurance market is a one that is not necessarily part of the medical market. This is an important explanation of the increases in premiums paid by SNF's, and for the reason insurers have withdrawn from many high-risk markets.

The intention of the no-fault program is to increase claims by extending compensation to all injuries, including injuries caused by fault (Horwitz & Brennan, 1995). In this case study, there are two no-fault programs in operation in the United States: (1) the Florida Birth-Related Neurological Injury Compensation Association (NICA), and (2) the Virginia Birth-Related Neurological Injury Compensation Program (NICP). In order to understand and analyze the Neurological Injury Compensation Program, extensive structured interviews were conducted with more than twenty key policymakers, NICA officials, leaders of organized medicine, and lawyers from both defense and plaintiff bars. The weaknesses of interviewing just the individuals include but are not limited to not tracking or knowing exactly how long these possible claimants lived. The NICP interviews also do not interview family members, an economist or an insurance adjuster, so do not take into account the possible changes that could occur in the economy.

Horwitz and Brennan (1995) suggests that empirical evidence about malpractice litigation shows that litigation only partially accomplishes its two major societal

functions in which modifications have been included in the health care reform proposals. Compensation of medical injury costs and deterrence of substandard practice were the two major societal functions (Horwitz & Brennan, 1995). It has been suggested that a thorough investigation of NICA would be feasible if primary data collection is used to evaluate the rate and degree of compensation for birth-related injuries. Furthermore, it is suggested that an evaluation of deterrence and defensive medicine should be investigated, meaning that those issues cannot be addressed without an analysis of medical injury rates, and careful surveys of physician behavior (Horwitz & Brennan, 1995).

The purpose of catastrophe losses is to “heighten understanding of public policy issues and broaden awareness of the complex competing interest underlying the issues of catastrophe losses” (Brummond, Quirke, Hunter & Warfel, 1994, p. 447). Frequency and severity of cyclones and other disasters are discussed as possible causes of the increase in insurance financing premiums. In 1992, Berz stated, “in areas of high insurance density the loss potential of individual catastrophes can reach a level where the national and international insurance industries run into serious capacity problems” (as cited in Brummond et al., 1994, p. 454). This article is relevant in this literature review because no matter which industry is being analyzed, preparation is essential. Catastrophe losses can be minimized through disaster preparedness, insurance coverage, and property loss mitigation. Brummond et al. suggest the development of computer modeling systems for projecting catastrophic losses so rate proposals and underwriting restriction plans can be evaluated based on a company’s own model.

Wright (2003) suggested five specific steps government should take to increase the oversight of the insurance industry:

1. Repeal the McCarran Ferguson Act of 1945, which exempts insurance companies from federal antitrust laws: due to the Act, the federal government does not get involved if insurance companies are engaged in collusion, price-fixing, and other anticompetitive practices.
2. Create a federal system of reinsurance, since private reinsurers can influence the prices charged and policies offered by primary insurers.
3. Adopt federal legislation requiring insurance companies to disclose financial data, including the bases for their price changes.
4. Investigate insurance industry practices and pricing; look for ways the federal government and state insurance departments can ensure that responsible pricing is enforced.
5. Regulate insurers' pricing and accounting principles. (p. 36).

Sutton-Bell, Corbertt, Lilly, and Marshall (1993) analyzed state health insurance plans. The purpose of this study was to describe what states, as employers, are doing to contain health care costs in their indemnity health insurance plans. The study used a survey method. Data were gathered first by requesting benefits booklets from personnel directors and insurance commissioners in each of the 50 states. Secondly, a descriptive survey of personnel directors and insurance commissioners was conducted. It was found that many benefits and cost controls are being used by medical expense insurance plans that cover state employees (Sutton-Bell et al.). The main limitation cited by the authors was that the study only reported what was described in the benefit brochures. In addition, states might have, for example, cost-containment, wellness programs, or case management controls. Overall, the study shows that loss prevention programs are moving

away from the traditional role of providing benefits only during illness to providing for the good health of their employees. Furthermore, it shows that states are attempting to control the cost of providing medical benefits rather than being a third party payer (Sutton-Bell et al.).

Risk Management Education and Intervention

AON Worldwide Actuarial Solutions (2001) is a company that conducts research analysis on liability claims and insurance. *General liability* is the exposure, which generally relates to those sums an entity becomes legally obligated to pay as damages because of a bodily injury (typically including personal and advertising injury) or property damage. *Professional liability* exposure relates to those sums an entity becomes legally obligated to pay as damages, associated claims, and defense expenses because of a negligent act, error or omission in the rendering or failure to render professional services. The number of claims reported is described as the frequency. *Frequency* is the ratio of the number of claims divided by exposures. The *size* of claims is referred to as the severity. *Severity* refers to the total dollar amount of a claim including indemnity and allocated loss adjustment expense. Finally, the amount of claims or the overall cost per exposure is referred to as loss cost. *Loss cost* is the cost exposure of settling and defending claims (AON, 2001, p. 26)

Risk management is important to this literature review because the biggest threat to the nursing home industry is litigation. Risk management is a system that attempts to identify, analyze, treat, and monitor an institution's exposure to adverse financial loss (Louisot, 2003). Analysis of an organization's risk exposures cannot be conducted without a clear understanding of that organization's goals and strategies (Louisot, 2003).

“A systems approach to risk analysis allows the risk manager to define a portfolio of exposures for the firm and to draft a risk map to illustrate the major risks that should draw top management attention. The objectives and mission of the organization should also be subjected to a risk analysis, in light of the ethics and values publicly announced by the organization and public beliefs” (Louisot, 2003, p. 48).

Shrivastava (1995) examined the nature of post-industrial modernization at risk societies. In post-industrial modernization, risk is in the center of the modernization process. “Risks are highly susceptible to social definition and social construction: consequently, perceptions of risk are reality for many practical purposes” (Shrivastava, 1995, p. 120). As a result, risk management programs should include education, consultation, and intervention components. Risk management is the prevention, reduction, and control of loss to residents, employees, visitors, volunteers, center reputation, and monetary loss. Aside from risk management being an institutional concern, administrators and healthcare providers in nursing homes should consider risk management as part of a nursing center professional plan (LaDuke, 2002).

Johnson and Bunderson (2002) conducted a multiple case comparative study on how different for-profit nursing home facilities with varying levels of lawsuit risk respond to the litigious environment in Florida. Their focus was on the structure of litigious environment patterns. The purpose of the study was to determine if nursing home staff members differed in their views of litigation risks and too understand how staff reacted to perceived risks. The sample included three different nursing home facilities in the state of Florida that were owned by the same corporation, however, they represented different levels of litigation cost to the parent company (Johnson &

Bunderson, 2002). Data collected were from interviews of administrative, corporate and clinical staff from these nursing home facilities.

During the interviews, 21 open-ended questions were asked and responses to questions were recorded. Nominal focus groups were used to provide information about how each home perceived the reasons that homes were being sued. Archival data sources were used to provide structural and historical information about the homes (Johnson & Bunderson, 2002). The findings of this study were as follows: The staff in the low risk site view litigation as unchallenging. In the medium-risk site, 25% saw litigation as a challenge and 25% of the staff in the high-risk site saw litigation as a current challenge. Differences were evident and significant across the sites regarding the administrative staff's knowledge of the Resident Bill of Rights. Furthermore, the entire staff in the low-risk site knew about the Resident Bill of Rights and 75% of the clinical staff believed legislation had an effect on their facility. In response to the question of why nursing homes are sued, the low-risk site identified quality of care and personnel neglect as factors associated with lawsuits. The high-risk site identified television ads and perceived poor care as the primary reasons for lawsuits. Finally, the medium-risk site identified internal and external issues as lawsuit determinants (Johnson & Bunderson, 2002).

Although the multiple case approach was appropriate, an examination of a broader sample of nursing homes is needed in order to be able to generalize results. According to Johnson and Bunderson (2002), "such an examination should consider variance in interpretations, diffusion, and enactment across nursing homes should be given" (p.20). Additionally, it is suggested that some consideration of the organization-level factors associated with more accurate and diffused environmental interpretations by helping to

document best administrative practices across nursing homes is made in response to litigation issues.

Communication is the key to risk management. According to a Kindred Healthcare (2003) inservice, the best way to prevent lawsuits is to recognize the reality of the world in which we are operating, which is the result of good or bad quality of care that a resident may receive from a nursing center. The victim mentality must be abandoned. Nursing home centers must be prepared to win battles before the fights begin. This may be accomplished by improving documentation, improving care, and by improving communication with residents, families, and physicians.

Williamson (1999) discussed the causes of recent growth in nursing home litigation. "The tensions between government standards, agency oversight, and stated reimbursement expose the industry to private litigation" (p. 423). Porell et al., (1998) tested a theoretical model in a study on nursing home outcomes. Person-level statistical models were used to estimate four health outcomes and to identify the factors associated with changes in resident health outcomes over time. The purpose of the study was to investigate resident and facility attributes associated with nursing home health outcomes. The study design was explanatory (correlational), and used a multivariate logistic regression model. Data were obtained from secondary sources. According to Porell et al., (1998) the use of outcome measures is for quality assurance or for reimbursement purposes. The data used were from the Management Minutes Questionnaire for case mix reimbursement in nursing homes. The study findings suggested that health outcomes of residents are the same despite the nursing home structure and ownership (Porell et al., p. 12). Despite the findings of potential importance in regulatory strategies of monitoring

nursing home outcomes, the risk-adjusted outcome must be validated before correlating it to nursing home quality. The reason for is that the performance measures for the facility level were not developed at the time of this study.

Mukamel and Brower (1998) conducted a study of quality of care and outcome measures in nursing homes. They compared quality rankings in 550 nursing homes in New York. The outcomes were a decline in functional status, worsening decubitus, and prevalence of physical restraints. The theoretical consideration that leads to the expected outcome-based quality did not provide any guidance as to the empirical importance of the methodology used to account for risk (Mukamel & Brower, 1998). This study was limited and did not include information about all risks that have been shown in previous studies to be correlated with the current quality outcomes.

As the cost of malpractice insurance increases, it is very important for providers to increase their focus on patient safety, and for clinical risk management strategies to decrease claims (Greve, 2002). It is the responsibility of the risk management department to communicate to the finance department and to create a strategy to ensure this communication happens. Administrators should consult the following documents in creating their facilities risk management strategies (Greve, 2002):

1. The Institute of Medicine should be considered because it has heightened the focus of the healthcare industry on patient-safety initiatives and clinical risk management.
2. *Crossing the Quality Chasm: A New Health Care System for the 21st Century* (Committee on Quality of Health Care in America, Institute of Medicine,

2001) should also be considered, because it advocates using a systems approach to reduce clinical risk.

3. Finally, the Joint Commission on Accreditation of Healthcare Organizations issued patient-safety standards that took effect in 2001.

A review of trends in the insurance market revealed that the price of liability insurance increased dramatically while the terms and conditions of coverage were constricted (Burwell et al., 2006, p. 1). After the enactment of the S.B. 1202 there was some evidence of a decline in litigation, however, many insurance carriers have not re-entered the market in Florida. Consequently, national nursing home chains have exited the State to minimize their liability exposure (Burwell et al.). In filling the gap in understanding long-term care liability, Boone (2003) examined the challenges that the State of Florida faces when dealing with long-term care liability coverage and insurers. The insurance market across the country is in big trouble when it comes to liability coverage of nursing homes. Uni-Ter Underwriting Management Corporation (UUMC), which is a subsidiary of U.S. RE that arranges insurance for long-term care facilities in 31 states, suggested that risk management is an ongoing process (Boone, 2003). The findings indicated that in order to manage risk, this company designated a staff member to take charge of the risk management program thirty days after the insurance is provided. UUMC also conducts on-site audits to monitor possible risks and the insurer is able to call a toll-free number to ask questions. Finally, a computerized incident reporting system through which incidents can be tracked and trended, can help assess possible claims. This study was very relevant to the subject matter in terms of information about

the insurance market and possible risk strategies that insurance companies could use to decrease the cost of liability claims.

In a study of risk management infrastructure, Bierc (2003) clearly identified a gap between operational reality and management perception of risk management. The reason for the gap is how companies view risk. Risk may be viewed as something to be avoided or mitigated, separated, categorized or addressed in silos, and organizations rarely understand the broad relevance of risk (Bierc, 2003). Another reason for this gap is the corporate leader's view of the infrastructure. According to Bierc (2003), "corporate infrastructure is often viewed two-dimensionally: hierarchical vs. functional" (Bierc, 2003, p. 59). Risk overlaps a third dimension of key business processes, which is viewed as a frequent oversight. As a result of this oversight, Bierc (2003) states the strategies for risk management are rarely achieved on purpose.

Bierc (2003) suggests that risk architecture is a new framework of better decision-making throughout organizations. "It incorporates the broad definition of risk; it establishes the linkages from corporate vision down to key business processes; and it begins by recognizing vision as the highest objective in any organization" (Beirc, 2003, p. 60). Therefore, this new strategic risk management (SRM) can create an "opportunity for any organization striving for greatness. SRM can provide the foundation for a powerful new risk management infrastructure that incorporates the reality of the risk architecture. Finally, it can establish an effective means of corporate transparency, as well as accountability and control" (Bierc, 2003, p. 60). These are also the key ingredients for good performance and good corporate governance. The study was straightforward and understandable. The study was about a view of risk and a top-down

approach, which incorporates strategic risk management to help organizations meet their goals. Overall, risk is anything that can influence the achievement of goals and objectives. Therefore, effective risk management strategies are important in nursing homes.

Brockett, Cooper, Golden, Rousseau, and Wang (2005) conducted a study that used data envelopment analysis (DEA) to study the relative efficiency of different organizational structures of liability insurance companies. DEA is used to evaluate target achievement of decision-making units (DMUs) and is applicable in measuring risk management performance (Brockett et al.). DMUs are responsible for converting input resources into outputs. According to Brockett et al., previous DEA models such as the Charnes, Cooper and Rhodes (CCR) in 1978 and the Banker, Charnes, and Cooper Model (BCC) in 1984 had a limitation whereby they estimated relative performance of a DMU but not its absolute performance. Therefore, the Risk Adjusted Measure (RAM) model, which is new to the insurance literature, was introduced as a model able to provide “ordinal level efficiency scoring that allows for subsequent nonparametric statistical analysis such as regression, rank statistical analysis, to be performed incorporating efficiency scoring as an explanatory variable in subsequent analysis” (Brockett et al., p. 394). Ultimately, the RAM DEA model is used to calculate a performance score of insurer risk management.

Data were collected from 1,114 stock and 410 mutual companies using 1989 property and liability tapes (Brockett et al., 2005). In selecting the variables, the rule of thumb was “*ceteris paribus*” which means, if it is desirable to increase the variable quantity, it is an output, however, if it is undesirable to have an increase in its value, it is

an input (Brockett et al., p. 398). The variables selected were represented by inputs and outputs (goals) which were fundamental to the validity of the study. The results indicated that the outputs were more efficient.

Data Mining

What Is Data Mining?

Data mining is the process of extracting knowledge hidden in large data sets. Hand, Mannila, and Smyth (2001) defined data mining as the “analysis of (often large) observational data sets to find unsuspected relationships and to summarize the data in a novel way that are both understandable and useful to the data owner” (p. 1). The data mining analysis, models or patterns are created from the relationships and summaries that are formed by the process. Data mining also deals with secondary data collected for the purposes other than data mining, which means that the data collection strategy has no correlation with the objectives of data mining. “Data mining is often set in the broader context of knowledge discovery in databases, or KDD. The KDD process involves selecting the target data, preprocessing the data, transforming them if necessary, performing data mining to extract patterns and relationships, and then interpreting and assessing the discovered structures” (Hand et al., p. 3).

Fayyad, Piatetsky-Shapiro, and Smyth (1996), discussed the history of KDD as well as data mining. Historically, it is stated that useful patterns in data have been called many terms such as data mining, knowledge extraction, information discovery, information harvesting, data archeology, and data pattern processing. The authors defined KDD as a nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data. “Data mining was defined as a step in the KDD process

that consists of applying data analysis and discovery algorithms that, under acceptable computational efficiency limitations, produce a particular enumeration of patterns (or models) over the data” (Fayyad et al., p. 41).

The KDD and data mining steps are also discussed. There are nine steps in the KDD process:

1. Developing an understanding of the KDD process
2. Creating a target data set such as samples
3. Data cleaning and preprocessing
4. Data reduction and projection
5. Matching the goals of KDD process (step 1) to a particular data mining method (i.e., summarization, classification, regression, clustering, etc.)
6. Exploratory analysis and model and hypothesis selection by choosing the data mining algorithm and selecting methods to be used for searching the data patterns
7. Data mining, which is the process of searching for patterns of interest
8. Interpreting mined patterns, possibly returning to any of steps 1 through 7 for further iteration
9. Acting on the discovered knowledge by using knowledge directly, incorporating the knowledge into another system for further action, or simply documenting it and reporting it to interested parties (p. 42).

Fayyad et al., (1996) also shared the challenges for future research and development and opportunities for Artificial Intelligence technology in KDD systems. Applications of the data mining and KDD process have been successfully used in astronomy. “A notable

success was achieved by SKICAT, a system used by astronomers to perform image analysis, classification, and cataloging of sky objects from sky-survey images” (p. 38). Furthermore, application areas include marketing, finance, fraud detection, manufacturing, telecommunications, and internet agents.

Li and Chandra (2007) conducted a study to investigate and develop a generic knowledge integration framework that can handle challenges posed in complex network management. The study used a conceptual Bayesian model to “elaborate the application to supply chain risk management and computer network attack correlation (NAC)” (Li & Chandra, p. 1089). “Bayesian networks are probabilistic graphical models representing joint probabilities of a set of random variables and their conditional independence relations” (Li & Chandra, p. 1095). Bayesian comes from Bayes’ theory, which was constructed in the 1960s. Bayesian network represent causal relationships among variables that are useful in representing uncertainty. Hand, Mannila, and Smyth (2001) considered using the Bayesian model when making a prediction about a new data point $\mathbf{x}(n + 1)$; whereby, the data point is not in the data set D (p. 119). Furthermore, the Bayesian model is used to “average over all possible values of θ , weighted by their posterior probability $p(\theta | D)$ ” (Hand et al., p. 120).

$$\begin{aligned} p(\mathbf{x}(n + 1) | D) &= \int p(\mathbf{x}(n + 1), \theta | D) d\theta \\ &= \int p(\mathbf{x}(n + 1) | \theta) p(\theta | D) d\theta \end{aligned}$$

The fundamental rule of probability of joint event A and B as the product of the probability of A conditioned on B (Jensen, 1996). Therefore, the probability of B is:

$$P(A, B) = P(A | B) P(B)$$

Additionally, if the state of B is known then no knowledge of C will change the probability of A . Therefore, A is independent given the variable of B , whereby each event of the conditional independence is represented by a node and the relationships among events are represented by arrows connecting the nodes. During each event, A and C are conditionally independent given B .

$$P(A \mid B) = P(A \mid B, C)$$

Li and Chandra's (2007) finding was the preliminary result that the Bayesian network model supported the proposed framework of knowledge integration for complex network management. In developing a risk management model through data mining, the Bayesian network model can be use as a tool to seek analytical solutions. Furthermore, when evaluating and comparing classifiers, the effectiveness of the independence Bayesian model can show that theoretical properties are not always an effective guide to practical performance (Hand et al, 2001).

Why Use Data Mining?

Data are collected daily in different industries for many reasons. In most cases, data are the most valuable assets in corporations. Therefore, if the valuable knowledge hidden in the raw data is revealed, then the knowledge can be turned into a crucial competitive advantage (Megaputer.com, 2004). In a case study about how data mining techniques were used to improve continuity of care, patient satisfaction, and enhancement of system revenue, processes were improved to minimize the loss of business in the Sinai Health System. This was done by analyzing compliance of patients in prenatal care and the delivery at the hospital whereby their primary care clinic was affiliated. The purpose of the case study is to "provide the health care marketing professional a method by which

to use proprietary consumer data to analyze consumer behavior and use the information gained to expand market opportunities” (Rafalksi, 2002, p. 607).

In the case study, a vertically integrated health care system is described as multiple levels of patient services including primary care, specialty care, inpatient hospital care, rehabilitation and home care (Rafalksi, 2002). Sinai Health System is a 432 bed, teaching, tertiary care, not-for-profit hospital which has a 125 bed rehabilitation hospital, a 190 physician multi-specialty medical group and a non-medical community health services organization (Rafalksi, 2002). In 1994, the hospital developed a data warehouse that contained demographic information from disparate billing databases. “An algorithm was developed to match patients from these disparate databases using certain fields of data such as last name, first name, address and birth date” (Rafalksi, 2002, p. 608).

Overall, the data warehouse was created with the purpose of enabling communication with patients throughout the health systems by allowing analysis of service utilization throughout the continuum of care. In analyzing data across the continuum of care and vertical integration, the vertically integrated systems were better positioned to provide clinical data at the point of care as required by governmental and private regulatory agencies to measure outcomes as to their accreditation, funding and patient safety process (Rafalksi, 2002).

The data mining method used in this case study about physician billing data were matched against hospital billing. The code used to identify women who were seen twice during their pregnancy in a primary care clinic owned by the parent company was a prenatal care code (Rafalksi, 2002). Therefore, groups of women were followed every

month for a period of nine months to determine whether they delivered their babies at a hospital of preference owned by a parent company. The reasons for performing this analysis were to improve the continuity of care, improve quality-birthing outcomes and minimize lost revenue.

The findings of the study showed a downward trend in prenatal and delivery rates. Approximately 1,400 patients who received prenatal care over 18 months did not deliver at the parent company's hospital. This number does not include fetal losses. It was estimated by the author that between \$3 and \$6 million of service revenue was involved in redirecting this volume back to the original hospital. In order to determine the root cause of the problem, the marketing team recommended to senior management that a survey be designed to improve processes in order to minimize lost business. A telephone-based survey was created using a computer-aided telephone interviewing (CATI) system (Rafalksi, 2002). The descriptive characteristics of the telephone sample showed that 1,209 records were usable. In summary, the results of the survey are used by management and marketing to improve processes that minimize lost business.

Chin (2003) discussed the advantages of data mining and how to discover and refine data in order to yield increased care and reimbursement in a physician's office. Chin (2003) used an example of data mining when Bayer Corp., announced in 2001 that it was withdrawing Baycol from the market. The physician's office was able to identify all patients taking the Baycol and notified them within 24 hours of the announcement. In this example, stored raw data was analyzed to identify trends, patterns and anomalies, which is data mining (Chin, 2003). In the physician's office, the electronic medical records software (EMRs) is used to capture large data. Furthermore, the practice

management system is another way that data can be mined in a physician's office. These tools are effective because the system has analytical database reporting tools, which employees can use to aggregate and extract data. Finally, Chin (2003) listed various ways that data mining can be used:

1. Identify contractual obligations that are being paid as stated in the contracts
2. Optimize revenue by capturing services rendered that are not billed
3. Identify patients who require preventative services whereby they schedule appointments which can retain the patient and their referrals
4. Identify patients for whom medications have been recalled from the market
5. Compare and measure quality of care provided
6. Conduct clinical research on different populations
7. Compare physician's productivity
8. Check on the accuracy of insurers' quality data from medical and pharmacy claims data.

In a study by Prather, Lobach, Goodwin, Hales, Hage, and Hammond (1997), exploratory factor analysis of a data mining clinical database was used to examine relationships among factors that affected perinatal outcomes in obstetrical patients who had the potential to give preterm birth. The purpose of the study was to show how medical production systems could be warehoused and mined for knowledge discovery. Previous research conducted at the Southern California Spinal Disorders Hospital used data mining to discover subtle factors affecting the success and failure of back surgery. Additionally, GTE Laboratories built a large data mining system that evaluated healthcare utilization to identify intervention strategies that cut cost (Prather et al., 1997).

This study used the Duke University Medical Center's clinical database of obstetrical patients to identify factors that contribute to perinatal outcomes. The following methods were used to analyze the data. First, a computer-based patient record system known as The Medical Record (TMR) was transferred into a data warehouse server. "TMR is a comprehensive longitudinal CPRS (computer-based patient record system) developed at Duke University over the last 25 years. The data collected in TMR include demographics, study results, problems, therapies, allergies, subjective and physical findings, and encounter summaries" (Prather et al., 1997, p. 102). Second, a data warehouse was created for analysis by extracting and cleaning the selected variables. A two-year sample data set was used (1993-1994).

The data were cleaned by "Paradox Application Language scripts to selectively identify problems and correct the errors. The script was used to scan the dataset and convert alphanumeric fields into numerical variables in order to permit statistical analysis" (Prather et al., 1997, p. 102). Finally, the data were mined using exploratory factor analysis. The authors stated that the reason exploratory factor analysis was used was because it has been successful in exploring claims and financial databases in obstetrics.

"Factor analysis is a statistical method used to identify which data elements can be combined to explain variations between patient groups. This mining technique is appropriate in research problems in which a large number of subjects are compared on a set of variables for which there is no designation of independence or dependence" (Prather et al., 1997, p. 103). SPSS for Windows version 5.0 was the software used to conduct the factor analysis. The results of the analysis produced three factors in the

dataset that required further exploration. Further study is required on a new paradigm for determining complex associations, which influence medical outcomes by combining data mining with the computerized patient record (Prather et al., 1997).

Data Mining Systems

A variety of data mining software is used across industries. Choosing a data mining tool depends on the cost effectiveness of the software. In this section, the different tools and whether each is used in healthcare or another industry for informative purposes are explored. In a study about data mining and customer relationship marketing in the banking industry, advances in computer hardware and data mining software that have made data mining available to many businesses was reported. The purpose of the study was to discuss the potential usefulness of data mining for customer relationship management (CRM) in the banking industry (Chye & Gerry, 2002). There were three major areas of the study. First, the CRM concept and data mining methodology and tools were introduced. Second, a literature review was presented about data mining and customer relationship management (CRM) in the banking industry. Finally, other potential data mining banking applications were suggested along with limitations of data mining.

Chye and Gerry (2002) defined data mining by using the SAS Institute definition as “the process of selecting, exploring and modeling large amounts of data to uncover previously unknown patterns of data” (p. 3). Additionally, Chye and Gerry (2002) discussed SAS’s five stages of data mining methodology: Sample, Explore, Modify, Model, and Assess (SEMMA). SPSS Clementine data mining software was used in this study for illustration. According to Chye and Gerry (2002), there are three data mining

tools that are usually appropriate for predictive modeling: logistic regression, neural network and decision tree.

The result of the predictive modeling using logistic regression was statistically significant. Furthermore, the prediction models obtained from logistic regression, neural network, and decision tree were not identical (p. 10). The limitations were:

1. Exhaustive mining of data will produce patterns that are a product of random fluctuations and significant patterns and relationships found may not be useful.
2. From a statistical perspective, data mining is not well developed for effective assessment, which may cause data dredging or fishing in hopes to identify patterns.
3. Successful application of data mining requires knowledge in the domain area and in the data mining methodology and tools (Chye & Gerry, 2002).

The PolyAnalyst 6 version software is used to conduct data mining analysis. According to Megaputer.com, the PolyAnalyst 6 suite is considered the world's most comprehensive and versatile tool. Furthermore, "The Data Mining Package includes PolyAnalyst, an industry leading data mining system" (Megaputer, 2007, ¶ 1).

PolyAnalyst is a powerful, scalable, and easy-to-use data mining tool. It features the industry's broadest selection of machine learning algorithms supported by robust data import, manipulation, visualization, scoring, and report generation capabilities.

Benefits of PolyAnalyst:

1. Step-by-step tutorials designed to teach data mining techniques
2. Special algorithms for the analysis of transactional data

3. Automatic reports designed for business professionals
4. Advanced visualization capabilities
5. Universal Model Application mechanism for scoring data in any external system through a standard protocol (Megaputer, 2007, ¶ 1).

Synopsis of the Literature

Theoretical literature reviewed indicated that litigation is associated with quality of care. There is a tendency to avoid research in nursing homes because of ethical and other barriers such as HIPPA guidelines and confidential patient information (Maas et al., 2002). A model of care based on an existing theory of the environment by Kayser-Jones (1991) and the relationship theory by Winnicott (1960), proposes that if the provider is reliable, empathic, and consistent with the nursing home environment, then a relationship will develop for the resident (as cited in McGilton, 2002). Greve (2002) gave suggestions for formulation of risk management strategies:

1. “The Institute of Medicine in the past two years has heightened the focus of the healthcare industry on patient-safety initiatives and clinical risk management.
2. The second report, *Crossing the Quality Chasm: A new Health Care System for the 21st Century*, strongly advocates using a systems approach to reduce clinical risk.
3. The Joint Commission on Accreditation of Healthcare Organizations issued patient-safety standards that took effect in 2001” (p. 54).

Finally, another model to enhance the quality of life of residents in nursing home settings was proposed, and three strategic issues were suggested: (1) continuity of care provider, (2) supportive environment for care providers, and (3) skills and knowledge

required by care providers. Concepts triggering lawsuits were suggested as a paradigm shift away from the traditional highly regulated agency model in nursing homes, which imposes strict regulations on providers. However, regulatory enforcement will continue to impact nursing home liability issues. (p. 4)

Most of the literature reviewed was empirical in nature. A hierarchical model used to identify factors that affect quality of care given to residents in the nursing home centers showed that such an analytical approach requires the investigator to specify how exploratory variables measured influenced the distribution of outcomes from one level to the next. Four variables were identified as influencing the relationship between cognitive functioning and quality of care: (1) The number of external collaborators the facility has, (2) type of training the manager has, (3) the size of the facility, and (4) the age distribution of the clientele (Bravo et al., 1999).

Empirical relationships among quality of care, liability of claims, and risk management are the basis for triggering lawsuits along with the negative perception by the media. Lawsuits are subjective to the plaintiff's intent, while risk management is subjective to the internal information being reported to the risk manager. Researchers believe that consistency of a risk management program can help decrease the liability claims and reduce future suits (Bravo et al., 1999).

Additionally, Bravo et al. (1999) conducted an exploratory analysis of the quality of care provided in nursing home centers. The purpose of the study was to identify correlates of the quality of care provided to the older persons in the nursing centers. The variables that correlated with quality of care were gender, socioeconomic status, cognitive functioning, and functional autonomy. This empirical study provides

determinants of quality of care and the interrelationships among quality scores assigned to sample residents.

Johnson et al. (2004) conducted a study that explored how nursing home characteristics affect the number of lawsuits filed against the facilities during the period of 1997 to 2001. The study included 478 nursing homes. The data were obtained from various databases such as the Westlaw's Adverse Filings, OSCAR, and complaint surveys and primary data were also used (Johnson et al., 2004). The findings indicated that the "deficiencies on the licensing survey and larger and for-profit nursing homes were positively related with higher numbers of lawsuits" (Johnson et al., 2004, p. 346). Furthermore, the study suggested that the facility that met the staffing requirements, minimum quality measures, non-profit, and was smaller would experience fewer lawsuits (Johnson et al., 2004).

The literature shows a causal link between quality of care, risk management and liability claims (Louisot, 2003). In the past, the U.S. legal system focused on regulation, however, research shows that lawsuits against nursing homes is the current trend in health law, and the standards are unpredictable (Stevenson & Studdert, 2003). The reason that claims are so high is primarily due to negative perceptions of the nursing home industry perpetrated by the media. Additionally, the mentality that people have of making an easy million and the guilt and fear factors that exist before a resident is admitted to the center tends to alleviate guilt associated with lawsuits (Johnson & Bunderson, 2002). Finally, aggressive, well-connected plaintiff attorneys use their influence to win lawsuits. In addition, Stower (1998) suggested that a proactive approach to health, safety and risk

management has brought significant improvements, enhanced quality of care and improved morale and motivation of nursing teams.

Several authors such as Wright (2003), Horwitz and Brennan (1995), Johnson and Bunderson (2002), and Louisot (2003), addressed factors associated with liability claims in nursing homes and effective risk management strategies to decrease claims. However, problems vary state by state, and liability insurance premiums for nursing homes continue to increase. This is evident in the 2000 and 2001 actuarial solutions study of general and professional liability claims. Researchers agree that the industry is not known for its efficiencies due to the portrayal of the nursing homes by the media. This is evident in Johnson and Bunderson's (2002) research of enacting litigious environments.

There are many gaps in the literature, and experts suggested the following:

1. Limitations that are produced by the underlying challenges in providing care to residents with cognitive impairment are suggested for future study
2. The policy implications for tort reform must be identified. For example, caps on damage awards and attorney fees must be streamlined without eliminating the incentives to deliver high-quality care that litigation may provide
3. In the study of risk management infrastructure, Bierc (2003) clearly identified a gap between operational reality and management perception
4. It is recommended that the MDS, OASIS, and functional rehabilitation data be used to provide a wealth of information for future research about nursing home characteristics, demographics, quality indicators of aggregate health characteristics of residents, risks, risk management, and liability claims

5. It is recommended that data mining challenges on how to translate CMS's criteria into variables that can be created within the context of a database view as an opportunity for the healthcare industry (Sokol et al., 2001)
6. It is further recommended that computer modeling systems be developed for projecting catastrophic losses so rate proposals and underwriting restriction plans can be evaluated based on a company's own model.

Overall, a good risk management strategy, used proactively to deal with possible risks in the nursing home centers, may decrease liability claims and enable providers to predict the possible lawsuits in nursing centers. The theoretical framework that will guide this study about data mining to identify quality of care factors associated with liability claims and risk management strategies in Florida nursing homes is presented next.

Theoretical Framework

The theoretical framework that will guide this study consists of Systems Theory and the Cross-Industry Standard Process for Data Mining (CRISP-DM). Schon and Argyris (1978) provided the theoretical framework of the learning society of increased change with the need for knowledge, which was the cornerstone of the learning organization theory. Senge (1990) explored the art and practice of the learning organization and distinguished five disciplines of the innovative learning organizations. The five disciplines are systems thinking, personal mastery, mental models, building shared vision, and team learning.

Systems Theory is a tool for making sense out of the world by helping to make clearer the interrelationships within and outside of the organization (Allen, 1997).

Systems theory "looks to connections and to the whole which allows people to look

beyond the immediate context and to appreciate the impact of their actions upon others as it is reciprocal” (Smith, 2001, p. 1). Furthermore, the building blocks of systems theory are relatively simple and give a broader perspective of creating the understanding necessary for better long-term solutions (Senge, 1990). Systems theory allows the significance of feedback mechanisms in organizations to be achieved. The delays and feedback loops are so important because in the short term, they can be ignored, as they are inconsequential, however, in the long term, it can be detrimental (p. 92).

In applying systems theory to this study, it is possible to move beyond a focus on the parts, to begin to see the whole as greater than the sum of parts; therefore, the organization can be appreciated as a dynamic process. For example, the nursing home is the environment, and the quality of care controls the internal or external feedback. The better the quality of care, the lower the risk (adverse incidents), which can lead to a decrease in the frequency, severity and loss cost of claims. Quality of care is the outcome that caregivers intend when they take care of residents who cannot take care of themselves. However, greater risks (adverse incidents) eventually lead to more liability claims because risk is no longer controlling the quality of care to the same extent or vice versa. “The systems viewpoint is generally oriented toward the long-term view. That is why delays and feedback loops are so important. In the short term, you can often ignore them; they are inconsequential. They only come back to haunt you in the long term.” (Senge, 1990, p. 92).

The *Cross-Industry Standard Process for Data Mining* (CRISP-DM) model was begun in 1996 by special interest group (SIG) which consisted of more than 200 members (Chapman et al., 2000). The CRISP-DM model is a standardized process that provides a

blueprint for conducting data mining projects. According to Squier, (2001), CRISP-DM is a uniform framework that is reliable, and repeatable. Furthermore, CRISP is an efficient process which helps people with little data mining skills. CRISP-DM offers systematic direction, tasks and objectives for every stage of the process going from general to specific (Chapman et al., 2000).

The CRISP-DM methodology is organized into four levels of constructs that consist of sets of tasks. The four levels are *phase*, *generic task*, *specialized task*, and *process instance* (Chapman et al., 2000). There are six phases and task structure. The phases are *business understanding*, *data understanding*, *data preparation*, *modeling*, *evaluation*, and *deployment* (Squier, 2001). According to Chapman et al. (2000), the generic task is intended to be general enough to cover all possible data mining situations. These tasks are to be as complete while covering both the whole process and all possible data mining applications and stable, whereas the model should be valid for yet unforeseen developments such as modeling techniques. The specialized task level is the description of how actions in the generic tasks should be carried out in certain specific situations. The process instance is a record of the actions, decisions and results of data mining that is organized according to the tasks defined at the higher levels, but represents what actually happened in a particular engagement, rather than what happens in general (p. 9).

In applying the CRISP-DM model to this study, Florida nursing homes represent the environment of business understanding that meets the objectives and requirements of the initial phase. The data understanding phase begins with the MDS data retrieval from CMS and proceeds with activities in order to get familiar with the data, to identify data quality problems, to discover first insights into the data or to detect interesting subsets to

form assumptions for hidden information. The data preparation phase covers all activities to construct the data that were fed into the modeling tool(s) from the initial raw data. Tasks will include table, record and attribute selection, as well as transformation and cleaning of data for modeling tools. In the modeling phase, various modeling techniques are selected as related to the research questions and applied to optimal values. In the evaluation phase, a risk management model(s) is built with high quality from the data analysis. The data mining steps are evaluated and reviewed to validate the construct of the model to answer the questions in the study. Upon deployment, the outcomes of the model(s) are organized and presented in the study.

Figure 2-1 presents a model that integrates the variables and the theoretical framework of the study. Systems theory and the CRISP-DM model are integrated in the study. Florida nursing homes represent the environment and business understanding of the initial phase that focuses on understanding the study objectives and requirements from a business perspective. The input in the schema represents the residents admitted to the nursing home to receive quality of care services during their stay. Outputs represent the risk management strategies that the facility must have in place in order to receive good feedback. The feedback is controlled by the internal and external viewpoints of the resident, representative or outside agency, etc. The outcome of risk may lead to liability of claims.

The data collected from the MDS, 1-day and 15-day adverse incidents reports, and monthly liability claims report were analyzed using the CRISP-DM model. After the six phases, as the process goes from general to specific, the generic task will follow. During the generic task, the data mining process and the data mining applications are

explored using the secondary data in the study. In the specialized task level, a predictive or clustering model is described along with other tasks that should be carried out in certain situations. Finally, in the process instance level, the actions, decisions, and results of the data mining analysis were recorded.

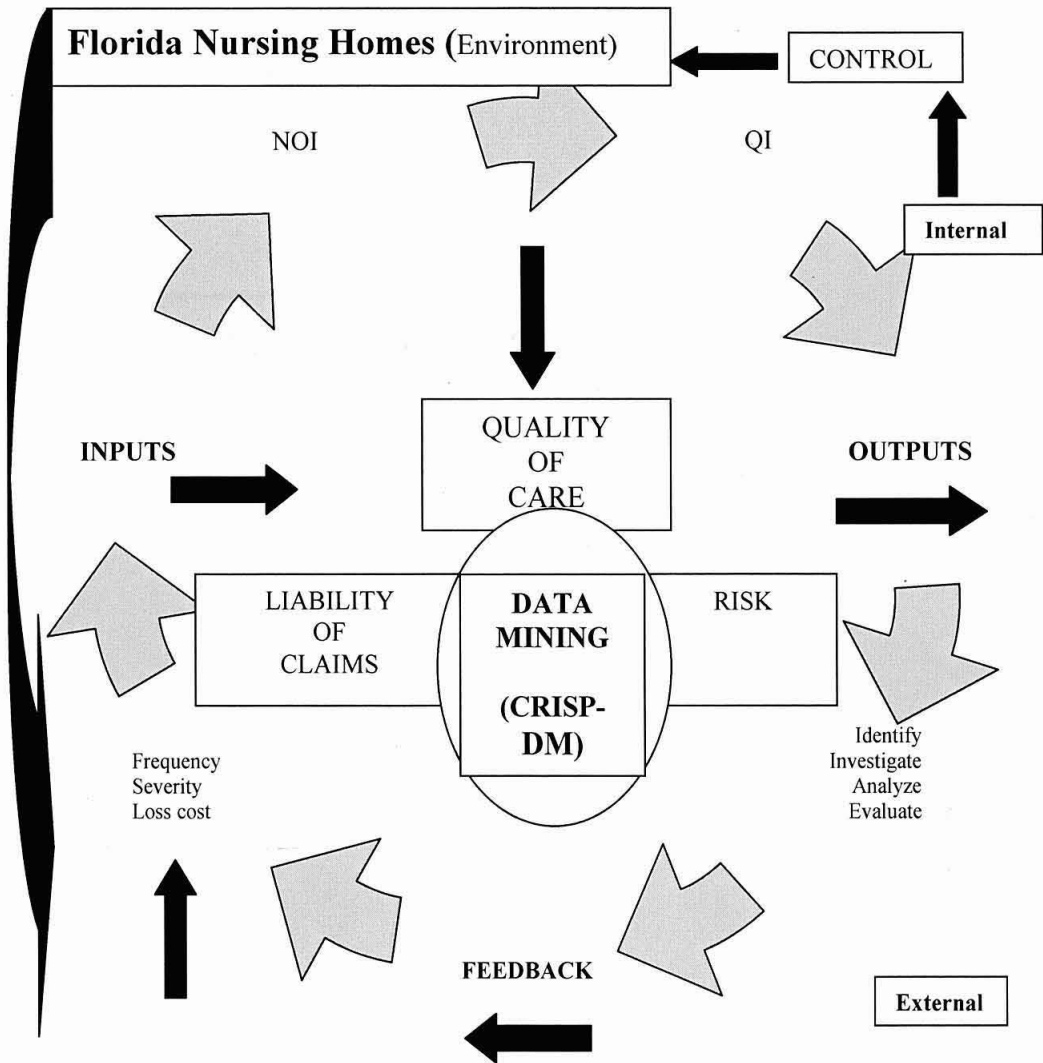


Figure 2-1. A theoretical framework describing the relationships of systems theory, quality of care, risk management and the CRISP-DM model

Research questions are proposed regarding data mining to identify quality of care factors associated with liability claims and risk management strategies in Florida nursing homes. These are based on the key gaps in the literature, the recommendations to be addressed in this study, and the theoretical framework that is to be used to guide this study.

Research Questions

1. What are the nursing home characteristics and quality of care factors that affect liability claims in Florida nursing homes?
 2. What risk management strategies affect liability claims in Florida nursing homes?
 3. What are effective risk management strategies that decrease liability claims in Florida nursing homes?
 4. Is there a risk management model, generated by data mining that may be used to predict liability claims and effectively manage risk?
- H1 There is a significant explanatory relationship among quality of care factors in nursing homes, nursing home characteristics, adverse incident outcome, incidence of falls, risk management strategies and severity of claims (total claims paid).
- H0 There is no significant explanatory relationship among quality of care factors in nursing homes, nursing home characteristics, adverse incident outcome, incidence of falls, risk management strategies and severity of claims (total claims paid).

Chapter II presented a literature review of quality of care in nursing homes, risk management, liability claims, and data mining. Based on the literature review, recommendations for future inquiry were identified as an exploratory and predictive (correlational) study about data mining to identify quality of care factors associated with

liability claims and risk management strategies in Florida nursing homes. A schematic model that integrates the variables and theoretical framework proposed for this study was presented and included systems theory, quality of care, risk management, and the CRISP-DM model. Chapter II concluded with research questions proposed that were based on the literature gaps, recommendations for future inquiry, and the theoretical framework for this study. Chapter III of the study discussed the research design, instrumentation, population, sample, data collection, and data analysis.

CHAPTER III

RESEARCH METHODS

The methods used to answer the research questions about risk management strategies and quality of care that affect liability claims in Florida nursing homes are described in Chapter III. The questions that were examined evolved from gaps in the literature. Chapter III included the research design, the sampling plan and setting, instrumentation, data collection procedures, and methods of data analysis. This chapter concluded with an evaluation of the research methods used in the study.

Research Design

A quantitative, non-experimental, exploratory, and predictive (correlational) research design was used to answer the research questions. The *independent variables* include quality of care factors in nursing homes, nursing home characteristics, and risk management strategies. Quality of care was measured using the MDS data set. The *nursing homes characteristics* examined include the number of beds, type of ownership, and whether the nursing home participates in Medicare and/or, Medicaid services. This information was obtained from the Nursing Home Compare link of CMS. In this study, a nursing home or skilled nursing facility was measured by the requirements of Florida statute 1819 or 1919(a), (b), (c), and (d) of the Act, which would include Medicare and Medicaid eligibility, and certification (AHCA, Long Term Care Survey, 2006). Risk management is the process through which loss is prevented, or the adverse effects are minimized after a loss. Finally, risk management strategies were measured using the nursing home staffing report that included the direct care staffing ratio per patient day for Registered Nurses (RNs), Licensed Practical Nurses (LPNs), and Certified Nursing

Assistants (CNAs). Polivka-West, Tuch, and Goldsmith (1999) defined risk management as the identification of actual and potential problems with solutions to avoid repeat adverse incidents.

The constructs being measured are quality of care factors in nursing homes, nursing home characteristics, risk management strategies, and liability claims. The data collected was individual resident information from each facility as well as aggregated data from each of the 106 facilities. The QI generated from the Minimum Data Set (MDS) was used to measure quality of care. For nursing home characteristics (i.e. the number of beds, type of ownership, and Medicare and Medicaid certified), the data was obtained from the nursing home compare link of CMS. Risk management was measured using nursing home staffing reports that were reported to AHCA semi-annually. The report was retrieved from AHCA FDAU.

The *dependent variables* that were studied are the notice of intent, type of incident, and the total amount paid for liability claims, which was associated with adverse incidents. The notice of intent represents the number of times each facility was threatened to be sued during the given year, while the type of incident was whether the individual experienced an adverse or non-adverse fall. Liability was defined by Levy (2004) as the quality or state of being legally obligated or responsible (p. 1). Liability claims were measured by the monthly liability claims (Notices of Intent) per resident that were submitted monthly to AHCA FDAU from each facility (see Appendix B, Part 6).

The Agency for Health Care Administration is currently the only agency that is gathering data on adverse incidents, notices of intent, regulatory deficiencies cited, and federal quality information (Boerger, 2004). AHCA is required to publish an annual and

semi-annual report to the legislature based on the nursing home reported data. Based on literature reviewed, no study has attempted to link data collected to create a risk management model that analyzes the factors associated with liability claims in long-term health centers and effective risk management strategies to decrease claims. The exploration of the data can result in developing a model; however, the difficulties of implementing data mining have prohibited organizations from becoming true learning organizations. The systems model integrated with the CRISP-DM model were used simultaneously to engage the nursing home environment through the life cycle of the data mining's six phases, generic task, specialized task, and process instances. To answer the research questions it was important to identify the effective risk management strategies that decrease claims. The literature review has provided much insight into risk management. Risk management is important to this research study because the biggest threat to the nursing home industry is litigation. Risk management is a system that attempts to identify, analyze, treat and monitor an institution's exposure to adverse financial loss (Louisot, 2003).

The exploratory and predictive research design used data mining of secondary data sets from the MDS resident-level data source, 1-Day and 15-Day adverse incident report, nursing home staffing report, and nursing home monthly liability claim report for the year 2006, to determine deeper relationships among the variables. AHCA currently collects data on adverse incidents, notice of intents, along with regulatory deficiencies cited, and federal quality information. The adverse incident report includes patient information that is confidential and is not discoverable or admissible in any civil or administrative action, therefore this study was limited to Florida nursing facilities. For

research question 1, Associated Discovery data mining technique identified clusters of records that exhibit similar behaviors or characteristics hidden in the data in which quality of care factors affect liability claims. For research questions 2, 3, and 4, data mining models such as logistic classification, classification trees and neural networks were used to develop classifications to predict liability claims in Florida nursing homes, as measured by the notice of intent, type of incident and total amount paid for expenses.

Population and Sampling Plan

Target Population

According to CMS (2007), the average older person population in all nursing homes in the United States is 58% and the average older person population in all nursing homes in the State of Florida is 61%. According to Jones (2002), there were 18,000 nursing homes in the US, which included 1.9 million beds and 1.6 million residents with an occupancy rate of 87 percent. Currently, there are an estimated 2.9 million Americans residing in nursing homes (CMS, 2007). In April 2006, Florida had a population of 18,233,777 people and there were 67,000 residents in Florida nursing homes, representing the target population in this study. The source of the population data used in the study was the Office of Economic and Demographic Research, State of Florida Legislature. There are 67 counties in Florida with 672 nursing homes. According to Florida State Health Facts, there were 587 paid medical malpractice claims in Florida with \$168,616,250 claims paid in 2007. The average amount of each claim paid in 2007 was \$287,251 (Kaiser Family Foundation, 2007).

Accessible Population

The accessible population includes 12,720 residents of 106 nursing homes in Florida. The accessible population is limited to the MDS resident assessment data within the 67 counties in the State of Florida that are Medicare and Medicaid certified, have 120 beds, are for-profit corporations, and are not located within a hospital. Characteristics of the nursing homes and risk management strategies of respective nursing homes of residents will also characterize the sample. Data from 2006 was used in the study. Data for the years 2004 through 2007 are available on CMS MDS assessment for nursing homes in Florida through Research Data Assistance Center (ResDAC).

Sampling Plan

The entire accessible population constituted the sample. There was no sampling plan. The sample includes resident assessments from 106 nursing home facilities that are at least 120 beds, for-profit, and certified by Medicare and Medicaid.

Sample Size

As of the third quarter of 2007, 258,083 assessments of residents were performed in all of the Florida nursing homes (CMS, 2007). Of these, 37,374 were admission assessments and 9,854 were annual assessments, conducted in the third quarter of 2007. Another 8,180 assessments were performed due to a significant change in the resident's health status. Furthermore, there were 45,671 quarterly assessments completed (CMS, 2007). Therefore, the data collection process was determined using the assessments that generate the MDS. The sample size was 12,720 independent residents from 106 nursing homes. The data were organized by 12,720 rows and 106 columns.

In this study, multiple regression analysis was used to test the model generated through data mining. There are 57 explanatory (or prediction) variables including two

nursing home characteristics, 24 quality indicators, 12 quality measures, 11 adverse incident outcomes, 1 for incidence of falls, and 7 risk management strategies that influence liability claims. According to Garson (2007), when using multiple regression analysis, the minimum sample size needed was estimated by multiplying the number of explanatory variables by 20. Therefore, the minimum sample size calculation would be 20×57 making the minimum sample size necessary to conduct multiple regression analysis, 1,140. Another method of estimating minimum sample size when using multiple regression analysis according to Green (1991), is based on the formula of $n=50 + 8(m)$, where m = the number of explanatory variables. Based on this model, the calculation of n (sample size) = $50 + 8(57)$ and the appropriate sample size needed would be at least 506.

According to Gay and Airasran (2001), to estimate the sample size needed for population validity purposes based on the accessible population size of 12,720 or a target population of 67,000 residents in Florida nursing homes, an adequate sample size would be 384 for a population of 100,000 or more. However, a sample size of 500 would be an even higher confident sample size (p. 135). In summary, to conduct the statistical analysis, and to ensure a sufficient size sample based on the population size, a range of 500 to 1,140 would represent an adequate and optimal sample range, respectively.

Eligibility Criteria

1. The geographic area and setting of the sample were limited to residents in Florida nursing homes.
2. The nursing homes were for-profit corporations not affiliated with a hospital or CCRC.
3. The nursing homes must be at least 120-bed capacity.

4. The nursing homes are not required to provide permission to participate in the study because the data are available on CMS MDS assessment for nursing homes in Florida through Research Data Assistance Center (ResDAC) on the following site: <http://www.resdac.umn.edu/MDS/Index.asp>.

Exclusion Criteria

1. Residents from facilities other than 120-bed capacity, non-profit, and not dual certified by Medicare and Medicaid were excluded.
2. Facilities not located in the State of Florida were excluded.

Setting

Secondary data are used in this study; therefore, the data has already been collected from 12,720 residents in the settings of 106 nursing homes in Florida. Secondary data was retrieved through the Research Data Assistance Center (ResDac). The data collection was limited to the Medicare.gov Nursing Home Compare Web site.

Instrumentation

The Minimum Data Set (MDS), AHCA Form 3110-0009, Confidential Nursing Home Initial Adverse Incident Report – 1 Day, and AHCA Form 3110-0010, 3110-0010A, and 3110-0010B, Confidential Nursing Home Complete Adverse Incident Report – 15 Day report; AHCA Form 3110-0012, Nursing Home Staffing Report, and AHCA Form 3110-0008, and AHCA Form 3110-0008A; and Nursing Home Monthly Liability Claim report completed by the MDS coordinator and Facility Risk Manager were all used in the study. The MDS consist of 24 categories and defined codes. These categories are expected to capture the core elements needed for a comprehensive assessment of the individual adult patient (Morris et al., 1990). There are six parts to the data collection

(See Table 3-1) created by the researcher. Part 1 was *Nursing Home Characteristics*, part 2 was *Quality of Care Factors in Nursing Homes*, part 3 was *Adverse Incident Outcome*, part 4 was *Type of Incident*, part 5 was *Risk Management Strategies*, and part 6 was *Liability of Claims*. The next sections presented the measurement of each construct. There are 66 items in the parts.

Table 3-1
Constructs of the Study and Measures

Part	Construct	Instrument	Measures	Number of Items
1	Nursing Home Characteristics	MDS	Bed capacity Chain	2
2	Quality of Care Factors	MDS	Quality indicator QI1-QI24	24
			Quality measures QM1-QM12	12
3	Adverse Incident Outcome	AHCA Form 3110-0009, Confidential Nursing Home Initial Adverse Incident Report – 1 Day, and AHCA Form 3110-0010, 3110-0010A, and 3110-0010B, Confidential Nursing Home Complete Adverse Incident Report – 15 Day	Death, brain or spinal damage, disfigurement, fracture, limit function, no consent, transfer, adult abuse, child abuse, elopement, and law enforcement AIO1-AIO11	11
4	Incidence of Falls	MDS	Falls Adverse or Non adverse incidents TOI1	1
5	Risk Management	Nursing Home Staffing Report was incorporated by reference by using AHCA Form 3110-0012, Nursing Home Staffing Report, as authorized by Section 400.141, F.S.	Staff RN, LPN, CNA, ratio, QA&A,PTSS, and FSS	7
6	Liability Claims	AHCA Form 3110-0008, and AHCA Form 3110-0008A, Nursing Home Monthly Liability Claim Report	LC1-LC9	9
Total				66

Table 3-2 was created by the researcher. It shows the variables in each part and the source of information in the study.

Table 3-2
Overview Table of Variables and Measurement

Variables	Source of Information
Part 1: Nursing Home Characteristics	MDS
Facility (identifier)	
Bed size (# of beds)	
Chain (facility part of a chain) Yes or No	
Part 2: Quality of Care Factors	MDS (Resident Level Assessment)
QI1-prevalence of any injury	
QI2-prevalence of falls	
QI3-prevalence of behaviors affecting others	
QI4-depression	
QI5-depression no treatment	
QI6-using 9 medications or more	
QI7-incidence of cognitive impairment	
QI8-bladder or bowel incontinence	
QI9-bladder and bowel no plan	
QI10-indwelling catheter	
QI11-prevalence of fecal impaction	
QI12-prevalence of UTI	
QI13-prevalence of weigh loss	
QI14-prevalence of tube feeding	
QI15-prevalence of dehydration	
QI16-bedfast residents	
QI17-decline in late loss ADLs	
QI18-decline in range of motion	
QI19-antipsychotic drug use	
QI20-antianxiety/hypnotic	
QI21-hypnotic use 2 times in the last week	
QI22-prevalence of physical restraints	
QI23-little or no activity	
QI24-prevalence of stage 1-4 pressure ulcers	
QM1 Res need for help with ADLs has increased	
QM2 Res who spend time in bed or chair	
QM3 Res with a catheter and left in bladder	
QM4 Low risk res who lose control of bowel and bladder	
QM5 Residents with a urinary tract infection	
QM6 Res whose ability to move worsened	
QM7 Res who are more depressed or anxious	
QM8 Res who have moderate to severe pain	
QM9 High risk res who have pressure ulcers	
QM10 Low risk res who have pressure ulcers	
QM11 Res who were physically restrained	
QM12 Residents who lose too much weight	
Part 3: Adverse Incident Outcome	1-Day and 15-Day AI reports
Death	
Brain or spinal damage	
Disfigurement	
Fracture	
Limit Function (neurological, physical or sensory)	
No consent	
Transfer	
Adult Abuse	
Child Abuse Elopement Law Enforcement	

Table 3-2 (Continued)

Variables	Source of Information
Part 4: Incident of Falls	MDS (Falls)
Adverse	
Non-Adverse	
Part 5: Risk Management	Nursing Home Staffing Report
Staff RN Hours per patient day (ppd)	
Staff LPN (ppd)	
Staff CNA (ppd)	
Direct Staff Ratio	
Quality Assurance	My Innerview
Patient satisfaction survey	My Innerview
Family satisfaction survey	
Part 6: Liability Claim	Monthly Liability Claim Report
Total paid	

Part 1: Nursing Home Characteristics

Description

The MDS data that was electronically submitted were used to create resident characteristics and QI profiles. Refer to Table 3-2 about nursing home characteristics. The *Facility Characteristics Report* provides information on the facility’s geographic location, bed capacity, type of ownership, and certified by Medicare and Medicaid was measured with a checklist. A fill in the blank format was used on the MDS to report the facility by the Medicare number, bed size, and ownership information in Florida nursing homes. (See Appendix B, Part 1).

Reliability of the Facilities Characteristics Report

A study by the Government Accountability Office GAO (2002) concluded, “The underlying MDS data were very reliable but that the reliability varied considerably within and across states. Aggregate reliability, however, is insufficient because quality indicators are reported separately for each facility” (p. 24). Reliability was estimated by the aggregate reliability.

Validity of the Facilities Characteristics Report

According to GAO (2002), “the validation study is based on a sample that is drawn from six states; it is not representative of nursing homes nationwide and may not be representative of facilities in these six states. Selected facilities were allowed to decline participation and about 50% did so. For those facilities in the validation study, Abt Associates deemed most of the indicators as valid, that is, better care processes were associated with higher quality indicator scores, taking into account resident and facility-level characteristics” (GAO, 2002, p. 21). Concurrent validity was established from the sample drawn for six states.

Part 2: Quality of Care Factors in Nursing Homes

Description

Refer to Table 3-2 for the quality of care factor indicators and measures. The *Minimum Data Set (MDS)* is the assessment instrument that was used to measure quality of care and nursing home characteristics variables in this study. It is a standardized form, which was developed by many researchers from a number of institutions (Morris et al., 1990). The assessment instrument is a federal tool that requires nursing home staff to indicate on the form a resident’s functional status and other conditions. The MDS is used to collect resident data, identify risk factors, support clinical risk evaluation, and create plans to guide care and services to nursing home residents (CMS.gov, 2007). The assessment and care plan process includes Resident Assessment Protocols (RAPS) and “Triggers” (Manard, 2002, p. 10). “When a resident’s assessment reveals one or more of

18 indicators of potentially problematic conditions, it triggers a required set of additional care planning activities designed to address the problem” (Manard, 2002, p. 10).

According to Manard (2002), “the initial version of the assessment was implemented in 1990 and has now been replaced by a second generation of assessment instrument and care planning protocols that have been implemented in nursing facilities nationwide” (p. 10). Furthermore, the electronic transmittal of the MDS data to CMS is operational, which was mandated in 1998 (Manard, 2002).

The Center for Health Systems Research and Analysis (CHSRA) QI has been warned by many researchers that the quality indicators should be used carefully since they are not direct measures of quality (Manard, 2002). The quality indicators are pointers that indicate potential problem areas that need further review and investigation. The MDS and QI were evaluated by well established a standard that was based on the testing of various characteristics psychometric properties that are reliable and valid. Psychometric properties and risk adjustment help determine how much confidence should be placed in inferences drawn from a nursing home’s performance on QI.

The quality indicators consist of 24 algorithms that were based on residents’ MDS quarterly assessments. For this study, resident MDS quarterly assessments are measures of the actual occurrence of the 24 algorithms, which can generate the prevalence of the residents affected by the condition. According to Manard (2002), 20 of the QIs are *prevalence* measures that give a percentage of residents in a facility with a particular condition. The other four QIs are *incidence* measures. The incidence data measures the number of new occurrences of particular conditions that developed from one assessment period to the next. Table 3-3 lists the 24 quality indicators and their domain. In the QI,

the risk adjusters were divided into high risk and low risk residents. These risk adjusters are limited to conditions that are determined by the MDS, quarterly assessment, and new admissions.

Table 3-3
List of Quality Indicators

Quality Indicator	Domain
1. Incidence of new fractures	Accidents
2. Prevalence of falls	
3. Prevalence of behavioral symptoms affecting others (verbally abusive, physically abusive, or socially inappropriate/disruptive behavior) (Risk Adjusted)	Behavioral/Emotional Patterns
4. Prevalence of symptoms of depression (sad mood plus at least 2 of the following: resident made negative statements, agitation or withdrawal, wakes with unpleasant mood, suicidal or has recurrent thoughts of death, weight loss)	
5. Prevalence of symptoms of depression and no antidepressant therapy	
6. Prevalence of residents using 9 or more different medications	Clinical Management
7. Incidence of cognitive impairment	Cognitive Patterns
8. Prevalence of bladder or bowel incontinence (Risk Adjusted)	Elimination/Incontinence
9. Prevalence of occasional bladder or bowel incontinence without a toileting plan	
10. Prevalence of indwelling catheters	
11. Prevalence of fecal impaction	
12. Prevalence of urinary tract infections	Infection control
13. Prevalence of weight loss	Nutrition/eating
14. Prevalence of tube feeding	
15. Prevalence of dehydration	
16. Prevalence of bedfast residents	Physical functioning
17. Incidence of decline in late loss ADLs	
18. Incidence of decline in range of motion	
19. Prevalence of antipsychotic use in the absence of psychotic and related conditions (Risk Adjusted)	Psychotropic drug use
20. Prevalence of antianxiety/hypnotic use	
21. Prevalence of hypnotic use more than two times in the last week	
22. Prevalence of daily physical restraints	Quality of life
23. Prevalence of little or no activity	
24. Prevalence of stage 1-4 pressure ulcers (Risk Adjusted)	

Reliability of MDS and the Indicators

According to Manard (2002), there are only four studies of inter-rater reliability for the MDS *underlying data* published in journals, and they have limited sample sizes.

The findings of these published studies were:

- Most of the items on the MDS met or exceeded acceptable standards for inter-rater reliability in published studies. The presence of end stage disease failed to meet acceptable standards.
- For the general nursing home population in a 33 resident nursing home, the inter-rater reliability was lower but within acceptable levels.
- For the cognitively impaired residents, the inter-rater reliability on assessments was significantly lower than on other assessments.

“The research team of Manard (2002) found that one of the nine QI studied (prevalence of little or no activity) did not meet generally acceptable standards of reliability. Additionally, the team’s clinical panel rejected two additional QI (fecal impaction and dehydration) before conducting formal validation studies” (Manard, 2002, p. 17). Other research that has been conducted for public reporting by federal sponsorship, researchers have explored the reliability; however, they have not been formally peer-reviewed and published (p. 17).

A reliability analysis was used to determine how correlated a set of questions or variables are with one another when it comes to a latent variable. In general, Cronbach’s alpha coefficients are used to provide information with respect to the internal consistency/reliability of the items. A Cronbach’s alpha of around .70 indicates that the questions or variables provide an adequate measurement for the latent variable while a

Cronbach's alpha of around .80 indicates that the questions or variables provide a good measurement for the latent variable (Nunnally, 1978; Salkind, 2006).

Validity of MDS and the Quality Indicators

The validity of the QI was evaluated using well-designed studies in order to have confidence in the measurement tool. The confidence of the MDS and QI was based on content validity. Moreover, the validity studies available have mixed results. Researchers evaluated the MDS and QI on face validity. The 24 QIs are limited because they do not measure or address certain aspects of quality (i.e. staff attitudes and quality of life) (Manard, 2002). In this study, validity of the quality indicators was established by divergent and convergent validity with liability claims using Pearson's *r* correlation coefficient.

Part 3: Adverse Incident Outcome

Description

Refer to Table 3-2 for the adverse incident outcomes. Nursing homes are required to monitor the internal actions, events, and the environment to provide the safest possible home for the residents (See Appendix G). A risk management program is designed to increase and improve the understanding of how events that cause harm to residents occur, and actions that should be taken to prevent those events. According to AON (2006), nursing home adverse incident outcomes include:

1. Death
2. Brain or spinal damage
3. Disfigurement
4. Fracture

5. Limit function (neurological, physical or sensory)
6. No consent
7. Transfer
8. Adult abuse
9. Child abuse
10. Elopement
11. Law enforcement

The adverse incident outcomes were measured by AHCA Form 3110-0009, Confidential Nursing Home Initial Adverse Incident Report – 1 Day, AHCA Form 3110-0010, 3110-0010A, and 3110-0010B, Confidential Nursing Home Complete Adverse Incident Report – 15 Day, which are incorporated by reference when reporting events as stated in Section 400.147, F.S. There is no scale indicated for these outcomes since only one can be checked, however, if the outcome is not present, a score on each item ranges from 0 (not present) to 1 (present) was recorded on the specific outcome that is indicated on the 1-day and 15-day adverse incident report. (See Appendix B, Part 3).

Reliability of 1-day and 15-day Adverse Incident Reports

No studies were found on the reliability of the 1-day and 15-day report forms. To estimate reliability, tests and retests using Phi coefficient correlation were conducted to determine whether the data are stable from the 1-day to the 15-day report.

Validity of 1-day and 15-day Adverse Incident Reports

The 1-day and 15-day report can be validated by the internal risk manager who is required to investigate each incident and determine whether the incident is adverse or

non-adverse. No research was found on these mandated forms. To establish construct validity, factor analyses of the scale were conducted.

Part 4: Incident of Falls

Description

Refer to Table 3-2 for the incidence of falls indicators. Incidence of falls was defined as an occurrence characterized by the failure to maintain an appropriate lying, sitting, or standing position, resulting in an abrupt, undesired relocation to the ground. Falls are common, recurrent events in the nursing home population, often resulting from elders' inability to compensate for environmental stresses and their underlying disabilities, as well as facility care practices that may be inadequate in reducing the risk of falls (Westmoreland & Baldini, 2005). The following risk factors associated with falling have been identified: sex, age, medication (antipsychotics, antidepressants, or antianxiety drugs), wandering, loss of balance, chairfast, bedfast, cognitive impairment, comorbidities, bedrails, trunk restraints, activity of daily living (ADL) impairment, urinary incontinence, unsteady gait, and cane/walker use (p. 268).

Furthermore, among elderly nursing home residents, a history of falls is another strong risk factor for incidence of falls. Thus, repeat fallers require comprehensive and individualized preventive interventions (p. 268). Nursing facilities utilize a multifactorial falls risk assessment and management program consisting of three components:

1. A questionnaire to identify risk factors for falls, which can be self-administered or administered by a professional
2. A thorough medical evaluation (including examination of vision, gait, balance, strength, postural vital signs, medication review, cognitive and functional status)

3. Follow-up interventions that may include a tailored exercise program, environmental modifications, and assistive devices.

Incident reports in nursing homes are kept separate from the medical records. Sources of data collection can be baseline interviews with nursing staff, residents, and significant others, and medical records containing MDS evaluations and hospital discharge summaries. However, this study will use the 1-year MDS assessment, the source of MDS falls events data for corresponding 30- and 180-day periods for each resident. In this study, the MDS resident level data were used to measure the incidence of falls specific to residents with new fractures on the most recent assessment and the prevalence of falls that were reported to AHCA as adverse. The score range is “0” for non-adverse and “1” for adverse. (See Appendix B, Part 4).

Reliability of Incident Report of Falls

Morris et al., (2002) indicated that the MDS falls variables have been shown to have adequate reliability. The reliability was estimated by the interrater assessed using the Spearman correlation coefficient. Internal consistencies were examined by Cronbach’s alpha.

Validity of Incident Report of Falls

According to VanSwearingen et al., (1996), criterion-related validity was evaluated by the ability of the Gait Abnormality Rating Scale (GARS-M), an assessment of gait designed to predict the risk of falling among community dwelling, frail older persons. The purpose was to distinguish between older individuals with and without a history of falls, as indicated by self-report or proxy report, previously shown to be an indication of relative risk of falling again (p. 998). An independent *t* test was used to

determine whether a difference existed between the GARSM scores of older adults with a history of falls and the GARS-M scores of older adults without a history of falls (p. 998). There were differences and criterion related validity was established. For this study, criterion related validity was established by comparing those with and without an incidence (adverse and non-adverse) of falls to cognitive abilities.

Part 5: Risk Management

Description

Refer to Table 3-2 for the risk management strategies of the study.

Staffing per patient day for RN, LPN, CNA's and ratios are measured by the monthly Nursing Home Staffing Report, which is incorporated by reference using AHCA Form 3110-0012, Nursing Home Staffing Report, as authorized by Section 400.141, F.S. The hours for each discipline were determined by calculating the total number of hours worked by each discipline during a two-week period prior to the inspection. Each calculation was divided by the number of residents residing in the homes during the two-week period prior to the inspection. The "Total hrs/res" represents the sum for the three disciplines. According to Rehnquist (2003), quality assessment and assurance committees (QA committees) represent key points of accountability for ensuring both quality of care and quality of life in nursing homes. The Omnibus Budget Reconciliation Act of 1987 (OBRA 87) required nursing homes to maintain QA committees that meet at least quarterly and identify and correct quality deficiencies and improve care. The Centers for Medicare & Medicaid Services (CMS) determines whether nursing homes meet those requirements through the survey and certification process. Quality Assurance was measured by the nursing home Medicare and Medicaid certification status, which is

indicated by a score of “0” for compliance and “1” for non-compliance. The Family and Resident satisfaction survey was measured by My Innerview management intelligence for healthcare at www.myinnerview.com. My InnerView is a Web-based program that helps facilities track quality and improve performance in real time. My Innerview collects quality data for facilities across six domains: family satisfaction, employee satisfaction, state survey results, quality of life, quality of care, and financial results. According to Grant et al., (2006), the family and resident satisfaction survey has four sub-scales and an overall scale. In this study, the four item subscale and the overall satisfaction scale used with responses ranging from 1 to 4, where 1=Poor, 2=Fair, 3= Good, and 4=Excellent. In addition to measuring global satisfaction, My Innerview researchers assessed three domains: (a) quality of life, (b) quality of care, and (c) quality of service. The findings were “nursing facilities continued to earn somewhat higher scores across quality of life items (80.1% “excellent” and “good”), followed by quality of care (77.6%) and quality of service (72.6%)” (Grant et al., 2007, p. 5).

A total of 32 questions were on the survey. Individually sealed packets containing a self-addressed, postage-paid envelope were sent to residents’ family members or other responsible parties. Responses were electronically compiled into a database, analyzed for integrity, and subjected to a variety of statistical analyses. My Innerview’s survey instrument has undergone extensive field-testing and has outstanding psychometric properties (Grant et al., 2006.).

According to CMS (2007), risk management requires regular planned risk assessments to identify areas of risk in the nursing home. The risk management committee should develop the risk plan and risk information must be translated into

decisions and mitigating actions. Implementing a corrective action plan should include early reporting and coordinated response procedures. There should be a plan for tracking and evaluating the effectiveness and overall performance of the program. Another basic component of risk management is a program audit that includes a written plan to monitor the safety of the nursing home.

According to Lynch et al. (2004), Florida nursing homes rank high nationally on both measures of staffing and quality. Staffing levels are measured as the ratio of the number of nursing staff hours worked each day by Registered Nurses, Licensed Practical Nurses, Certified Nurse's Aides, and the total number of residents in the facility. In 2006, legislation was passed in Florida addressing minimum staffing requirements for nursing homes. The rules call for 2.7 hours of direct care/ resident / day as of January 2007, with at least one certified nursing assistant per 20 residents. Additionally, they call for a minimum of one licensed nurse for 1.0 hour of direct care/ resident / day and never below one nurse for 40 residents. That same year, Florida was also successful in enacting a law requiring a registered nurse's presence in the operating room during the entire surgical procedure. Currently, the nursing per patient day (ppd) for licensed nurses is 1.0 and 2.9 for CNAs. To figure the hours needed in a day the formula is (census x ppd = hours/hours per shift). See Appendix B, Part 5.

Reliability of Nursing Home Staffing Report

Cronbach's coefficient alpha was used to establish reliability of the satisfaction scales of My Innerview survey instrument (Grant et al., 2007). See Appendix F, Staffing form used by AHCA to determine compliance.

Validity of Nursing Home Staffing Report

There was relatively no research that has been conducted on these mandated forms. However, Grant et al. (2007) found a positive correlation between family and employee survey by using My Innerview survey instrument and concurrent validity of the family (Grant et al., 2007).

Part 6: Liability Claims

Description

Refer to Table 3-2 for the liability claims constructs. Chapter 429.23 of the internal risk management and quality assurance program of the Florida Statutes requires that nursing facilities report within one business day after the occurrence of an adverse incident (Florida Legislature, 2007). The preliminary report must identify the resident affected, the type of adverse incident, and the status of the facility's investigation. The 15-day report must include a full report to the agency with the results of the facility's investigation into the adverse incident. It is also required that nursing homes report any liability claims filed against the facility on a monthly basis. The report includes the name of the resident, the dates of the incident leading to the claim, and the type of injury or violation of rights alleged to have occurred. In order to determine loss cost, the data will include the following variable:

1. Total paid in dollars.

Chapter 429.23 of Florida Statute 5 states that the liability reports are not discoverable in any administrative action, except in actions brought forth by the agency to enforce the rule. The 1-day and 15-day adverse incident reports was sent to the Agency Facility Data Analysis Unit (FDAU) via facsimile, online, or mail delivery upon the

nursing facility's completion of the investigation. The agency then reviews the forms for completeness and data are entered into the Florida Regulatory Administration and Enforcement System (FRAES LE). Public Law 2004-400 requires that nursing facilities submit copies of liability claims filed against the facility monthly to the agency. The measures were recorded according to the number of notice of intents (NOIs) received by month. (See Appendix B, Part 6)

Reliability of Monthly Liability Report

No studies were found of the reliability of the monthly liability claims report forms, however, the form has been the same since 2002.

Validity of Monthly Liability Report

The monthly liability report can be validated by the nursing homes since they are required to report the notice of intent to AHCA. There was relatively no research that has been conducted on these mandated forms. In this study, concurrent validity was established by correlating amounts of liability claims paid with one another.

Procedures: Ethical Considerations and Data Collection Methods

1. This study used the Minimum Data Sets 2.0 resident assessment instrument data collected from Florida nursing homes.
2. On September 6, 2007, ResDAC was contacted regarding information on obtaining CMS MDS assessment data for nursing homes in Florida. (See Appendix A)
3. An approximate price for one year of data, one state, all assessments is \$1,000. (See Appendix C).

4. A request for the data was requested and per ResDac, the principal advisor had to sign the data request documents as the User; the principal investigator would be the data custodian. (See Appendix D).
5. An application was submitted to the IRB and upon approval of IRB, the data collection process were initiated.
6. An IRB application was submitted. The principal investigator sought an exemption from IRB review since the research involves the use of secondary data. Data collection began after approval was received from Lynn University's Institutional Review Board.
7. Approval of Lynn University's IRB help assured that this study followed procedures to protect human subjects by reviewing the proposal submitted by the principal investigator.
8. Informed consent was not be necessary in this study since the data has already been collected and were retrieved from CMS, whereby the principal investigator will have to follow protocols. (See Appendix D).
9. "CMS requires that ResDAC review all requests for identifiable data files for completeness and accuracy prior to submission to CMS. The identifiable data requests are reviewed by a CMS Privacy Board. The CMS Privacy Board generally convenes the fourth Thursday of the month. Once mailed, data request packets was reviewed by ResDAC staff within 5-7 days. However, ResDAC recommends e-mailing requests materials to ResDAC one month prior to the CMS Privacy Board meeting to allow time for making updates to the

documentation, for mailing the packet to CMS, and for the request to be received and assigned for CMS review”(CMS, 2007) (See Appendix B).

10. The data were analyzed using PolyAnalyst 6.0.
11. The facility identifiers were present in the data. CMS purged the data with instructions on how to protect the privacy of residents. Furthermore, secondary data sets that are unrestricted datasets were sufficiently purged of identifying information and the researcher believes there was no significant threat to respondent privacy. The results of this study may be published in a dissertation, scientific journals or presented at professional meetings. In addition, individual privacy was maintained in all publications or presentations resulting from this study. Data were reported as grouped responses. All the data gathered during this study, which was previously described, were kept strictly confidential by the researcher. Data were stored in locked files and destroyed at the end of the research. All information was held in strict confidence and will not be disclosed unless required by law or regulation.
12. The data and electronic file were kept confidential and were stored electronically on a password protected computer.
13. The data will be kept for five years and then destroyed.
14. Upon completion of the data collection, the principal investigator submitted the IRB Report of Termination of Project, Form 8.

Methods of Data Analysis

To assess the objectives of this study, several different statistical tests were conducted. These included a logistic regression analysis with classification, a

classification and regression tree (CART) for classification purposes, neural networks for classification purposes and simple-linear and multiple-linear regression analyses. Logistic regression was used to assess how well the quality care variables performed at classifying the type of incident the participant experienced (adverse or non-adverse fall). Logistic regression is used in order to determine whether a single or several independent variables significantly predict the dependent variable. This is similar to the other regression analyses except that the dependent variable is dichotomous. This means that the dependent variable is binary or is comprised of two categories. By using the logistic regression model one is able to indicate whether the independent variable significantly predicts the probability or odds of the dependent variable occurring. For the purpose of the logistic regression model, the independent variables can be either continuous or categorical.

A CART was then used to determine how well the quality care variables performed at classifying the type of incident (adverse or non-adverse fall). The idea behind the classification tree method is that a binary hierarchical tree is created to predict the class of response variables by using the selected explanatory variables in the model (Breiman et al., 1984; Spruill et al., 2002). The initial step in the tree building process starts at the root node (RN). At the RN, every possible variable in the model is looked at and partitioned or split into two separate homogeneous groups. The classification tree model is used to determine which quality of care variables could be used to predict the type of incident. In particular, the classification tree model can be used to classify the number of adverse and non-adverse incidents based on the values of the independent variables in the model. Similarly, the CART was used to classify the notice of intents.

This was used to determine how well the quality of care variables performed at predicting the number of notices of intent the nursing homes received at an aggregated level (i.e. at the nursing home level).

In addition to the logistic regression and CART analyses, neural networks were used to classify the notices of intent and type of incident (adverse and non-adverse fall). The idea behind artificial neural networks (ANN) is that they emulate a computer-based representation of the neural structure in the human brain. The term "artificial" is applied to these neural networks because it has been debated philosophically as to how a computer-based program can copy the functions of the human brain (Faraway, 2006). In terms of statistical analysis, ANN is used for a number of different applications such as recognition, regression, and classification with the results of these applications being comparable to regular statistical methods. The neural network model is used to determine which quality of care variables could be used to predict the type of incidents. In particular, the neural network model can be used to classify the number of adverse and non-adverse incidents based on the values of the independent variables in the model.

To assess whether the adverse affects could significantly predict the total amount paid by the nursing homes, a simple linear regression was conducted. The simple linear regression analysis was conducted to determine the individual effects the independent variables (adverse incidents) had on the dependent variable (total amount paid). Simple linear regression is used to determine if a continuous independent variable is a significant predictor of a continuous dependent variable. The general formula for the simple linear regression model is

$$Y = A + BX + e$$

where Y is the dependent variable (total amount paid). A is the intercept of the model which is equal to the value of the dependent variable when the independent variable is equal to zero. B is the coefficient for the independent variable and indicates how many units change there is in the dependent variable for every one unit increase in the independent variable. X is the value of the independent variable that is observed in the data (i.e. death, brain or spinal damage, etc.). Moreover, e is the random error term that is normally distributed with a mean of zero and a constant variance (Keuhl, 2000).

Subsequently, to determine whether there was a significant multivariate relationship between the variables in the study, a multiple linear regression analysis was conducted. Multiple linear regression is used to determine if several continuous independent variables are significant predictors of a continuous dependent variable while taking into account the other independent variables in the model. The general formula for the simple linear regression model is $Y = A + B_1X_1 + B_2X_2 + \dots + B_pX_p + e$ where Y is the dependent variable (total amount paid), A is the intercept of the model which is equal to the value of the dependent variable when the independent variable is equal to zero, B_1, B_2, \dots, B_p are the coefficients for the independent variables and indicates how many units change there is in the dependent variable for every one unit increase in the independent variable when controlling for the other independent variables in the model, X_1, X_2, \dots, X_p are the values of the independent variables that are observed in the data (i.e. either death, brain or spinal damage, etc.), and e is the random error term that is normally distributed with a mean of zero and a constant variance. The multiple linear regression model is used to determine whether there was a significant relationship

between an individual independent variable and dependent variable in the study, while controlling for the other independent variables in the model.

Evaluation of Research Methodology

This study was examined for internal validity and external validity by identifying the strengths and weaknesses of research methods. Internal validity is the cause and effect relationship between the independent and dependent variables are established (Salkind, 2000). External validity is the ability to generalize findings. The strengths and weaknesses of the research methods are as follows.

Internal Validity

Strengths

1. A quantitative, non-experimental, exploratory, and predictive (correlational) research design is stronger than a descriptive study. The secondary data covers a large population.
2. The instruments selected contributed to the study's internal validity since the CRISP-DM is a standardized process that allows the study to be replicated.
3. By using the data mining analysis methodology in this study with the data that are already available, relationships can be determined between the variables and a thorough exploratory assessment can be conducted.
4. A prediction model was developed to predict risk management strategies.
5. The sample size was large enough to conduct the data mining analysis.

Weaknesses

1. A non-experimental research is weaker than an experimental design.

2. The 24 QI are limited because they do not measure or address certain aspects of quality (i.e. staff attitudes and quality of life) (Manard, 2002).

External Validity

Strengths

1. The data are available on CMS MDS assessment for nursing homes in Florida through Research Data Assistance Center (ResDAC).
2. The MDS data that are electronically submitted are used to create resident characteristics and QI profiles.

Weaknesses

1. The accessible population were limited to 106 of 672 nursing homes within the 67 counties in the State of Florida that are Medicare and Medicaid certified, have 120 beds, are for-profit corporations, are not located within a hospital, and use both resident and family council.

Chapter III discussed the research methods that addressed the research questions on risk management strategies and quality of care that affect liability claims in nursing homes, and are used to create a risk management model based on available data using the data mining method. Additionally, the chapter described the research design, the sampling plan, and setting, instrumentation, data collection procedures, ethical considerations, methods of analysis, and evaluation of the research methods. Chapter IV of the study will present results of the data mining analysis and risk management models that are created to answer the questions of the study.

CHAPTER IV

RESULTS

In this study about the quality of care factors associated with liability claims and risk management strategies in Florida nursing homes, the data mining results are presented. Chapter IV presents the data mining tasks of model building and pattern detection, results of answers to research questions, and results of testing the hypothesis for this study. The method of data analysis includes psychometric analysis, descriptive statistics, and data mining including regression, classification, and neural networks.

Data Producing Sample

The data producing sample consisted of nursing home resident assessments in Florida that were selected based on 106 nursing home facilities with the capacity of 120-beds, for-profit, and certified by Medicare and Medicaid Services. The sample was comprised of resident MDS assessments that represented quality indicators and quality measures of 12,720 resident assessments from January through December 2006.

Reliability of Measurements Scales

A reliability analysis is used to determine how correlated a set of questions or variables are with one another when it comes to a latent variable. This is often used in conjunction with the factor analysis to illustrate that the questions or variables provide an adequate measure of the underlying variable. In general, Cronbach's alpha coefficients are used to provide information with respect to the internal consistency/reliability of the items, with a Cronbach's alpha of around .70 indicating that the questions or variables provide an adequate measurement for the latent variable, or a Cronbach's alpha of around

.80 indicating that the questions or variables provide a good measurement for the latent variable. A reliability analysis was conducted for each of the quality of care measurements described in Table 4-1. The reliability coefficients had a range from .804 for the fecal variable to .991 for both the overall symptom variable and whether they used a feeding tube. This indicated that each of the variables were highly reliable measurements.

Table 4-1***Reliability Analysis for Independent Variables included in the Analysis (N =12,720)***

Column name	Cronbach's Alpha	Number of Items
<i>Quality Variables</i>		
Incidents of New Fractures	.857	12
Prevalence of Fall	.943	12
More Depressed or Anxious	.946	12
Behavior Symptom Overall	.991	12
Behavior Symptom High Risk	.989	12
Behavior Symptom Low Risk	.970	12
Depression without Antidepressant Therapy	.967	12
Use 9 or More Different Medication	.990	12
Cognitive Impairment	.907	12
Lost Control of Bowel or Bladder	.989	12
Catheter Inserted and Left in Bladder	.974	12
Bladder or Bowel Incontinence without Toileting Plan	.976	12
Fecal Impaction	.804	12
Urinary Tract Infection	.956	12
Resident Lose too Much Weight	.960	12
Tube Feeding	.991	12
Moderate or Severe Pain	.984	12
Spend most of their Time in Bed or Chair	.930	12
Ability to Move Around Room gets Worse	.983	12
Decline in ROM	.917	12
Antipsychotic Use with Absence of Psychotic Conditions Overall	.927	12
Antipsychotic Use with Absence of Psychotic Conditions High Risk	.984	12
Antipsychotic Use with Absence of Psychotic Conditions Low Risk	.944	12
Anti-anxiety/Hypnotic Use	.984	12
Hypnotic Use more than 2 Times Last Week	.989	12
Resident Physically Restrained	.982	12
Little or No Activity	.974	12
Pressure Ulcer High Risk	.960	12
Pressure Ulcer Low Risk	.942	12
Short Stay Patients with Delirium	.978	12
Short Stay Patients with Moderate or Severe Pain	.981	12
Short Stay Patients with Ulcer	.972	12

Nursing Home Characteristics

The number of Florida nursing homes in the AHCA Nursing Home Compare as of December 2006 was 676. The nursing homes were sub-divided into sub-groups based on whether the homes were 120-beds ($n=106$) and the type of ownership, for profit or non-profit. The summary statistics for the continuous variables included in this study of the nursing homes are presented in Table 4-2. These summary statistics include the minimum and maximum values, the mean, range of the values, the standard deviation, and the median of the variables. The quality variables had 12,720 observations from the 106 different nursing homes. For the quality dataset, the variable with the highest average value was the medication variable ($M = .65$, $SD = .09$), followed by the antipsychotic high-risk variable ($M = .41$, $SD = .20$). The remaining summary statistics for the other variables in the study are presented in Table 4-2.

Quality of Care Factors in Nursing Homes

The summary statistics for the continuous variables included in this study are presented in Table 4-2. These summary statistics include the minimum and maximum values, the mean, the range of the values, the standard deviation, and the median of the variables. The quality variables had 12,720 observations from the 106 different nursing homes. For the quality dataset, the variable with the highest average value was the medication variable ($M = .65$, $SD = .09$), followed by the antipsychotic high-risk variable ($M = .41$, $SD = .20$).

Table 4-2
Descriptive Statistics for Independent Variables (N =12,720)

Column name	Min	Max	Range	M	SD	Median
<i>Quality of Care Factors</i>						
Incidents of New Fractures	0.00	0.05	0.05	0.02	0.01	0.02
Prevalence of Fall	0.03	0.21	0.18	0.12	0.04	0.12
More Depressed or Anxious	0.01	0.26	0.25	0.11	0.05	0.10
Behavior Symptom Overall	0.02	0.40	0.39	0.14	0.08	0.13
Behavior Symptom High Risk	0.03	0.44	0.41	0.17	0.09	0.16
Behavior Symptom Low Risk	0.00	0.34	0.34	0.06	0.06	0.04
Depression without Antidepressant Therapy	0.00	0.11	0.11	0.03	0.02	0.02
Use 9 or More Different Medication	0.40	0.86	0.45	0.65	0.09	0.66
Cognitive Impairment	0.00	1.00	1.00	0.13	0.11	0.11
Lost Control of Bowel or Bladder	0.18	0.82	0.64	0.50	0.12	0.49
Catheter Inserted and Left in Bladder	0.02	0.17	0.15	0.09	0.04	0.09
Bladder or Bowel Incontinence without Toileting Plan	0.00	1.00	1.00	0.35	0.27	0.31
Fecal Impaction	0.00	0.01	0.01	0.00	0.00	0.00
Urinary Tract Infection	0.04	0.26	0.22	0.12	0.04	0.12
Resident Lose too Much Weight	0.01	0.30	0.30	0.11	0.04	0.10
Tube Feeding	0.01	0.24	0.23	0.08	0.05	0.07
Moderate or Severe Pain	0.01	0.41	0.41	0.10	0.08	0.08
Spend most of their Time in Bed or Chair	0.00	0.18	0.18	0.04	0.04	0.04
Ability to Move Around Room gets Worse	0.03	0.33	0.29	0.15	0.06	0.14
Decline in ROM	0.02	0.19	0.17	0.06	0.03	0.06
Antipsychotic Use with Absence of Psychotic Conditions Overall	0.00	0.37	0.37	0.14	0.07	0.15
Antipsychotic Use with Absence of Psychotic Conditions High Risk	0.00	0.86	0.86	0.41	0.20	0.41
Antipsychotic Use with Absence of Psychotic Conditions Low Risk	0.00	0.37	0.37	0.12	0.07	0.11
Anti-anxiety/Hypnotic Use	0.07	0.52	0.45	0.26	0.09	0.26
Hypnotic Use more than 2 Times Last Week	0.01	0.21	0.20	0.07	0.04	0.07
Resident Physically Restrained	0.00	0.31	0.31	0.10	0.07	0.09
Little or No Activity	0.00	0.20	0.20	0.02	0.03	0.01
Pressure Ulcer High Risk	0.05	0.41	0.35	0.15	0.06	0.14
Pressure Ulcer Low Risk	0.00	0.20	0.20	0.03	0.03	0.02
Short Stay Patients with Delirium	0.00	0.28	0.28	0.02	0.04	0.01
Short Stay Patients with Moderate or Severe Pain	0.01	0.58	0.57	0.23	0.12	0.21
Short Stay Patients with Ulcer	0.04	0.49	0.45	0.22	0.09	0.21

Note. Min is the minimum observed value for each variable. Max is the maximum observed value for each variable. M is the mean of the variables. SD is the standard deviation of the variables.

Adverse Incident Outcome

The summary statistics for the adverse incidents variables are presented in table 4-3. This includes summary statistics such as the mean, median, minimum, and maximum values. For the adverse incidents, the average values for each had a wide range. The child abuse variable was found to have no variation in the data (they were all the same values).

Table 4-3
Summary Statistics for Adverse Incidents Outcomes (N=12,720)

	Range	Minimum	Maximum	Sum	Mean	SE	SD	Variance
Death	2	0	2	19	.31	0.08	0.59	0.35
Brain or spinal damage	1	0	1	1	.02	0.02	0.13	0.02
Disfigurement	1	0	1	3	.05	0.03	0.22	0.05
Fracture	68	0	68	513	8.41	1.49	11.64	135.38
Limit function	1	0	1	8	.13	0.04	0.34	0.12
No consent	5	0	5	21	.34	0.11	0.87	0.76
Transfer	116	0	116	1055	17.30	2.83	22.09	487.78
Adult Abuse	137	0	137	963	15.79	2.87	22.43	502.97
Child Abuse	0	0	0	0	.00	0.00	0.00	0.00
Elopement	41	0	41	354	5.80	1.09	8.47	71.79
Law Enforcement	52	0	52	363	5.95	1.28	9.96	99.11
Notice of Intent	6	1	7	173	1.63	0.11	1.14	1.30
Total Amount Paid	25,000	100,000	125,000	10,655,000	100,518.87	313.87	3,231.49	10,440,000.00

Note. SE is the standard error of the variables. SD is the standard deviation of the variables. Each variable has 12, 720 observations.

Incident of Falls

The frequency distributions for the dependent variables included in this analysis follow. This included calculating the frequency and percentage of observations that belonged to each group within the notice of intent and type of incident dependent variables. The majority of the observations in the dataset belonged to the notice of intent group 1 (67.9%). The notice of intent represented the number of notice of intents to sue

that each of those facilities received from the attorneys of former residents of the nursing home. They are putting them on notice that they are suing them. This means that the majority had just one notice. This was followed by those who had received two notices (14.2%) and for the third group of notice of intent (10.4%). Alternatively, none of the observations had six notices of intent meaning that no one had six notices of intents for the year. As for the type of incident, just over half of the participants belonged to group 1 of the type of incident dependent variable. The data for the dependent variables in this study were from the liabilities claims data sets that were obtained from the AHCA annual reports. The results for these variables are presented in Table 4-4.

Table 4-4
Descriptive Statistics for Dependent Variables

Variable	Frequency (N = 106)	Percent
<i>Notice of Intent</i>		
1	72	67.9
2	15	14.2
3	11	10.4
4	4	3.8
5	3	2.8
6	0	0.0
7	1	.9
<i>Type of Incident</i>		
Non-Adverse Fall	51	48.1
Adverse Fall	55	51.9

Risk Management

The facility staffing reports are based on Florida's 2001 legislation, which called for minimum patient care hour staffing standards for nurses and certified nursing assistants (CNAs). The legislation required the Agency for Health Care Administration (AHCA) to adopt regulations setting minimum daily resident care hours for CNAs to 2.6 hours in January 1, 2003, and increasing to 2.9 hours of direct care per resident per day

beginning in July 1, 2006. The minimum CNA-to-patient ratio was set at 1:20. Licensed nurses staffing standards was set at a minimum of one hour a day in direct service to residents, and the ratio for licensed nurse-to-resident ratio was 1:40. According to *memberfamily.net*, the State average number of nursing personnel by category are for RN = .52, LPN = 1.0, CNA = 3.04 and total nursing service = 4.55. Table 4-5 describes the State average nursing service hours and the facility average hours per day per patient for the 106 Florida nursing homes.

Table 4-5
Hours per Day per Patient by State and Facility

Description	State Average	Facility Average (N = 106)
Registered Nurse (RN)	.52	.45
Licensed Practical Nurse (LPN)	1	.97
Certified Nursing Assistant (CNA)	3.04	2.94
Total Nursing Service	4.55	4.36

Liability Claims

In order to determine whether any of the adverse incidents could be used to predict the liability claims from the data collected from the 106 Florida nursing homes, a linear regression analysis was conducted. The linear regression analysis would allow the researcher to address the research hypothesis that states the adverse incidents are able to predict the liability claims for the nursing homes. For the first analysis that was conducted the dependent variable was the total amount paid for the liabilities, while the independent variable was the law enforcement variable. This meant that the regression with the law enforcement independent variable and the total amount paid (dependent variable) would determine whether the number of law enforcement observed patients would be able to predict the total amount paid by the participants. Based on this information it was found that there was not a significant relationship between the

independent and dependent variable, $t(59) = .21, p = .84$. This indicated that the independent variable did not significantly predict the total amount paid by the participants. In fact, this model was only able to explain .1% of the variation in the total amount paid, as indicated by the R square value for the model. These results are presented in the following tables.

Table 4-6
Model Summary for Amount Paid and Enforcement

Model	R	R ²	Adjusted R ²
1	.027 ^a	.001	-.016

Table 4-7
ANOVA for Amount Paid and Enforcement

ANOVA ^b						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	770820.524	1	770820.524	.042	.838 ^a
	Residual	1.075E9	59	1.821E7		
	Total	1.075E9	60			

a. Predictors: (Constant), Law Enforcement

b. Dependent Variable: Total Amount Paid

Table 4-8
Parameter Estimates for Amount Paid and Enforcement

Model	Coefficients ^a						
	Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95% Confidence Interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
1 (Constant)	100833.889	638.009		158.045	.000	99557.236	102110.543
Law Enforcement	11.385	55.343	.027	.206	.838	-99.356	122.126

a. Dependent Variable: Total Amount Paid

Again to address the research hypothesis that the adverse incidents were able to predict, or were significantly related to the liability claims, a linear regression analysis

was conducted. For the next analysis that was conducted the dependent variable was the total amount paid for the liabilities, while the independent variable was the elopement variable. This meant that the regression with the elopement independent variable and the total amount paid (dependent variable) would determine whether the number of elopements observed would be able to predict the total amount paid by the participants. This is because the number of elopements was an adverse incident. Based on this information it was found that there was not a significant relationship between the independent and dependent variable, $t(59) = .25, p = .80$. This indicated that the independent variable did not significantly predict the total amount paid by the participants. In fact, this model was only able to explain .1% of the variation in the total amount paid, as indicated by the R squared value for the model. These results are presented in the following tables.

Table 4-9
Model Summary for Amount Paid and Elopement

Model	R	R ²	Adjusted R ²
1	.033 ^a	.001	-.016

a. Predictors: (Constant), Elopement

Table 4-10
ANOVA for Amount Paid and Elopement

ANOVA ^b						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1164309.628	1	1164309.628	.064	.801 ^a
	Residual	1.074E9	59	1.821E7		
	Total	1.075E9	60			

a. Predictors: (Constant), Elopement

b. Dependent Variable: Total Amount Paid

Table 4-11
Parameter Estimates for Amount Paid and Elopement

Model	Coefficients ^a				95% Confidence Interval for B		
	Unstandardized Coefficients	Std. Error	Standardized Coefficients	t	Sig.	Lower Bound	Upper Bound
1 (Constant)	100806.231	663.954		151.827	.000	99477.662	102134.800
Elopement	16.440	65.014	.033	.253	.801	-113.652	146.533

a. Dependent Variable: Total Amount Paid

To address the research hypothesis that the adverse incidents were able to predict, or were significantly related to the liability claims, a linear regression analysis was conducted. For the next analysis that was conducted the dependent variable was the total amount paid for the liabilities, while the independent variable was the adult abuse variable. This meant that the regression with the adult abuse independent variable and the total amount paid (dependent variable) would determine whether the number of adult abuse cases observed would be able to predict the total amount paid by the participants. Based on this information, it was found that there was not a significant relationship between the independent and dependent variable, $t(59) = .26, p = .80$. The results indicate that the independent variable did not significantly predict the total amount paid to the participants. In fact, this model was only able to explain .1% of the variation in the total amount paid, as indicated by the R^2 value for the model. These results are presented in the following tables.

Table 4-12
Model Summary for Amount Paid and Adult Abuse

Model	R	R ²	Adjusted R ²
1	.034 ^a	.001	-.016

a. Predictors: (Constant), Adult Abuse

Table 4-13
ANOVA for Amount Paid and Adult Abuse

ANOVA ^b						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1217999.262	1	1217999.262	.067	.797 ^a
	Residual	1.074E9	59	1.821E7		
	Total	1.075E9	60			

a. Predictors: (Constant), Adult Abuse

b. Dependent Variable: Total Amount Paid

Table 4-14
Parameter Estimates for Amount Paid and Adult Abuse

Coefficients ^a							
Model	Unstandardized Coefficients		Standardized Coefficients		95% Confidence Interval for B		
	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1 (Constant)	100801.346	669.947		150.462	.000	99460.786	102141.906
Adult Abuse	6.353	24.562	.034	.259	.797	-42.796	55.502

a. Dependent Variable: Total Amount Paid

To address the research hypothesis that the adverse incidents were able to predict, or were significantly related to the liability claims, a linear regression analysis was conducted. For the next analysis that was conducted, the dependent variable was the total amount paid for the liabilities, while the independent variable was the number of times the patient was transferred variable. This meant that the regression with the transfer independent variable and the total amount paid (dependent variable) would determine whether the number of transfers observed would be able to predict the total amount paid by the participants. Based on this information it was found that there was not a significant relationship between the independent and dependent variable, $t(59) = -13.03, p = .60$. This indicated that the independent variable did not significantly predict the total amount paid by the participants. In fact, this model was only able to explain .5% of the variation

in the total amount paid, as indicated by the R^2 value for the model. These results are presented in the following tables.

Table 4-15
Model Summary for Amount Paid and Transfer

Model	R	R ²	Adjusted R ²
1	.068 ^a	.005	-.012

a. Predictors: (Constant), Transfer

Table 4-16
ANOVA for Amount Paid and Transfer

ANOVA ^b						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4965916.721	1	4965916.721	.274	.603 ^a
	Residual	1.070E9	59	1.814E7		
	Total	1.075E9	60			

a. Predictors: (Constant), Transfer

b. Dependent Variable: Total Amount Paid

Table 4-17
Parameter Estimates for Amount Paid and Transfer

Coefficients ^a							
Model	Unstandardized Coefficients		Standardized Coefficients		95% Confidence Interval for B		
	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1 (Constant)	101126.926	694.881		145.531	.000	99736.472	102517.380
Transfer	-13.026	24.898	-.068	-.523	.603	-62.847	36.795

a. Dependent Variable: Total Amount Paid

To address the research hypothesis that the adverse incidents were able to predict, or were significantly related to the liability claims, a linear regression analysis was conducted. For the next analysis that was conducted, the dependent variable was the total amount paid for the liabilities, while the independent variable was whether the patient had no consent for what they did. This meant that the regression with the no consent

independent variable and the total amount paid (dependent variable) would determine whether the number of no consents observed would be able to predict the total amount paid by the participants. Based on this information, it was found that there was not a significant relationship between the independent and dependent variable, $t(59) = 23.28$, $p = .97$. This indicated that the independent variable did not significantly predict the total amount paid by the participants. In fact, this model was only able to explain less than .1% of the variation in the total amount paid, as indicated by the R^2 value for the model. These results are presented in the following tables.

Table 4-18
Model Summary for Amount Paid and No Consent

Model	R	R ²	Adjusted R ²
1	.005 ^a	.000	-.017

a. Predictors: (Constant), No consent

Table 4-19
ANOVA for Amount Paid and No Consent

ANOVA ^b						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24807.412	1	24807.412	.001	.971 ^a
	Residual	1.075E9	59	1.823E7		
	Total	1.075E9	60			

a. Predictors: (Constant), No consent

b. Dependent Variable: Total Amount Paid

Table 4-20
Parameter Estimates for Amount Paid and No Consent

Coefficients ^a							
Model	Unstandardized Coefficients		Standardized Coefficients		95% Confidence Interval for B		
	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1 (Constant)	100893.625	588.215		171.525	.000	99716.609	102070.640
No consent	23.281	631.049	.005	.037	.971	-1239.446	1286.007

a. Dependent Variable: Total Amount Paid

To address the research hypothesis that the adverse incidents were able to predict, or were significantly related to the liability claims, a linear regression analysis was conducted. For the next analysis that was conducted the dependent variable was the total amount paid for the liabilities, while the independent variable was the limit function variable. This meant that the regression with the limit function independent variable and the total amount paid (dependent variable) would determine whether the number of limit functions observed would be able to predict the total amount paid by the participants. Based on this information, it was found that there was not a significant relationship between the independent and dependent variable, $t(59) = -1037.74, p = .52$. This indicated that the independent variable did not significantly predict the total amount paid by the participants. In fact, this model was only able to explain .7% of the variation in the total amount paid, as indicated by the R^2 value for the model. These results are presented in the following tables.

Table 4-21
Model Summary for Amount Paid and Limit Function

Model	R	R ²	Adjusted R ²
1	.083 ^a	.007	-.010

a. Predictors: (Constant), Limit function

Table 4-22
ANOVA for Amount Paid and Limit Function

ANOVA ^b						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7485307.764	1	7485307.764	.414	.523 ^a
	Residual	1.068E9	59	1.810E7		
	Total	1.075E9	60			

a. Predictors: (Constant), Limit function

b. Dependent Variable: Total Amount Paid

Table 4-23
Parameter Estimates for Amount Paid and Limit Function
Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients		95% Confidence Interval for B		
	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1 (Constant)	101037.736	584.395		172.893	.000	99868.365	102207.107
Limit function	-1037.736	1613.713	-.083	-.643	.523	-4266.768	2191.296

a. Dependent Variable: Total Amount Paid

To address the research hypothesis that the adverse incidents were able to predict, or were significantly related to the liability claims, a linear regression analysis was conducted. For the next analysis that was conducted the dependent variable was the total amount paid for the liabilities, while the independent variable was the fracture variable. This meant that the regression with the fracture independent variable and the total amount paid (dependent variable) would determine whether the number of fractures observed would be able to predict the total amount paid by the participants. Based on this information, it was found that there was not a significant relationship between the independent and dependent variable, $t(59) = -26.78, p = .57$. This indicated that the independent variable did not significantly predict the total amount paid by the participants. In fact, this model was only able to explain .1% of the variation in the total amount paid, as indicated by the R^2 value for the model. These results are presented in the following tables.

Table 4-24
Model Summary for Amount Paid and Fracture

Model	R	R ²	Adjusted R ²
1	.074 ^a	.005	-.011

a. Predictors: (Constant), Fracture

Table 4-25
ANOVA for Amount Paid and Fracture

ANOVA ^b						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5826112.545	1	5826112.545	.321	.573 ^a
	Residual	1.070E9	59	1.813E7		
	Total	1.075E9	60			

a. Predictors: (Constant), Fracture

b. Dependent Variable: Total Amount Paid

Table 4-26
Parameter Estimates for Amount Paid and Fracture

Coefficients ^a							
Model	Unstandardized Coefficients		Standardized Coefficients		95% Confidence Interval for B		
	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1 (Constant)	101126.869	674.563		149.915	.000	99777.071	102476.667
Fracture	-26.782	47.242	-.074	-.567	.573	-121.313	67.750

a. Dependent Variable: Total Amount Paid

To address the research hypothesis that the adverse incidents were able to predict, or were significantly related to the liability claims, a linear regression analysis was conducted. For the next analysis that was conducted the dependent variable was the total amount paid for the liabilities, while the independent variable was the disfigurement variable. This meant that the regression with the disfigurement independent variable and the total amount paid (dependent variable) would determine whether the number of disfigurements observed would be able to predict the total amount paid by the participants. Based on this information, it was found that there was not a significant relationship between the independent and dependent variable, $t(59) = -948.28, p = .71$. This indicated that the independent variable did not significantly predict the total amount paid by the participants. In fact, this model was only able to explain .2% of the variation in the total amount paid, as indicated by the R^2 value for the model. These results are presented in the following tables.

Table 4-27***Model Summary for Amount Paid and Disfigurement***

Model	R	R ²	Adjusted R ²
1	.049 ^a	.002	-.015

a. Predictors: (Constant), Disfigurement

Table 4-28***ANOVA for Amount Paid and Disfigurement***ANOVA^b

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2565008.479	1	2565008.479	.141	.709 ^a
	Residual	1.073E9	59	1.818E7		
	Total	1.075E9	60			

a. Predictors: (Constant), Disfigurement

b. Dependent Variable: Total Amount Paid

Table 4-29***Parameter Estimates for Amount Paid and Disfigurement***Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% Confidence Interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
1 (Constant)	100948.276	559.923		180.290	.000	99827.872	102068.680
Disfigurement	-948.276	2524.833	-.049	-.376	.709	-6000.456	4103.904

a. Dependent Variable: Total Amount Paid

To address the research hypothesis that the adverse incidents were able to predict, or were significantly related to the liability claims, a linear regression analysis was conducted. For the next analysis that was conducted, the dependent variable was the total amount paid for the liabilities, while the independent variable was the brain or spinal damage variable. This meant that the regression with the brain or spinal damage independent variable and the total amount paid (dependent variable) would determine whether the number of brain or spinal damages observed would be able to predict the total amount paid by the participants. Based on this information, it was found that there

was not a significant relationship between the independent and dependent variable, $t(59) = -916.67, p = .83$. This indicated that the independent variable did not significantly predict the total amount paid by the participants. In fact, this model was only able to explain .1% of the variation in the total amount paid, as indicated by the R^2 value for the model. These results are presented in the following tables.

Table 4-30

Model Summary for Amount Paid and Brain or Spinal Damage

Model	R	R ²	Adjusted R ²
1	.028 ^a	.001	-.016

Table 4-31

ANOVA for Amount Paid and Brain or Spinal Damage

ANOVA ^b						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	826502.732	1	826502.732	.045	.832 ^a
	Residual	1.075E9	59	1.821E7		
	Total	1.075E9	60			

a. Predictors: (Constant), Brain or spinal damage

b. Dependent Variable: Total Amount Paid

Table 4-32
Parameter Estimates for Amount Paid and Brain or Spinal Damage

Model	Coefficients ^a				95% Confidence Interval for B		
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Lower Bound	Upper Bound
	B	Std. Error	Beta				
1 (Constant)	100916.667	550.958		183.166	.000	99814.202	102019.131
Brain or spinal damage	-916.667	4303.119	-.028	-.213	.832	-9527.188	7693.854

a. Dependent Variable: Total Amount Paid

To address the research hypothesis that the adverse incidents were able to predict, or were significantly related to the liability claims, a linear regression analysis was conducted. For the next analysis that was conducted the dependent variable was the total amount paid for the liabilities, while the independent variable was the death variable. This meant that the regression with the death independent variable and the total amount paid (dependent variable) would determine whether the number of deaths observed would be able to predict the total amount paid by the participants. Based on this information, it was found that there was not a significant relationship between the independent and dependent variable, $t(59) = -812.60, p = .38$. This indicated that the independent variable did not significantly predict the total amount paid by the participants. In fact, this model was only able to explain 1.3% of the variation in the total amount paid, as indicated by the R^2 value for the model. These results are presented in the following tables.

Table 4-33
Model Summary for Amount Paid and Death

Model	R	R ²	Adjusted R ²
1	.114 ^a	.013	-.004

a. Predictors: (Constant), Death

Table 4-34
ANOVA for Amount Paid and Death

ANOVA ^b						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.392E7	1	1.392E7	.774	.383 ^a
	Residual	1.061E9	59	1.799E7		
	Total	1.075E9	60			

a. Predictors: (Constant), Death

b. Dependent Variable: Total Amount Paid

Table 4-35 Parameter Estimates for Amount Paid and Death

Model	Unstandardized Coefficients		Standardized Coefficients		95% Confidence Interval for B		
	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1 (Constant)	101154.743	614.601		164.586	.000	99924.930	102384.557
Death	-812.597	923.796	-.114	-.880	.383	-2661.109	1035.915

a. Dependent Variable: Total Amount Paid

The initial analysis had intended on assessing the liabilities of claims in Florida nursing homes. However, due to some restrictions from the Agency for Health Care Administration (AHCA) the complete dataset for the liability information could not be obtained. The major problem encountered was the Florida Statutes regarding adverse incidents that did not allow for a comprehensive database as planned. For this reason, the analysis was conducted with the notice of intent and type of incidents as the dependent variables. For the analysis, data mining techniques were used. This included logistic regression classification, classification trees, and neural networks. By using, each of these techniques one is able to determine how well groups of independent variables perform at classifying a certain dependent variable that was categorical. For this study, the dependent variables were the notice of intent and type of incident as reported in the 2006 Actuarial report.

Research Question 1

What are the nursing home characteristics and quality of care factors that affect liability claims in Florida nursing homes?

Logistic Regression Classification Results

Due to the limitation of the Agency for Healthcare Administration (AHCA) data regarding liability and adverse incident, the study was affected. To address this research question the following analyses were conducted. An appealing method that is used to represent how well the fitted model performs in predicting the response variable is a classification table. Classification tables are constructed by cross-classifying the response variable with dichotomous variables derived from the estimated probabilities of the logistic regression model and the actual outcome (Hosmer & Lemeshow, 2000). In order to obtain each one of the derived dichotomous variables, a cut point value, $c \in \{0,1\}$, needs to be specified. If the estimated probability is found to be greater than c , then the dichotomous variable is set equal to 1, otherwise, it is set equal to 0. A value of 0.50 is the most commonly used value for c , but other values can be used if it is known *a priori* that a certain type of incident are expected to occur (Hosmer & Lemeshow, 2000). The type of incident was coded as a dichotomous variable with values of 0 and 1 as presented in Table 4-1.

The logistic regression model is used to determine which quality of care variables could be used to predict the type of incident. In particular, the logistic regression model can be used to classify the number of adverse and non-adverse incidents based on the values of the independent variables in the model. The independent variables that were

included in this study were operationalized as continuous level variables. These included all of the quality of care variables from the AHCA annual reports. Several of the independent variables included in the analysis were found to be significant predictors for the type of incident. These variables included the overall symptom variable, $\chi^2(1) = 6.25$, $p = .01$, the high risk symptom, $\chi^2(1) = 6.74$, $p = .01$, the low risk symptom, $\chi^2(1) = 9.47$, $p < .01$, the impairment, $\chi^2(1) = 4.01$, $p < .05$, the urinary infection variable, $\chi^2(1) = 5.79$, $p = .02$, the weight gain variable, $\chi^2(1) = 4.40$, $p = .04$, the ROM, $\chi^2(1) = 5.84$, $p = .02$, the overall antipsychotic variable, $\chi^2(1) = 6.20$, $p = .01$, the high risk antipsychotic variable, $\chi^2(1) = 10.37$, $p < .01$, the low risk antipsychotic variable, $\chi^2(1) = 6.30$, $p = .01$, the little activity variable, $\chi^2(1) = 4.52$, $p = .03$, the low risk ulcer variable, $\chi^2(1) = 5.85$, $p = .02$, the short stay pain variable, $\chi^2(1) = 5.31$, $p = .02$, and the short stay ulcer variable, $\chi^2(1) = 8.60$, $p < .01$. The remaining variables were found not be significant predictors of the type of incident. The results from the logistic regression analysis are presented in Table 4-36.

Table 4-36
Logistic Regression Results for Type of Incidents

Parameter	B	SE	χ^2	df	p
(Intercept)	14.17	5.75	6.07	1	0.01*
Fractures	42.65	51.03	0.70	1	0.40
Fall	12.96	10.68	1.47	1	0.23
Depressed	-10.24	8.51	1.45	1	0.23
Symptom Overall	128.87	51.56	6.25	1	0.01*
Symptom HR	-109.79	42.29	6.74	1	0.01*
Symptom LR	-49.96	16.23	9.47	1	< .01*
Antidepressant	-29.17	20.64	2.00	1	0.16
Medication	-7.40	5.03	2.17	1	0.14
Impairment	-9.97	4.98	4.02	1	< 0.05*
Bowel	-1.88	3.06	0.38	1	0.54
Catheter	-0.55	13.05	0.00	1	0.97
Bladder	2.08	1.63	1.62	1	0.20
Fecal	120.72	649.30	0.04	1	0.85
Urinary	-25.52	10.60	5.79	1	0.02*
Weight	17.70	8.44	4.40	1	0.04*
Tube	-15.53	9.98	2.42	1	0.12
Pain	12.80	8.46	2.29	1	0.13
Bed	-19.57	11.24	3.03	1	0.08
Move	3.95	8.06	0.24	1	0.62
ROM	-32.59	13.49	5.84	1	0.02*
Antipsychotic Overall	111.52	44.79	6.20	1	0.01*
Antipsychotic HR	-13.45	4.18	10.37	1	< 0.01*
Antipsychotic LR	-116.36	46.36	6.30	1	0.01*
Anti-anxiety	-1.47	6.33	0.05	1	0.82
Hypnotic	-10.22	12.52	0.67	1	0.41
Restrained	-7.12	6.15	1.34	1	0.25
Little Activity	30.23	14.21	4.52	1	0.03*
Ulcer HR	24.66	10.20	5.85	1	0.02*
Ulcer LR	12.94	11.97	1.17	1	0.28
Delirium	-4.32	10.54	0.17	1	0.68
SS Pain	10.21	4.43	5.31	1	0.02*
SS Ulcer	-19.16	6.53	8.60	1	< 0.01*

To determine how well this model did at classifying the types of incident, a cross classification of the observed and predicted values was created. The cross-classification table illustrates the number of observations that were correctly classified, as well as the number of observations that were misclassified. Based on these results, the model was

able to correctly classify 76.5% for the types of incident. Similarly, the model was able to correctly classify 90.9% for the type of incident. This indicated that overall, the model was able to correctly classify 84.0% of the observations.

Table 4-37
Classification Results for Logistic Regression Type of Incident

		Predicted Category Value		
		Non-Adverse	Adverse	Percent Correct
Type of Incident	Non-Adverse Fall	4680	1440	76.5%
	Adverse Fall	600	6000	90.9%
	Overall Percent	41.5%	58.5%	84.0%

In terms of the research questions, the results reported in Tables 4-36 and 4-37 provides evidence that the quality of care variables perform quite well at predicting the type of incidents. In fact, the model was able to correctly predict the type of incidents 84.0% of the time. Moreover, the variables that provide the most significant classifications were the overall symptom variable, the high risk symptom, the low risk symptom, the impairment, the urinary infection variable, the weight gain variable, the ROM variable, the overall antipsychotic variable, the high risk antipsychotic variable, the low risk antipsychotic variable, the little activity variable, the low risk ulcer variable, the short stay pain variable, and the short stay ulcer variable.

Research Question 2

What risk management strategies affect liability claims in Florida nursing homes?

Neural Networks

To address this research question the following analyses were conducted. The idea behind artificial neural networks (ANN) is that they emulate a computer-based

representation of the neural structure in the human brain. The term "artificial" is applied to these neural networks because it has been debated philosophically to how a computer-based program can copy the functions of the human brain (Faraway, 2006). In terms of statistical analysis, ANN are used for a number of different applications such as recognition, regression, and classification with the results of these applications being comparable to regular statistical methods. The neural network model is used to determine which quality of care variables could be used to predict the type of incidents. In particular, the neural network model can be used to classify the number of adverse and non-adverse incidents based on the values of the independent variables in the model.

The type of incident was coded as a dichotomous variable with values of non-adverse and adverse falls as presented in Table 4-1. The notice of intent was coded as a categorical variable with values of 0 to 7 as presented in Table 4-1. The independent variables that were included in this study were operationalized as continuous level variables. These included all of the quality of care variables from the AHCA annual reports. One of the advantages to using ANN over the regular statistical methods is that it is distribution free, meaning that no prior assumptions need to be made on the distribution of the data. ANN also have the ability to *learn* from the input data which allows them to make better predictions for future observations based on the information already provided to the model. Although ANN have these advantages over other statistical models, it has disadvantages as well. One disadvantage is that the parameters or weights of the model are very hard to interpret. Another disadvantage of ANN is that statistical inference cannot easily be made because of the lack of standard errors (Adielsson, 2005; Faraway, 2006). Because of this, it is very difficult to determine

whether an explanatory variable used by the neural network for classification is actually significant. Even though ANN have these disadvantages, the use of them for statistical applications can be very informative since they are non-parametric and could reveal trends or other relationships that may not be noticed by standard regression methods. The resulting neural network for the independent and type of incident variables is presented in Figure 4-1.

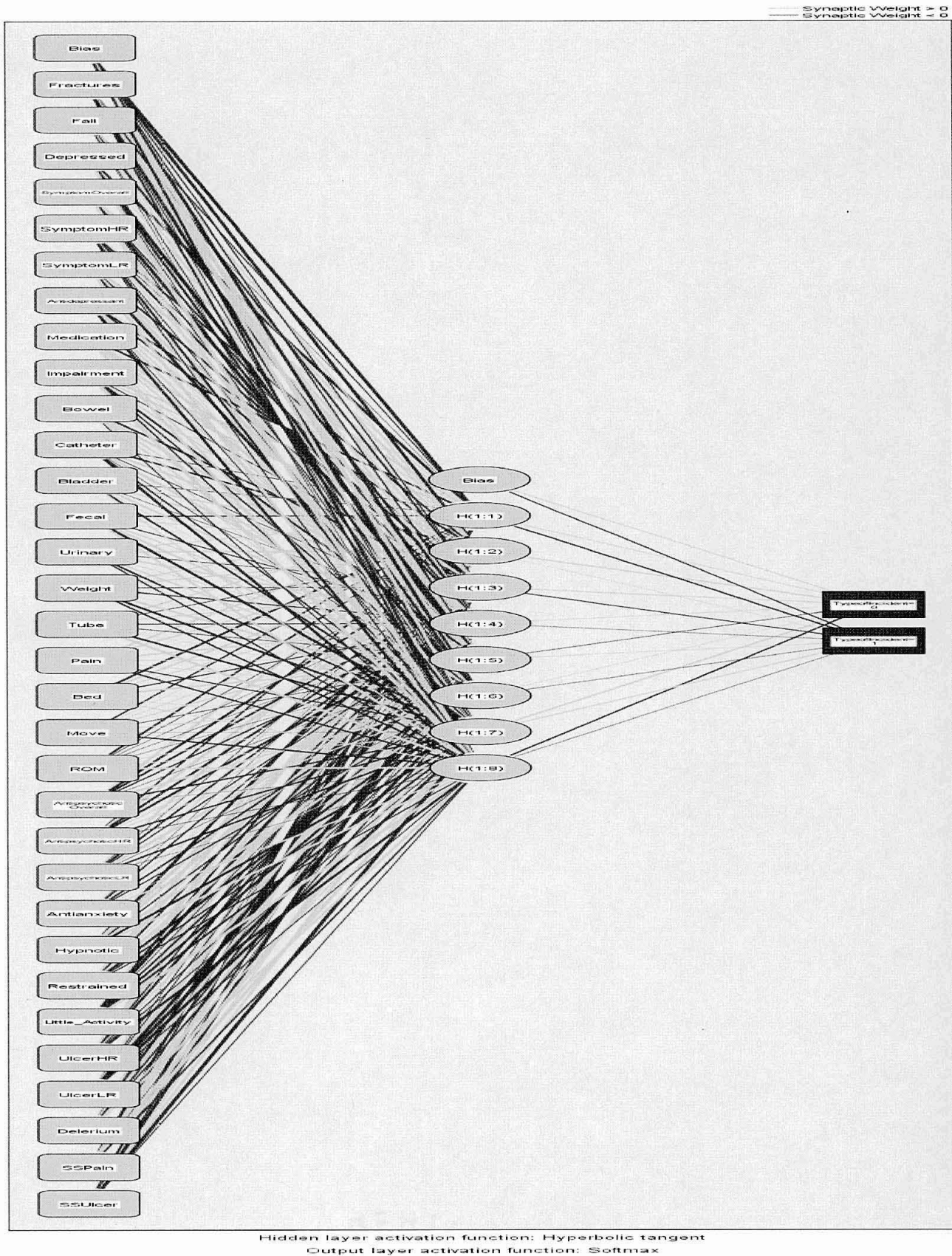


Figure 4-1. Neural network for type of incident.

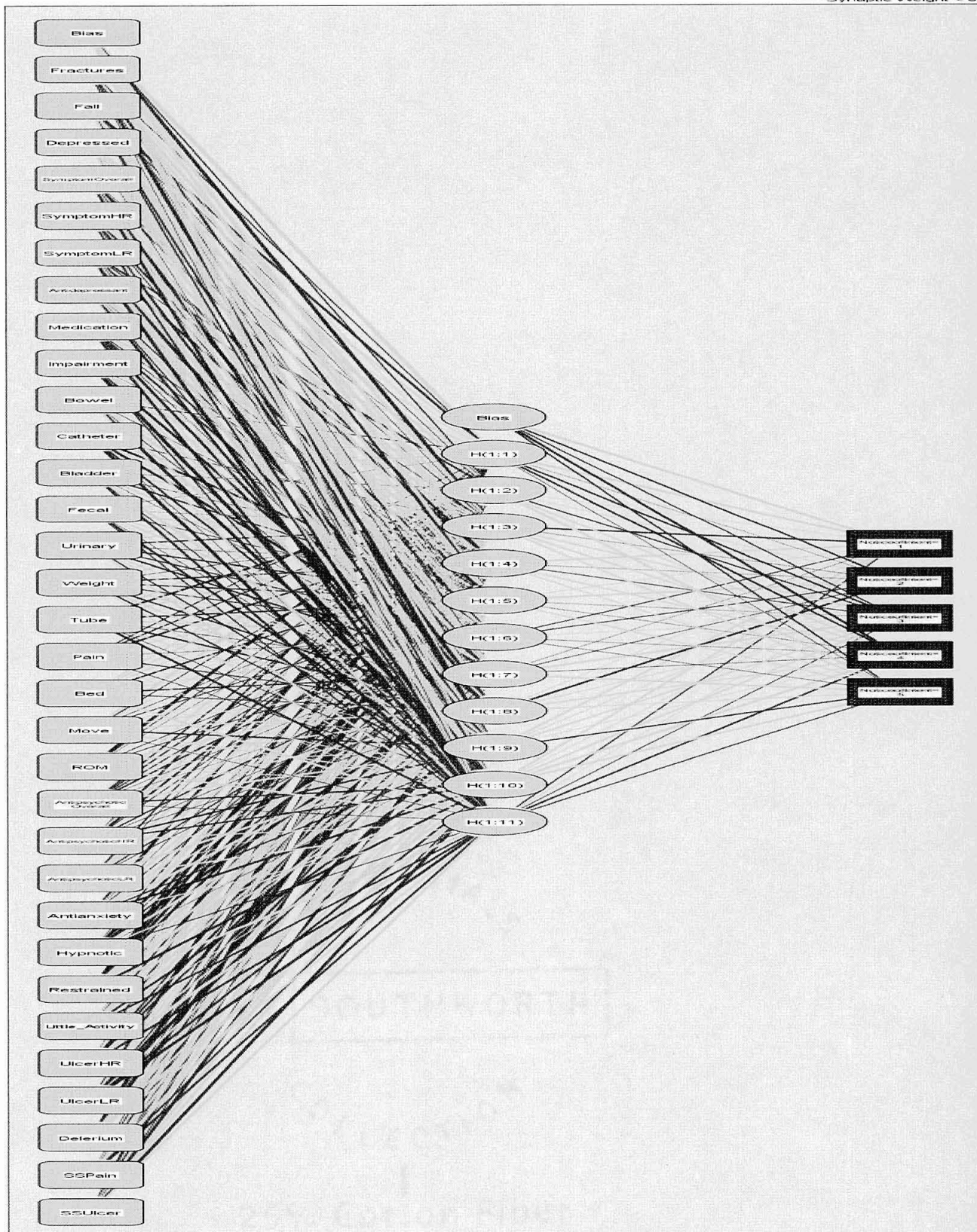
To determine how well the neural network did at classifying the groups for the type of incident, the classification results are presented below. The classification results are presented by using a cross tabulation table for the observed and predicted values. For the neural network classification procedure, a training dataset and a test dataset were used. For the training dataset, approximately 20% of the observations were used. The test dataset was then comprised of the remaining 80% of the observations. For the training dataset, the model was able to correctly classify those in group 0 for the type of incident 92.9% of the time. Similarly, the model was able to correctly classify those in group 1 for the type of incident 71.4% of the time. This indicated that overall, the model was able to correctly classify 85.7% of the observations. For the test dataset, the model was able to correctly classify those in group 0 for the type of incident 75.7% of the time. Alternatively, the model was only able to correctly classify those in group 1 for the type of incident 33.3% of the time. This indicated that overall, the model was able to correctly classify 51.8% of the observations. These results are presented in Table 4-38.

Table 4-38
Classification Results for Neural Networks for the Type of Incident

Sample	Observed	Predicted		Percent Correct
		Non-Adverse	Adverse	
Training	Non-Adverse Fall	1560	120	92.9%
	Adverse Fall	600	600	71.4%
	Overall Percent	71.4%	28.6%	85.7%
Testing	Non-Adverse Fall	3360	1080	75.7%
	Adverse Fall	3840	1920	33.3%
	Overall Percent	70.6%	29.4%	51.8%

The resulting neural network for the independent and notice of intent variables is presented in Figure 4-2. To determine how well the neural network did at classifying the

groups for the notice of intent the classification results are presented below. The classification results are presented by using a cross tabulation table for the observed and predicted values. For the neural network classification procedure, a training dataset and a test dataset were used. For the training dataset, approximately 20% of the observations were used. The test dataset was then comprised of the remaining 80% of the observations. For the training dataset, the model was able to correctly classify those in group 1 for the notice of intent 100.0% of the time. Alternatively, the model was able to correctly classify those in group 2 for the notice of intent 25.0% of the time. The remaining groups were then classified as group 1. This indicated that overall the model was able to correctly classify 66.7% of the observations. For the test dataset, the model was able to correctly classify those in group 1 for the notice of intent 88.1% of the time. Alternatively, the model was able to correctly classify those in group 3 for the notice of intent 11.1% of the time. The remaining groups were then classified as group 1. This indicated that overall, the model was able to correctly classify 63.1% of the observations. These results are presented in Table 4-39.



Hidden layer activation function: Hyperbolic tangent
Output layer activation function: Softmax

Figure 4-2. Neural network for notice of intent.

Table 4-39***Classification Results for Neural Networks for the Notice of Intent***

Sample	Observed	Predicted					Percent Correct
		1	2	3	4	5	
Training	1	1560	0	0	0	0	100.0%
	2	360	120	0	0	0	25.0%
	3	240	0	0	0	0	.0%
	4	120	0	0	0	0	.0%
	5	120	0	0	0	0	.0%
	Overall Percent		95.2%	4.8%	.0%	.0%	.0%
Testing	1	6240	120	600	0	120	88.1%
	2	1320	0	0	0	0	.0%
	3	960	0	120	0	0	11.1%
	4	360	0	0	0	0	.0%
	5	240	0	0	0	0	.0%
	Overall Percent		90.5%	1.2%	7.1%	.0%	1.2%

In terms of the research questions, this provides evidence that the quality of care variables perform adequately at predicting the types of incidents. In fact, the model was able to correctly predict the types of incidents 51.8% of the time for the test dataset. This meant that the quality of care variables could be used to predict the type of incident in which the participants would belong. As for the notice of intent variable, this provides evidence that the quality of care variables perform adequately at predicting the notice of intent groups. In fact, the model was able to correctly predict the notice of intent 63.1% of the time for the test dataset. This meant that the quality of care variables could be used to predict the notice of intent in which the participants would belong.

Research Question 3

What are effective risk management strategies that decrease liability claims in Florida nursing homes?

Classification Trees

To address this research question the following analyses were conducted. A classification and regression tree (CART) procedure was developed for the training data by using the variables in Table 4-1. The idea behind the classification tree method is that a binary hierarchical tree is created to predict the class of response variables by using the selected explanatory variables in the model (Breiman et al., 1984; Spruill et al., 2002). The initial step in the tree building process starts at the root node (RN). At the RN, every possible variable in the model is looked at and partitioned or split into two separate homogeneous groups. The classification tree model is used to determine which quality of care variables could be used to predict the type of incident. In particular, the classification tree model can be used to classify the number of adverse and non-adverse incidents based on the values of the independent variables in the model.

The independent variables that were included in this study were operationalized as continuous level variables. These included all of the quality of care variables from the AHCA annual reports. The variable that is deemed the best splitting point is then used to split the root node into two homogeneous groups that become the first two branches of the tree, denoted S1 and S2. Each observation in the model is then fed through the tree building process, so that, if the value of the RN variable for that observation is less than the calculated split point value, then the observation will go to the branch on the left side; otherwise, it would go to the branch on the right side. This is for a continuous variable, if

it were discrete, then the splitting point would be if an observation belonged to one group, it would go to the left branch; otherwise, it would go to the branch on the right side if it belonged to the other group. In terms of tree growing, the best splitting point is determined to be the variable that has the fewest number of misclassifications or the lowest impurity (highest purity) (Breiman et al., 1984; Spruill et al., 2002).

To determine how well the decision tree did at classifying the groups for the type of incident, the classification results are presented below. The classification results used a cross tabulation table for the observed and predicted values. For the decision tree classification procedure, a training dataset and a test dataset were used. For the training dataset, approximately 20% of the observations were used. The test dataset was then comprised of the remaining 80% of the observations. For the training dataset, the model was able to correctly classify those in the non-adverse falls for the type of incident 0.0% of the time. Alternatively, the model was able to correctly classify those in the adverse fall group for the type of incident 100.0% of the time. This indicated that overall the model was able to correctly classify 66.7% of the observations. For the test dataset, the model was able to correctly classify those in group non-adverse fall for the type of incident 0.0% of the time. Alternatively, the model was only able to correctly classify those in group adverse fall for the type of incident 100.0% of the time. This indicated that overall, the model was able to correctly classify 47.6% of the observations. These results are presented in Table 4-40.

Table 4-40
Classification Results for Decision for the Type of Incident

Sample	Observed	Predicted		Percent Correct
		Non-Adverse	Adverse	
Training	Non-Adverse Fall	0	960	.0%
	Adverse Fall	0	1920	100.0%
	Overall Percentage	.0%	100.0%	66.7%
Testing	Non-Adverse Fall	0	5160	.0%
	Adverse Fall	0	4680	100.0%
	Overall Percentage	.0%	100.0%	47.6%

To determine how well the decision tree did at classifying the groups for the notice of intent the classification results are presented below. The classification results are presented by using a cross tabulation table for the observed and predicted values. For the decision tree classification procedure, a training dataset and a test dataset were used. For the training dataset, approximately 20% of the observations were used. The test dataset was then comprised of the remaining 80% of the observations. For the training dataset, the model was able to correctly classify those with one notice of intent 100.0% of the time. The remaining groups were then classified as having one notice of intent. This indicated that overall, the model was able to correctly classify 71.4% of the observations. For the test dataset, the model was able to correctly classify those with one notice of intent 100.0% of the time. The remaining groups were then classified as having one notice of intent. This indicated that overall, the model was able to correctly classify 70.5% of the observations. These results are presented in Table 4-41.

Table 4-41
Classification Results for Decision Trees for the Notice of Intent

Sample	Observed	Predicted				Percent Correct
		1	2	3	4	
Training	1	1200	0	0	0	100.0%
	2	240	0	0	0	.0%
	3	120	0	0	0	.0%
	4	120	0	0	0	.0%
	Overall Percentage	100.0%	.0%	.0%	.0%	71.4%
Testing	1	6572	0	0	0	100.0%
	2	1378	0	0	0	.0%
	3	1060	0	0	0	.0%
	4	318	0	0	0	.0%
	Overall Percentage	100.0%	.0%	.0%	.0%	70.5%

In terms of the research questions, this provides evidence that the quality of care variables perform adequately at predicting the types of incidents. In fact, the model was able to correctly predict the types of incidents 47.6% of the time for the test dataset. This meant that the quality of care variables could be used to predict the type of incident in which the participants would belong. As for the notice of intent variable, this provides evidence that the quality of care variables perform well at predicting the notice of intent groups. In fact, the model was able to correctly predict the notice of intent 70.5% of the time for the test dataset. This meant that the quality of care variables could be used to predict the notice of intent in which the participants would belong.

Research Question 4

Is there a risk management model, generated by data mining, that may be used to predict liability claims and effectively manage risk?

Due to the limitation of the Agency for Healthcare Administration (AHCA) data regarding liability and adverse incident, the study was affected. To address this research question the following analyses were conducted. Prior to conducting the neural network

data mining technique, a multiple regression analysis was conducted. This was done to determine whether the adverse incidents could be used to predict the liability claims together and a multiple regression analysis was conducted. A significant model would indicate that the adverse incidents could be used to predict the liability claims of the nursing home. The adverse incidents are then included in a neural network data mining technique to determine how well they perform at predicting and classifying the participants based on their liability claims. Multiple linear regression is used to determine if several continuous independent variables are significant predictors of a continuous dependent variable while taking into account the other independent variables in the model. The general formula for the simple linear regression model is

$$Y = A + B_1X_1 + B_2X_2 + B_pX_p + e$$

where Y is the dependent variable, A is the intercept of the model which is equal to the value of the dependent variable when the independent variable is equal to zero, B_1, B_2, \dots, B_p are the coefficients for the independent variables and indicate how many units change there is in the dependent variable for every one unit increase in the independent variable when controlling for the other independent variables in the model X_1, X_2, \dots, X_p are the values of the independent variables that are observed in the data and e is the random error term that is normally distributed with a mean of zero and a constant variance. For the analysis that was conducted, the dependent variable was the total amount paid for the liabilities, while the independent variables were all of the variables presented previously. This meant that the regression with the all of the independent variables and the total amount paid (dependent variable) would determine whether any of the independent variables would be able to predict the total amount paid by the participants. Based on this

information, it was found that there was not a significant relationship between the independent and dependent variables, $F(10, 50) = .58, p = .82$. This indicated that the independent variables did not significantly predict the total amount paid by the participants. In fact, this model was only able to explain 10.5% of the variation in the total amount paid, as indicated by the R^2 value for the model. These results are presented in the following tables.

Table 4-42

Model Summary for Total Amount Paid and Adverse Incidents Independent Variables

Model	R	R ²	Adjusted R ²
1	.324 ^a	.105	-.074

Table 4-43

ANOVA for Total Amount Paid and Adverse Incidents Independent Variables

ANOVA ^b						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.131E8	10	1.131E7	.587	.816 ^a
	Residual	9.623E8	50	1.925E7		
	Total	1.075E9	60			

a. Predictors: (Constant), Law Enforcement, Brain or spinal damage, Disfigurement, No consent, Limit function, Death, Fracture, Adult Abuse, Elopement, Transfer

b. Dependent Variable: Total Amount Paid

Table 4-44
Parameter Estimates for Total Amount Paid and Adverse Incidents Independent Variables

Model	Coefficients ^a						
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95% Confidence Interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
1 (Constant)	101488.239	770.983		131.635	.000	99939.674	103036.805
Death	-1936.010	1321.664	-.271	-1.465	.149	-4590.650	718.629
Brain or spinal damage	-1033.011	4839.909	-.031	-.213	.832	-10754.253	8688.232
Disfigurement	-1717.564	2767.775	-.088	-.621	.538	-7276.804	3841.675
Fracture	-26.495	233.886	-.073	-.113	.910	-496.269	443.278
Limit function	-1353.210	2144.700	-.109	-.631	.531	-5660.967	2954.546
No consent	404.040	967.810	.083	.417	.678	-1539.864	2347.943
Transfer	-92.145	138.796	-.481	-.664	.510	-370.926	186.635
Adult Abuse	18.570	63.192	.098	.294	.770	-108.354	145.494
Elopement	119.234	195.031	.239	.611	.544	-272.497	510.965
Law Enforcement	165.956	133.393	.390	1.244	.219	-101.972	433.883

a. Dependent Variable: Total Amount Paid

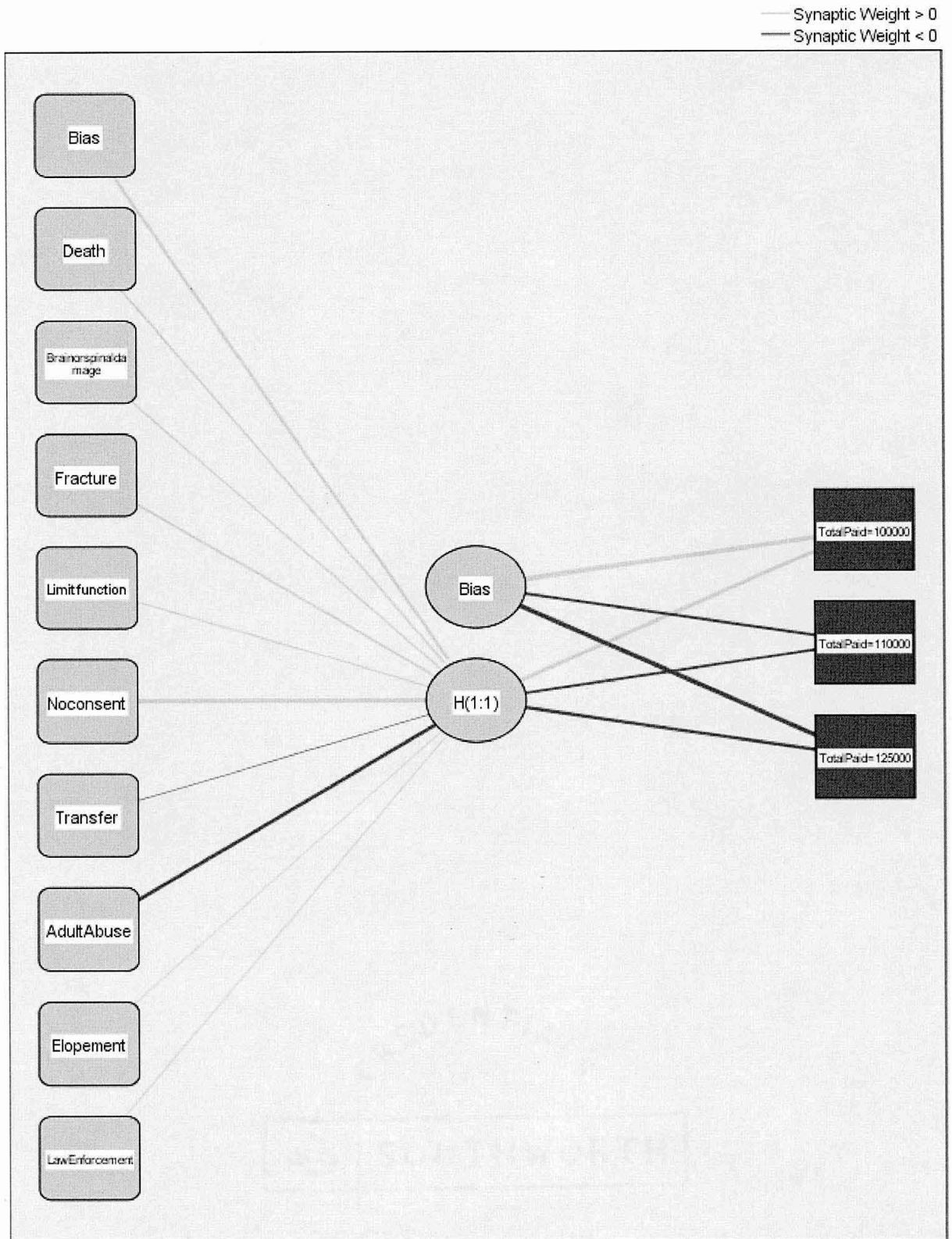
Overall, the logistic regression model was able to correctly classify 84.0% of the observations in the type of incident grouping variable. Alternatively, the neural network procedure was only able to correctly classify 51.8% of the observations in the type of incident grouping variable, based on the test data set. The decision tree was not as good as the neural network, and not as good as the logistic regression model, since the decision tree was able to correctly classify 47.6% of the observations in the type of incident grouping variable. As for the notice of intent grouping variable, the neural network was able to correctly classify 63.1% of the observations, based on the test data set. On the other hand, the decision tree was able to correctly classify 70.5% of the observations based on the test data set. This indicated that the decision tree performed better at predicting the notice of intent than the neural network did.

Research Hypothesis

There is a significant explanatory relationship among quality of care factors in nursing homes, nursing home characteristics, adverse incident outcome, incidence of falls, risk management strategies and severity of claims (total claims paid). A neural network was conducted using all of the variables presented in table 4-44. The results in table 4-45 represent the number of observations used in the training dataset for the neural network. It also presents the number of observations used in the test data set. The information presented in the diagram below presents the neural network model. This indicates the connections between the independent and dependent variables.

Table 4-45
Training and Test Dataset Division for Neural Network
Case Processing Summary

		N	Percent
Sample	Training	43	71.7%
	Testing	17	28.3%
	Valid	60	100.0%
	Excluded	46	
	Total	106	



Hidden layer activation function: Hyperbolic tangent

Output layer activation function: Softmax

Figure 4-3. Neural network for the independent and dependent variable

The values in the following table represent the parameter estimates for the neural network. These values represent the weights or the estimates that connect the independent variables with the hidden layer and the hidden layer to the dependent variable. This means that the weight or estimate between the death variable and the hidden layer is equal to .96. The same would then be concluded for the remaining variables in the model.

Table 4-46
Parameter Estimates for Neural Network Model

Predictor		Parameter Estimates			
		Predicted			
		Hidden Layer 1	Output Layer		
		H(1:1)	[TotalPaid=10000 0]	[TotalPaid=11000 0]	[TotalPaid=12500 0]
Input Layer	(Bias)	1.329			
	Death	.955			
	Brainorspinaldamage	.762			
	Fracture	1.052			
	Limitfunction	.707			
	Noconsent	1.952			
	Transfer	-.009			
	AdultAbuse	-1.802			
	Elopement	.143			
	LawEnforcement	.279			
Hidden Layer 1	(Bias)		3.465	-1.291	-2.303
	H(1:1)		1.909	-1.249	-1.693

The results in table 4-47 represent the classification capability of the neural network. For instance, the model was able to correctly classify 95.3% of the observations in the training dataset. This meant that based on the independent variables, one would be able to classify the participant into the correct total amount paid group 95.3% of the time. For the testing dataset, the model was able to correctly classify 100% of the observations in the testing dataset. This meant that based on the independent variables, one would be

able to classify the participant into the correct total amount paid group 100% of the time. This indicated that the independent variables would provide good assessments of the total amount paid by the participants. The following graphs then provide graphical illustrations for the classification of the total amount paid based on the independent variables in the model.

Table 4-47
Classification Results for Neural Network with Total Amount Paid and Adverse Incidents Independent Variables

		Classification			
Sample	Observed	Predicted			Percent Correct
		100000	110000	125000	
Training	100000	41	0	0	100.0%
	110000	1	0	0	.0%
	125000	1	0	0	.0%
	Overall Percent	100.0%	.0%	.0%	95.3%
Testing	100000	17	0	0	100.0%
	110000	0	0	0	.0%
	125000	0	0	0	.0%
	Overall Percent	100.0%	.0%	.0%	100.0%

Dependent Variable: Total Amount Paid

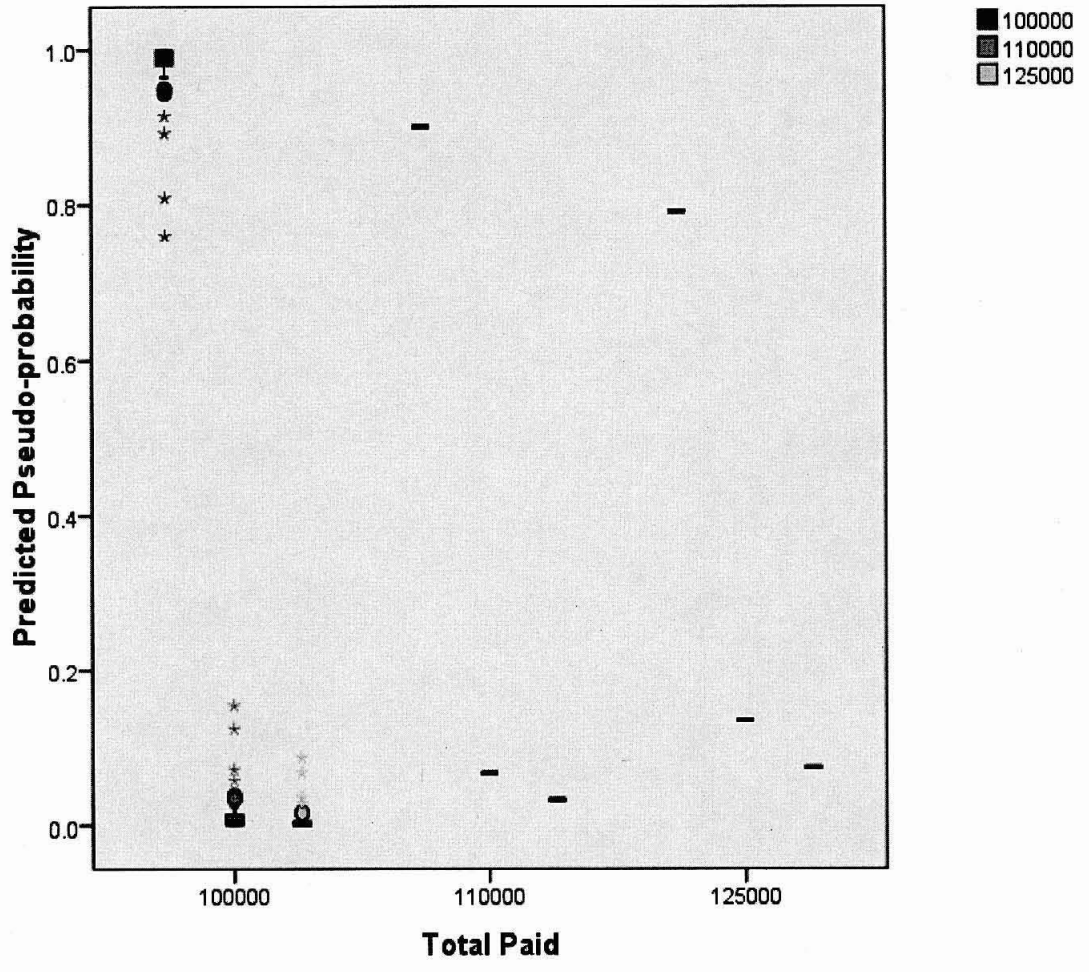


Figure 4-4. Predicted probability for the total amount paid

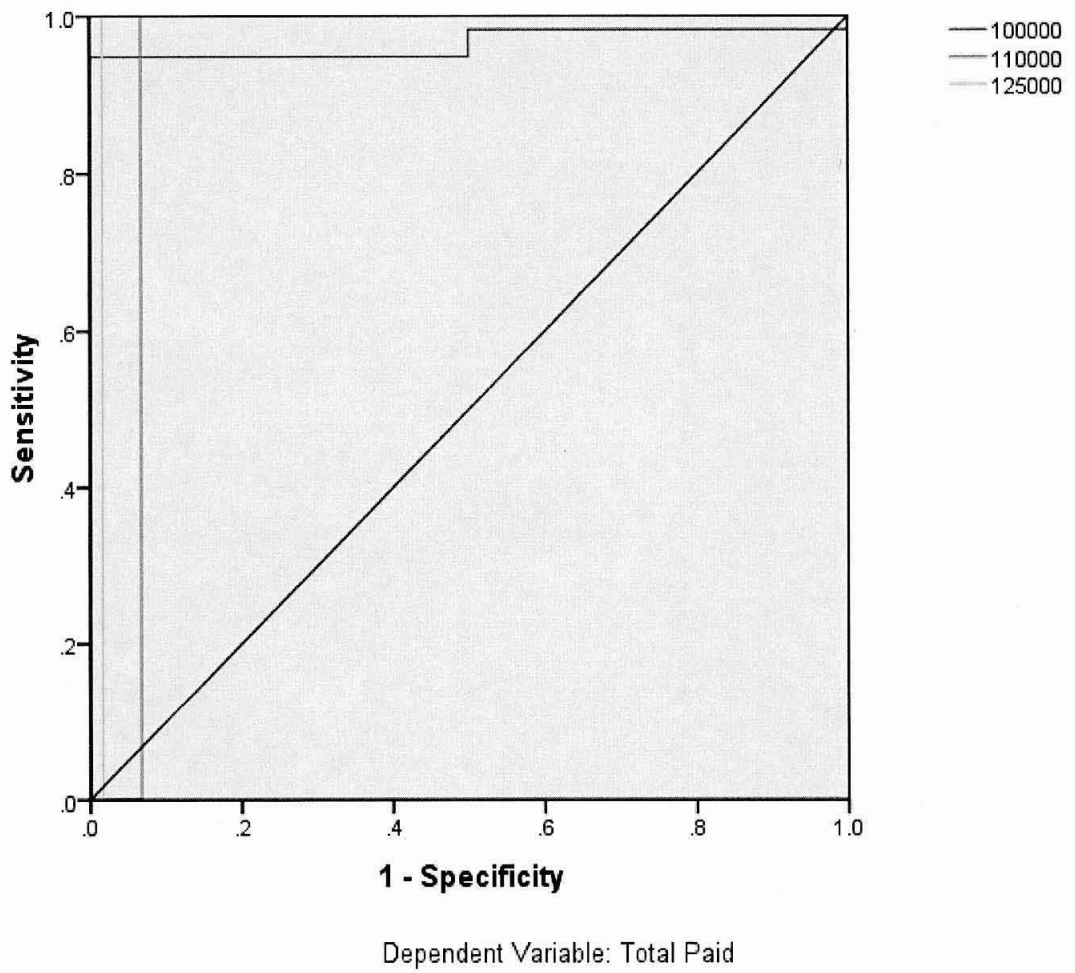
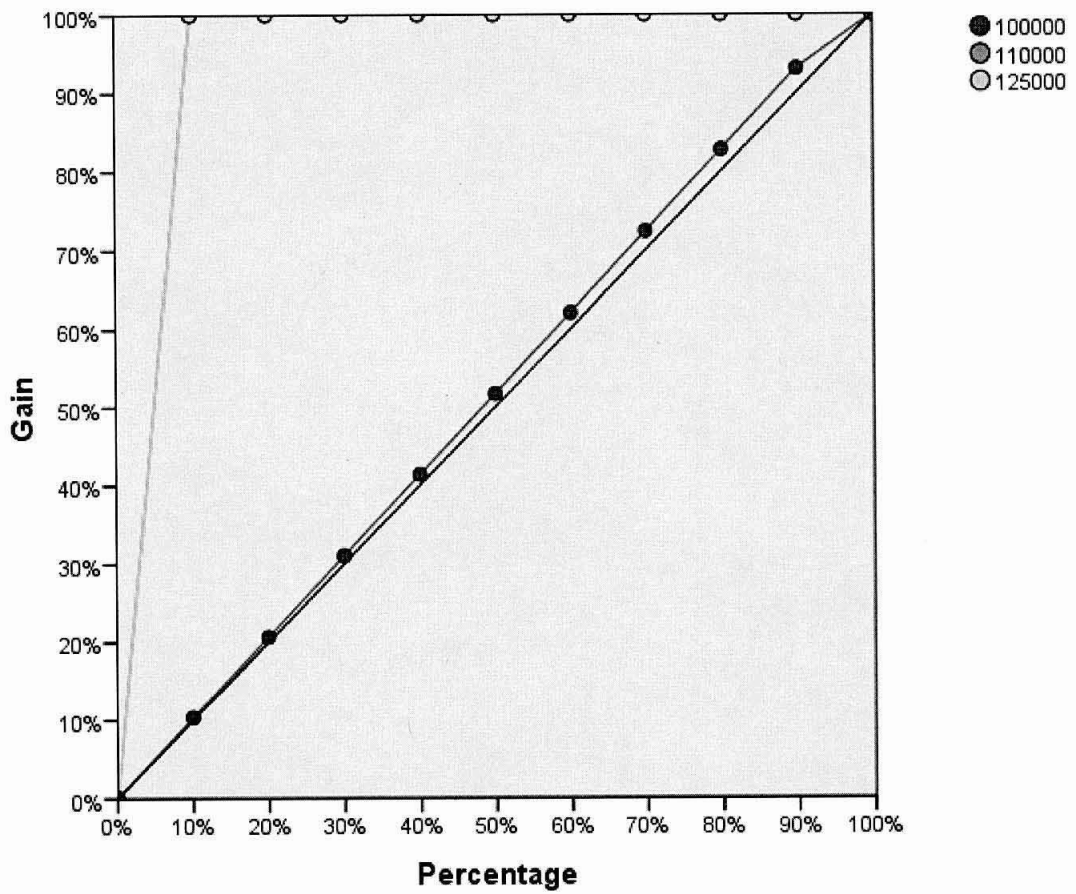


Figure 4-5. The ROC curve plotting sensitivity by 1 – specificity for the neural network model with total amount paid and adverse incidents independent variables



Dependent Variable: Total Paid

Figure 4-6. Percentage by gain plot for the neural network model with total amount paid and adverse incidents independent variables

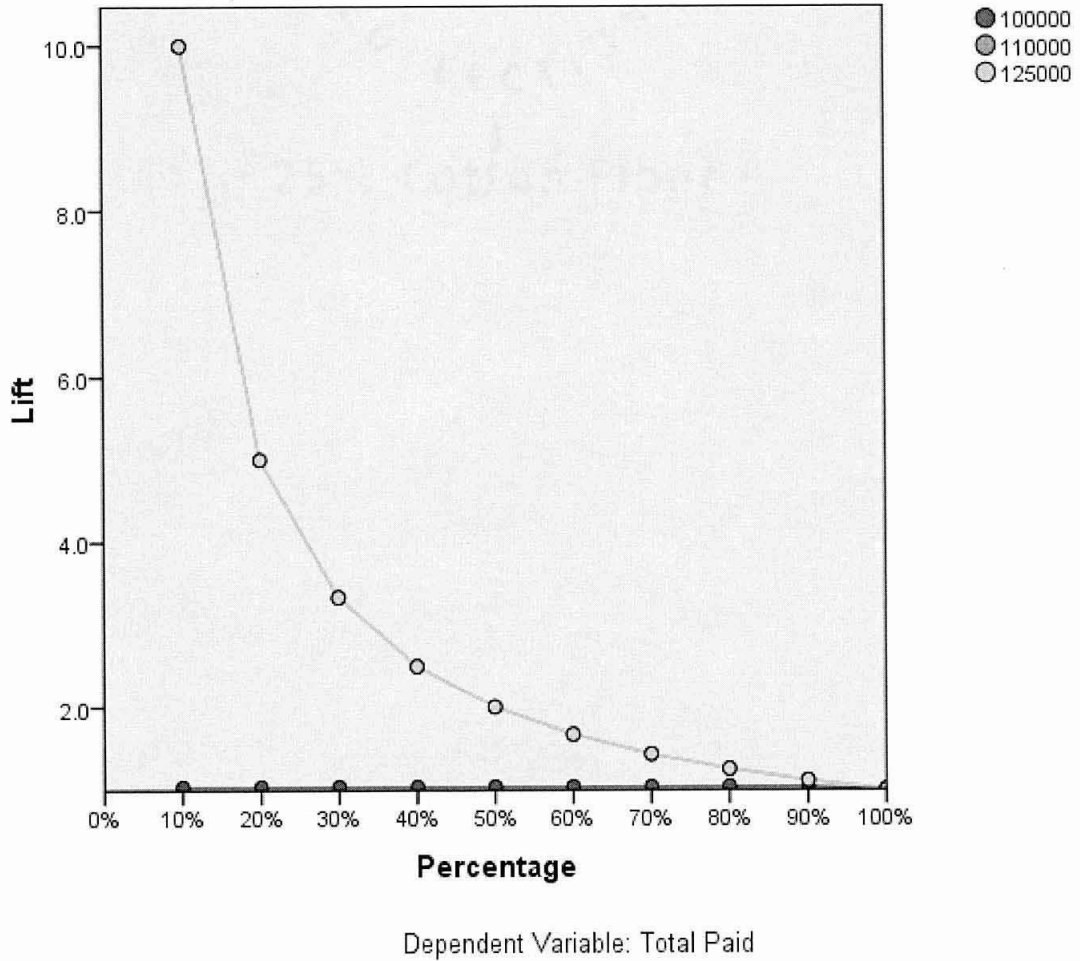


Figure 4-7. Percentage by lift plot for the neural network model with total amount paid and adverse incidents independent variables

Chapter IV presented the results of the study. This chapter included descriptions of the sample, reliability and validity of the measures, socio-demographic characteristics of the sample, answers to the research questions, testing of the hypothesis, and other findings from this study. Chapter V presents the discussion of the findings of this study, including the interpretations, limitations, practical implications, conclusions, and recommendations for future study about quality of care factors associated with liability claims and risk management strategies in Florida nursing homes.

CHAPTER V

DISCUSSION

Chapter V presents a discussion of the results. This study examined quality of care factors associated with liability claims and risk management strategies in Florida nursing homes. The purposes of this exploratory and predictive (correlational) research study using data mining were to determine quality of care indicators associated with liability claims in Florida nursing homes, risk management strategies associated with liability claims, and to create a risk management model to improve quality of care. Chapter V presents the summary and interpretations of the findings, practical implications, conclusions, limitations, and recommendations for future study.

Summary and Interpretations

In this study, 106 nursing home facilities with the capacity of 120-beds, for-profit, and certified by Medicare and Medicaid Services were used in the sample. The sample was comprised of resident MDS assessments that represented quality indicators and quality measures of 12,720 resident assessments from January through December 2006. There was a problem with retrieving the data about the adverse incidents from AHCA, whereby the reports were exempt from release pursuant to chapter 400 of the Florida Statutes. By having the adverse incident data, the study would have been enhanced significantly with information that could have help focus on the specificity of the risk factors.

Research Question 1: What are the nursing home characteristics and quality of care factors that affect liability claims in Florida nursing homes?

The results of this study indicated that quality of care is able to predict the type of incidents 84.0% of the time. Some of the most significant classifications were types of symptoms, impairment, urinary infection, weight gain, range of motion (ROM), antipsychotics, low risk ulcer, short stay pain, and short stay ulcer.

These findings importantly demonstrate that the 24 quality-of-care indicators used in the study constitute as good measurements for quality of care in nursing homes. The fact that they predicted correctly the type of incidents that occurred 84% of the time indicates that they measure what they were supposed to. This has been a problem for researchers in the past; Clauser and Bierman (2003) noted problems with the way quality of care data is collected. However, the fact that this data is collected does not solve all of those problems. Specifically, Clauser and Bierman noted that the method of information collection is not well coordinated since the Medicare system provides services in multiple settings and from different providers. This limitation necessitates an administrative solution, but this study shows that the current indicators are well suited to measuring quality of care. Additionally, there was also lack of data in certain areas that would have significantly enhanced the study.

Research Question 2:

What risk management strategies affect liability claims in Florida nursing homes?

The findings in this study suggest that the quality of care variables perform adequately at predicting the types of incidents. In fact, the model was able to correctly predict the types of incidents 51.8% of the time for the test dataset. This meant that the quality of care variables could be used to predict the type of incident in which the participants would belong. As for the notice of intent variable, this provides evidence that

the quality of care variables perform adequately at predicting the notice of intent groups. In fact, the model was able to correctly predict the notice of intent 63.1% of the time for the test dataset. This meant that the quality of care variables could be used to predict the notice of intent in which the participants would belong.

Research Question 3: What are effective risk management strategies that decrease liability claims in Florida nursing homes?

The results of this study provided evidence that the quality of care variables perform adequately at predicting the types of incidents. In fact, the model was able to correctly predict the types of incidents 47.6% of the time for the test dataset. This meant that the quality of care variables could be used to predict the type of incident in which the participants would belong. As for the notice of intent variable, this provides evidence that the quality of care variables perform well at predicting the notice of intent groups. In fact, the model was able to correctly predict the notice of intent 70.5% of the time for the test dataset. This meant that the quality of care variables could be used to predict the notice of intent in which the participants would belong.

Research Question 4: Is there a risk management model, generated by data mining, that may be used to predict liability claims and effectively manage risk?

The results of this study indicate that the logistic regression model was able to correctly classify 84.0% of the observations in the type of incident grouping variable. Alternatively, the neural network procedure was only able to correctly classify 51.8% of the observations in the type of incident grouping variable, based on the test data set. The decision tree was not as good as the neural network, and not as good as the logistic

regression model, as it was only able to correctly classify 47.6% of the observations in the type of incident grouping variable.

In the notice of intent grouping variable, the neural network was able to correctly classify 63.1% of the observations based on the test data set and the decision tree was able to correctly classify 70.5% of the observations based on the test data set. This indicated that the decision tree performed better at predicting the notice of intent than the neural network did.

These results suggest that the decision tree model was better able to correctly classify notice of intent than the other methods. Use of this research model could help to identify areas of concern for further study, as well as areas in which specific nursing homes need to improve their operations. As a diagnostic tool, a combination of the logical regression and decision tree methods for classification could be used to diagnose and manage problems with care in nursing homes. Measures associated with those diagnostics, such as training and education for facilities' staff, could help reduce the risk of lawsuits.

Summary Results of Hypothesis Testing

To test the hypothesis, linear regression was used to find the explanatory model. There is a significant explanatory relationship among quality of care factors in nursing homes, nursing home characteristics, adverse incident outcome, incidence of falls, risk management strategies and severity of claims (total claims paid). To address the research hypothesis that the adverse incidents were able to predict, or were significantly related to the liability claims, a linear regression analysis was conducted.

For the next analysis that was conducted, the dependent variable was the total amount paid for the liabilities, while the independent variable was the brain or spinal damage variable. This meant that the regression with the brain or spinal damage independent variable and the total amount paid (dependent variable) would determine whether the number of brain or spinal damages observed would be able to predict the total amount paid by the participants. Based on this information, it was found that there was not a significant relationship between the independent and dependent variable, $t(59) = -916.67, p = .83$. This indicated that the independent variable did not significantly predict the total amount paid by the participants. In fact, this model was only able to explain .1% of the variation in the total amount paid, as indicated by the R^2 value for the model.

The regression with the death independent variable and the total amount paid (dependent variable) would determine whether the number of deaths observed would be able to predict the total amount paid by the participants. Based on this information, it was found that there was not a significant relationship between the independent and dependent variable, $t(59) = -812.60, p = .38$. This indicated that the independent variable did not significantly predict the total amount paid by the participants. In fact, this model was only able to explain 1.3% of the variation in the total amount paid, as indicated by the R^2 value for the model.

Theoretical Implications

The challenges facing the nursing home industry are increasingly important to the population of the United States. As one source noted, "As the baby boomers move into the 65 and older age categories, the number of elderly persons will double to

approximately 70 million, or 20% of the population by 2030” (Williamson, 1999, p. 422). This demographic shift will have to be supported by a vibrant, efficient, and high-quality nursing home system.

High levels of liability and the rising cost and increasing scarcity of adequate insurance are some of the largest barriers to achieving this goal. In Florida “insurance companies continue to exit the state and cannot provide coverage when faced with this magnitude of losses, explosion in growth of claims, and extreme unpredictability of results” (Actuarial Solutions, 2001, p. 3). As the quote suggests, the problem of increased liability, and the difficulty of quantifying that risk makes insurance companies reluctant to enter into the market for nursing home insurance.

This study aimed to help alleviate the exodus of insurance companies by providing a better way to measure and predict losses due to liability. Kindred Healthcare Inservice (2003) stated that “loss” must meet four criteria before insurance can be purchased: (1) Loss must be predictable; one must be able to estimate accurately future losses; (2) Loss must be measurable; one must be able to tell when a loss has occurred and place a value on it; (3) Loss must be accidental, loss cannot be inevitable; and (4) Loss cannot be catastrophic, or likely to affect a large percentage of exposure units at the same time. The report by Wright (2002) suggested that,

The 2001 Florida Task Force study examined the claims in residents’ rights lawsuits against nursing homes in Hillsborough County, Florida. The researchers concluded that, of the 225 cases for which court files were available, none appeared to meet the legal definition of “frivolous,” that is, clearly devoid of merit. The primary cause of action in all the cases was the right to receive “adequate and appropriate health care.” (The analysis included lawsuits brought under residents’ rights statutes only.) Nearly all (95 percent) of the cases involved one or more of the following harmful incidents: pressure sores, falls, dehydration and malnutrition, or weight loss. (p. 12)

This quote is highly significant because it notes that the claims are not frivolous. While tort reform to legislate limits on awards or other restrictions on claims has been suggested it is reasonable to believe, based on this quote, which higher quality of care would also result in fewer lawsuits. It is also necessary to continue gathering data about the frequency of Notices of Intents (NOI) and the quality of care in order to continue to look for correlations. Of course, the Florida Task Force's qualification that their study only included cases brought under residents' rights statutes is also significant; it is possible that the total of lawsuits brought by residents reflects a different reality.

This study represented an attempt to find correlations between quality of care indicators and NOIs based on 24 quality of care indicators measured on residents' quarterly assessments. These indicators were tested by Manard (2002) and with a small number of exceptions were found to be valid. The sample was a set of 106 for-profit nursing homes with 120-beds and which were certified by Medicare and Medicaid.

Various strategies have been used to mitigate the effect of liability claims. This study supports Johnson and Bunderson's (2002) findings, who concluded that the entire staff in the lowest risk site they surveyed knew about the Resident Bill of Rights and 75% of the clinical staff believed legislation had an effect on their facility, suggesting that an effective strategy would be to train staff extensively, including educating them on the rights of patients. Johnson and Bunderson also concluded that in lawsuits against nursing homes, quality of care and personnel neglect identified at the low-risk site were contributing factors. This suggests that the personnel displayed an active understanding of what quality care entailed, specifically that their understanding that quality of care and staff attention were methods of reducing the risk of lawsuits.

In contrast, the high-risk site identified television ads and perceived poor care as the primary reasons for lawsuits. This suggests that the staff that had a victim mentality, perceiving that external factors and perceptions determined the number of lawsuits, were less effective at preventing them. As a Kindred Healthcare In-service (2003) noted, this victim mentality must be abandoned. Nursing home centers must be prepared to win battles before the fight begins. This may be accomplished by improving documentation, improving care, and by improving communication with residents, families, and physicians. This study supported the Kindred findings.

In a study of risk management infrastructure, Bierc (2003) clearly identified a gap between operational reality and management perception of risk management. This risk constitutes something that must be assessed at the highest levels of the organization, rather than in discrete departments. He suggests that new Strategic Risk Management (SRM) can help organizations create a global vision of what risk they will accept and how to respond to that risk, rather than relying on departmental leadership, which frequently leads to unintended consequences that detract from the overall strategy. This study did not support Bierc's findings as a nursing home is an entity whereby risk should be looked at on all levels from upper management, middle management, and everyone at the facility level.

However, some of the sources of risk to the nursing home industry are outside the control of nursing homes themselves. These include negative perceptions of nursing homes and the high settlement costs to which they lead. This study supported findings by Wright's (2003) study on the cost and availability of nursing home insurance concluded that increased litigation, premium cuts, lower ROI, the perceived unpredictability of

claims, and other business decisions made insurers unwilling to offer products to the nursing home market. The lack of affordable insurance products is a major limitation on the ability of Florida nursing homes to manage their risk.

Williams and Bone (2003) stated, “As a result of ... skyrocketing costs, many insurance carriers have left the market completely; furthermore, those companies that have remained have had to raise premiums and deductibles and scrutinize their book of business, likely choosing not to renew many policies” (p. 1). This suggests that the insurance industry is not well-suited to solving the problems that lead to high levels of liability, and that it is better able to cut its losses by moving to other industries. This study supported Williams and Bone’s (2003) findings.

This study supported the findings by Wright’s (2002) pressure ulcer project. The purpose of the project was to determine whether vulnerable patients were more prone to develop pressure ulcers as a result of their physical being (i.e. mobility). They were specifically looking for a guideline for pressure ulcer risk assessment and prevention because of the “differing risk assessment tools, different patient groups, healthcare settings and uncertainty regarding how to measure incidence and collate data” (p. 2). This project was one example of an effort to minimize risk by researching an effective standard for care; additionally, pressure ulcers are a leading cause of NOIs (Wright, 2002), in the nursing home industry, so that study provides a blueprint for future research.

Practical Implications

The implications of this research are that while there are various ways that nursing homes can work to reduce the risk that they are sued, there are also significant

limitations to their ability to effectively manage that risk. This tends to support the arguments for regulation of the insurance industry and limits on damages that can be awarded to plaintiffs. Wright, (2003) suggested,

- (1) Repeal the McCarran Ferguson Act of 1945, which exempts insurance companies from federal antitrust laws. Due to the Act, the federal government does not get involved if insurance companies are engaged in collusion, price-fixing, and other anticompetitive practices.
- (2) Create a federal system of reinsurance, since private reinsurers can influence the prices charged and policies offered by primary insurers.
- (3) Adopt federal legislation requiring insurance companies to disclose financial data, including the bases for their price changes.
- (4) Investigate insurance industry practices and pricing and look for ways the federal government and state insurance departments can ensure that responsible pricing is enforced.
- (5) Regulate insurers' pricing and accounting principles. (p. 36)

This suggestion is supported by the results of this study, since it provides for both strict oversight of the insurance industry and a better system to support that industry. Wright's suggestion for federal reinsurance would help the nursing home insurance market become less dependent on external forces and better able to meet the needs of the nursing home industry. That dependence on external forces currently contributes to the lack of affordable nursing home insurance; primary insurers are relatively powerless to offer large numbers of policies unless they have the reinsurance to back them (Wright). With reinsurance companies skeptical of nursing homes, other sources of support are necessary. Other practical implications include:

1. Nursing homes could improve quality by adapting to the culture change, as it will help promote quality of life for the residents.
2. Increase communication to residents and representatives by nursing staff will help families understand the plan of care.
3. Resident satisfaction has to be a focus because it can affect their behavioral intentions and can also decrease grievances.
4. Staff training and education programs with positive outcomes must be developed for staff educational development.
5. Nursing homes must continue to maintain and enhance the physical plant as it relate to time. Many current and future residents expect a state of the art nursing home with functional amenities.

Conclusions

The influences that quality of care and risk management strategies has on liability claims in nursing homes are important because the rising vulnerability of the nursing home industry is driving them out of business. There were many gaps in the literature, and following are suggested:

1. Limitations that are produced by the underlying challenges in providing care to residents with cognitive impairment are suggested for future study
2. The policy implications for tort reform must be identified. For example, caps on damage awards and attorney fees must be streamlined without eliminating the incentives to deliver high-quality care that litigation may provide

3. In the study of risk management infrastructure, Bierc (2003) clearly identified a gap between operational reality and management perception
4. It is recommended that the MDS, OASIS, and functional rehabilitation data be used to provide a wealth of information for future research about nursing home characteristics, demographics, quality indicators of aggregate health characteristics of residents, risks, risk management, and liability claims
5. It is recommended that data mining challenges on how to translate CMS's criteria into variables that can be created within the context of a database view as an opportunity for the healthcare industry (Sokol et al., 2001)
6. It is further recommended that computer modeling systems be developed for projecting catastrophic losses so rate proposals and underwriting restriction plans can be evaluated based on a company's own model.

This study examined the results for significance in the context of the research questions and a review of the literature. It concluded that in terms of the first research question, there was a strong correlation between quality of care indicators and the incidents that led to liability claims. This suggested that the indicators were good, and that certain indicators were associated with higher rates of accuracy. To the second research question, this study concluded that various risk management strategies have been used in Florida, of which the most common seem to be methods for training staff. To the third research question, this study concluded that while various risk management strategies such as training and educating staff do have an effect on the number and severity of lawsuits, they are not necessarily sufficient to decrease nursing homes' exposure to risk substantially. Other variables such as the public perception of nursing

homes have a large effect on the outcomes of lawsuits, and are outside the control of individual facilities. To the final research question, this study concluded that the success of the measurements indicated that there are indeed diagnostic tools that can identify areas of risk, but the external factors noted in the answer to the previous question still apply.

The goal of this dissertation was to take available data that has been gathered from Florida nursing homes for years about quality of care, liability claims and risk management and to use data mining process to analyze the data. The implementation and application of the data mining process is a huge contribution to the study as the healthcare industry especially the nursing homes has not yet applied this concept as a way to analyze large data set that are being warehoused.

Limitations

This study on the quality of care factors in nursing homes and risk management strategies to decrease liability claims used data mining to analyze data from Florida nursing homes. The limitations of the study are as follows:

1. A non-experimental design is weaker than an experimental design.
2. The data sample represented only nursing homes with at least 120 beds, which were Medicaid and Medicare certified, and which were privately owned for-profit facilities.
3. The results may not be generalizable to the extent that other sizes and kinds of facilities are run in accordance with different strategies and goals or are subject to different laws. However, these results are generalizable to the extent that other facilities are similar to the ones tested in those areas.

4. The Agency for Health Care Administration (AHCA) could not release the data for liability claims as requested as there are protected by chapter 400 of the Florida Statutes. This could have changed the results significantly.
5. The notice of intent was available for release with redaction.
6. The liability reports were available for release with redaction.
7. The liability claim form data was available for release with redaction.
8. The adverse incident reports were exempt from release.

Recommendations for Future Study

Based on the results of this study, it is necessary to conduct various kinds of research to determine the best global solutions for the challenges surrounding nursing homes' vulnerability to lawsuits. These challenges encompass a broad range of topics (Johnson & Bunderson, 2002; Louisot, 2003; Williamson, 1999) and no single solution is likely to be able to solve all of them. Specifically, there is a public policy dimension represented in the dual need for insurance industry regulation and careful tort reform. As the AON (2003) study pointed out, caps on non-economic damages are the most effective tort reform policy provision for reducing nursing home patient liability claim severity. This would lead to increased insurability for nursing homes due to the reduction in, and increased measurability of likely losses due to lawsuits. Additionally, public policy should focus directly on insurance availability to best determine a strategy for ensuring that sufficient insurance is available.

There is also a medical dimension to the improvements recommended by this study. Wright (2002) found that many, if not most lawsuits brought against, nursing

homes are not frivolous. Therefore, there is a clear need for nursing homes to set higher standards of care and implement plans to achieve those standards. Methods for doing so must include careful assessment of quality of care indicators as well as comprehensive staff training.

1. This study was limited to examining the adverse incidents reports in Florida nursing homes.
2. A future study can measure how the different type of adverse incident affect the frequency, cost and type of liability of claims filed.
3. The findings could not be generalized as some of the data were redacted due to HIPAA privacy rule.
4. A future study may use different sampling method to collect data which may include a survey invitation to provide more information versus using secondary data.
5. A future study may include all types of facilities that are non-profit and private with more or less beds than 120.
6. Future studies may examine the relationships among the type of socio-demographic characteristics, length of stay, and characteristics among payer.

Finally, this study noted various implications, limitations, and recommendations. The implications and recommendations were essentially that the solution to the problems facing the nursing home industry requires a holistic focus on the legal and financial context of that industry; specifically, solutions should focus on problems with the availability of insurance, as well as tort reform that would reduce the impact of individual

lawsuits. That holistic focus, in conjunction with efforts to further improve the nursing home industry itself, could help ensure that as millions of Americans begin to retire, they have the necessary resources and infrastructure to support them.

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Appendix A
ResDAC Information

Re: MDS

From:

ResDAC_GMBarosso [REDACTED]

To:



Date:

Mon, 10 Sep 2007 12:32 pm

The approximate price for any number of facilities within one state, all assessments is \$1000.

Gerrie

[REDACTED] wrote:

Thank you very much for your help; I'm going to probably need data from 2006-2007 if possible for 106 nursing facilities in Florida. Do you think that will make a difference in the price? Thanks.

-----Original Message-----

From: ResDAC_GMBarosso [REDACTED]

To: [REDACTED]

Sent: Thu, 6 Sep 2007 11:23 am

Subject: Re: MDS

Hi, Ernande

Thank you for contacting ResDAC for information on obtaining CMS MDS assessment data for nursing homes in Florida.

Information on the files, including links to how to request the data are available from <http://www.resdac.umn.edu/MDS/Index.asp> An approximate price for one year of data, one state, all assessments is \$1000. If you decide you move forward with a data request, you'll need to submit the request for a formal cost estimate.

As a student, you advisor would be signing your data request documents as the User; you would be the data custodian.

Please let us now if you have additional questions,

Gerrie

[REDACTED] wrote:

Good evening,

My name is Ernande Fortune, I am a PhD student at Lynn University. I am doing a research on Florida Nursing Homes using secondary data. I am writing to find out how I can get MDS data for the Florida nursing homes (67) counties that are Medicare and Medicaid certified. Please let me know if you can help me.

Nursing Home Data

Appendix B

ResDAC Request 25625

From:

[REDACTED]

To:

[REDACTED]

Date:

Wed, 9 Jan 2008 3:35 pm

Anna,

The MDS assessment data will come as an ASCII text.csv file. You will receive a SAS Input statement in order to read in the data.

Barbara Frank
ResDAC

AHCA

Public Records Coordination Office

http://ahca.myflorida.com/Executive/Communications/public_records.shtml

Please direct all requests for public records to:

Public Records Coordinator
2727 Mahan Drive, Ft. Knox #3, Mail Stop #2
Tallahassee, FL 32308-5403

[REDACTED]

Fax

PublicRecordsReq@ahca.myflorida.com

We believe the Agency for Health Care Administration's ability to respond promptly and accurately to all public records requests is an integral part of our mission to champion accessible, affordable, quality health care for all Floridians.

In an effort to increase our ability to respond to such requests in a timely and comprehensive manner, the Agency has chosen to coordinate all Public Records Requests made to the Agency through its Public Records Coordination Office.

NOTE: The Agency for Health Care Administration's Public Records Coordination Office only deals with public records that involve the Agency (see AHCA homepage for details).

Public Records Procedure:

You can make a public records request by contacting this office by phone, fax, email, or regular mail. Please make sure your name, email address, mailing address, and telephone number are on the request so we can contact you if we have any questions. When a public records request is made, please include as much information as possible relating to your

request so we can respond promptly and accurately. This information can include but is not limited to:

- The name of the provider and/or facility about which you are requesting information
- The address for that provider/ facility
- The type of provider/facility (example: Assisted Living, hospital, nursing home)
- A clearly stated time-period for which you are requesting records and the specific type of information you are interested in.
- Other information that is available to you that you feel would help identify the documents you are seeking.

The following is a summary of fee changes:

Electronic documents:

- Documents under 25 pages with no redaction were provided by email at no charge.

Documents over 25 pages were provided on a CD free of charge. Documents that require redaction were provided on a CD with a service charge based on staff labor costs necessary to complete the redaction

Paper copies:

- \$.15 per page plus staff labor costs necessary to complete any required redaction.
- An additional \$.05 per page is assessed for double-sided copies.

Requests for data or special reports:

- A special service charge based on staff labor costs were charged for requests that require extensive use of information technology resources or clerical or supervisory assistance.

If the cost to process the request will exceed \$10.00, Agency staff will call or otherwise notify the requestor of the anticipated cost of the documents requested. This is an estimate and the actual cost may be slightly higher or lower upon completion. Prepayment is required before the documents are sent out.

If you have any further questions please contact the Public Records Coordination Office at [REDACTED]

Communications and Legislative Affairs | Community Resources | Legislative Affairs | Media Relations | Public Records

Variables	Description	Resident Int ID	Resident Int ID	Resident Int ID	Resident Int ID	Resident Int ID	Resident Int ID	Resident Int ID	Resident Int ID
Part 1	Nursing Home Characteristics								
Facility Capacity	# of beds	120	120	120	120	120	120	120	120
Chain	1-Yes 2-No								
Part 2	Quality of Care Factors								
QI1	Incidence of new fractures								
QI2	Prevalence of falls								
QI3	Prevalence of behaviors affecting others								
QI4	Prevalence of symptoms of depression								
QI5	Prevalence of depression with no tx								
QI6	Use of 9 or more different medications								
QI7	Incidence of cognitive impairment								
QI8	Prevalence of bladder or bowel incont.								
QI9	Bladder or bowel incont. with no plan								
QI10	Prevalence of indwelling catheter								
QI11	Prevalence of fecal impaction								
QI12	Prevalence of urinary tract infections								
QI13	Prevalence of weight loss								
QI14	Prevalence of tube feeding								
QI15	Prevalence of								

	dehydration
QI16	Prevalence of bedfast residents
	Decline in late loss
QI17	ADLs
	Decline in range of motion
QI18	Antipsychotic use in absence of med
QI19	Prevalence of anti-anxiety/hypnotic use
QI20	hyp use more than 2 times in last wk
QI21	Prevalence of daily physical restraints
QI22	Prevalence of little or no activity
QI23	Prevalence of stage 1–4 pressure ulcers
QI24	Res need for help with ADLs has incr
QM1	Res who spend time in bed or chair
QM2	Res with a catheter and left in bladder
QM3	Low risk res who lose control of b and b
QM4	Residents with a urinary tract infection
QM5	Res whose ability to move worsen
QM6	Res who are more depressed or anxious
QM7	Res who have moderate to severe pain
QM8	High risk res who have pressure ulcers
QM9	Low risk res who have pressure ulcers
QM10	

QM11	Res who were physically restrained
QM12	Residents who lose too much weight
Part 3	Adverse Incident Outcome
AIO1	Death
AIO2	Brain or spinal damage
AIO3	Disfigurement
AIO4	Fracture
AIO5	Limit function (1neuro, 2phys, or 3sen)
AIO6	No consent
AIO7	Transfer
AIO8	Adult Abuse
AIO9	Child Abuse
AIO10	Elopement
AIO11	Law Enforcement
Part 4	Type of Incident
TOI	1-Adverse or 2-Non-adverse (Falls)
Part 5	Risk Management
StaffRN	Hours per patient day (ppd)
StaffLPN	Hours per patient day (ppd)
StaffCNA	Hours per patient day (ppd)
Staff ratio	Direct staff to resident ratio
QA&A	QA&A in place (1-yes, 2-no)
PTSS	Patient satisfaction survey (1-yes, 2-no)
FSS	Family satisfaction survey (1-yes, 2-no)
Part 6	Liability Claim

	Individual claim status (1open or
LC1	2close)
LC2	Accident date
LC3	Close date
LC4	Indemnity paid
	Allocated loss
	adjustment expense
LC5	paid
LC6	Total Paid
LC7	Indemnity Incurred
	Allocated loss
	adjustment expense
LC8	inc.
LC9	Total incurred

Appendix C

Data Cost

Request for a formal CMS Cost Estimate

To request a formal cost estimate for *Identifiable Data Files* from CMS, email a copy of this page to ResDAC at [REDACTED]. Broadly, the cost of the data files vary by file type and the number of years requested. If you want to receive a cost estimate for a grant submission it's recommended to send your request two weeks prior to the date needed.

To: ResDAC staff
From: [Click **here** and type your name & phone number]
Date: 8/6/2009
Re: Cost estimate for [Click **here** and type researcher (PI) & institution]

Study Description:

Researcher is requesting a CMS cost estimate for a study entitled "[click here and enter study title]". This study is funded by [Click here and enter funding source or where grant is being submitted]. This study intends to examine the [Click here and enter study purpose]. Study objectives include [Click here and enter study objectives] .

Data File Construction:

Study population and extract methodology:

DisplayText cannot span more than one line!

Years of interest:

[Click here and enter years data to be requested]

Is it your intention to link these data with data received by CMS in the past?

[Click here indicate yes or no. If yes, what is the last year of data sent to you by CMS?]

Are you submitting a finder file for a cohort of individuals you plan to link with the CMS data?

DisplayText cannot span more than one line!

Select Media

CD or USB Hard Drive (USB HD will be sent if the data volume is > than 52 gigs)

DVD or USB HD (USB HD will be sent if data volume is >250Gigs)

USB Hard Drive *

3490E IBM Standard label cartridges; compressed *

LTO tape

** If USB Hard Drive or 3490E IBM cartridge media are selected, the researcher were expected to pay an additional fee (\$150) for media.*

----- ResDAC staff to complete information found below-----

Data Files Requested:

MEDICARE DATA

Crosswalk and Conversion Files

SSN to RDDC Bene ID Conversion File -used to link submitted SSN finder with Medicare administrative data from RDDC.

HIC to RDDC Bene ID Conversion File-used to link submitted HIC finder with Medicare administrative data from RDDC.

RDDC Bene ID to HIC Crosswalk File - used to link Medicare administrative data from RDDC with any data researcher may have received from CMS historically. *Indicate year of CMS data file from which the HICs should be identified.*

Enrollment

Name & Address	most current
Denominator	[type years of data]

Utilization

MedPAR 838	[type years of data]
Outpatient SAF	[type years of data]
Inpatient SAF	[type years of data]
HHA SAF	[type years of data]
Hospice SAF	[type years of data]
SNF SAF	[type years of data]
DME SAF	[type years of data]
Carrier SAF	[type years of data]

Other Files

UPIN Master File (aka MPIER file)	[type years of data]
UPIN Group File	[type years of data]
UPIN Member File	[type years of data]

MEDICAID DATA

Crosswalk and Conversion Files

SSN to RDDC Bene ID Conversion File

HIC to RDDC Bene ID Conversion File

RDDC Bene ID to SSN/MSIS ID/HIC Crosswalk File - used to link Medicaid administrative data from RDDC with any data researcher may have received from CMS historically. *Indicate year of CMS data file from which the identifiers should be identified.*

Enrollment and Utilization Files

[type states of interest]	[type years of data]
[type data files of interest, PSF, OT, IP, LTC and/or RX]	

ASSESSMENT DATA

MDS Nursing Home Assessment Data	[type years of data]
[target or submission date]	

OASIS Home Health Assessment Data
[target or submission date]
IRF-PAI Assessment Data
[target or submission date]

[type years of data]

[type years of data]

Appendix D

ResDac Document Request

Requesting MDS Data

The Long Term Care Minimum Data Set (MDS) and Facility QI reports are considered Research Identifiable Files (RIFs). For description of RIF data, [click here](#).

Researchers need to submit to CMS a data request packet containing a written request, study protocol, evidence of funding, and Data Use Agreements (DUA). If CMS approves the data file releasing, researchers need to pay the cost incurred in the processing of data. Approval for data release is based on the information contained within this documentation. CMS review criteria can be found [here](#).

The data request process varies slightly for requestors from Federal agencies, state government, Congress, or their contractors. For a comprehensive description of the data request process for these entities go [here](#).

Once you are ready to request the data, fill out the information in the data request packet. CMS has asked that ResDAC review all requests for MDS data prior to review by CMS's Data Review Board (DRB) Committee. CMS's DRB will review your request to determine whether the release of CMS's MDS data meets CMS's data release criteria and is allowable under the Privacy Act of 1974.

Required Documentation

1. Written request letter

The Written Request Letter, submitted on organizational letterhead, outlines the primary purpose(s) for which the data are required. If requested, ResDAC will provide a draft of a Written Request letter for review. The Written Request should contain the following elements:

- The purpose for which the data are needed
- A brief description of the methodology in which the data were used
- Delineation of the data requirements
- Criteria for data selection or searches

2. Study plan or protocol

The Study protocol is a 10-12 page document that delineates the objective, background, methods, and importance of the study being proposed. An overview of suggested elements are found in the "CMS Study Protocol Format" document included in this packet. CMS will evaluate the purpose for which the data were used to determine whether:

- The purpose requires individually identifiable records
- The project is of sufficient importance to warrant effect, or risk, on beneficiary privacy
- There is reasonable probability that use of data will accomplish purpose, i.e., project is soundly designed and properly financed
- CMS requires that researchers identify all elements to be used in the analysis. In the "Analysis Plan" section under EVALUATION AND ANALYSIS PLAN add a table that includes the variables to be used in the analysis. Possible table format: Data element name (e.g., Prevalence Physical Restraints Daily); Data element number in RAI (e.g., P4c, P4d, P4e); How to be used in the analysis (e.g., dependent variable, independent variable; specific aim 1-x)

3. Data Use Agreement (DUA)

The DUA delineates the confidentiality requirements of the Privacy Act and CMS's data release policies and procedures. Instructions for completion are included in the "DUA" document supplied with this packet. This agreement specifies that the requestor will:

- Ensure the data were used only for the specific purpose stated in the agreement
- Develop and implement the appropriate procedural, technical, and physical safeguards to prevent unauthorized use
- Not release any files without prior CMS approval
- Return or destroy file(s) by the date specified
- Not publish or release information that would permit the identification of a beneficiary

Signature Addendum: If anyone besides the requester or custodian is going to handle CMS data, a signature addendum may be required. View examples of when the addendum is required, for the signature addendum form, and for instructions on how to incorporate it into the DUA

4. Internal Review Board (IRB) Documentation of Waiver Approval

Under the Privacy Rule, CMS is permitted to disclose protected health information for research either with individual authorization, or without individual authorization. To use or disclose protected health information without individual authorization, CMS must obtain documentation that an IRB or a CMS

Privacy Board has approved a waiver of research participants' authorization for use/disclosure of information about them for research purposes. If the researcher provides CMS with documentation of IRB waiver approval, the data request were reviewed under an expedited CMS review process.

For a data use or disclosure to be permitted by CMS based on documentation of approval of an alteration or waiver, under the HIPAA privacy rule, the documentation provided to CMS must include:

- Identification of the IRB and the date on which the alteration or waiver of authorization was approved;
- A statement that the IRB has determined that the alteration or waiver of authorization, in whole or in part, satisfies the three criteria in the Rule;
- A brief description of the protected health information for which use or access has been determined to be necessary by the IRB;
- A statement that the alteration or waiver of authorization has been reviewed and approved under either normal or expedited review procedures; and
- The signature of the chair or other member, as designated by the chair, of the IRB, as applicable.

This documentation can be a copy of your IRB waiver documentation if it contains all items listed above. If what you receive from your IRB does not include the above items, you will need to include additional documentation which includes the above requested items. This additional documentation can be a photocopy of information submitted to your IRB or a written summary clearly referencing the study, Principal Investigator, IRB the submission was directed to and date of the IRB submission.

Visit the Office of Civil Rights (OCR) website for additional guidance on the Privacy Rule as it relates to research

<http://www.hhs.gov/ocr/hipaa/guidelines/research.rtf>.

5. Evidence of Funding

CMS requires documentation that the project has been adequately financed to allow for its completion. Evidence of funding is usually a copy of the face sheet of the grant, contract, or cooperative agreement. CMS is required to obtain compensation for its costs incurred in the processing of data, and costs will vary depending upon the number of records in the finder file, the number of records searched, and the method of retrieval. Payment is made to CMS after the data request is approved. The researcher should receive an approval letter that details the cost of the files and provides instructions for reimbursement.

6. CMS Data Request Form (formerly Data Use Checklist) - (*new* - editable PDF)

[**WARNING:** Data entered in this form can only be saved using the paid version of Adobe Acrobat (not just the free Adobe Reader). Adobe Reader can still print the form once filled in, but were unable to save an electronic version of the form. Adobe Acrobat users can save an electronic version of the form by clicking on the "save" icon [floppy disk] in Adobe Acrobat/Reader Toolbar. If preferred, all users can print a copy of the form and fill it out manually.]

The Data Use Checklist is a compilation of all the information submitted in the request packet and were used internally among all the divisions at CMS working on the data request. See "Data Use Checklist" document included in this packet. Please note that this check list is used to order a number of different CMS data files, and therefore some sections may not be applicable to Long Term Care MDS requests. If you are only ordering Long Term Care MDS data, you do not need to complete Section #5 (Finder File Information) and in Section 7 (a & b) the only available format is IBM 3480 or 3490E tape cartridge in EBCDIC format, Variable length record. (The table regarding trailer selection can be ignored.)

7. Privacy Board Review Summary Sheet

The CMS Privacy Review Board uses this document as a permanent record of the Privacy Board review.

8. Request Letter of Support from Project Officer (federally funded projects only)

The letter of support from a federal project officer is only applicable for those researchers whose project is funded by a federal granting institution. The project officer will also be required to sign the DUA.

9. Long Term Care MDS Resident Assessment Instrument
Long Term Care MDS Workbench Variable Selection & Justification Worksheet

The research design needs to be focused, ensuring the researcher requests the minimum data necessary to conduct the study. Using the 'Long Term Care MDS Workbench Variable Selection & Justification Worksheet', the researcher must identify and justify the need for the data elements to be used in the analysis. For example, a study that proposes to analyze the number of falls occurring in a nursing home should only requests those data elements relating to falls, their occurrence, prevention or description of related characteristics.

MDS data request packets should be sent to:

Maribel Franey, Division Director
Division of Privacy Compliance Data Development (DPC)
Centers for Medicare & Medicaid Services (CMS)

OIS/EASG/DPC N2-04-27
7500 Security Blvd.
Baltimore, Maryland 21244-1850

Appendix E

Incident and Accident QA&A Log

Appendix F

Calculating Staffing for Long Term Care Facilities

Facility Name:	Surveyor Name:
Facility Provider #	Date reviewed:
Survey Date:	
Completed by:	
Completed on:	_____

For Two Week Pay Period Immediately Prior to Survey - or Other Period Requested by Surveyor

Week One	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday				
Date												
Census										Total Census:		

HOURS: Enter the number of LPN and RN hours actually worked per day for the dates above

*RN Hours												
LPN Hours												
Total Nursing												

RATIO: Enter the number of licensed nurses (RN and LPN) on duty each shift (the number, not the hours)

Nurses/"first shift"												
Nurses/2nd shift"												
Nurses/"3rd shift"												

HOURS: Enter the number of CNA hours actually worked per day for the dates above

CNA Hours											Total Hours:	
Daily Average												

RATIO: Enter the number of C.N.A.'s on duty each shift for the dates above (the number, not the hours)

CNAs/"first shift"												
CNAs/"2nd shift"												
CNAs/"third shift"												

For Two Week Pay Period Immediately Prior to Survey - or Other Period Requested by Surveyor											
Week Two	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday			
Date											
Census										Total Census:	
HOURS: Enter the number of LPN and RN hours actually worked per day for the dates above											
*RN Hours											
LPN Hours											
Total Nursing											
RATIO: Enter the number of licensed nurses (RN and LPN) on duty each shift (the number, not the hours)											
Nurses/"first shift"											
Nurses/"2nd shift"											
Nurses/"3rd shift"											
HOURS: Enter the number of CNA hours actually worked per day for the dates above											
CNA Hours										Total Hours:	Weekly Average:
Daily Average											
RATIO: Enter the number of C.N.A.'s on duty each shift for the dates above (the number, not the hours)											
CNAs/"first shift"											
CNAs/"2nd shift"											
CNAs/"third shift"											

Appendix G

Adverse Incident Report QA&A Log

Appendix H
IRB Approval for Research



Principal Investigator: Ernande Fortune

Project Title: Data Mining to Identify Quality of Care Factors Associated with Liability Claims and Risk Management Strategies in Florida Nursing Homes

IRB Project Number: 2008-009 Request for IRB Exemption of Application and Research Protocol for a New Project

IRB Action by the IRB Chair or Another Member or Members Designed by the Chair

Review of Application and Research Protocol and Request for Exemption Status:

Approved X; Approved w/provision(s) _____

COMMENTS

Consent Required: No X Yes _____ Not Applicable _____ Written _____ Signed _____

Consent forms must bear the research protocol expiration date of _____.

Application to Continue/Renew is due:

- (1) For an Expedited IRB Review, one month prior to the due date for renewal X
- (2) For review of research with exempt status, by a College or School Annual Review of Research Committee _____. If the academic unit ("The Colleges and Schools") where the researcher is assigned does not have a committee in place, the application to Continue/Renew is submitted to the IRB, for an Expedited IRB Review no later than one month prior to the due date.

Other Comments: The IRB approval expiration date is 4/24/09

Name of IRB Chair Farideh Farazmand

Signature of IRB Chair _____

Date: 04/24/08

Cc. Dr. Scialli

Institutional Review Board for the Protection of Human Subjects
Lynn University
3601 N. Military Trail Boca Raton, Florida 33431

Appendix I

Data Use Agreement (DUA) Form CMS-R-0235

INSTRUCTIONS FOR COMPLETING THE DATA USE AGREEMENT (DUA) FORM CMS-R-0235

**(AGREEMENT FOR USE OF CENTERS FOR MEDICARE & MEDICAID SERVICES (CMS)
DATA CONTAINING INDIVIDUAL IDENTIFIERS)**

This agreement must be executed prior to the disclosure of data from CMS' Systems of Records to ensure that the disclosure will comply with the requirements of the Privacy Act, the Privacy Rule and CMS data release policies. It must be completed prior to the release of, or access to, specified data files containing protected health information and individual identifiers.

Directions for the completion of the agreement follow:

Before completing the DUA, please note the language contained in this agreement cannot be altered in any form.

- First paragraph, enter the Requestor's Organization Name.
- Section #1, enter the Requestor's Organization Name.
- Section #4 enter the Study and/or Project Name and CMS contract number if applicable for which the file(s) will be used.
- Section #5 should delineate the files and years the Requestor is requesting. Specific file names should be completed. If these are unknown, you may contact a CMS representative to obtain the correct names. The System of Record (SOR) should be completed by the CMS contact or Project Officer. The SOR is the source system the data came from.
- Section #6, complete by entering the Study/Project's anticipated date of completion.
- Section #12 will be completed by the User.
- Section #16 is to be completed by Requestor.
- Section #17, enter the Custodian Name, Company/Organization, Address, Phone Number (including area code), and E-Mail Address (if applicable). The Custodian of files is defined as that person who will have actual possession of and responsibility for the data files. **This section should be completed even if the Custodian and Requestor are the same.** This section will be completed by Custodian.
- Section #18 will be completed by a CMS representative.
- Section #19 should be completed if your study is funded by one or more other Federal Agencies. The Federal Agency name (other than CMS) should be entered in the blank. The Federal Project Officer should complete and sign the remaining portions of this section. If this does not apply, leave blank.
- Sections #20a AND 20b will be completed by a CMS representative.
- Addendum, CMS-R-0235A, should be completed when additional custodians outside the requesting organization will be accessing CMS identifiable data.

Once the DUA is received and reviewed for privacy and policy issues, a completed and signed copy will be sent to the Requestor and CMS Project Officer, if applicable, for their files.

DATA USE AGREEMENT

DUA #

**(AGREEMENT FOR USE OF CENTERS FOR MEDICARE & MEDICAID SERVICES (CMS)
DATA CONTAINING INDIVIDUAL IDENTIFIERS)**

CMS agrees to provide the User with data that reside in a CMS Privacy Act System of Records as identified in this Agreement. In exchange, the User agrees to pay any applicable fees; the User agrees to use the data only for purposes that support the User's study, research or project referenced in this Agreement, which has been determined by CMS to provide assistance to CMS in monitoring, managing and improving the Medicare and Medicaid programs or the services provided to beneficiaries; and the User agrees to ensure the integrity, security, and confidentiality of the data by complying with the terms of this Agreement and applicable law, including the Privacy Act and the Health Insurance Portability and Accountability Act. In order to secure data that reside in a CMS Privacy Act System of Records; in order to ensure the integrity, security, and confidentiality of information maintained by the CMS; and to permit appropriate disclosure and use of such data as permitted by law, CMS and Lynn University ^(Requestor) enter into this agreement to comply with the following specific paragraphs.

1. This Agreement is by and between the Centers for Medicare & Medicaid Services (CMS), a component of the U.S. Department of Health and Human Services (HHS), and Lynn University ^(Requestor) hereinafter termed "User."
2. This Agreement addresses the conditions under which CMS will disclose and the User will obtain, use, reuse and disclose the CMS data file(s) specified in section 5 and/or any derivative file(s) that contain direct individual identifiers or elements that can be used in concert with other information to identify individuals. This Agreement supersedes any and all agreements between the parties with respect to the use of data from the files specified in section 5 and preempts and overrides any instructions, directions, agreements, or other understanding in or pertaining to any grant award or other prior communication from the Department of Health and Human Services or any of its components with respect to the data specified herein. Further, the terms of this Agreement can be changed only by a written modification to this Agreement or by the parties adopting a new agreement. The parties agree further that instructions or interpretations issued to the User concerning this Agreement or the data specified herein, shall not be valid unless issued in writing by the CMS point-of-contact or the CMS signatory to this Agreement shown in section 20.
3. The parties mutually agree that CMS retains all ownership rights to the data file(s) referred to in this Agreement, and that the User does not obtain any right, title, or interest in any of the data furnished by CMS.
4. The User represents, and in furnishing the data file(s) specified in section 5 CMS relies upon such representation, that such data file(s) will be used solely for the following purpose(s).

Name of Study/Project

Data Mining to id Qual of Care Factors Associated with Liability Claims and RM Strategies in FL NHs

CMS Contract No. (if applicable)

The User represents further that the facts and statements made in any study or research protocol or project plan submitted to CMS for each purpose are complete and accurate. Further, the User represents that said study protocol(s) or project plans, that have been approved by CMS or other appropriate entity as CMS may determine, represent the total use(s) to which the data file(s) specified in section 5 will be put.

The User agrees not to disclose, use or reuse the data covered by this agreement except as specified in an Attachment to this Agreement or except as CMS shall authorize in writing or as otherwise required by law, sell, rent, lease, loan, or otherwise grant access to the data covered by this Agreement. The User affirms that the requested data is the minimum necessary to achieve the purposes stated in this section. The User agrees that, within the User organization and the organizations of its agents, access to the data covered by this Agreement shall be limited to the minimum amount of data and minimum number of individuals necessary to achieve the purpose stated in this section (i.e., individual's access to the data will be on a need-to-know basis).

5. The following CMS data file(s) is/are covered under this Agreement.

File	Years(s)	System of Record
MDS QI/QM numerator and denominator data for 106 facilities is FL Yearly	2006	

6. The parties mutually agree that the aforesaid file(s) (and/or any derivative file(s)) including those files that directly identify individuals and those that can be used in concert with other information to identify individuals may be retained by the User until, Date 9/1/2013 hereinafter known as the "Retention Date." The User agrees to notify CMS within 30 days of the completion of the purpose specified in section 4 if the purpose is completed before the aforementioned retention date. Upon such notice or retention date, whichever occurs sooner, the User agrees to destroy such data. The User agrees to destroy and send written certification of the destruction of the files to CMS within 30 days. The User agrees not to retain CMS files or any parts thereof, after the aforementioned file(s) are destroyed unless the appropriate Systems Manager or the person designated in section 20 of this Agreement grants written authorization. The User acknowledges that the date is not contingent upon action by CMS.

The Agreement may be terminated by either party at any time for any reason upon 30 days written notice. Upon notice of termination by User, CMS will cease releasing data from the file(s) to the User under this Agreement and will notify the User to destroy such data file(s). Sections 3, 4, 6, 8, 9, 10, 11, 13, 14 and 15 shall survive termination of this Agreement.

7. The User agrees to establish appropriate administrative, technical, and physical safeguards to protect the confidentiality of the data and to prevent unauthorized use or access to it. The safeguards shall provide a level and scope of security that is not less than the level and scope of security requirements established by the Office of Management and Budget (OMB) in OMB Circular No. A-130, Appendix III--Security of Federal Automated Information Systems (<http://www.whitehouse.gov/omb/circulars/a130/a130.html>) as well as Federal Information Processing Standard 200 entitled "Minimum Security Requirements for Federal Information and Information Systems" (<http://csrc.nist.gov/publications/fips/fips200/FIPS-200-final-march.pdf>); and, Special Publication 800-53 "Recommended Security Controls for Federal Information Systems" (<http://csrc.nist.gov/publications/nistpubs/800-53-Rev2/sp800-53-rev2-final.pdf>). The User acknowledges that the use of unsecured telecommunications, including the Internet, to transmit individually identifiable or deducible information derived from the file(s) specified in section 5 is prohibited. Further, the User agrees that the data must not be physically moved, transmitted or disclosed in any way from or by the site indicated in section 17 without written approval from CMS unless such movement, transmission or disclosure is required by a law.

8. The User agrees to grant access to the data to the authorized representatives of CMS or DHHS Office of the Inspector General at the site indicated in section 17 for the purpose of inspecting to confirm compliance with the terms of this agreement.

9. The User agrees not to disclose direct findings, listings, or information derived from the file(s) specified in section 5, with or without direct identifiers, if such findings, listings, or information can, by themselves or in combination with other data, be used to deduce an individual's identity. Examples of such data elements include, but are not limited to geographic location, age if > 89, sex, diagnosis and procedure, admission/discharge date(s), or date of death.

The User agrees that any use of CMS data in the creation of any document (manuscript, table, chart, study, report, etc.) concerning the purpose specified in section 4 (regardless of whether the report or other writing expressly refers to such purpose, to CMS, or to the files specified in section 5 or any data derived from such files) must adhere to CMS' current cell size suppression policy. This policy stipulates that no cell (eg. admittances, discharges, patients) less than 11 may be displayed. Also, no use of percentages or other mathematical formulas may be used if they result in the display of a cell less than 11. By signing this Agreement you hereby agree to abide by these rules and, therefore, will not be required to submit any written documents for CMS review. If you are unsure if you meet the above criteria, you may submit your written products for CMS review. CMS agrees to make a determination about approval and to notify the user within 4 to 6 weeks after receipt of findings. CMS may withhold approval for publication only if it determines that the format in which data are presented may result in identification of individual beneficiaries

10. The User agrees that, absent express written authorization from the appropriate System Manager or the person designated in section 20 of this Agreement to do so, the User shall not attempt to link records included in the file(s) specified in section 5 to any other individually identifiable source of information. This includes attempts to link the data to other CMS data file(s). A protocol that includes the linkage of specific files that has been approved in accordance with section 4 constitutes express authorization from CMS to link files as described in the protocol.
11. The User understands and agrees that they may not reuse original or derivative data file(s) without prior written approval from the appropriate System Manager or the person designated in section 20 of this Agreement.
12. The parties mutually agree that the following specified Attachments are part of this Agreement:

-
13. The User agrees that in the event CMS determines or has a reasonable belief that the User has made or may have made a use, reuse or disclosure of the aforesaid file(s) that is not authorized by this Agreement or another written authorization from the appropriate System Manager or the person designated in section 20 of this Agreement, CMS, at its sole discretion, may require the User to: (a) promptly investigate and report to CMS the User's determinations regarding any alleged or actual unauthorized use, reuse or disclosure, (b) promptly resolve any problems identified by the investigation; (c) if requested by CMS, submit a formal response to an allegation of unauthorized use, reuse or disclosure; (d) if requested by CMS, submit a corrective action plan with steps designed to prevent any future unauthorized uses, reuses or disclosures; and (e) if requested by CMS, return data files to CMS or destroy the data files it received from CMS under this agreement. The User understands that as a result of CMS's determination or reasonable belief that unauthorized uses, reuses or disclosures have taken place, CMS may refuse to release further CMS data to the User for a period of time to be determined by CMS.

The User agrees to report any breach of personally identifiable information (PII) from the CMS data file(s), loss of these data or disclosure to any unauthorized persons to the CMS Action Desk by telephone at (410) 786-2850 or by e-mail notification at cms_it_service_desk@cms.hhs.gov within one hour and to cooperate fully in the federal security incident process. While CMS retains all ownership rights to the data file(s), as outlined above, the User shall bear the cost and liability for any breaches of PII from the data file(s) while they are entrusted to the User. Furthermore, if CMS determines that the risk of harm requires notification of affected individual persons of the security breach and/or other remedies, the User agrees to carry out these remedies without cost to CMS.

14. The User hereby acknowledges that criminal penalties under § 1106(a) of the Social Security Act (42 U.S.C. § 1306(a)), including a fine not exceeding \$10,000 or imprisonment not exceeding 5 years, or both, may apply to disclosures of information that are covered by § 1106 and that are not authorized by regulation or by Federal law. The User further acknowledges that criminal penalties under the Privacy Act (5 U.S.C. § 552a(i) (3)) may apply if it is determined that the Requestor or Custodian, or any individual employed or affiliated therewith, knowingly and willfully obtained the file(s) under false pretenses. Any person found to have violated sec. (i)(3) of the Privacy Act shall be guilty of a misdemeanor and fined not more than \$5,000. Finally, the User acknowledges that criminal penalties may be imposed under 18 U.S.C. § 641 if it is determined that the User, or any individual employed or affiliated therewith, has taken or converted to his own use data file(s), or received the file(s) knowing that they were stolen or converted. Under such circumstances, they shall be fined under Title 18 or imprisoned not more than 10 years, or both; but if the value of such property does not exceed the sum of \$1,000, they shall be fined under Title 18 or imprisoned not more than 1 year, or both.
15. By signing this Agreement, the User agrees to abide by all provisions set out in this Agreement and acknowledges having received notice of potential criminal or administrative penalties for violation of the terms of the Agreement.
16. On behalf of the User the undersigned individual hereby attests that he or she is authorized to legally bind the User to the terms this Agreement and agrees to all the terms specified herein.

Name and Title of User <i>(typed or printed)</i>		
Dr. Cynthia Patterson, Vice President For Academic Affairs		
Company/Organization		
Lynn University, Inc.		
Street Address		
3601 N. Military Trail		
City	State	ZIP Code
Boca Raton	FL	33431
[Redacted] (include Area Code)		[Redacted]
[Redacted]		Date
[Redacted]		SEP 08 2007

17. The parties mutually agree that the following named individual is designated as Custodian of the file(s) on behalf of the User and will be the person responsible for the observance of all conditions of use and for establishment and maintenance of security arrangements as specified in this Agreement to prevent unauthorized use. The User agrees to notify CMS within fifteen (15) days of any change of custodianship. The parties mutually agree that CMS may disapprove the appointment of a custodian or may require the appointment of a new custodian at any time.

The Custodian hereby acknowledges his/her appointment as Custodian of the aforesaid file(s) on behalf of the User, and agrees to comply with all of the provisions of this Agreement on behalf of the User.

Name of Custodian <i>(typed or printed)</i>		
Ernande Fortune		
Company/Organization		
Lynn University		
[Redacted]		
[Redacted]		
City	State	ZIP Code
[Redacted]	FL	33431
[Redacted]		E-Mail Address <i>(if applicable)</i>
[Redacted]		[Redacted]
Signature		Date
[Redacted]		[Redacted]

18. The disclosure provision(s) that allows the discretionary release of CMS data for the purpose(s) stated in section 4 follow(s). (To be completed by CMS staff.) _____

19. On behalf of _____ the undersigned individual hereby acknowledges that the aforesaid Federal agency sponsors or otherwise supports the User's request for and use of CMS data, agrees to support CMS in ensuring that the User maintains and uses CMS's data in accordance with the terms of this Agreement, and agrees further to make no statement to the User concerning the interpretation of the terms of this Agreement and to refer all questions of such interpretation or compliance with the terms of this Agreement to the CMS official named in section 20 (or to his or her successor).

Typed or Printed Name		Title of Federal Representative
Signature		Date
Office Telephone (Include Area Code)	E-Mail Address (if applicable)	

20. The parties mutually agree that the following named individual will be designated as point-of-contact for the Agreement on behalf of CMS.

On behalf of CMS the undersigned individual hereby attests that he or she is authorized to enter into this Agreement and agrees to all the terms specified herein.

Name of CMS Representative (typed or printed)		
Title/Component		
Street Address		Mail Stop
City	State	ZIP Code
Office Telephone (Include Area Code)	E-Mail Address (if applicable)	
A. Signature of CMS Representative		Date
B. Concur/Nonconcur — Signature of CMS System Manager or Business Owner		Date
Concur/Nonconcur — Signature of CMS System Manager or Business Owner		Date
Concur/Nonconcur — Signature of CMS System Manager or Business Owner		Date

According to the Paperwork Reduction Act of 1995, no persons are required to respond to a collection of information unless it displays a valid OMB control number. The valid OMB control number for this information collection is 0938-0734. The time required to complete this information collection is estimated to average 30 minutes per response, including the time to review instructions, search existing data resources, gather the data needed, and complete and review the information collection, if you have any comments concerning the accuracy of the time estimate(s) or suggestions for improving this form, please write to: CMS, 7500 Security Boulevard, Attn: Reports Clearance Officer, Baltimore, Maryland 21244-1850.

Form CMS-R-0235 (05/08)

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