# NURSING DIAGNOSES IN THE CARE OF HOSPITALIZED PATIENTS WITH TYPE 2 DIABETES MELLITUS: PATTERN ANALYSIS AND CORRELATES OF HEALTH DISPARITIES

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# ABSTRACT

KENNEDY O. ONORI: Nursing Diagnoses in the Care of the Hospitalized Patient with Type 2 Diabetes Mellitus: Pattern Analysis and Correlates of Health Disparities
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This study examined the human needs of 445 adults admitted to hospital with the primary medical diagnosis of Type 2 Diabetes Mellitus [ICD-9CM 250.0-9] and compared the pattern of nursing diagnoses (human needs) with those of 5321 patients having Type 2 DM but admitted to hospital for other reasons and with the 78,480 inpatients with no DM. Length of hospital stay, intensive care unit use and discharge dispositions were examined, controlling for race, poverty, marital status and age, to determine if the nursing diagnosis variables were distinctive for any of the three patient groups. A subset of 14 nursing diagnoses was identified from the literature on the care of Type 2 DM to determine how they varied among the three groups. The 61 nursing diagnoses were also fitted in regression models to explain variances in patient length of stay and to explore patient diabetes status. A multinomial logistic (logit) regression model that included the predictor variables of patient age, race, marital status, socioeconomic position (insurance type), and sex was used to predict patient discharge disposition.

This study was a secondary analysis of data collected over a three-year period by nurses in the daily assessment and care of their hospitalized patients. Donabedian's structure, process, and outcome model of quality of care provided the conceptual framework for this study. The statistical software SAS (9.3) was used for the analysis.

Nursing diagnosis use pattern did not consistently distinguish patients with type 2 diabetes mellitus from other patients. Patient information gathered by nurses in the provision of care to their patients is qualitative in nature -with holistic perspective independent of International Classification of Diseases codes. Nursing diagnosis was related to patient length of stay. The number of different nursing diagnoses was the most important predictor of patient length of stay in a model that included patient age, sex, marital status and socioeconomic position.

Patient race, age, and socioeconomic position were predictive of patient discharge disposition (discharge to own home, discharge to home with home health services, discharge to nursing homes, or discharge to other healthcare facility) but not substantially related to patient length of stay. This methodological study has helped address two related questions in the negative; when the disease is known are the needs of the patient known and when the needs of the patient are known, is the disease known?

*Keywords:* Nursing diagnoses, nursing care, medical diagnoses, chronic diseases, chronic illnesses

# DEDICATION

To my wife, Karen and my daughter Kenna, you are the center of my universe.
Thank you for your support and patience.

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## ABBREVIATIONS

| | |
|---|---|
| DRG | Diagnosis Related Group |
| HMO | Health Management Organization |
| ICD | International Classification of Diseases |
| ICU | Intensive Care Unit |
| IDDM | Insulin Dependent Diabetes Mellitus |
| NANDA | North American Nursing Diagnosis Association |
| NIDDM | Non-Insulin Dependent Diabetes Mellitus |
| NMIS | Nursing Management Information System |
| NMDS | Nursing Minimum Data Set |
| NSI | Nursing Severity Index |
| T1DM | Type 1 Diabetes Mellitus |
| T2DM | Type 2 Diabetes Mellitus |
| UHDDS | Uniform Hospital Discharge Data Set |

# CHAPTER 1

# INTRODUCTION

Over the past few decades diabetes has emerged as a major health issue in the United States, and now rivals heart disease, stroke, and cancer as a major cause of death and healthcare expenditure. Diabetes is currently the seventh leading cause of death by disease in the United States (CDC, 2011b), and ranks 5$^{th}$ and 4$^{th}$ as cause of death among Blacks and American Indians or Alaska Natives respectively (CDC, 2011b; Heron, 2012). Diabetes is a non-communicable disease with huge societal implications, accounting for 7.7 million hospital stays and $83 billion in hospital costs in 2008 (Fraze, Jiang, & Burgess, 2010). According to the Agency for Healthcare Research and Quality (AHRQ) report, hospital stays for patient with diabetes were longer, more costly, and more likely to originate in the emergency department than stays for patient without diabetes (Fraze et al., 2010).

For the individual diagnosed with diabetes, the economic burden and human suffering may be enormous. Without proper management, persons with diabetes could develop major comorbidities such as cardiovascular disease, stroke, diabetic neuropathy, nephropathy, and even depression within a few years of diagnosis (Gæde, Lund-Andersen, Parving, & Pedersen, 2008; Nathan, 1993; Riley, McEntee, Gerson, & Dennison, 2009). These complications, particularly in late stages of the disease exert a profound impact on the quality of life and present a daily source of stress. Late stages of the disease with the associated complications might result in severe disability (i.e., limb amputation, kidney failure, and blindness) thus, placing physical and psychological burdens on individuals with diabetes and family caregivers alike who often care for the person with diabetes (Luger & Chabanuk, 2009). To society, the impact of diabetes is equally serious. The American Diabetes Association estimates that 25.6 million or 11.3% of all people 20 years or older in the United States had diabetes in 2010 (CDC, 2011a). Data from the 2011 National Diabetes Fact Sheet indicate that 1.9 million new case of diabetes were diagnosed among people 20 years or older in 2010 alone (CDC, 2011a). Furthermore, the diabetes population and diabetes associated expenditure are expected to double within the next 25 years, further stressing an already burdened U.S healthcare system (E. S. Huang, Basu, O'Grady, & Capretta, 2009).

Diabetes is expensive to manage. The increasing healthcare expenditure in the U.S is due in large part to the management of chronic health conditions with diabetes high on the list of diseases. In 2012, the total costs of diagnosed diabetes care was an estimated $245 billion, representing a 41% increase from 2007 figures of $174 billion (ADA, 2013). With a new breakdown of $176 billion in direct medical coats and $69 billion in reduced productivity in the form of disability, work loss, and premature mortality (respectively, $116 billion, and $58 in 2007), these estimates highlights the impact of diabetes on society.

The impact of diabetes on society also has a demographic consequence. Type 2 diabetes disproportionately affects several minority groups. Although diabetes can affect any segment of the population, it is particularly prevalent among Blacks, Hispanic Americans, Native Americans, and the elderly (Black, 2002). According CDC data from a 2007-2009 national survey, after adjusting for population age differences, the prevalence of diabetes by race/ethnicity among people aged 20 years or older was 7.1% for non-Hispanic whites, 8.4% for Asian Americans, 12.6% for non-Hispanic Blacks, and 11.8% for Hispanics (CDC, 2011a). Income is another demographic marker for diabetes management. For example, the rates of hospital stays among diabetes patients, increased as the income level of the patient ZIP Code decreased (Fraze et al., 2010). In a Healthcare Cost and Utilization Project (H-CUP) statistical brief, Fraze and Jiang report that there were 3,232 diabetes-related hospital stays per 100,000 persons from the lowest income quartile compared with 1,762 stays per 100,000 persons from the highest income quartile (Fraze et al., 2010), suggesting that income plays a major role in disease management and an important factor in preventing complications that lead to hospital admissions.

## Statement of the Problem

Diabetes is a complex disease and diabetes care is an even more complex proposition with issues beyond glycemic control. A large body of evidence exists that supports a range of interventions to improve diabetes outcomes. These standards of care are intended to provide clinicians, patients, researchers, payers, and other interested individuals with the components of diabetes care, general treatment goals, and tools to evaluate the quality of care (ADA, 2012b). Self-management behaviors (e.g. daily glucose checks and exercise) are the foundation for good diabetes care (CDC, 2011b). Successful self-management of diabetes equates to increased treatment compliance and reduced incidence of complications and hospitalization. Conversely, poor glycemic control and poor disease management often results in diabetes-related complications and are major reasons for hospitalization and readmissions (Ahern & Hendryx, 2007; H.J. Jiang, Stryer, Friedman, & Andrews, 2003; Tomlin, Dovey, & Tilyard, 2008).

Effective management therefore, offers a way of minimizing both the impact of diabetes on the individual by preventing or delaying the onset of debilitating complications (Nair, 2007) and societal impact of the disease by preventing or delaying expensive complication-related hospitalizations and readmissions (Anderson, 2007; Leff et al., 2009; Paradis et al., 2010; Vasquez, 2009). Because nurses play an important role in chronic disease management (Blank et al., 2011; Chiu & Wong, 2010; Han et al., 2010; Henderson & Nite, 1978; Hiss, Armbruster, Gillard, & McClure, 2007; Smeulders et al., 2010), they can have a tremendous impact in improving health outcomes for the hospitalized patient with diabetes. Many studies have linked nursing activities to patient health outcomes (Blegen, Goode, Spetz, Vaughn, & Park, 2011; Brooten & Naylor, 1995; Courtney et al., 2009; Halloran & Kiley, 1985; Welton & Halloran, 2005). By virtue of their close and sustained interactions with their patients, nurses are uniquely positioned to have a more comprehensive assessment of their patients' physical and psychosocial needs and are therefore important partners with their patients in treating and managing this very complex disease.

The information that nurses gather in the process of caring for their patients, for example, nursing diagnoses as bases for intervention planning, discharge planning, and nurses' evaluations of these interventions are a measure of patient outcomes and a proxy measure of quality of care. Given this, it is reasonable to expect that nurses' activities (i.e. the structure and processes of nursing care) and their impact on patient outcomes are unique and are independent of other healthcare professions'. Welton and Halloran (1999) demonstrated that nursing diagnoses are an independent predictor of patient outcome and highlights the contribution of nurses to patient care independent of medicine although doctors and nurses were treating the same patients at the same time. There is however, little in the literature to date that examines the relationship of nursing versus medical diagnoses in explaining patient health outcomes among a specific group of hospitalized patients- patients with diabetes mellitus.

## Purpose of the Study

Given the importance of patient data collected by nurses particularly in guiding nursing interventions and informing discharge planning, it is hypothesized here that the complexity of selected nursing diagnoses is related to patient illness severity and therefore has some influence on health outcomes and subsequently, patient discharge disposition. A patient's discharge disposition is affected by many factors, prominent of which are the patient's disease, length of stay, level of independence at discharge, and other patient characteristics such as age, sex, marital status, and payer type. An understanding of the relationship between the patterns of nursing diagnoses and patient factors can shed light on the decision process for patient discharge disposition. For example, it is important to know how the diagnosis of non-compliance, altered health maintenance or knowledge deficit affects patient's level of independence, and how this interacts with the above listed patient factors to decide the discharge disposition of the patient with diabetes. Successfully linking nursing diagnoses to nursing interventions that affect patient outcomes, might also further underscore the importance of nursing diagnoses as valuable patient data that are indicative of the quality of care provided by nurses.

Demonstrating that patients' information, for example, nursing diagnoses has value in differentiating patients with the same medical conditions might be indicative of the importance and uniqueness of nursing data. This might support the argument that nursing activities and indeed nursing information are independent of the medicine model and merits inclusion in the Uniform Hospital Discharge Data set (UHDDS).

This study therefore, examines (1) the relationships between nursing diagnoses use pattern and patients' International Classification of Diseases 9$^{th}$ revision (ICD-9) diagnosis codes, (2) the relationships between nursing diagnoses use pattern and patients' factors of hospital length of stay, age, marital status, race/ethnicity, payer type, and discharge disposition, and (3) the relationships between patients' factors and patients' discharge disposition.

*Research Questions*

The research questions (RQ) are:

**RQ1**: Can nursing diagnoses use pattern distinguish patients with primary diagnosis of type 2 diabetes mellitus (ICD-9CM 250.0-9) from other patients on the patient outcome of length of stay?

**RQ2**: What nursing diagnoses are associated with patients hospitalized for diabetes as primary diagnosis?

**RQ3**: What is the magnitude and direction of the correlation between the discrete independent variable of the number of nursing diagnoses and the continuous dependent variables of length of stay (LOS) and intensive care unit (ICU) days among hospitalized patients with diabetes?

**RQ4**: What is the relationship, between patients' discharge disposition (home, rehabilitation facility, nursing home, death, etc.) and the independent variables of age, gender, marital status, race/ethnicity, and payer type?

**RQ5**: Which of the 61 nursing diagnoses are more influential in explaining the variance in patient length of stay?

## Theoretical Framework

The goal of any healthcare provider-patient (client) interaction is to improve the patient's health condition and/or to enhance the patient's health outcomes. The end results of hospital care thus, are a surrogate measure of the quality of care provided and are linked to the structure and processes used by physicians and nurses (Donabedian, 1969). The extent to which both parties are successful in achieving good health outcomes depends on the interactions of a myriad of factors. With hospitalized patients, these interactions of factors occur within the structure of the institution. A theoretical framework that captures these dynamics is a system described by Donabedian as the structure, process, and outcome model.

The Donabedian model is one of the most recognized and widely used models for quality assessment of delivered health care (Rodkey & Itani, 2009). According to Donabedian, an essential feature of this model is that the events and processes that it portrays occur not in a vacuum but within particular settings (Donabedian, 1968). These settings might be tangibles and intangibles contributed by all the parties involved- client (patient), healthcare provider (doctors, nurses, etc.), and environment (institutions, communities, etc.). Donabedian argued that the characteristics of these settings, which include formal and informal organization, as well as social, economic and cultural factors, profoundly influence all the elements in the model: need, client behaviors in response to need, provider behaviors in response to client initiative, and client-provider interactions. With hospitalized patients, institutional structures (features) are hypothesized to influence patient care processes, which in turn, influence patient outcomes. Therefore, in considering the quality of nursing care, attention might be directed at issues that might be characteristic of three approaches to evaluation described in Donabedian’s model as structure, process, and outcome. Figure 1 is a diagrammatic representation of Donabedian’s model.

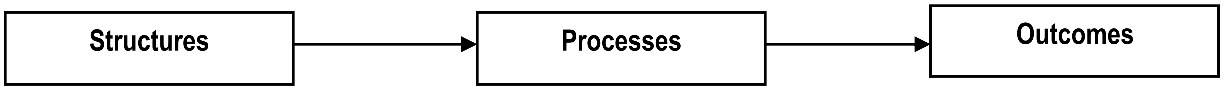


*Figure 1.* The Interrelated Components of Structure, Process, and Outcome.

Donabedian (1969) explains that the evaluation of structure entails the appraisal of the resources utilized in the delivery of care and of their organization. It includes the properties of facilities, equipment, manpower, and financing. The evaluation of process is an appraisal of the care itself; the nursing audit is an example of this approach. The evaluation of outcomes is the assessment of the end results of care, which are usually specified in terms of patient health, welfare, and satisfaction (Donabedian, 1969).

Study Model Overview

Applying this model to the management of hospitalized patients with diabetes brings the variables at play into focus as depicted in figure 2.

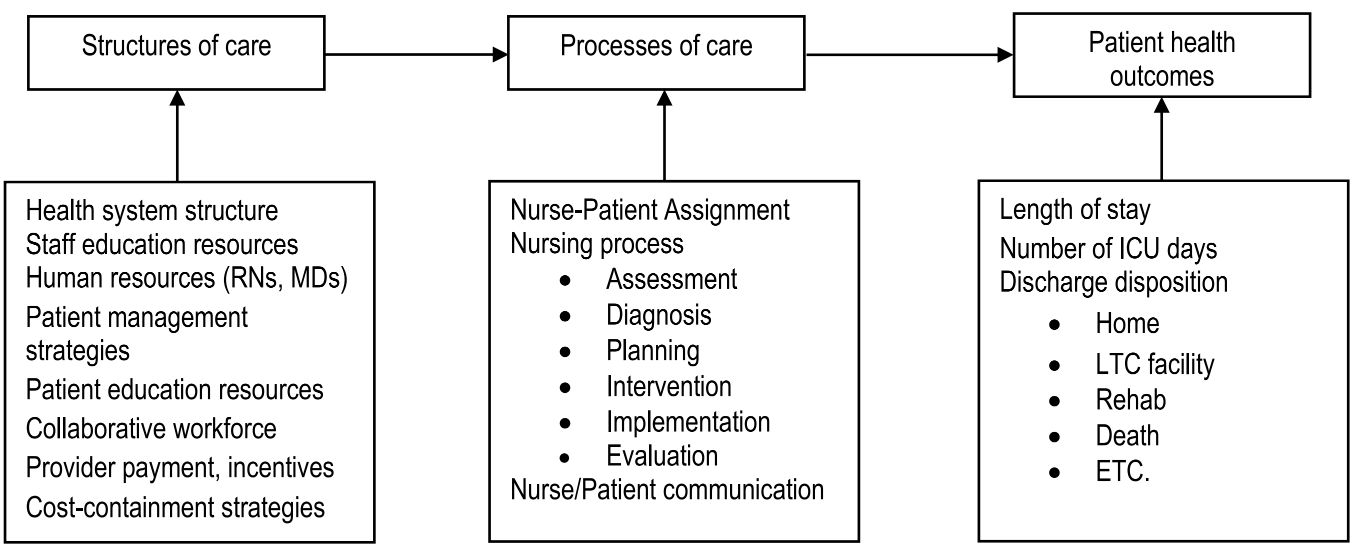


*Figure 2.* Interrelated Components of Structures Model in Hospitalized Patients Using the Nurse-Patients Summary Dataset.

In figure 2, the structures of care represent the prevailing culture or system in place within the institution (hospital) that guides patient care while simultaneously meeting other institutional objectives such as staff management and cost containment. In the study hospital only registered nurses (70% with earned BSN) were assigned to patients. This institution emphasized high patient satisfaction and thus made an effort to deliver excellent patient care at some additional cost. This is an important distinction in patient health outcomes because cost containment and excellent patient care are not always mutually inclusive. Processes of care include the activities in seeking care by the patient and the practitioner's activities in making a diagnosis and recommending or implementing treatment (Donabedian, 1988). Processes of care, in this context represents the steps taken by assigned nurses (focus is on nurses because the study is concerned with nursing diagnoses) to manage their patients' health conditions. The influence of structures on processes might be in the form of guidelines, policies and procedures, availability of resources and equipment that aids in care delivery, continuing education opportunities, staff support, staff recognition and validation, etc. Outcome is the effects of care on the health status of patients (Donabedian, 1988), and in this context, an evaluation of patient discharge disposition represents the outcome measure. This is because nurses for example, might view a discharge of patients to their own homes as a success, having been able to help the patient attain or get near pre-admission level of functioning; on the other hand, a discharge to nursing home or to another acute care facility might signify nursing failure. Although an argument could be made that patient discharge disposition is a poor measure of patient health outcome because some patients might prefer a discharge to a nursing home perhaps due to a lack of an adequate support system to enable a discharge to own home. A plausible counter argument is that the inability of nursing to help the patient attain a level of independence that eliminates the option or the need for discharge to a nursing home is due to many factors, factors that are related to both patient and nursing care. And these factors are worth investigating.  For this reason, the information that nurses collect and record in the implementation of the nursing assignment process, particularly diagnoses and evaluation of intervention, becomes an important barometer of quality of care which is closely linked to patient health outcomes.

The Nurse-Patient Summary data set (Halloran, Kiley, & England, 1988) was accumulated from two data-gathering systems. These are the International Classification of Diseases (ICD) 9th revision and the derivative diagnose-related groups (DRGs), and a tool containing a list of 61 nursing diagnoses. The ICD is used by the physicians to classify patient health conditions. Nursing diagnoses are derived from nurses' assessments of patients' health needs amenable to nursing interventions that guide nurses in the management of their patients' health conditions. It is necessary to offer a brief overview of these two methods of data-gathering of patient records.

*International Classification of Diseases (ICD) and Diagnosis-related group (DRG)*

The extent to which the medical diagnosis of diabetes is valid in the proposed secondary analyses of this data collected by Halloran et al. (1988) depends less on the test used in the diagnosis of diabetes in the hospitalized patients than on the structural and process dimensions of care quality measurement as defined by Donabedian (1988). All physicians making the diagnosis were either board certified internists or in training and under supervision of board certified internists- what Donabedian calls structure. Further, the physicians were members of the staff of a teaching hospital and were required to practice 'textbook' medicine, in Donabedian's framework- processes (personal communication, E. J. Halloran, February 16, 2012). At the minimum, we can ascertain that all patient diagnoses are based on the ICD-9-CM code list. For example, code 250 (diabetes) was used to represent diabetes, diabetes mellitus, high blood glucose, juvenile diabetes, and adult-onset diabetes or diabetic neuropathy. The use of the administrative databases such as the Uniform Hospital Discharge Data Set (UHDDS) that employs the International Classification of Diseases, 9$^{th}$ Revision (ICD-9) to summarize the results and findings of physicians as a recording tool of patient medical condition are well documented (Guttmann et al., 2010; Quan et al., 2008; Quan, Parsons, & Ghali, 2004). These administrative databases often include the demographic characteristics and diagnoses of patients and codes for procedures.

The ICD-9 is an example of a component of administrative database that is readily available, inexpensive to acquire, computer readable, and typically encompass large populations (Iezzoni, 1997). Although there is a current debate over the accuracy and thus, the utility of administrative databases in clinical research, they represent a rich source of not only general patient information but also of disease epidemiology. The three major producers of administrative databases are the federal government (including the Health Care Financing Administration [HCFA], which administers Medicare and oversees Medicaid; the Department of Defense; and the Department of Veterans Affairs), state governments, and private insurers (Iezzoni, 1997), and because their source documents contain the minimum amount of information required to perform the relevant administrative function (for example, to verify and pay the claims) they do not often contain much clinical information suitable for clinical research. However, their usefulness as a source of patient demographic information and disease epidemiology is adequate for identifying and categorizing patients by disease presentation for the purpose of secondary analyses. The value of the ICD codes in the proposed data analysis is in their use as a patient classification tool. For example, ICD code 250 represents patients with diabetes mellitus, 290 for patients with dementia and 410 for patients with acute myocardial infarction, etc. This allows for a possible comparison of nursing diagnosis use pattern for any group of patients in the Nurse-Patient Summary data set.

*Nursing Data*

Although the healthcare delivery system is based on the physician's medical model of diagnosing and treating illness, as evidenced by the prominence of the ICD codes in the UHDDS, nursing's impact on the delivery of health care services is perhaps even more significant even if not fully appreciated in the patient discharge summary. Nurses provide those services that the patent would perform unaided to maintain health or its recovery if the patient had the strength, will or knowledge; and they perform those activities that would enable the patient to gain independence as rapidly as possible (Henderson & Nite, 1978).

Werley and Lang (1988) defines the Nursing Minimum Data Set (NMDS) as "…a minimum set of items of information with uniform definitions and categories concerning the specific dimension of professional nursing" (p. 7), composed of six components. These six components of the NMDS are nursing assessment, nursing diagnoses, nursing interventions, patient health outcomes, nursing intensity and patient demographic information (Werley & Lang, 1988). In the Nurse-Patient Summary data set, nursing diagnoses predominate, interventions are recorded at the nurse-patient assignment level, outcomes are the resolution of nursing diagnoses, demographics are drawn from the uniform hospital discharge data set (UHDDS) and intensity is derived from the number of and frequency of different nursing diagnoses. The Nurse-Patient Summary data set recorded all the nurses assigned to each patient and supplemented the nurse database with information about nurse education, experience, and certifications (E. J. Halloran, personal communication, February 16, 2012).

Nurses record patient data in several ways and in several forms. The traditional way nurses record information had been to document patient's health-related activities in the form of 'progress notes' in hard copy patient charts, though this form is now rapidly being replaced by computerized charting. Another method by which nurses gather and record patient data is as an abstracted form of patient classification system. Patient classification tools such as nursing management information system (NMIS) have been used to determine nursing resource needs of patients by hospitals across the United States for many years (Jelinek & Pierce, 1982). The Nurse-Patient Summary checklist based primarily on nursing diagnoses (Halloran, Patterson, & Kiley, 1987) is an example of a tool that nurses use to collect patient data. This tool provided the foundation on which the Nursing Severity Index (NSI) was developed (Rosenthal, Halloran, Kiley, & Landefeld, 1995; Rosenthal, Halloran, Kiley, Pinkley, & Landefeld, 1992). In the process of developing and validating the nursing severity index, Rosenthal and colleagues (1992) found that the initial hospital rating of 61 nursing diagnoses from the Nurse-Patient Summary checklist explained variations in mortality rates of hospitalized patients. The findings suggest that an alternative source of data can independently predict patient mortality using data collected exclusively by nurses.

This distinction in utility of the ICD-9 and the derivative DRGs and nursing data is important because nurses and physicians represent different physical and organizational structural components of care (Donabedian, 1988), and as Welton and Halloran (2005) contend, are functionally different. They argue that not only are the processes of care different between nurses and physicians, the administration of each is functionally separate as evidenced by different lines of authority, different licensing requirements, different education, and so forth. Furthermore, outcomes expectations may be different as well. Physicians may see deaths as a failure when nurses see a peaceful death as desirable outcome in late stages of chronic diseases. And as stated earlier, nursing home discharges might indicate failure of nursing to archive pre-hospitalization level of independence for the patient, while physicians might view the transition of care to this level as appropriate.

# CHAPTER 2

# REVIEW OF THE LITERATURE

*Overview*

This chapter is a brief review of the literature that is focused on four main concepts - nursing diagnosis, Medical diagnosis of diabetes, nurses' role in diabetes management, and patient factors (e.g. patient age, sex, marital status, race/ethnicity, education, family/social support, and payer type as a proxy measure of socioeconomic position) that in the context of this study are important concepts in the health outcomes of the patient with diabetes. A review of historical and contemporary works and studies that have attempted to examine the link between nursing diagnosis and patient outcomes is presented. A brief discussion is also presented on the reliability and validity of nursing diagnoses.

## Nursing Diagnosis

The circumstances under which nurses practice have always affected their roles in diagnosis and decision-making (Henderson & Nite, 1978). In many instances, nurses have to rely on their assessment skills to make a judgment on the condition of their patients and plan an appropriate intervention independent of physicians. The importance of the nurse's role in the diagnosis and treatment of patients' conditions is exemplified in the statement by Henderson and Nite (1978) in noting that:

Nurses working on islands and in remote rural areas where there are no doctors have been forced to take histories, do physical examinations, analyze their findings, "diagnose" or label the "presenting problem" or problems, and institute action or "treatment," and they have been very effective (Henderson & Nite, 1978).

This statement by this preeminent nurse pioneer highlights the long history of nursing diagnosis even before it was formally defined in nursing literature. Although not described as nursing diagnoses, Abdellah and colleagues published a list of nursing problems that are the basis for the development of a scientific body of knowledge that is uniquely nursing. In their classic work: *Patient-Centered Approach to Nursing*, Abdellah, Beland, Martin, and Matheney (1960) listed 21 nursing problems that formed the bases for the movement to a patient-centered curriculum for nursing education programs. These 21 nursing problems (Appendix B) represent the core of patient problems amenable to nursing interventions and feature prominently in contemporary lists of nursing diagnoses.

Fry (1953) first introduced the term nursing diagnosis in 1953 to describe a step necessary in developing nursing care plan (Carpenito-Moyet, 2006). In1973, a national task force was convened in St. Louis, Missouri under the auspices of the First National Conference for the Classification of Nursing Diagnoses (J. J. Fitzpatrick et al., 1989). The mandate to the delegates was to formulate a standardized language for nursing diagnoses by developing and constructing the nursing diagnosis classification system. The deliberations in this first national conference built on the early work of Gebbie and Lavin at defining and creating a list of nursing diagnoses. Gebbie and Lavin (1974) pioneered what is widely considered as the earliest effort to organize a standardized nursing diagnosis terminology (Wong, 2008). In their seminal article "Classifying Nursing Diagnoses, Gebbie and Lavin (1974) published a list of 34 tentative nursing diagnoses which they described as the identification of those patient problems or concerns most frequently identified by nurses. They argue that these problems, which are usually identified by nurses before they are recognized by other healthcare workers, are amenable to some nurse-sensitive interventions prescribed in the present or potential scope of nursing practice (Gebbie & Lavin, 1974). In 1982 the conference was opened to the general nursing community and thus the North American Nursing Diagnosis Association (NANDA) was formed (J. J. Fitzpatrick et al., 1989).

However, during the diagnosis-review cycle of 1986 to 1988, NANDA still did not have an approved definition of nursing diagnoses (Carpenito, 1991). In 1987 the American Nurses Association adopted NANDA's International Classification, and in 1989, the International Council of Nurses recognized NANDA as the definitive source of nursing diagnoses (Carpenito-Moyet, 2006). At the ninth conference of NANDA, the General Assembly approved an official definition of nursing diagnosis (NANDA, 1990). In 1990 NANDA, in conjunction with Board of Directors and the Taxonomy Committee  defined nursing diagnosis as a clinical judgment about individual, family, or community responses to actual or potential health problems/ life processes which provides the basis for definitive therapy toward achievement of outcomes for which the nurse is accountable (Carpenito, 1991). Through the widespread testing, acceptance and expansion of NANDA's definition, it gained international recognition (Wong, 2008). More recently, nursing diagnosis has been succinctly described as the conclusions or judgments made about the component of patient situations of concern to nurses (Renpenning, SozWiss, Denyes, Orem, & Taylor, 2011).

Prior to this point, patient issues of concern for which nurses were accountable and provided interventions were labeled "nursing problems" (Müller Staub, Needham, Odenbreit, Ann Lavin, & Van Achterberg, 2007). These problem statements often lacked structure and universal meaning for nurses (M. Lunney, 2003; Zielstorff, Tronni, Basque, Griffin, & Welebob, 1998). These problems were worded in freestyle and nursing goals and interventions were chosen according to these patient problems  (Müller Staub et al.). Indeed, "nursing problems" were sometimes used to describe problems of nurses rather than patients' health problems leading to inaccurate problem formulation and consequently, inappropriate nursing goal setting (Müller Staub et al.). Because of these inconsistencies, nursing diagnoses struggled to establish its own identity mainly in the validity and accuracy of the labels used. In recent years however, patient problem statements have become more structured and clearer in describing patient conditions (Von Krogh, Dale, & Nåden, 2005). Nursing diagnoses have also become slightly more accepted as a method of describing patients' needs that are amenable to nursing interventions (Vincent & Coler, 1990). This trend towards a wider acceptance and use of nursing diagnosis is probably due to the increasing amount of research studies establishing the validity of nursing diagnoses (Levin, Lunney, & Krainovich-Miller, 2004). For example, in an attempt to determine the diagnostic content validity of the most used nursing diagnoses Levin (1984) conducted a review of the research related to nursing diagnoses. This review revealed approximately 70 studies, 35 of which were concerned with identifying and/or validating nursing diagnostic labels. Of these 35 studies, the majority (26) focused on identifying defining characteristics, etiologies and diagnostic labels. Despite this gap in validation studies, it is encouraging to see that even at this early stage of development of nursing diagnosis, the nursing profession has been concerned with efforts to standardize the language nurses use to describe their patients' condition and efforts were already underway to elevate the status of nursing diagnosis.

Some of the works intended to standardize terminology have been described in descriptive studies because the papers were concerned with examining the incidence of use of many of the nursing diagnoses already on the NANDA list (Levin, Krainovitch, Bahrenburg, & Mitchell, 1989). These studies include Castles, 1982; Collard, Jones, Fitzmaurice, Murphy, 1983; Halfmann & Pigg, 1984; Halloran, Kiley & Nadzam, 1986; Jones & Jakob, 1982; Kim, et. al, 1982; Kim, et. al, 1984; Leslie, 1981; Martin & York, 1984; Miaskowski & Garafallou, 1986; Silver, Halfmann & McShane, 1984; and Simmons, 1980 as cited in Levin et al. (1989).

Fundamental to making a diagnostic statement is the understanding that there is a diagnostic process that must take place before labeling. Renpenning et al. (2011) argues that both the process and the labels must have a common meaning that is derived from a conceptual theoretical understanding of the object of nursing to be useful to nursing practice. The focus of nursing diagnosis is different from that of medicine. A nursing diagnosis is unlike a medical diagnosis in that nursing diagnoses are based in a conceptual model of human action, not human disease (though these are not unrelated) E. J. Halloran (personal communication, March 10, 2011) (Renpenning et al., 2011). A quick review of the literature on nursing diagnosis studies indicates that while much has been written on validation of nursing diagnosis, particularly in enumerating defining characteristics that support the growing list of nursing diagnoses, little has been done in linking nursing diagnosis to patient outcomes. This gap is especially acute in the subpopulation of patients with diabetes. Hospitalized patients with diabetes represent an excellent population suitable for investigating the link between nursing diagnosis and patient health outcomes because of the complex disease management processes.

*Validity of Nursing Diagnosis*

A valid nursing diagnosis is one that is well grounded in evidence and is able to withstand the criticism of professional nurses (Fehring, 1987). Renpenning et al. (2011) describes two primary ways of arriving at a nursing diagnosis. One is using an intuitive process whereby nurses describe and label phenomena that they see in clinical situations. These labels are developed in a shared process with other nurses and knowledge is developed from common understanding of what nursing is, and substantiated with knowledge from other sciences. The knowledge generated this way is then used as a basis for taking action. The second way of establishing nursing diagnoses is theoretically based. Working from a general theory of nursing, the process-operations of nursing are described, categories are established, and appropriate labels are constructed. Consideration of process leads to a discussion of domain and structure of knowledge (Renpenning et al., 2011).

In a review of the literature on the discussion of the validity of nursing diagnosis, the importance of the phrase "defining characteristics" in describing the relevance of the diagnostic labels used by nurses is evident. Elaborating on the validity of nursing diagnosis, Gordon (1987) asserts that validity describes the degree to which a cluster of defining characteristics describes a reality that can be observed in client-environmental interaction. In affirming this definition, Fehring adds that a set of defining characteristics expands the understanding of a nursing diagnosis and contends that a nursing diagnosis is essentially a cluster of characteristics that nurses put a label on for communication purposes. These defining characteristics are valid when they actually occur and can be identified as a cluster in the clinical situation (Fehring, 1987).

There is no doubt that the issue of determining accuracy of nursing diagnosis is problematic on many levels, particularly as nurses' information about their patients are often influenced by nurses' own lived experiences, which include sociocultural background and personal biases and also professional experiences which include level of education, clinical assessment skills, and years of experience working with a specific patient population. Some of these problems also stem from the nature of the information itself, and that is the inherent variability of human responses to their health status. Rapley, O'Connell, and Lunney (1997) argue that while humans may have similar cellular responses, individual behavioral responses are less predictable. They reasoned that the physiologically derived nursing diagnoses, which may be linked to a patient‘s medical condition make the cues for the nursing diagnosis more easily identified as they are based on signs and symptoms that arise from the pathology, and are thus, more apparent and objective. They further contend that, diagnosing these types of problems is not influenced by the nurse’s values and beliefs or their cultural background. Therefore it is easier to list, for example, the defining characteristics for the nursing diagnoses of urinary incontinence, activity intolerance, and impaired gas exchange. On the other hand, nurses, for example, may struggle with justifying with objective defining characteristics, the nursing diagnoses of knowledge deficit, disturbed self-concept, noncompliance and even pain- which tend to present with less concrete physical symptoms.

These issues notwithstanding, nursing diagnosis’ claim to validity and reliability has many merits. Symptomatic nursing diagnoses such as pain, anxiety, fear, and others related to human functions such as breathing, nutrition, and elimination are related to the professional literature in nursing, especially evidence-based textbooks such as *Principles and Practices of Nursing*, 6th edition (Welton & Halloran, 2005). The manner in which nursing information is collected also gives credence to nursing diagnosis. Nursing diagnosis can be collected concurrently in the clinical environment and summarized in the hospital discharge abstract. This type of patient classification is superior to techniques that rely on coding after a patient is discharged such as ICD-9-CM and diagnostic-related group (DRG) codes (Welton & Halloran, 2005). Furthermore, nurses, by virtue of having close and sustained contact with their patients, more than any other healthcare professional are uniquely positioned to have a more holistic assessment of their patients’ healthcare needs. Hence, nurses are privy to patient problems or needs that are sensitive to nursing intervention. And the most common way of documenting these problems is through the use of nursing diagnoses (Halloran et al., 1988). Nursing diagnosis therefore has become an important source of patient health information and healthcare providers from various fields have come to rely on this information gathered by nurses to inform the care that they provide.

To further underscore the validity of nursing diagnosis, nursing diagnoses serve as the basis for intervention and is validated by patient outcomes. Outcomes that link diagnoses and interventions direct nurses to focus on the outcomes of the care they provide (Micek et al., 1996). If patient outcome is the focus for evaluating the effectiveness and appropriateness of patient care, it follows therefore that the validity of nursing diagnosis is a factor in the effectiveness of nursing intervention as evidenced by achievement of desired health outcomes. Nursing information, which essentially, is a recording of the nursing process- assessment, diagnosis, planning, implementation, and evaluation, is thus, an important database of nursing activity and account of nursing's contribution to healthcare. Patient data, particularly nursing diagnoses have been used in studies to explain variations in many patient outcomes such as hospital length of stay (Halloran et al., 1988), patient functional status (Halloran, 1988), severity of illness (Rosenthal et al., 1995; Rosenthal et al., 1992) and hospital discharge outcomes (Welton & Halloran, 2005).

## Medical Diagnosis of Diabetes

A diagnosis of diabetes mellitus has far-reaching implications and should be made with absolute certainty. Because of the considerable consequences and the life-long impact of the label of diabetes, if a diagnosis of diabetes is made, the clinician must be certain that the diagnosis is fully established (Alberti & Zimmet, 1998). But the complex nature of diabetes makes a definitive diagnosis of diabetes difficult. This is compounded by the fact that clinicians and other healthcare professionals do not often agree on a single, universal test or criteria for establishing a diagnosis of diabetes. An individual's health status also impacts the clinician's ability to diagnose diabetes. For example, severe hyperglycemia detected during acute infective, traumatic, circulatory or steroid therapy conditions is transitory and should not in itself be regarded as diagnostic of diabetes (Alberti & Zimmet, 1998).

Currently there are several tests in use and differentially favored by clinicians and researchers in a variety of settings. Although they each have shortcomings, these tests have been in use for a long time. These diagnostic tests include fasting plasma glucose (FPG), oral glucose tolerance test (OGTT), glycated hemoglobin levels ($HbA_{1c}$), and random blood glucose concentration (Peters, Davidson, Schriger, & Hasselblad, 1996). However, the lack of agreement on a single, reliable test for diagnosing diabetes, in the least, means that the criteria for finding and treating diabetes is disjointed and only perpetuates the issue of under-diagnosis (Saudek et al., 2008).

Furthermore, many physiological manifestations of early and late stages of diabetes are also associated with other diseases not related to diabetes. For example, excessive thirst often associated with diabetes (Clark, Fox, & Grandy, 2007) mimics the major side effect of lithium carbonate therapy (Burgess et al., 2001; Lee, Jampol, & Brown, 1971). Polyuria (excessive urination) seen in untreated diabetes is also seen in antidiuretic hormone deficiency (Stuart, Neelon, & Lebovitz, 1980). Thus, there is a need to reexamine the validity and reliability of diabetes diagnosis particularly among certain groups for which application of current criteria for establishing the presence of diabetes is ambiguous.

*Definition*

What is diabetes mellitus? The term diabetes mellitus describes a metabolic disorder of multiple etiologies characterized by chronic hyperglycemia (high blood glucose level) with disturbances of carbohydrate, fat and protein metabolism resulting from defects in insulin secretion, insulin action, or both (ADA, 2010; Silverthorn, 2007; WHO, 1999). Type 1 diabetes, formerly known as juvenile diabetes is a much less common condition, accounting for about 5% of all diabetes cases in the United States (ADA, 2012a), but is the more prevalent form among children and adolescents. In this autoimmune disease, there is a permanent destruction of insulin-producing beta cells of the pancreas resulting in inadequate or complete cessation of insulin production by the pancreas (Ritchie, Ganapathy, Woodward-Lopez, Gerstein, & Fleming, 2003). Lifestyle choices such as sedentary tendencies and body weight status do not appear to play a primary role in the development of this form of diabetes, but they may hasten its appearance (Ritchie et al.). Figure 3 shows the types and stages of diabetes and level of insulin dependency.

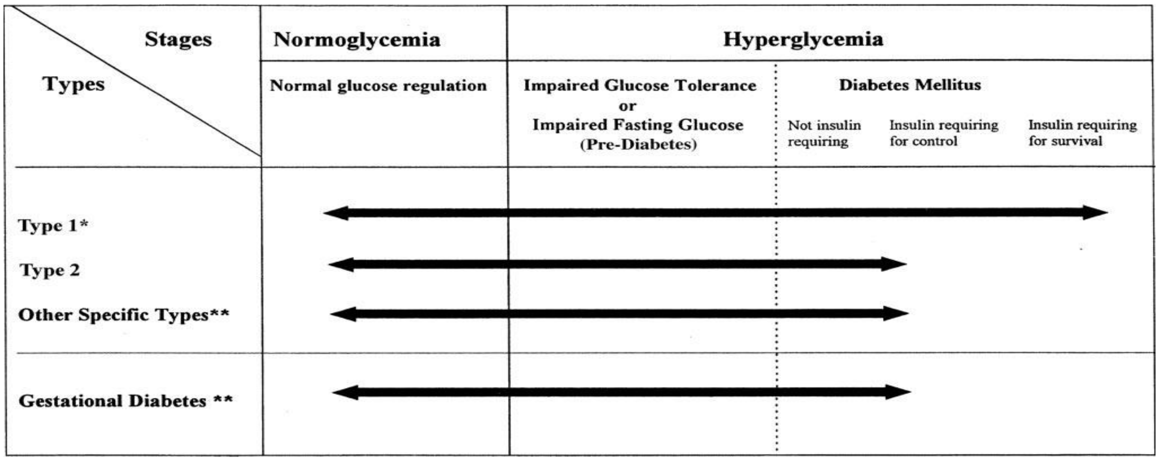


*Figure 3.* Disorders of Glycaemia: Etiologic Types and Stage. Adopted from the World Health Organization (WHO) 1999 report on diagnosis and classification of diabetes mellitus.

Type 2 diabetes mellitus (T2DM), variously known as adult-onset or non-insulin dependent diabetes mellitus (NIDDM) is a chronic condition that affects the way the body metabolizes glucose. In Type 2 Diabetes Mellitus, there is a delayed response to an ingested glucose load (Silverthorn, 2007). The body is either resistant to the effects of insulin, a hormone that regulates the absorption of glucose into cells, or the body may produce some, but not enough insulin to maintain a normal glucose level. Type 2 diabetes involves various degrees of beta cell failure (rather than absolute) resulting in peripheral insulin resistance which is the reduced ability of the liver, fat, and muscle cells to respond to insulin (DeFronzo, 1988). There is yet another type of diabetes-gestational diabetes mellitus is carbohydrate intolerance with onset or first recognition during pregnancy (Metzger et al., 2007). Gestational diabetes mellitus affects about 14% of pregnant women in the United States (Jovanovic & Pettitt, 2001). Although this type is not a focus of this paper, it is important however, to point out that the current discussion of reliability and validity of diagnosis of diabetes also applies to this important form of diabetes if for no other reason, but the fact that it has been shown to persists after the pregnancy or convert to type 2 diabetes mellitus a few years later (Jovanovic & Pettitt, 2001; Kim, Newton, & Knopp, 2002).

*Diagnosing Diabetes Mellitus*

Historically, the oral glucose tolerance test (OGTT) has been the main method for diagnosing diabetes (Lundbaek, 1962; Molinaro, 2011; Peters et al., 1996). Diagnosis is made based on results of multiple measures of elevated fasting plasma (>126 mg/dl) or an abnormally high plasma glucose level (>200mg/dl) (T. T. Huang & Goran, 2003). The OGTT involves the ingestion of an oral glucose solution containing up to 75grams of dextrose (or equivalent carbohydrate content) following a fasting period of 8 to 14 hours (WHO, 1999). The underlying premise is that in non-diabetic individuals, the spike in blood glucose levels at any point during the two hours following an ingestion of 75grams of a sugary solution is less than 200mg/dl and this is quickly followed by a drop to pre-ingestion level. In an individual with diabetes, serum glucose levels rise higher than normal during the two-hour period post glucose solution ingestion, and fails to come back down as fast. A blood glucose level of 140mg/dl to 199mg/dl (milligrams per deciliter) indicates impaired glucose tolerance, and a result above 200mg/dl indicates a diabetic condition (T. T. Huang & Goran, 2003). The problem with this test is that it is cumbersome and inconvenient. The main issue with the OGTT is that it requires the patient to fast 8-14 hours prior to testing for a baseline measurement blood glucose level. In making a case for an intravenous glucose tolerance test, an alternative that has so far failed to gain wide acceptance, Lundbaek listed some shortcomings of the oral glucose tolerance test. He described the OGTT as a clumsy test that takes too long to perform and the result dependent on ‘the state of the digestive tract’(Lundbaek, 1962).

Another commonly used diagnostic test is the fasting plasma glucose test (FPG) However, despite its wide acceptance, the use of this plasma glucose test has also been associated with some shortcomings. For example, the FPG test requires that the patient fast for at least eight hours- a major problem because of the challenge for a physician or a laboratory to enforce or for a patient to adhere to (Molinaro, 2011). In addition, there is also within and between patient biological variability in the measurement of plasma glucose levels (Ollerton et al., 1999; Troisi, Cowie, & Harris, 2000) that can confound result interpretation. In their analysis of data from the US population–based Third National Health and Nutrition Examination Survey (1988-1994), Troisi and colleagues found diurnal variations in fasting plasma glucose levels in participants aged 20 years or older with no previously diagnosed diabetes, who were randomly assigned to morning (n=6483) or afternoon (n=6399) examinations. The result of this study indicates that the time of day a patient is tested for diabetes could affect the result of the test and thus affect the physician's impression about the patient's diabetes status. (Peters et al., 1996). Despite their acceptance, plasma glucose tests (fasting plasma glucose test and oral glucose tolerance test) are not optimal.

The requirement that patients must fast prior to testing and the need for multiple testing at different times and at different visits are serious obstacles, these obstacles can affect the reliability and validity of diabetes diagnosis. For these reasons there is a renewed interest in the hemoglobin $A_{1c}$ test ($HbA_{1c}$). This test is a measure of the average blood glucose level over the previous 2 to 3 month period. It is determined by measuring the percentage of glycated (glycosylated) hemoglobin, or $HbA_{1c}$, in the blood (Buell, Kermah, & Davidson, 2007; M.B. Davidson, Schriger, Peters, & Lorber, 1999). One major advantage of $HbA_{1c}$ over other tests used in diagnosing diabetes is that it does not require that patients fast prior to being tested

(Saudek et al., 2008). Indeed, the $HbA_{1c}$ has several advantages over the FPG or the OGTT. Whereas a few days of dieting or increased exercise in preparation for a doctor visit can significantly affect FPG and OGTT, $HbA_{1c}$ accurately reflects longer-term glycemic status (Saudek & Golden, 1999). Furthermore, even though the $HbA_{1c}$ is only a surrogate measure for average blood glucose, two major (Barr, 2001; Manley, 2003) trials that relate glycemic control to diabetic microvascular complications uniformly use $HbA_{1c}$ as the measure of glycemia. As a result, the $HbA_{1c}$ is thus the measurement best proven to correlate with at least diabetic retinopathy, nephropathy and neuropathy (Saudek et al., 2008) which together, perhaps represent the greatest source of complications for people with diabetes.

In establishing the validity of the $HbA_{1c}$, discussion must necessarily focus on the accuracy, sensitivity, and specificity of $HbA_{1c}$ as a screening and diagnostic tool for diabetes. In a study to examine the relationship between $HbA_{1c}$ and plasma glucose (PG) levels in patients with type 1 diabetes using data from the Diabetes Control and Complications Trial (DCCT) Rohlfing et al. (2002) analyzed the Third National Health and Nutrition Examination Survey (NHANESIII) for the sensitivity and specificity of $HbA_{1c}$ in the diagnosis of diabetes based on fasting plasma glucose (FPG). They concluded that $HbA_{1c}$ provided a specific and convenient approach to screening for diabetes and suggested a value of 6.1% or greater, 2 SD above the mean in the normal NHANES III population.

In the same vein, in an effort to determine the sensitivity and specificity with which various A1C levels identified people with diabetes, Buell et al. (2007) recently completed a similar analysis based on the 1999–2004 NHANES data. The diagnosis of diabetes was considered established if FPG was 126 mg/dl or greater. Using a ROC analysis, they found that $HbA_{1c}$ of 5.8% or greater is the point that yielded the highest sum of sensitivity (86%) and specificity (92%). They concluded that $HbA_{1c}$ of 5.8% would be an appropriate cut point above which to proceed to further evaluation.

This suggests that $HbA_{1c}$ is a valid and accurate test in evaluating and diagnosing the glycemic status of patients. Indeed, the International Expert Committee on diabetes in a 2009 report concluded that overall, the $HbA_{1c}$ assay has merit for the diagnosis of diabetes (Nathan, 2009). Also, in a report prepared for the World Health Organization (WHO), diabetes experts described the $HbA_{1c}$ test as a simpler alternative to blood glucose estimation or the OGTT with equal or almost equal sensitivity and specificity to glucose measurement (Alberti & Zimmet, 1998). Furthermore, most of the problems that hitherto hindered a wider acceptance and adoption of the test as a diagnostic tool have been addressed in recent years. Most prominent among these, are the issues of standardization of the $HbA_{1c}$ test and the availability of the test in developing countries and other remote parts of the world. Under the auspices of the National Glycohemoglobin Standardization Program (NGSP), remarkable strides have been taken in standardizing $HbA_{1c}$ assays in many nations worldwide (Little, 2003; Little et al., 2001; Sacks, 2005). Regarding the issue of availability, Saudek et al. (2008) argues that although blood glucose measurement is the most widely available test, the addition of $HbA_{1c}$ among accepted diagnostic criteria would not adversely affect centers that cannot perform the test.

## Patient Factors Affecting Health Outcomes

### *Age*

Age is an important determinant of health outcomes. Older adults for instance often suffer from several chronic diseases; these diseases might include diabetes, heart disease hypertension and diseases of the respiratory system. Studies have shown that patients with multiple comorbidities often have poorer health outcomes and are likely to have longer hospital stays and readmissions. In a systematic literature review, Scott (2003) found that increasing age and the co-existence of diabetes mellitus, renal disease, chronic obstructive lung disease, major mental health disorders, and significant co-morbidity burden were associated with underuse of effective therapies resulting in poorer health outcomes for older hospitalized patients.

Age is related to the number of chronic illnesses presented at admission. Older patients tend to have more chronic disease. They also tend to have advanced stages of diseases by virtue of having had the diseases over a longer period (Kirkland & Sinclair, 2011). For example, in type 2 diabetes, a 20 year diabetic is likely to have fewer complications compared to an 80 year old who has had several decades of the disease. In a recent study, $HbA_{1c}$ levels, an indicator of glycemic control rose by 0.10% per decade in people between ages 40 and 74 (M. B. Davidson & Schriger, 2010), suggesting poorer disease control. Poor disease management leads to more complications.

As chronic diseases advance to late stages, they tend to have more impact on daily functioning, independence, and even quality of life. In the case of diabetes, older age tend to usher in diabetes related complications and impaired cognitive ability (Kirkland & Sinclair) which can dictate patient discharge disposition following hospitalization. One finding that is counterintuitive was reported by Higashi and colleague (2007), in which patients with several chronic diseases reported higher quality of care. The quality of care increased as the number of medical conditions increased. The study involved a total of 7680 patients in three cohorts of community-dwelling adult patients in the Community Quality Index study, the Assessing Care of Vulnerable Elders study, and the Veterans Health Administration project. The researchers found that for each additional condition presented by patients there was an associated increase in the quality score of 2.2% (95% confidence interval [CI], 1.7 to 2.7) in the Community Quality Index cohort, of 1.7% (95% CI, 1.1 to 2.4) in the Assessing Care of Vulnerable Elders cohort, and of 1.7% (95% CI, 0.7 to 2.8) (Higashi et al., 2007). This finding suggests that the number of illnesses, at least in this group did not negatively affect perception of quality of care; rather the increased utilization of care services was predictor of quality of care. Age therefore, it would seem, is a stronger predictor of health outcomes. The authors did not discuss if any, the additive effects of age.

*Marital Status and Family/Social Support*

Marital status is a variable of interest because of the presumptive support that married patients receive from their spouses upon discharge to home. Several researchers have documented the relationship of marital status and patient health outcomes that affect discharge dispositions. For example, in a study (*N*=6006) that aimed to compare characteristics of patients discharged to the community and those discharged to nursing homes, and to identify predictors of nursing home placement, Smith and Stevens (2009) found that significant predictors of being discharged to nursing homes included longer hospitalizations, not understanding one's illness, being female, living alone, not having a caregiver, needing assistance with dressing, and having a fall risk (Smith & Stevens, 2009). In another study to determine if predisposing factors, such as age, gender, race, living situation (alone or with family or friends), marital status, education, and income were related to poor outcomes as evidenced by post-discharge service use (re-hospitalizations, ED visits, and acute unscheduled physician office or clinic visits) for elders hospitalized with an acute exacerbation of heart failure, being single was related to re-hospitalization (Roe-Prior, 2007). During the 12-week period after the initial hospitalization, 43 patients had all-cause re-hospitalizations (total of 57 readmissions), in the model with the best fit (Multiple regression), being unmarried predicted all-cause re-hospitalization (Roe-Prior, 2007). In a similar study, though with non-statistically significant statistical result, Luttik, Jaarsma, Veeger, and van Veldhuisen (2006) found that married patients had 12% less events in the 9-month follow-up period compared with patients living alone. This study examined the impact of having a partner on quality of life, the number of hospital readmissions, and 9-month survival in patients with heart failure.

The findings from these studies point to the importance of family support or spousal support in at least short-term outcomes of hospitalized patients following discharge. The availability of such support is often a determinant of discharge disposition other than death. Healthcare providers including the nurse who is often an integral part of the discharge-planning team will often inquire about family members who can help with patient care after discharge. In the older patient, this family member is often the spouse, although it could also be the patient's adult children. The purpose of such inquiry by the nurse is to know which responsible party should be entrusted with discharge instructions, whom the patient may depend on for post discharge care and keeping scheduled post discharge doctor's appointments. In the present era of diagnosis-related group (DRG) rather than cost-based system of reimbursement, length of stay is often determined by the patient's diagnosis and predetermined course of patient management. As a consequence, patients are leaving the hospital sooner and perhaps sicker than in the past. Thus, family support is needed to help with care at home, and the question about marital status becomes a proxy measure for the availability of home care following discharge. Where this is lacking, healthcare providers might consider alternative discharge disposition for the patient.

*Sex*

Sex is an important determinant variable of patient health outcomes. There is evidence that women have a longer lifespan than men. Women, for example,  live longer and make up a larger proportion of the Medicare population (Medpac, 2010). Women live with greater disability and have more chronic diseases than men (Kronman, Freund, Hanchate, Emanuel, & Ash, 2010). For example, chronic conditions such as diabetes, arthritis, dementia, depression, and obesity are more common in women (Jenum, Holme, Graff-Iversen, & Birkeland, 2005; Lubitz & Riley, 1993). Men and women also tend to have different coping mechanisms for their diabetes diagnosis. Findings from their study on coping with diabetes suggest that adults with type 2 diabetes use a variety of coping methods, with their basic coping styles influenced by race and gender (DeCoster & Cummings, 2004). Given the fact that women, in general outlive their spouses, it is reasonable to expect that post hospitalization, older women in general may have less spousal support and this can impact their discharge disposition. This point is highlighted by the fact that women tend to outnumber men as residents of nursing homes. Women and certain other population groups, for example, those living alone, are likely to spend a longer time in institutional care (Martikainen et al., 2009).

*Race/Ethnicity*

African Americans, Hispanic Americans, Native Americans, and the elderly are disproportionately affected by diabetes (Black, 2002; Mahler & Adler, 1999). According CDC data from a 2007-2009 national survey, after adjusting for population age differences, the prevalence of diabetes by race/ethnicity among people aged 20 years or older was 7.1% for non-Hispanic Whites, 8.4% for Asian Americans, 12.6% for non-Hispanic Blacks, and 11.8% for Hispanics (CDC, 2011a). The prevalence and risk of diabetes-related complications are higher for African Americans, Hispanics, American Indians, and Alaskan natives (Welch et al., 2006). African Americans for example, are 2-4 times more likely than non-Hispanic whites to develop renal disease, blindness, amputations, amputation-related mortality (Emanuele et al., 2005; Lanting, Joung, Mackenbach, Lamberts, & Bootsma, 2005). African Americans and Latinos are also more likely to have higher hemoglobin $A_{1C}$ levels than Caucasians (E. S. Huang, Brown, et al., 2009). Further, Miech and colleagues found that disparites exist in diabetes-related mortality rates. In an analysis of diabetes mortality rates using two different national data sources, the U.S. National Vital Statistics, and the U.S. National Health and Nutrition Examination Surveys (NHANES) collected in 1988–1994 and 1999–2004, Miech and colleagues found that overall, diabetes-related mortality across education levels widened from the late 1980s to 2005, and in the subgroups of men, women, blacks, whites, and Hispanics (Miech, Kim, McConnell, & Hamman, 2009).

Minority groups are also more likely to have disability from their chronic illnesses. Older adults in the United States who are members of minority populations have an increased risk for negative health outcomes (Clay, Roth, Safford, Sawyer, & Allman, 2011). In a study ($N$ = 2966) examining the independent contributions of selected medical conditions to disability rates among black and white people, Whitson and colleagues (2011) found that Blacks were more likely than Whites to report disability. After controlling for age, sex, marital status and socioeconomic differences, higher rates of obesity and diabetes in older black Americans account for a large amount of the racial disparity in disability (Whitson et al., 2011).

In another study designed to evaluate the relation of chronic conditions, gender, and race to the incidence of activities of daily living limitation in older adults, Dunlop, Manheim, Sohn, Liu, and Chang (2002), found that gender and race predicted moderate functional limitation onset, after controlling for age and education. The study suggests that arthritis, diabetes, prior cerebrovascular disease, incontinence, and impaired vision were significant predictors of moderate functional limitation onset after controlling for demographic variables (Dunlop et al., 2002). This is consistent with findings from other studies in which health disparities persist even after controlling for socioeconomic-related variables such as education, and income.

Writing on behalf of the Institute of Medicine, Nelson (2002) asserts that racial and ethnic disparities in health care exist even when insurance status, income, age, and severity of conditions are comparable, death rates from cancer, heart disease, and diabetes are significantly higher in racial and ethnic minorities than in whites. This assertion was contained in a report by the Institute of Medicine Committee on Understanding and Eliminating Racial and Ethnic Disparities in Health Care issued in March 2002 (Nelson, 2003). The report states that while there is no evidence that any significant proportion of healthcare professionals in the United States harbors overtly prejudicial attitudes, it admits that our society still reflects attitudes and behaviors that can fairly be called discriminatory. The report explains that doctors and other clinicians are human and are influenced by the environment in which they live and practice, and that among the multiple complex factors that influence their decisions, bias and stereotypical behavior may play a role.

Regarding patient diabetes outcome, Peek, Cargill, and Huang (2007) confirmed the widely held view that racial and ethnic minority groups bear a disproportionate burden of the diabetes epidemic and that they have higher prevalence rates, worse diabetes control, and higher rates of complications. In their systematic review of health care interventions, Peek and colleagues found good evidence for the ability of current health care interventions to enhance diabetes care, improve diabetes health outcomes and potentially reduce health disparities among racial/ethnic minorities. However, despite evidence that a culturally tailored approach could enhance self-care and glycemic control (Utz et al., 2008), Peek and her colleagues found that the majority of interventions in their review involved the application of standard diabetes quality improvement programs to racial/ethnic minority populations.

Aside from systematic barriers that affect health outcomes at the societal level, members of racial minority groups face obstacles at the doctor’s office level. There is evidence that race/ethnicity-related healthcare disparities stem from healthcare provider prejudices and biases. For instance, physicians' perceptions of patients are influenced by patients' race and socio-economic status. Van Ryn and Burke (2000) in a study to examine the effect of patient race and socioeconomic status on physicians' perceptions of patients, found that Black coronary artery disease patients were more likely to be seen as at risk for noncompliance with cardiac rehabilitation, substance abuse, and having inadequate social support. Findings from this study suggest that physicians view Black patients as less intelligent than White patients, even after controlling for patient sex, age, income and education (Van Ryn & Burke).

The extent to which a diabetes patient can achieve good glycemic control depends on many factors, these factors are diverse and range from the simple such as the type of diabetes diagnosis to the complex interplay of environmental, cultural, and socioeconomic factors. In type 1 diabetes, strict adherence to a prescribed insulin regimen often keeps blood glucose levels under control, although, this group of diabetics is more prone to extremes of blood glucose levels. In type 2 diabetes, there are many more factors at play. Because type 2 diabetes tends to manifest in older people, personal health behaviors tends to be an important predictor of how well the individual is able to manage the disease. Sedentary life style, weight status, dietary habit, and socioeconomic position and race/ethnicity affect ability to achieve good glycemic control. Although, the disease has a genetic and family history link (Gerich, 1998; McCarthy & Zeggini, 2009; Molinaro, 2011), these links only explain the high rates of diabetes among the racial/ethnic minority groups and does not explain the health disparities. While the prevalence of a disease within a specific population might be suggestive of some familial or genetic predisposition, persistent poor health outcomes and complications might be due to some societal factors for which members of the group has little control. There is evidence that the heavy burden of diabetes in terms of related complications among minority groups is due to disparities in the healthcare system (Peek et al., 2007), and lower utilization rates of preventive services (Welch et al., 2006).

In terms of resource utilization, there also exist disparities among minority populations. Researchers have found that minority patients are more likely to refuse treatment and delay seeking care for their comorbid conditions (Balsa & McGuire, 2003; Van Ryn & Burke, 2000). On the issue of hospital admission, research suggests that racial and ethnic minorities are more likely to experience a preventable hospital readmission. African Americans were more likely than Whites to be re-hospitalized for many diagnoses including heart failure (McHugh, Margo, & Kang, 2010). Non-White Hispanics and Blacks had higher readmission rates related to diabetes than Whites (H. Joanna Jiang, Andrews, Stryer, & Friedman, 2005). Black Medicare patients also had higher rates of readmission following heart failure treatment than White Medicare patients (Rathore et al., 2003) .

Though diabetes is not currently one of the readmission conditions considered by Centers for Medicare and Medicaid Services (CMS), for reimbursement purposes, in the future when diabetes is included in this list, hospitals with high readmission rates would have to address this issue or risk losing reimbursement dollars. Hospitals can avoid these penalties by shifting their clientele base and focusing on patients that are more likely to be compliant with treatment regimen and therefore, have reduced incidence of readmissions. Groups with high incidence of chronic disease rates and high incidence of complications requiring hospital admissions might be adversely affected by such a move. Since nurses provide critical in-hospital care, deliver essential patient teaching and discharge instructions, and work with families and outside institutions to ensure smooth transitions and prevent readmissions (McHugh et al., 2010), it is important within the context of this study to examine the relationship between nursing diagnosis and patient discharge disposition and to see if patient race/ethnicity has an interactive effect with socioeconomic position on the discharge disposition.

*Education*

Level of patient education, like the type of health insurance (Medicare, Medicaid, or private pay) is another variable that is often used to gauge patient's socioeconomic position. Education either in the form of formal education (graded as High School, College, Some

College, or Advance Degree) or health literacy is an important determinant of health behavior and therefore patient health outcomes. Health literacy was defined by Chung et al. (2006) as "a measure of a patient's ability to read, comprehend, and act on medical instructions." Patient education level has been shown to be an important variable in the treatment of individuals with complex and chronic medical conditions. Individuals with limited formal education or limited health literacy have been shown to have poorer health outcomes when compared to persons with higher levels of education (Jeppesen, Coyle, & Miser, 2009).

Poor health outcomes were related to difficulty understanding their disease process (Gazmararian, Williams, Peel, & Baker, 2003; Paasche-Orlow & Wolf, 2007), and healthcare provider instructions (Norris & Nissenson, 2008; Persell, Osborn, Richard, Skripkauskas, & Wolf, 2007). In a cross-sectional survey of 733 uninsured, low-income, rural women aged 40–64 years participating in the Well-Integrated Screening and Evaluation for Women Across the Nation (WISEWOMAN) project, Ahluwalia, Tessaro, Greenlund, and Ford (2010) showed that lower education level was also a significant predictor for uncontrolled hypertension. A high proportion of women in the project had uncontrolled hypertension, hypercholesterolemia, and diabetes at baseline.

*Payer Type/Socioeconomic Position*

Payer type such as private health insurance, self-pay, Medicare, Medicaid, health management organizations (HMOs), etc. is an indicator of the patient's available healthcare resources and potential determinant of patient's discharge disposition. Studies have used this variable as a proxy measure for socioeconomic position.  Several studies have also used socioeconomic position as a blanket de facto reference for minority groups. This is due in part to the fact that many minority groups are underserved and socioeconomically disadvantaged and live in socioeconomically depressed communities (Richardson & Norris, 2010). Socioeconomic position is a variable that features prominently in the literature and has been widely raised in the discussion of quality of healthcare. Invariably, these discussions lead to the identification of essentially two groups with disparate health outcomes- one with desired or near desired health outcomes and the other with poor health outcomes. It is essential therefore, that socio-demographic characteristics like education, race, income and type of health insurance should be considered very important confounders in the discharge disposition of hospitalized patients.

While much has been written about the importance of nurses' activities and the growing importance of nursing diagnosis in guiding nursing interventions, gaps exists in current literature for studies aimed at examining the use of nursing diagnoses and the link to interventions and outcomes in the care of diabetes patients. Consistency among diagnoses, interventions, and outcome classifications is crucial in evidence-based linkages of nursing activity to patient health outcomes (Margaret Lunney, Delaney, Duffy, Moorhead, & Welton, 2005). The nursing portion of an administrative record that might include ICDs, DRGs, and UHDDS is a means not only to document and compare, but also to ensure and improve the quality of nursing care (Müller-Staub, 2009). The current research examines an administrative dataset with two records of patient care (nursing and medicine) and how nursing diagnoses and medical diagnoses are related to the health outcome of the hospitalized patient with diabetes. This research is unique in that it uses dynamic data collected by nurses concurrently in the care of their assigned patients each day during the duration of patients' hospital stay. Nursing diagnoses are selected and applied in guiding interventions based on real-time changes in the health condition of the patients.

At a systemic level, there exists still, a discrepancy in the recognition of the importance of nurses' actions and the influence of nursing as a profession in improving health outcomes of both hospitalized patients and those in the community. This discrepancy is exemplified in the fact that nurses' activity is not reflected anywhere on the Uniform Hospital Discharge Data Set (UHDDS). The UHDDS has among other pertinent patient information, patient's primary medical diagnoses, this information is crucial for reimbursement because many third party payers (including Medicare) base reimbursement primarily on principal diagnosis. With the exclusion of nursing data and nursing's activity in this document, the contributions of nursing to patient outcome are not taken into account in administrative databases. The current proposal which is primarily focused on nursing diagnosis and patient health outcomes, hopefully will add to the argument for the inclusion of nurses' activity in the UHDDS.

# CHAPTER 3

# METHODOLOGY

*Overview*

The study examines nursing diagnoses use pattern and the association with patients' specific chronic health condition, type 2 diabetes mellitus and the ability of the observed patterns to discriminate patients' with this chronic disease. The focus is on how well nursing diagnoses explain variations in patient outcomes related to length of stay and patient discharge disposition (home, nursing home, rehabilitations facility, death, etc.) in the context of patient age, sex, marital status, race/ethnicity, and payer type. To this end, several statistical tests were conducted on this very large dataset.

*Research Questions*

The research questions, hypotheses, and statistical tests are:

RQ1: Can a nursing diagnoses model distinguish patients with the primary diagnosis of type 2 diabetes mellitus (ICD-9CM 250.0-9) from other patients using length of stay (LOS) as the dependent or criterion variable?

$H_0$: There are no multiple correlations between nursing diagnoses use pattern and patients' ICD-9CM 250.0-9 diagnosis codes.

$H_1$: There are positive and significant correlations between nursing diagnoses and patients' ICD diagnosis codes.

Using the 445 patients admitted to the hospital with a primary diagnosis of type 2 diabetes mellitus (ICD-9CM 250.0-9) Question 1 examines the mean length of stay in a homogenous group of patients with the same disease and similar demographic characteristics on how the nursing diagnoses explained length of stay variation. Multiple regression was used to examine these two set of variables. By knowing the disease can the pattern of nursing diagnoses be anticipated?

RQ2: Which nursing diagnoses are associated with patients hospitalized with primary diagnosis of type 2 diabetes Mellitus (ICD-9CM 250.0-9)?

$H_0$: There are no specific groups of nursing diagnoses associated with patients hospitalized for diabetes mellitus.

$H_1$: Certain specific groups of nursing diagnoses are associated with patients hospitalized for diabetes mellitus.

Question 2 isolates a set of nursing diagnoses that nurses recorded for the 445 patients with diabetes mellitus. Comparison of nursing diagnoses for patient with diabetes (ICD code 250) as primary diagnosis and nursing diagnoses for patients without diabetes was conducted. Nursing diagnoses often associated with diabetes in the professional literature with diabetes were identified and compared with those recorded by assigned nurses in the care of patients with primary diagnosis of type 2 diabetes mellitus. By knowing nursing diagnoses can the disease be anticipated? Research question 2 answers this question by identifying and comparing the relative importance of nursing diagnoses gleaned from diabetes literature to be important in the care of patients with diabetes with other patient groups.

RQ3: What is the magnitude and direction of the correlation between the number of nursing diagnoses and of length of stay and intensive care unit days among hospitalized patients with primary diagnosis of type 2 diabetes mellitus?

$H_0$: There is no correlation between the number of nursing diagnoses and patient length of stay, and intensive care unit days among patients hospitalized with diabetes mellitus.

$H_1$: There is a correlation between the number of nursing diagnoses and patient length of stay, and intensive care unit days among patients hospitalized with diabetes mellitus.

Question 3 is concerned with patients' length of stay and ICU days and the number of nursing diagnoses recorded during the hospitalizations. A correlation between length of stay/ICU days and the number of nursing diagnoses is used to address this question. Because this question examines the means of all 61 nursing diagnoses relation to patients' length of stay and ICU days (when applicable), an analysis of variance (ANOVA) is used to examine this inquiry.

RQ4: Which of the 61 nursing diagnoses are most influential in explaining the variances in the length of stay among patients with primary diagnosis of type 2 diabetes mellitus?

$H_0$: There is no difference in importance between nursing diagnoses in explaining the variance in patients' length of stay.

$H_1$: Certain nursing diagnoses are more important than others in explaining the variance in patients' length of stay.

Rather than the number (amount) of nursing diagnoses (Question 3), Question 4 aims to examine how the different nursing diagnoses or groups of nursing diagnoses are related to patient's length of stay. Because some nursing diagnoses are more severe than others, it is hypothesized that certain nursing diagnoses will explain a greater percentage of the variance in patients' length of stay. To verify this, multiple regression was used to address this inquiry. The 61 nursing diagnoses represented predictor variables and patient length of stay is a continuous dependent variable.

An assumption is made based on the provisions of the central limit theorem that the data has a normal distribution. The central limit theorem allows that whenever N is sufficiently large ($N > 40$), the distribution of the sample mean is approximately normal even when the population is non-normal (Elliott, 2010).

RQ5: What is the relationship between patients' discharge disposition (Home, Rehabilitation facility, nursing home, death, etc.) and patients' age gender, race/ethnicity, marital status, and payer type?

$H_0$: No relationship exists between patients' discharge disposition (home, nursing home, rehabilitation facility, death, etc.) and patients' sex, marital status, race/ethnicity, and payer type among patients with diabetes.

$H_1$: A relationship exists between patients' discharge disposition (home, nursing home, rehabilitation facility, death, etc.) and patients' sex, marital status, race/ethnicity, and payer type among patients with diabetes.

Question 5 examines the effects of the patients' factors of age, sex, marital status, race, and type of insurance (payer type) on a patients' discharge disposition. This question predicts a patients' discharge disposition based on patients' factors. It also identifies the factors with the most influence (that is the relative strength of each predictor variable) on a patient's discharge type. Because the dependent variable- patient discharge disposition (dependent on the predictor variables) is categorical in nature rather than continuous, a logit regression procedure that allows for the examination of dichotomous dependent variables might be used in this analysis (Urdan, 2010). Ordinary logit models (logistic regression) are well-suited to analyze categorical data (Jaeger, 2008).

*Type of Data*

The dataset comprising 353 variables and 146,964 observations is a large data set and this necessitates a description and listing of the variables, table 3.0.1 offers a sample of key variables (see Appendix D for complete list of variables). The Nurse/Patient Summary data set has nonparametric data (nominal and ordinal and parametric data (interval and ratio). Nominal data are discrete and categorical such as the numbers applied to non-numerical variables. For example, in the context of the Nurse-Patient Summary dataset, gender might be listed as 1=female, 2=male; discharge disposition might be listed as 0=home, 1=nursing home, 3=rehabilitation facility, 4=died, etc.). Although nominal data may have numbers, these numbers are not used in statistical calculations. Ordinal data are also discrete number variables; they represent quantities that have a natural ordering. Often, the ordering might be used to indicate preference or order of importance as in a Likert scale. However, because the values between the intervals are not known with certainty, or the intervals might not be equal, ordinal data are not used for many statistical calculations. For example, the number of nursing diagnoses might be different for each patient, but one cannot say with certainty that the patient with five different nursing diagnoses is sicker than the patient with four. This is because all nursing diagnoses are not equally important to the patients' health outcomes and the selection of nursing diagnoses may be affected by the nurse's experience in using nursing diagnosis, education, and even job experience.

Interval data are similar to ordinal in that they are ordered in logical sequence, however unlike ordinal data; interval data represent continuous variables, and the intervals are equal and have arithmetic value. Patients' weight, height, and patients' body temperature are examples of continuous, interval variables. However, with interval data, a zero reading has no real meaning, for example, zero degrees does not mean the absence of temperature (Bailey, 1997) pp. 121. In interval data, the difference between 90 kilograms and 85 kilograms is equal to the difference between 75 and 70 kilograms. Ratio or numeric data are numbers that are continuous with equal intervals between numbers, and have meaningful zero point (Bailey, 1997). In the current data set, patients' length of stay is an example of parametric continuous variable.

Table 3.0.1

*List of Variables*

| | ***Variable Name*** | ***Variable Description*** | ***Non-Parametric*** | | ***Parametric*** | |
|---|---|---|---|---|---|---|
| | | | **Nominal** | **Ordinal** | **Interval** | **Numeric** |
| 1-61 | SUMX1-61 | 61 Nursing dx | | | | yes |
| 62 | SUMDAYS | Sum of ratings | | | | yes |
| 63 | AGE | Patient's age | | | | yes |
| 64 | SEX | Patient's gender (M/F) | yes | | | |
| 65 | RACE | Patient's race | yes | | | |
| 66 | LOS | Length of stay | | | | yes |
| 68 | ICUDAYS | Days in ICU | | | | yes |
| 69 | DISHDISP | Discharge disposition | | yes | | |
| 70 | DRG | Diagnosis Related Group | yes | | | |
| 71 | MARSTATE | Marital status | yes | | | |
| 72 | ADMSORCE | Admission source | | yes | | |
| 73 | FINCLASS | Patient's insurance type | | yes | | |

*Design*

This study uses a descriptive correlational design involving a retrospective data analysis of nursing diagnoses recorded by nurses in the care of adult hospitalized patients with type 2 diabetes mellitus. This is a secondary data analysis of a large data set of patient information including nursing diagnoses, payer type and demographic information collected by nurses on a daily bases over the duration of each patient's hospital stay at a single Midwest university hospital (Kiley, Halloran, Monahan, Nosek, & Patterson, 1986). Data were available for patients admitted between 1986 and 1989. The utility of descriptive correlational design is in the examination of relationships between variables suspected to be related based on current literature (Brink & Wood, 1998).

*Sample*

This data set consists of daily observations of patients by their assigned nurses using nursing diagnosis. The data were collected at a large urban teaching hospital in Midwestern United States (Halloran et al., 1988). Nurses recorded information for many of the 123,241 patients admitted to the hospital during the four year period (1986-1989) of data collection. The dataset include patients' medical diagnoses, diagnosis related group (DRG) classifications, and nursing diagnoses. Other data collected pertain to patient's demographic information such as age, sex, race, marital status, and health insurance type. Pediatric and psychiatric patients will be omitted from the analyses in the proposed study due to wide extremes of variability. In the case of pediatric patients, the pediatric subpopulation is to be left out because the normal newborns had little variability and the sick premature infants had high variability in the variable of length of stay (LOS) (Welton, 1999). With regards to the psychiatric population, the psychiatric population typically had longer length of stay compared to adult acute care population (Welton). An overview of the dataset reveals a patient population with mean age of 33.1 years (*SD* 27.6) with a range of 0-101years. The subpopulation of interest (*n* 9516) which includes all patients with a medical diagnosis of any type of diabetes mellitus (either as primary of secondary diagnosis) has a mean age of 56.7 years (*SD* 19.5) with a range of 0 to 101 years. The sample is comprised of 59.1% males (48.9% females); Whites were 51.2%, Blacks were 48.3%, and other groups made up 0.6%.

*Setting*

The original data collection took place in a large Midwestern healthcare system compromised of four hospitals: an adult medical-surgical hospital with 500 beds, a children's hospital for medical and surgical care with 220 beds, a women's hospital for labor and delivery, normal newborn nursery and selected oncology services with 120 beds, and a mental health hospital for adults, adolescents, and children with 90 beds. All four component institutions were organized and managed as one 930-bed university affiliated, urban general hospital (Welton, 1999). All attending physicians were members of a medical staff appointed by and to the faculty of the school of medicine, and all nurse leaders above the level of head nurse were appointed to and by the nursing school faculty. The nursing management consisted of:

- Assistant Directors of Nursing—11,
- Directors of Nursing—4,
- Vice Presidents of Nursing—4,
- Senior Vice President for Nursing—1,
- Dean, School of Nursing—1.

There was a preference for nurses holding at least a bachelor's degree (or better – MSN, ND). Seventy per cent of the Registered Nurses were graduates of BSN programs of study and associate degree holders, diploma, and other nurses made up the remaining 30%. While many of the nurses were on their first professional assignments out of school, they were supervised by nurses who were also faculty members at a prominent Midwestern nursing school. This leadership structure is part of an experiment to change the existing nursing management structure at Case Western Reserve Medical Center in the late 1960s. The experiment was an effort to introduce the concept of academic leadership for nursing into two complex institutions, the university hospitals and the university itself (J. J. Fitzpatrick, Halloran, E. J., & Algase, D. L., 1987; Schlotfeldt & MacPhail, 1969).

The setting where the nursing data were originally recorded used structural and process standards for hiring nurses and assigning them to patients. The patient or case assignment was made on two levels: primary and daily. Primary nurses were assigned to all patients within twenty-four hours of admission. The primary nurses managed their individual patients' care when on duty and were responsible for formulating patient plans of care. The daily assignment meant that primary nurses were also assigned to other patients and all shifts, however, attempts were made to assign primary nurses to their patients whenever they were on duty. This meant that primary assignment and the daily assignment often overlapped (Welton, 1999).

### *Data Collection*

The nurse-patient summary ratings were done using the Nurse-Patient Summary datasheet (see appendix A) by the day shift assigned nurses who may also have been the patients' primary nurses. Nurses rating patients using the Nurse-Patient Summary sheet (N-P Sum) were advised that the ratings would not influence staff size or nurse-patient ratio assignment. This eliminated one threat to reliability because nurses did not expect staffing ratios to improve based on data collected using the Nurse-Patient Summary sheet.

Each nurse used a bar code reader (figure 4) to indicate any of the sixty-one (61) nursing diagnoses that were applicable each day during the course of the ward stay for each patient.

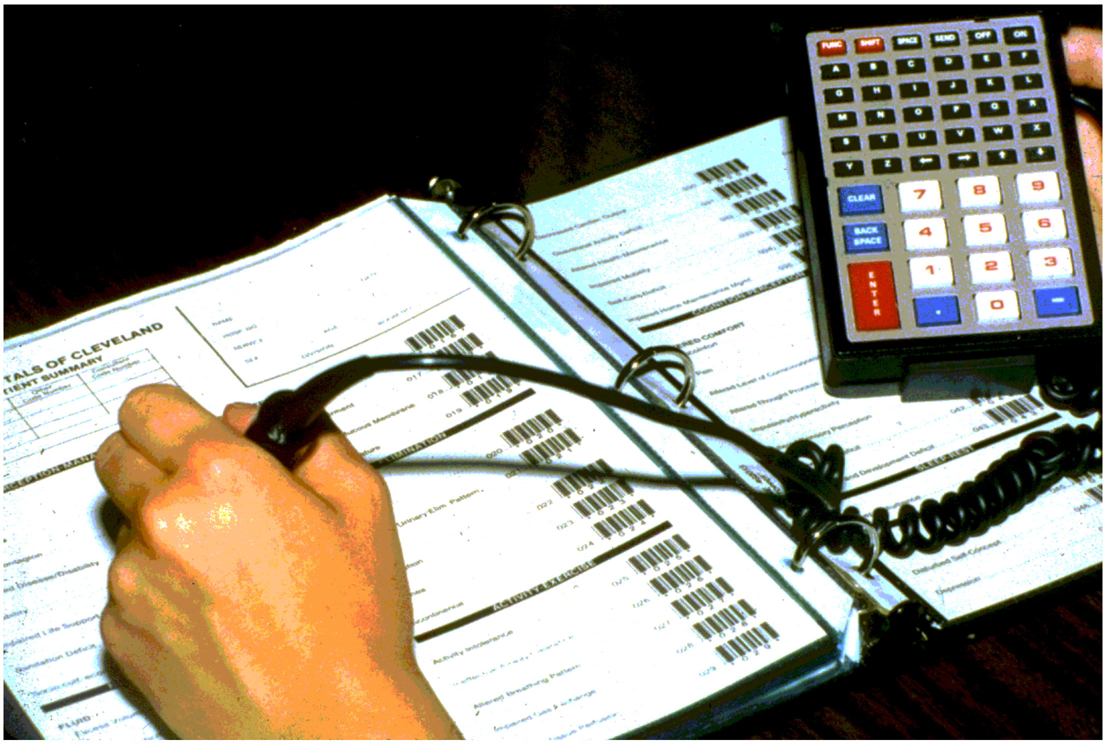


*Figure 4.* A Nurse Recording Patient Data Using a Bar Code Scanner.

Information about nursing dependency was gathered daily by the patient's primary nurse on the day shift. The nurse used a portable hand-held computer terminal, wand scanner or light pen and a bar-coded checklist. The checklist contained 61 bar codes representing 61 nursing diagnosis judgments. It also contained an identification code for each nurse providing care to the patients. The nurse assigned to a patient assessed the patient and assigned the appropriate nursing diagnoses. Using the wand scanner, the nurse enters into the computer terminal the patient's identification number, the bar code for each nurse who cared for the patient in the past 24 hours, and the nursing diagnosis codes that apply to the patient on that particular day. These data determined the patient's nursing dependency during a hospital length of stay. Every day at 1:00

p.m., all data entered into the computer terminal that day were transmitted over telephone wire to the hospital's computer mainframe (Halloran et al., 1988). Table 3.0.2 is a breakdown by year of nurse patient rating during the data collection period.

Table 3.0.2

*Annual Nurse-Patient Rating During Data Collection*

| Year | Patients | Patient days | Observations | % of days |
|---|---|---|---|---|
| 1986 | 32,903 | 247,118 | 217,492 | 88.0 |
| 1987 | 33,214 | 242,366 | 186,713 | 77.0 |
| 1988 | 34,151 | 244,669 | 153,908 | 62.9 |
| 1989 | 22,973 | 163,917 | 88,901 | 54.2 |
| **Total** | **123,241** | **898,070** | **647,014** | **72.0** |

Although the data are relatively old, this is one of the richest data sets of its kind to combine daily nursing problems and patient hospital outcomes (Welton & Halloran, 2005).

*Measures and Instruments*

The Nurse/Patient Summary (Appendix A) was used to record nursing diagnoses. The Summary was developed by Halloran and Kiley in 1983 to collect NMDS information that described nurse-sensitive patients' healthcare needs. These patient needs are stated as health problems that can be treated by nurses. For this study nursing diagnoses were defined as those health problems amenable to nursing care and approved by the North American Nursing Diagnosis Association (NANDA) at the time of data collection. The items in the Nurse/Patient Summary were originally derived from three sources. Selection of the items was based on: (a) nursing diagnoses approved for clinical testing by NANDA in 1982; (b) elaboration of some of those nursing diagnoses; and (c) terms from the nursing literature hypothesized by Halloran and

Kiley to describe patients 'needs for nursing care and identified by nine nurses engaged in advanced clinical practice at University Hospitals of Cleveland, Cleveland, Ohio (Nosek, 1986).

A valid nursing diagnosis is one that is well grounded on evidence and is able to withstand the criticism of professional nurses (Fehring, 1987). A quick review of the literature on the discussion of the validity of nursing diagnosis one notes the importance of the phrase “defining characteristics” in describing the relevance of the diagnostic labels used by nurses. Elaborating on the validity of nursing diagnosis, Gordon (1987) asserts that validity describes the degree to which a cluster of defining characteristics describes a reality that can be observed in client-environmental interaction. In affirming this definition, Fehring adds that a set of defining characteristics expands the understanding of a nursing diagnosis and contends that a nursing diagnosis is essentially a cluster of characteristics that nurses put a label on for communication purposes. These defining characteristics are valid when they actually occur and can be identified as a cluster in the clinical situation (Fehring, 1987). Even though early works by Abdellah and Henderson predates the publication of a formal list of nursing diagnoses, evidence of the validity of nursing diagnosis can be found in historical and contemporary nursing literature. This evidence can be found in the historical works of Abdellah et al. (1960) and Henderson (1960). Elements of Abdellah’s list of 21 nursing problems (Appendix B) are prominent in well tested contemporary nursing diagnoses.

## Confounder Variables

The widely accepted maxim in research that correlation does not equal causation is related to the issue of confounder bias. In social science research in which the ‘major players’ are human beings and the environment (both physical and social environment), there are many factors at play that potentially could affect or determine human responses to a particular condition. These factors or variables which are usually not the primary focus of the researcher may have a spurious effect on the study results and if not properly accounted for could lead to misleading conclusions by the researcher. A confounder variable is an extraneous variable that co-varies with the variable of interest (Shadish, 2002). Confounding, sometimes referred to as confounding bias, is essentially a ‘mixing’ or ‘blurring’ of effects (Grimes & Schulz, 2002). A confounding factor operates through its association with both the independent and the dependent variables, producing an indirect statistical association (Brink & Wood, 1998). In other words, the link of a dependent variable to an independent variable is confounded when a researcher attempts to relate an exposure (independent variable) to an outcome (dependent variable), but actually measures the effect of a third factor, termed a confounding variable (Grimes & Schulz). Figure 5 below depicts the effect of a confounder on an outcome in epidemiological research.

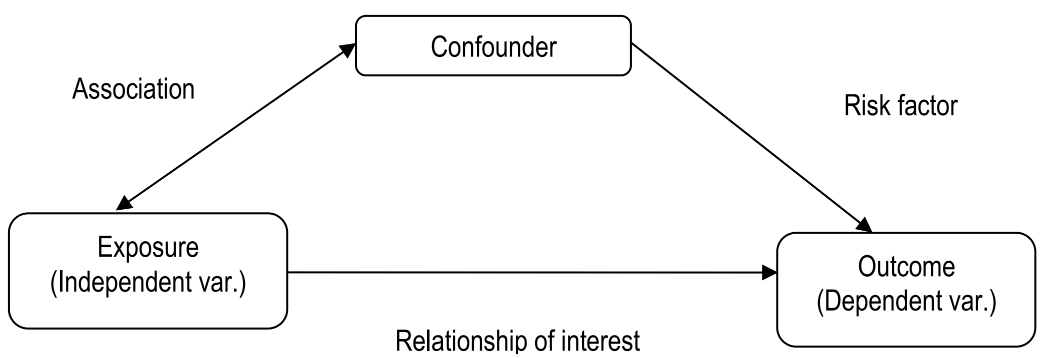


*Figure 5.* Effects of Confounding Variables on Outcome Variable.

Applying this schematic to what might be obtainable in a study investigating the relationship between type 2 diabetes and patient diabetes outcome; one might have the following relationship:

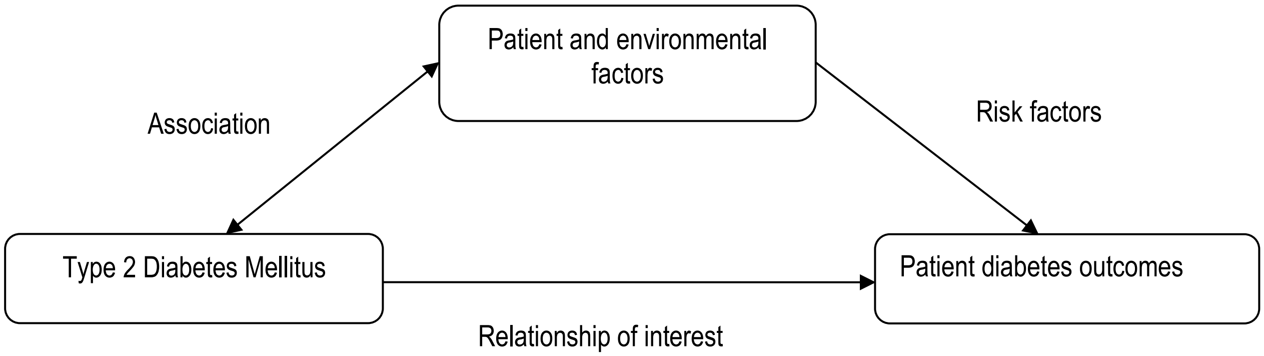


*Figure 6.* Confounder Variables in Type 2 Diabetes Mellitus Outcome Investigation.

The patient and environmental factors in figure 6 might be patient's age, family history, socioeconomic position, knowledge of the disease process, marital status as a function of family support, access to health care, and perhaps race and ethnicity among others. Environmental factors might be related to neighborhood characteristics such as proximity to healthcare facilities, access to recreational and exercise facilities and access to healthy foods.

The complex nature of the effect of a confounder is exemplified in the following scenario: Suppose there is a correlation between exercise self-efficacy and a certain complication of type 2 diabetes mellitus (T2DM). Does the lack of exercise self-efficacy lead to T2DM complication or does having a complication of T2DM limit the ability to engage in regular exercise? The two possibilities warrants further investigation because each possibility is a reasonable expectation and may be true. For example due to lack of knowledge, individuals may be wary of regular exercise due to misguided fear of triggering hypoglycemia. But until that investigation is completed by a researcher one may not know which one is the cause of the other. Of course, it is also possible that no causal relationship exists between exercise self-efficacy and T2DM complication; rather, a third variable (confounder) is the reason for the seeming interrelatedness. Such confounder could be a person's weight (obesity) that leads to both development of a T2DM complication and lack of exercise self-efficacy. Thus, it is important in research, particularly, in human research to identify and understand the different kinds of confounders that can affect relationship between the independent and dependent variables of interest.

### *Sources of Confounder Variables in healthcare Database Research*

Sources of confounder variables are numerous; they can come from the system, provider, or patient levels, interaction of these variables are often complex and are not readily apparent (Brookhart, Stürmer, Glynn, Rassen, & Schneeweiss, 2010). Jager, Zoccali, MacLeod, and Dekker (2008) posits that in order for a variable to be a potential confounder, it needs to have the following three properties: 1) the variable must have an association with the disease, that is, it should be a risk factor for the disease; 2) it must be associated with the exposure, that is, it must be unequally distributed between the exposed and non-exposed groups; and 3) it must not be an effect of the exposure, nor be a factor in the causal pathway of the disease. Figure 7 depicts the interrelation of variables that might determine a patient’s discharge disposition.

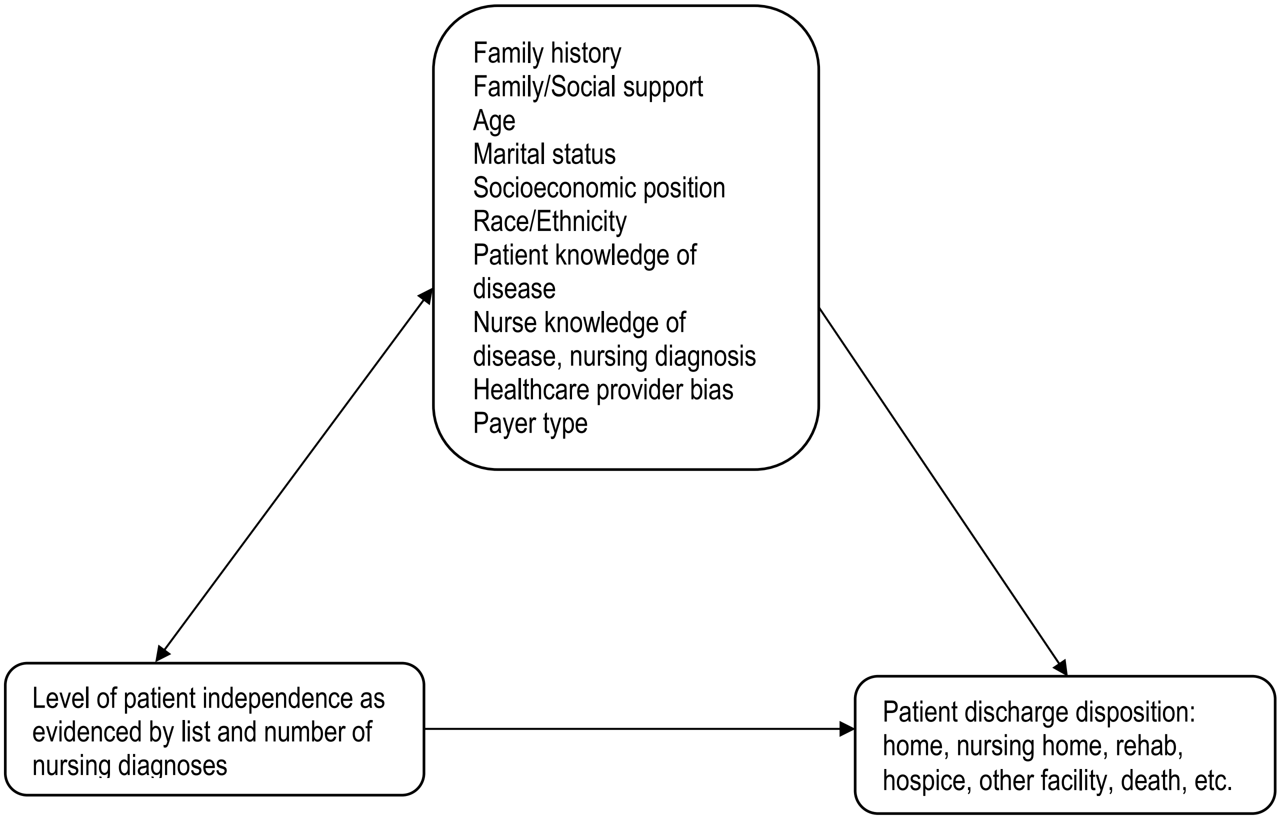


*Figure 7.* Variables Potentially Affecting Patient Discharge Disposition.

In the example of confounder effect for diabetes outcome depicted in figure 7, several of the confounders meet the above listed three properties for potential confounders. Family history, for example, is a risk factor associated with the development of type 2 diabetes (Harrison et al., 2003; Sargeant, Wareham, & Khaw, 2000). With respect to the second property that stipulates an unequal distribution within the population, many factors are associated with diabetes, but these factors are not necessarily causative of diabetes. Family history, for example is associated with diabetes but not causative of diabetes, for not all persons with a family history of diabetes develop diabetes. In an analysis of 10 studies that studied the link of family history of diabetes and the subsequent development of diabetes, Harrison et al. (2003) reported that most studies reported only a two-fold to six-fold increased risk of type 2 diabetes associated with a positive family history compared with a negative family history of diabetes. Regarding the third property, a confounding variable cannot be the effect of the independent variable. Thus, having a family history of diabetes or being of a certain age, or being a member of a certain racial/ethnic group is not the result or the consequence of having diabetes.

Confounder identification must be grounded on an understanding of the causal network linking the variables under study (Hernán, Hernández-Díaz, Werler, & Mitchell, 2002), and controlling for the confounding variables might be a difficult task if a secondary data analysis is proposed on observational data. The challenges of confounding control are particularly acute in studies using healthcare databases where information on many potential confounding factors is lacking and the meaning of variables is often unclear (Brookhart et al., 2010), as is often the case in secondary data analyses.

In epidemiologic studies that use primary data collection, the timing of data collection and the detail and accuracy of data are to a large extent under the control of the investigator (Schneeweiss & Avorn, 2005), the investigator identifies relevant variables and adjusts for potential confounders based on background knowledge of subject matter (a priori subject matter knowledge) and available literature. This is in stark contrast to healthcare-related administrative databases where a record is generated if there is an encounter with the health care system that is accompanied by a diagnosis and one or several procedures or the prescribing of medicines (Schneeweiss & Avorn). This type of record might lack consideration for relevant variables and potential confounders. The consequence of this is possible bias if such data are used without proper scrutiny.

*Dealing with Confounders*

There are several ways a researcher could deal with confounders. These include randomization, restriction, matching, and stratification (Jager et al., 2008). Grimes and Schulz (2002) contend that confounders can be handled before or after the study is conducted, they suggest that the simplest way is by exclusion. For example, if hypertension is suspected to be a confounder in a study involving individuals with type 2 diabetes, the researcher could enroll patients without hypertension. These methods work well in dealing with confounders before the conduct of the study or during data analyses when the researcher is still able to exclude subjects with confounders or is able to determine and plan for potential confounders based on the literature or prior experience.

In a secondary analysis, however, where the subjects are already enrolled and the primary study has been completed, the researcher's options might be limited. The researcher could employ certain statistical approaches such as multivariable outcome models and propensity score methods to remove the confounding effects of such factors if they are captured in the data (Brookhart et al., 2010). The former is more commonly used and it is what is meant when investigators use the phrases: 'controlling for', 'adjusting for' or 'holding a variable constant'; this is achieved using multiple regression (Urdan, 2010).

*Impact of Nursing Diagnoses on Patient Discharge Disposition*

The demographic and socioeconomic characteristics of individual patients- patient factors of age, sex, marital status, race/ethnicity and type of insurance coverage (Self-pay, Blue Cross, Medicare, Medicaid, HMO, etc.) will be fitted in multiple regression models with nursing diagnoses and examined for effects on length of stay, ICU days, and discharge disposition. A selected set of nursing diagnoses will also be analyzed to determine their correlation to patients' ICD codes at discharge, length of stay, ICU stay and discharge disposition.

An appropriate set of nursing diagnoses applied in the care of a patient not only informs other nurses, but might also aid other members of the healthcare team in forming a judgment about the condition of the patient and readiness for discharge. The impact of nursing diagnoses on patient discharge disposition is affected by many nurse-related and patient-related factors. For example, the nurses' ability to identify and apply nursing diagnoses in the care of their patient is affected by their understanding of the nursing diagnosis labels. The patient's readiness for discharge to home, to a rehabilitation facility, or to a nursing home is dictated by the patient's level of independence. Likewise, the patient factors of overall health status, age, and marital status, amongst others can play a role in his discharge disposition. Imbedded in all these relationships are confounders. A complex relationship exists between these variables and controlling for every single one is important as attempt is made to minimize the effect of confounders on the relationship between the independent variable of nursing diagnosis and the dependent variable of patient discharge disposition.

A causal analysis, complete with a path diagram, is often used in the understanding of the interrelationship of the network of variables of interest. According to Cohen, Cohen, West, and Aiken (2003), the basic strategy of causal analysis is to represent the network of variables involved, explicitly stating the causal direction, sign (+ or -), and nature of the relationship, if any, between all pairs of variables that are considered. Observational data like the Nurse-Patient Summary data set are then employed to determine whether the model is consistent with them to estimate the strength of the hypothesized causal relationships Cohen et al. (2003). From the list of potential confounders listed in Figure 5, the strength of the relationship, and thus the effect of each confounder variable on the relationship between the independent and dependent variables are reasonably expected to be different, testing of the various models using multiple regression would yield information about the strength of the relationships and the relative strength of each predictor variable (Urdan, 2010).

### *Variables of Interest*

In considering the impact of nursing diagnoses on patient discharge disposition, it is reasonable to consider the following patient variables as potential confounders that must be controlled for: patients' age, sex, marital status, race/ethnicity, payer type (private health insurance, self-pay, Medicare, Medicaid, HMO, etc.), and length of hospital stay. This list is not as comprehensive as that in figure 5 due to the limitations of recorded variables in the data set. These variables are potential confounders because they represent patient factors that can either directly affect a patient's health status or influence a patient's healthcare decisions. These variables will be plugged in regression models with certain nursing diagnoses for determination of the best fit models in predicting patient health outcomes (discharge disposition).

### *Data Analysis Plan*

Statistical software SAS 9.3 (SAS Institute, Cary NC) will be used to analyze the data for this study. The proposed study will explore methods of using data collected by nurses, for example, nursing diagnosis, to quantify the patient's conditions and link the resulting measurement to patient health outcomes. This inquiry will utilize a variety of statistical tests to examine the relationships between the different independent and dependent variables. For the proposed study, the following continuous dependent variables-length of stay (LOS), intensive care unit stays (ICU days), mean nursing diagnoses for the hospital stay, and discharge disposition will be examined using a combination of the following statistical tests: Pearson Correlation Coefficients, multivariate linear regression (Multiple Regression), and factorial analysis of variance (Factorial ANOVA).

These tests examine such questions as:

- What is the magnitude and direction of the correlation between the discrete independent variable of number of nursing diagnoses and continuous dependent variables of LOS, ICU days?
- Does LOS increases as the mean number of nursing diagnoses increases? And if so, what percentage of the variance in LOS is explained by certain nursing diagnoses thought (from the diabetes literature) to be indicative or suggestive of diabetic condition?
- What is the relationship, if any, between patients' discharge disposition (home, rehabilitation facility, nursing home, death, etc.) and the nominal, independent variables of gender and race/ethnicity, marital status, and payer type?
- What percentage of the variance in LOS is explained by nursing diagnoses (1-61)?
- Which of the 61 nursing diagnoses are more influential in explaining the variance in patient length of stay?

For the study, descriptive statistics such as mean, and standard deviation of continuous variables, and frequency of categorical variables are examined. Inter-correlations between repeated measures of major variables are conducted with steps taken to minimize violations of the five statistical assumptions: linearity, independence, homoscedasticity, symmetry, and normal distribution (Kleinbaum, Kupper, Miller, & Nizam, 1998; Montgomery, Peck, & Vining, 2006). A regression model approach was used to analyze the variables. A linear regression model assumes that a continuous outcome variable Y can be explained by one or more predictor variables of X:

$$Y = X\beta + \varepsilon$$

Where Y is an independent or outcome variable for a subject, X is an independent variable for a subject, $\beta$ is a regression coefficient for the independent variable X, and $\varepsilon$ is an error for a subject (Campbell, Grimshaw, & Elbourne, 2004). In the case of a model with several independent variables as is the case in the Nurse-Patient Summary data set, the following equation is a more appropriate representation of a possible regression model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \ldots \beta_i X_i + \varepsilon_i$$

In this example, Y is the (response) dependent variable (for example, length of stay) and Xs are explanatory independent variables (for example, number of nursing diagnoses, patient age, patient race/ethnicity, and payer type) that affect or influence Y. $\beta_0$ is the intercept or the point on the vertical axis of a graph that is intersected by line of the equation. The $\beta_1 \ldots \beta_i$ are slope coefficients, and $\varepsilon_i$ a normally distributed error term. The slope coefficient indicates how big a change in Y to expect from 1-unit increase in X (Allison, 1999). In the example with multiple independent variables, the slope coefficient indicates how big a change in patient length of stay (dependent variable) for every additional nursing diagnosis ($X_1$) holding all other independent variables ($X_2 \ldots X_i$) constant.

The large data set is well suited for the statistical tests that will be conducted in the proposed secondary analyses. Because the data set is large and has many independent and dependent variables, multiple regression is an appropriate technique for data analysis that allows for predictions about the value of the dependent variables given certain values of the independent (predictor) variable (Urdan, 2010). Multiple regression involves models that have two or more predictor variables and a single dependent variable (Urdan). Thus, in the Nurse-Patient Summary data set, a model containing several nursing diagnoses might be predictive of the health status of hospitalized patients. More specifically, a model containing certain specific nursing diagnoses, patients' age, and race/ethnicity might be predictive of patients' diabetes status. Multiple regression is a powerful statistical technique because it allows for the evaluation of 1) the relationship of a set of predictor variables with the dependent variable, 2) the strength of the relationship between each predictor variable and the dependent variable while controlling for the other predictor variables in the model, 3) the relative strength of each predictor variable, and 4) of whether there are interaction effects between the predictor variables (Urdan, 2010).

Multiple regression with its versatility in hypothesis testing is a particularly useful technique in the proposed analyses because of its application in examination of relationships between variables. For example, any relationship of interest, whether between independent variables and an outcome or between independent variables and a dependent variable, can be characterized in terms of the strength of the relationship or its effect size (Cohen et al., 2003); thus the question of how much of the total variance in the dependent variable is associated with the independent variables of interest is addressed. Cohen and colleagues argue that the most attractive feature of multiple regression as an analytical technique is its automatic provision of regression coefficients, proportion of variance, and correlational measures of various kinds, all of which are kinds of effect size measures.

Factorial analysis of variance (ANOVA) can also be an appropriate approach for examining the relationship of these variables. The large data set also makes it easy to meet some important assumptions of statistical tests, namely, population independence, normally distributed populations, and homogeneity of variance between groups. ANOVA allows for the examining of main effects of the different conditions and interaction or moderator effects. An interaction effect is present when the differences between the groups of one independent variable (e.g. diabetic patients and non-diabetic patients, or patients with nursing diagnosis #1 and patient with nursing diagnosis #2) on the dependent variable (e.g. discharge disposition) vary according to the level of a second independent variable (e.g. length of stay) (Urdan, 2010). Another added benefit of conducting factorial ANOVA, is that it allows for the examining the effects of one variable while controlling for the effects of other independent variables. For instance, it is possible to test whether there are significant differences between the groups of one independent variable on the dependent variable while controlling for the effects of the other independent variable(s) on the dependent variable (Urdan, 2010). In the Nurse-Patient Summary data set, factorial ANOVA will allow for the examining of the effect of patient's race/ethnicity on discharge disposition while controlling for the effects of patient age on discharge disposition. Alternatively, one could examine the effect of the mean number of nursing diagnoses on patients' length of stay while controlling for the effect of patient age on the length of stay.

*Missing Data*

Perhaps the most important threat to validity when conducting a secondary data analysis is the issue of missing data. This is particularly true when research data concerns the qualities, characteristics or activities of human beings (Penny & Atkinson, 2011). Patterns of missing data are more important than the amount of missing data (Tabachnick & Fidell, 2001), therefore, the univariate procedure in SAS will be used to visualize distribution of data points, outliers and pattern of missing data. There are several methods for dealing with missing data or at least reducing its impact on the validity of findings. These include case deletion, mean imputation, Regression Imputation, and multiple imputations (Faris et al., 2002; Penny & Atkinson, 2011; Scheffer, 2002). The choice of which method to use depends on the nature of the missing data, in other words, the pattern of the missing data and the type of variables (dichotomous or continuous) involved (Penny & Atkinson, 2011; Scheffer, 2002).

According to Penny and Atkinson (2011), data can be missing in one of three different ways: missing completely at random (MCAR), missing at random (MAR), or not missing at random (NMAR). If the missing data do not depend on the data themselves, for example, if respondents unintentionally failed to answer a few questions in the questionnaire, the missing data is described as completely missing at random. If the missing value or information is related to data observed in the data set, then the data are termed missing at random. However, if the missing value or information is related to data or information that is not available, (not collected or not sought) then the data are not missing at random. Preliminary analysis done so far on the Nurse-Patient Summary data set indicates there are data missing at random. Nurses were told they may not rate their patient(s) if they felt taking the time to do so would interfere with providing needed nursing care. Thus, there are discrepancies between number of days patients stayed in the ward (LOS) and the number of times patients were rated. This situation occurred at random. Penny and Atkinson states that when data are missing solely out of chance as is the case in MCAR, then case deletion is an appropriate method for dealing with this problem. However, caution should be exercised because substantially reducing the sample size will lead to decreased statistical power (Penny & Atkinson, 2011). When comparing methods used in resolving missing data in small versus large data sets, more flexibility is allowed for large data sets containing less than 5% random missing data (Tabachnick & Fidell, 2001). Given the size of the data set, it is not anticipated that loss of statistical power will be a problem with the Nurse-Patient Summary data set. Final decisions about missing data will not occur until after careful evaluation and assessment of patterns, amounts, and how the missing data may affect the sample size.

*Human Subjects*

As a secondary data analysis, the proposed study is not considered human research as no humans are involved. Patient and nurse data were encrypted prior to secondary analysis. Encryption code for the entire data is maintained at the subject institution in Ohio. This study will use data that was part of a nursing information system previously collected at a university affiliated medical center serving as a regional referral center and health care provider to the local urban and suburban population in the Midwestern United States between January 1986- June 1989. The database is a record that includes the encrypted patient identification numbers, date of the observations, and the health problems (nursing diagnoses) identified on a 61 item Nurse/Patient summary sheet. It is hypothesized that an understanding of the interaction effects of patient factors (age, sex, race/ethnicity, marital status, and socioeconomic position) with disease factors (severity, complexity of treatment/management, emotional and physical burden, and costs) will enable care providers to anticipate patient healthcare needs at discharge for future improvement in patient health outcomes.

Subjects' identifiers (names and medical record numbers) are encrypted. Subjects' collected information cannot be traced or linked (associated) by name or medical record numbers to respective subjects. The primary investigators also do not have access to personal or identifying information (medical record number) linking each patient with the cases in the dataset. However, clearance from the Institutional Review Board at the University of North Carolina (UNC) has been obtained for the use of the database for this study. The proposal does not involve the study of subjects' behavior. However, insight into health behavior tendencies may be gleaned from certain nursing diagnoses. A check mark made by the nurse on the Nurse/Patient Summary sheet indicates "applicable" for each of the 61 nursing diagnoses of interest, thus a patient can conceivably have between 1 to 61 different nursing diagnoses each day over the duration of hospital stay.

# CHAPTER 4

## RESULTS

Data for subjects with primary diagnosis of type 2 diabetes mellitus (*n* = 445) and for subjects with a secondary diagnosis of type 2 mellitus (*n* = 5,318) were compared with data for subjects with neither forms of diabetes (type 1 or type 2) either as a primary or secondary diagnosis (*n* = 78,480). Of particular interest is the pattern of nursing diagnoses among these three groups of patients. It is hypothesized that there is variation in nursing diagnoses use pattern and this variation accounts for the differences across patient groups on several patient variables including length of stay in hospital. Length of hospital stay is the variable that represents the time nurses spend with patients; the longer the stay, the more time nurses spend with the patients. Length of stay has long been associated with utilization of hospital resources and was the criterion variable used in the construction and testing of diagnoses related groups (PHA, 1974; Shin, 1977). Also of particular interest is the influence of patient factors i.e. age, marital status, race, and socioeconomic status on health behaviors, and how nurses ameliorate the impact of these socio-demographic factors through the use of the nurse-patient assignment process (nursing diagnoses and interventions) to achieve desired patient health outcomes.

Figure 4.0.1 is a patient distribution flow chart that gives a broad breakdown of patient groups. With a dataset of this size, there are bound to be some observations with missing data. For example, the merging of two datasets to form the HIFX4 dataset resulted in a not missing at random (NMAR) of patient information as described by Penny and Atkinson (2011). The dataset also had information missing completely at random (MCAR). For example, in the data collection period, nurses were instructed to omit nursing diagnoses assignment whenever this process would interfere with routine patient care. As result, several patients did not have a single nursing diagnosis assigned. Also patients discharged on the same day of admission would not have a length of stay assigned. All these patients were excluded from this secondary analysis.

Three groups are identified within the general population of hospitalized patients: patients with a primary diagnosis of T2DM (*n* = 445), hereafter referred to as the PrimDx group, patients with secondary diagnosis of T2DM (*n* = 5,318) hereafter referred to as the SecDx group, and a third group- patients without primary or secondary diagnosis of T2DM or T1DM (*n* = 78,480) henceforward referred to as the No Diabetes group. These groups comprised the entire patient population (excluding newborns and mental health admissions) admitted to the University Hospitals of Cleveland (UHC) during the data collection period spanning 1986-1989. Patients with primary diagnosis of type 2 diabetes mellitus (T2DM) were chosen as the main focus of this study because of the complex nature of the disease management and the important role that care providers such as nurses play in helping patients achieve self-management of their health conditions.

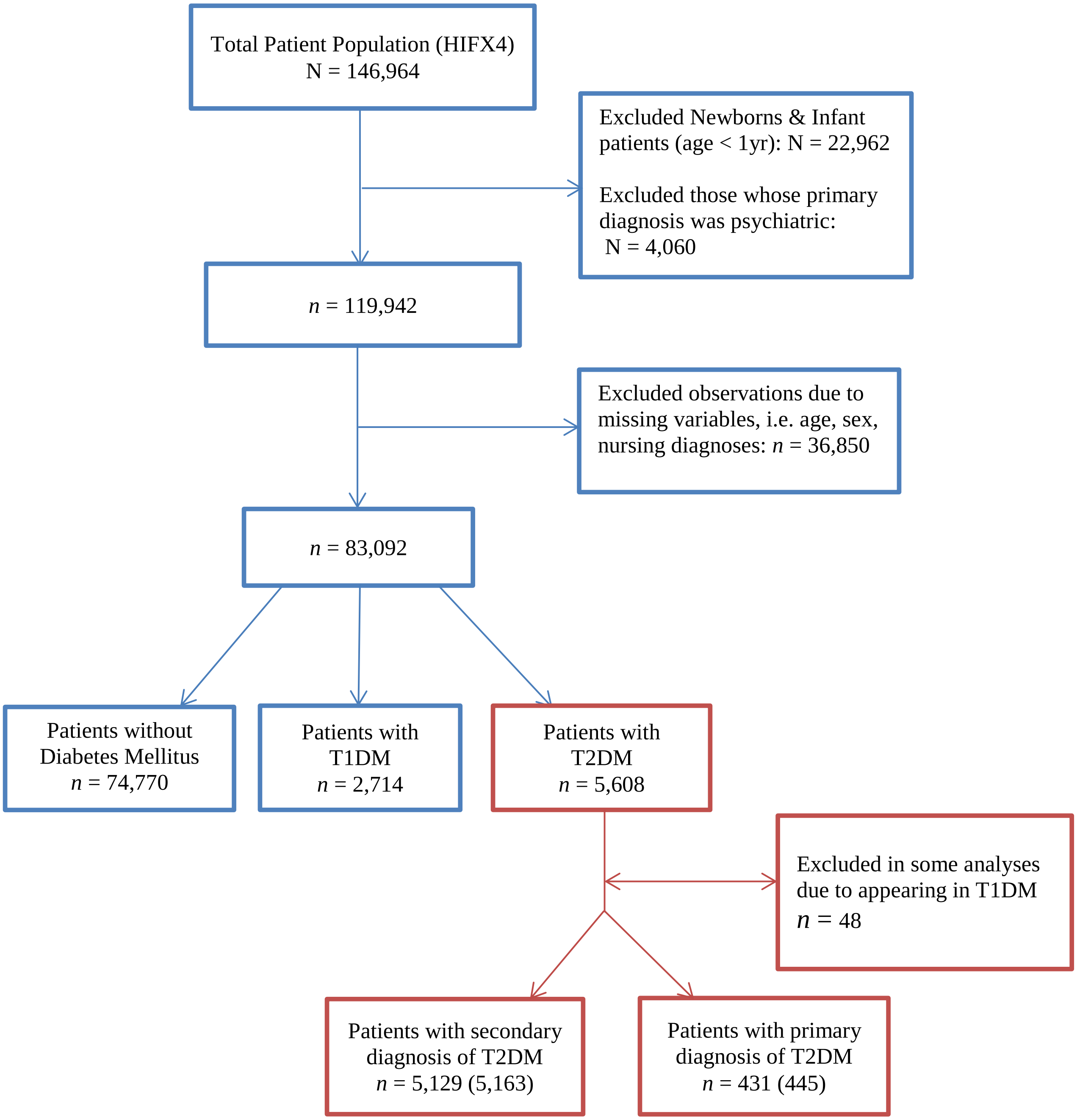


*Figure 8.* Patient Distribution Diagram for HIFX4 Dataset.

Table 4.0.1 presents the distribution of the entire patient population excluding infants and newborns (age < 1 year), and patients with mental health diagnoses for whom information on race and gender was provided. Type 2 diabetes in children typically does not occur until pre-adolescence and adolescence years, usually after age 10 (Aschemeier, Lange, Kordonouri, &

Danne, 2008; Beckwith, 2010) hence children under 1 year of age were excluded in the analysis. Table 4.0.1 offers the gender and racial breakdown of the population. The table shows that the majority of the patient population was White (58.9%) and Blacks represented about 40.5% the population.

Table 4.0.1

*Total Population by Gender and Race*

| | N | % |
|---|---|---|
| **Gender Total:** | **83,090** | **100.0** |
| Females | 50,393 | 60.65 |
| Males | 32,697 | 39.35 |
| | | |
| **Total Black(s)** | **33,657** | **40.51** |
| Females | 22,499 | 27.08 |
| Males | 11,158 | 13.43 |
| **Total White(s)** | **48,903** | **58.86** |
| Females | 27,578 | 33.19 |
| Males | 21,325 | 25.66 |
| **Total Other(s)** | **530** | **0.64** |
| Females | 316 | 0.38 |
| Males | 214 | 0.26 |
| **Total** | **83,090** | **100.0** |

Table 4.0.2 shows the distribution of type 2 diabetes mellitus across race. The percentage of T2DM as secondary diagnosis was slightly higher for Whites than for Blacks. However, among patients for whom issues of T2DM were the primary reason for admission to the hospital, Black patients where in the majority (305 of 445 or 68.5%) compared to Whites (30.8%). Thus, the incidence of T2DM as primary reason for admission to the hospital was proportionately higher among Black patients. This trend is somewhat different among patients who had T2DM

but were admitted for other health reasons other than for diabetes (secondary diagnosis of T2DM). White patients had a slight majority among patients for whom diabetes-related issues were not the primary reason for admission. White patients with T2DM were more likely to be admitted for issues perhaps unrelated to diabetes than Blacks.

Because even a secondary diagnosis of type1 or type 2 diabetes might affect the treatment of the hospitalized patient and thus, dictate nursing interventions, the population of patients without any form of diabetes represented the control group and was compared with the other patients in the two diabetes groups. Table 4.0.2 depicts racial and gender composition of these two groups.

Table 4.0.2

*Patients with Primary or Secondary Diagnosis of Type 2 Diabetes by Race*

| Patient Race | Type 2 Diabetes Mellitus | | | |
|---|---|---|---|---|
| | Secondary Diagnosis | | Primary Diagnosis | |
| | *n* | % | *n* | % |
| Black | 2,398 | 46.45 | 305 | 68.54 |
| White | 2,727 | 52.82 | 137 | 30.79 |
| Other | 38 | 0.74 | 3 | 0.67 |
| Total | 5,163 | 100.00 | 445 | 100.00 |

## Research Question 1

Question 1 was, "Can a nursing diagnoses model distinguish patients with the primary diagnosis of type 2 diabetes mellitus (ICD-9CM 250.0-9) from other patients using length of stay (LOS) as the dependent or criterion variable?"

In addressing this question, patients in the PrimDx group were compared with patients in the No Diabetes group on the variable of length of stay. Analysis of variance (ANOVA) was also conducted to examine how the groups differed on the variable of mean length of stay. Finally, regression models using a list of 61 nursing diagnoses were designed and examined to identify use patterns that might be explanatory of mean length of stay variances across the patient groups. It is hypothesized that if the use of nursing diagnoses in the care of patients is based on a disease model rather than on a holistic approach that is patient focused, then nursing diagnoses use pattern should be descriptive or predictive of medical conditions. In the present case, diagnosis of T2DM was assigned to patients by physicians using the ICD-9 system. Thus, a specific list of nursing diagnoses might differentiate one group of patients from another. If the hypothesis holds true, patients with type 2 diabetes for example, (ICD code 250) might be differentiated from other patients. And likewise, a different combination of nursing diagnoses might differentiate patients with heart failure (ICD code 428) from others. Table 4.1.1 shows the mean and range of length of stay across patient groups.

Table 4.1.1

*Average Length of Stay (days) across Patient Groups*

| **Patient Group** | ***n*** | **Mean** | **Std. Dev.** | **Coefficient of variation** | **Variance** | **Min** | **Max** |
|---|---|---|---|---|---|---|---|
| No Diabetes | 74,818 | 7.1 | 9.8 | 1.38 | 96.5 | 1.0 | 947.0 |
| Secondary dx of T2DM | 5,163 | 8.8 | 9.9 | 1.13 | 97.1 | 1.0 | 129.0 |
| Primary dx of T2DM | 445 | 9.4 | 10.9 | 1.16 | 119.7 | 1.0 | 105.0 |

Table 4.1.1 offers some interesting figures. It shows that among the three groups of patients, those without a diagnosis of diabetes had the shortest average length of stay compared to patients with either primary or secondary diagnosis of type 2 diabetes mellitus. Unexpectedly, the no diabetes group also had the smallest variance in length of stay. Surprisingly, between the two diabetes groups, there was more variance in length of stay in the much smaller and more homogenous primary T2DM group. Figure 9 is a graphic presentation of the mean length of stay across the same three patient groups. To get a better sense of members of these groups, an analysis of the age of the patients was conducted to see how patient age was related to length of stay.

Table 4.1.2

*Correlation between Age and Length of Stay*

| Groups | *n* | Mean Age | Correlation of age and Length of Stay | |
|---|---|---|---|---|
| | | | *r* | *p*-value |
| No Diabetes | 74,818 | 39.4 | .136 | < .0001 |
| Secondary T2DM | 5,163 | 64.3 | .038 | .0067 |
| Primary T2DM | 445 | 57.2 | .165 | .0005 |

From Table 4.1.2, we see that patients with primary diagnosis of T2DM were on average, younger than patients with secondary diagnosis of T2DM. Age was also more closely correlated yet not with a high magnitude with length of stay in patients with primary diagnosis of T2DM.

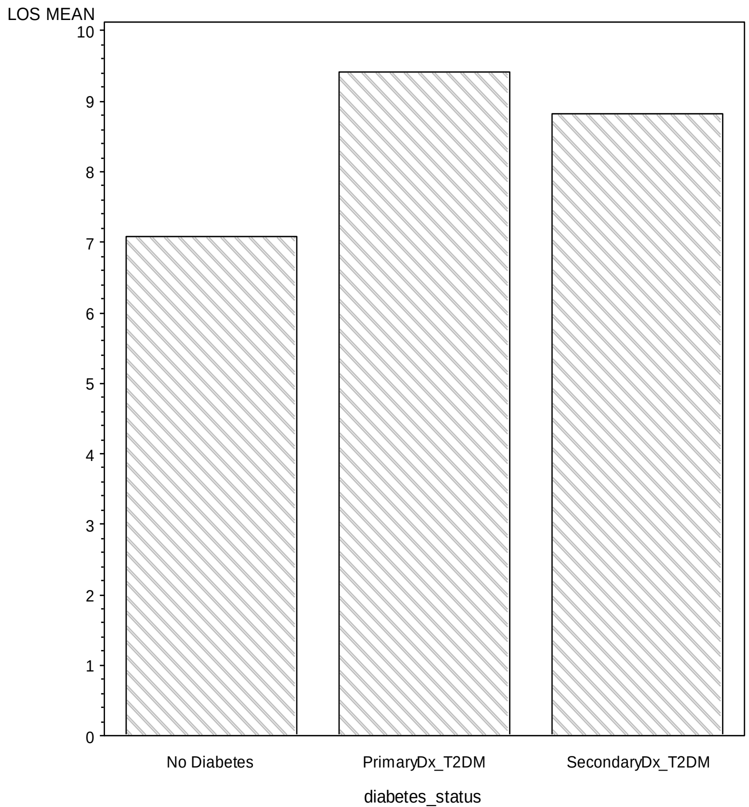


*Figure 9.* Mean Length of Stay across Patient Groups.

To further explore these variations in mean length of stay across patient groups an analysis of variance was performed to better evaluate the level of significance of the difference in mean length of stay. The *F*-statistic result for the overall one-way ANOVA model is significant ($F = 40.7$, $P < .0001$). Hence, a conclusion is reached that average lengths of stay are not the same for the three patient groups. But with an R-square of .000965 patient group contributes very little to the variation in the data. This notwithstanding, there was some variation between groups on the variable of length of stay. Thus a *post hoc* test was needed to examine group differences. Since a one-way ANOVA enables for the simultaneous comparison of all three groups against each other, the Tukey option was chosen as the *post hoc* test. The Tukey option is one test among several that can be employed to control for experimentwise error rate and to examine pairwise differences between groups. The Tukey option was chosen over the Bonferroni option because while the Bonferroni option is a much more conservative approach for detecting differences in group means (alpha =.05) in test controls for type I experimentwise error rate, it generally has a higher type II error rate than the Tukey option (SAS, 2013). Further, while the Tukey option is appropriate in instances when group sizes are equal, there were no differences in the results from both *post hoc* test options –Tukey or Bonferroni as applied.

Three pairwise comparisons were generated: 1) patients with primary diagnosis of T2DM versus patients without a diabetes diagnosis, 2) patients with secondary diagnosis of T2DM versus patients without a diabetes diagnosis, and 3) patients with primary diagnosis of T2DM versus patients with secondary diagnosis of T2DM. Two of the three pairwise comparisons were significant at the .05 alpha level. The two diabetes groups were different from the patient population without any diagnosis of diabetes. However, the difference in average length of stay between patients with primary and secondary diagnosis of T2DM was not statistically significant.

Because both age and diabetes status seem to be associated with length of stay, a general linear model (GLM) including patient age, diabetes status, and their interaction was fit in a model in an attempt to explain variation in average length of stay.

Table 4.1.3

*Summary of General Linear Model Result with Interaction Term on Length of Stay*

| **Variables** | ***F*-Value** | ***p*-Value** |
|---|---|---|
| **Age** | 40.91 | <.0001 |
| **Diabetes Status** | 4.67 | .0094 |
| **Age*Diabetes Status** | 4.60 | .0100 |

Results of the general linear model (Table 4.1.3) suggests that the interaction term of patient age and patient diabetes status is significant (*F*= 4.60, *p*-value .01) at the .05 alpha significance level. But an *R*-square of .019466 indicates that only about 2% variation in patients' length of stay is explained by the model.

Finally, the pattern of nursing diagnoses was examined to see how it differed across patient groups. Here again a general linear model was fitted this time with the 61 nursing diagnoses. A backward elimination method was used to fit the variables into the model. In an attempt to avoid the confounding effects of other variables such as patient age, race, etc., only nursing diagnoses variables were allowed in the model. The backward elimination technique was chosen because it is a dynamic selection technique that begins by calculating statistics for a model which includes all of the independent variables. The variables are then deleted from the model one at a time until all variables remaining in the model add a statistically significant enhancement to the final model at a predetermined alpha level to stay in the model (SAS, 2013). This technique also allows for comparison of how the final model is improved from the full model.

Table 4.1.4 is a summary of the regression model. Two different R-square values are presented for each patient group, a full model *R*-square and a final model *R*-square. A full model

R-square represents the percentage of the variance in length of stay explained by the full model that includes all 61 nursing diagnoses variables. A final model *R*-square is the percentage of length of stay variance explained by the more parsimonious model that included only nursing diagnoses variables that meet the criteria for inclusion and retention in the model.

Table 4.1.4

*Summary of Relation of 61 Nursing Diagnoses and Variation in Patient Length of Stay*

| Groups | *n* | R-Square | | # of Nursing dx in final model | *F*-Value | *P*-value |
|---|---|---|---|---|---|---|
| | | Full model | Final model | | | |
| No Diabetes | 74,818 | .1572 | .1570 | 52 | 267.78 | <.0001 |
| Secondary T2DM | 5,163 | .1747 | .1646 | 15 | 67.62 | <.0001 |
| Primary T2DM | 445 | .3429 | .2729 | 8 | 23.43 | <.0001 |

Results in table 4.1.4 also suggest that nursing diagnoses use pattern in the population of patients with primary diagnosis of T2DM, a much more homogenous group in terms of presenting health condition, is more explanatory of variance in length of stay compared to nursing diagnoses in the other two patient groups. In the *No Diabetes* group, the final model excluded the following nine nursing diagnosis variables: Sanitation deficit, Nutrition more required, Potential for violence, Pain, Altered tissue perfusion, Impulsivity/Hyperactivity, Altered thought process, and Altered parenting.

The final model for the SecDx group excluded 46 nursing diagnoses and retained 15 nursing diagnoses. These 15 variables included Knowledge deficit, Infection/Contagion, Fluid volume deficit, Impaired mobility, and Self-care deficit among others. For the PrimDx group, a group considered most homogenous, the final model was fitted in 53 steps with 53 variables removed to arrive at a parsimonious 8-variable final model. Variables retained included Sociocultural-economic considerations, Actual skin impairment, Constipation, Impaired mobility, Self-care deficit, Depression, and Pain. This list of nursing diagnosis variables included only two nursing diagnoses (Socio-cultural-economic considerations and skin impairment) hypothesized from current diabetes literature to be important factors in the care of the patient with type 2 diabetes.

In summary, the inquiry to determine if a model of nursing diagnoses is descriptive of patients' presenting diseases is inconclusive. The motive of this inquiry was to see if a nursing diagnoses model is able to distinguish patients with the primary diagnosis of type 2 diabetes mellitus (ICD-9CM 250.0-9) from other patients using length of stay as the dependent variable. This inquiry succeeded in establishing that the average length of stay in this population of hospitalized patients categorized in to three groups (*No diabetes*, *Secondary T2DM, and Primary T2DM*) was different. While there are no nursing diagnoses use patterns that are uniquely characteristic of any of the patient groups, even in the most homogeneous group from a medical diagnosis perspective, the finding that the nursing diagnosis model explained unexpected variation in LOS is suggestive of the importance of nurses in managing the care of these patients. In caring for their patients, nurses are taught to use a holistic approach and provide care for their patients based on the nursing needs of each patient rather than a disease label that might not be sensitive to all the health needs of the patient.

## Research Question 2

Question 2 was, "Which nursing diagnoses are associated with patients hospitalized with primary diagnosis of type 2 diabetes mellitus (ICD-9CM 250.0-9)?"

The aim of research question 2 was to identify a list of nursing diagnoses associated with a certain population of patients hospitalized with type 2 diabetes mellitus. This is in contrast to research question 1 where the aim was to find a model of nursing diagnoses that distinguished patients with type 2 diabetes Mellitus (ICD-9CM 250.0-9) from other patients using length of stay as patient outcome. In answering this question, an examination of the list of nursing diagnoses of patients known to have a primary diagnosis of T2DM ($n$=445) was compared with the list of nursing diagnoses for the two other patient groups- those without any type of diabetes diagnosis ($n$=74,770) and those for whom T2DM ($n$=5,163) is only a secondary diagnosis. The goal was to evaluate the clinical significance (occurrence frequency) of each of the 61 nursing diagnoses across the three groups of patients. It is hypothesized that a specific set of nursing diagnoses is uniquely associated with patients with a primary diagnosis of T2DM and sets these patients apart from other hospitalized patients on nursing care needs.

In addressing this research question, a number of variables were used. The relative importance (RI) of each nursing diagnosis was determined by dividing the total number of days that a nursing diagnosis was applied ($\text{Sumx}_i$) in the care of a patient by the total number of times that patient was rated (Sumdays). The following equation summarizes this process:

$$RI\ of\ Sum_x = \frac{\text{\# of days for patient}_i}{\text{Sumdays for patient}_i}$$

The variable Sumdays rather than length of stay (LOS) was used because there are days during the length of stay for which a patient might not have been rated by the nurse. During data collection, nurses were advised to omit patient rating if it would otherwise interfere with patient care. The result obtained represents the importance of each nursing diagnosis to each patient. Because this index is the total number of each nursing diagnosis in relation to the total number of days a patient was rated, it represents the significance of each nursing diagnosis to each patient's health condition. Thus, as an example, among patients with primary medical diagnosis of type 2 diabetes mellitus (ICD code 250.0), a nursing diagnosis of skin impairment (nursing diagnosis #16) with an index of 0.37 is of more clinical significance on health condition than a diagnosis of alteration in mucous membrane (nursing diagnosis #18) with an index of 0.05 (see Appendix F).

Related to the nursing diagnosis index, is the percentage of unique nursing diagnosis present for each patient during their stay. For example, for each of the 61 nursing diagnoses, the value of 1 is recorded if applicable, and 0 if not at any time during a patient's stay. Thus, there is a tally of nursing diagnoses across all patients that yielded the percentage of occurrence of each nursing diagnoses across patients. This represents the prevalence of each nursing diagnosis for each patient population. From appendix F, we see that the nursing diagnosis of noncompliance (nursing diagnosis #2) is more prevalent among patients with a primary diagnosis of T2DM (35%) compared to those with a secondary diagnosis of T2DM (24%) and those without any diagnosis of diabetes (15%).

Sixty-one (61) nursing diagnoses indexes were tabulated for the three groups of patients: patients with primary diagnosis of T2DM, patients with secondary diagnosis of T2DM, and patients without any diagnosis of diabetes mellitus. A list of thirteen nursing diagnoses hypothesized to be associated with patients with type 2 diabetes mellitus based on diabetes care literature were identified and examined for mean frequency and relative importance across the three groups (Appendix F). Table 4.2.1 is an excerpt of Appendix F and lists the hypothesized 14 nursing diagnoses. This table includes the proportion or percentage of occurrences and the relative importance of these nursing diagnoses to this population of hospitalized patients.

Table 4.2.1

*Percentage and Relative Importance of Key Nursing Diagnoses across Patient Groups*

| | **Nursing Diagnoses** | **No Diabetes diagnosis (*n* = 78,466)** | | **Secondary diagnosis of T2DM (*n* = 5319)** | | **Primary diagnosis of T2DM (*n* = 445)** | |
|---|---|---|---|---|---|---|---|
| | | % | RI | % | RI | % | RI |
| 1 | 2. Noncompliance | .15 | .0531 | .24 | .0814 | .35 | .1347 |
| 2 | 4. Prolonged disease/disability | .68 | .5412 | .92 | .7779 | .95 | .8212 |
| 3 | 8. Sociocultural consideration | .22 | .1010 | .21 | .0637 | .26 | .0845 |
| 4 | 14. Nutrition, more than req. | .08 | .0298 | .23 | .0871 | .38 | .1585 |
| 5 | 15. Nutrition, potential for excess | .06 | .0181 | .21 | .0658 | .40 | .1471 |
| 6 | 16. Skin impairment | .70 | .5361 | .63 | .4352 | .52 | .3701 |
| 7 | 17. Potential skin impairment | .62 | .3725 | .67 | .3976 | .64 | .3648 |
| 8 | 32. Altered health maintenance | .37 | .1718 | .42 | .1613 | .49 | .1947 |
| 9 | 34. Self-care deficit | .61 | .3903 | .66 | .4273 | .54 | .3323 |
| 10 | 36. Discomfort | .83 | .6199 | .83 | .5654 | .69 | .4337 |
| 11 | 37. Pain | .58 | .3649 | .52 | .2703 | .39 | .1692 |
| 12 | 42. Knowledge deficit | .84 | .6435 | .90 | .6706 | .91 | .7310 |
| 13 | 47. Depression | .24 | .0938 | .31 | .1025 | .24 | .0842 |

RI= Relative Importance

The group of patients with primary diagnosis of T2DM is considered the most homogenous of the three patient groups. This is because the primary reason for admission based on the ICD code at discharge was type 2 diabetes mellitus. While these patients may have had other medical conditions, they all had one common issue as the reason for admission- a health condition necessitating admission that is type 2 diabetes mellitus or very closely related to type 2 diabetes mellitus. This group contrast sharply with the other patient groups where in one instance, the patients do not have any form of diabetes and in the other instance, the patients have type 2 diabetes only as a secondary diagnosis and diabetes is not the reason for which treatment is sought.

It is hypothesized that in this more homogenous group, the percentage of occurrence and the relative importance of these nursing diagnoses should be high in relation to the other patient groups. However, on close examination of this list, the results are mixed. The expected trend of higher rate of occurrences and higher relative importance only held true in five of the thirteen nursing diagnoses (in red highlight). However, the expected trend held true with several key nursing diagnoses. These include the diagnoses of Noncompliance, Prolonged disease/disability, and Knowledge deficit. It is important to note also that the trend surprisingly failed to hold true with several nursing diagnoses. These include Sociocultural/economic considerations and Pain. The relative importance of Sociocultural/economic considerations was expected to be highest in this group because of the documented higher rate of minority patients (68.5% Blacks). Pain associated with diabetic neuropathy affects approximately 50% of patient with diabetes (Tesfaye et al., 2011), however in this group of patients with primary diagnosis of T2DM, the diagnosis of pain was recorded 39% of the time compared to over 50% for the other two groups.

In light of this mixed result a second method- logistic regression was used to identify and extricate a list of nursing diagnoses and to see how this new list compares to the list of nursing diagnoses hypothesized to be associated with T2DM in hospitalized patients. Nursing diagnoses, along with other demographic variables such as a patient age, race, etc., represents descriptive characteristics of the hospitalized patient, it is reasonable to expect that a set of these descriptors should be able to differentiate one type of patients from another. The utility of logistic regression is to correctly predict the category of outcome for individual cases as it fits the most parsimonious model. To accomplish this, the 61 nursing diagnoses are the independent or predictor variables while the response or dependent variable is represented by diabetes status which has two levels- no diabetes and primary diagnosis of T2DM. Patients with a secondary diagnosis of T2DM were excluded so logistic regression could be used. A backward selection technique was used to fit the logistic model to categorize the patients into two groups based on the nursing diagnoses use pattern.

The final model removed 35 nursing diagnoses retaining a total of 26 nursing diagnoses. Eight of these 26 nursing diagnoses were also present in the list of 14 nursing diagnoses hypothesized to be associated with the care of patients with primary diagnosis of T2DM. These 8 nursing diagnoses (in blue highlight), were Noncompliance, Prolonged disease/disability, Nutrition, more than required, Nutrition, potential excess, Self-care deficit, Discomfort, Pain, and Knowledge deficit. Table 4.2.2 is a list of the final model. The beta estimates column shows the relationship of the corresponding nursing diagnoses to diabetes status. In this logistic regression, the betas indicate nursing diagnoses important in classification of patients into either the PrimDx or No Diabetes groups. Because this inquiry is concerned with patients with primary diagnosis of type 2 diabetes mellitus, the PrimDx group is selected as the reference group. Positive betas represent nursing diagnoses prevalent with patients with primary diagnosis of T2DM and therefore, placed in the PrimDx group. Conversely, negative betas represent nursing diagnoses less prevalent with patients with T2DM.

Table 4.2.2

*Analysis of Maximum Likelihood Estimates*

| Nsg. dx. # | Variables | Estimate | Standard Error | Wald Chi-Square | Pr > ChiSq |
|---|---|---|---|---|---|
| 2 | Noncompliance | 0.9335 | 0.1863 | 25.1059 | <.0001 |
| 3 | Infection/Contagion | 0.4006 | 0.1367 | 8.5938 | 0.0034 |
| 4 | Prolonged disease/Disability | 1.4162 | 0.1588 | 79.5314 | <.0001 |
| 5 | Instability | -0.6360 | 0.2510 | 6.4208 | 0.0113 |
| 10 | Volume deficit | 0.5699 | 0.2373 | 5.7643 | 0.0164 |
| 12 | Bleeding | -1.5463 | 0.2521 | 37.6119 | <.0001 |
| 14 | Nutrition, more than required | 1.4418 | 0.1678 | 73.8219 | <.0001 |
| 15 | Nutrition, potential for excess | 2.2548 | 0.1803 | 156.3531 | <.0001 |
| 25 | Activity intolerance | -0.5149 | 0.1527 | 11.3721 | 0.0007 |
| 26 | Ineffective airway clearance | -1.4050 | 0.3697 | 14.4454 | 0.0001 |
| 27 | Altered breathing pattern | -1.1092 | 0.3081 | 12.9571 | 0.0003 |
| 28 | Impaired gas exchange | -0.6767 | 0.3443 | 3.8621 | 0.0494 |
| 29 | Altered tissue perfusion | 0.7113 | 0.1692 | 17.6688 | <.0001 |
| 30 | Decreased CO | -0.6471 | 0.2664 | 5.8981 | 0.0152 |
| 31 | Diversional activity deficit | -0.3602 | 0.1500 | 5.7686 | 0.0163 |
| 33 | Impaired mobility | 0.6191 | 0.1513 | 16.7496 | <.0001 |
| 34 | Self-care deficit | -0.3976 | 0.1635 | 5.9127 | 0.0150 |
| 35 | Impaired home maintenance/mgt. | 0.4861 | 0.1420 | 11.7135 | 0.0006 |
| 36 | Discomfort | -0.7127 | 0.1344 | 28.1330 | <.0001 |
| 37 | Pain | -1.2063 | 0.1729 | 48.6557 | <.0001 |
| 42 | Knowledge deficit | 0.9318 | 0.1427 | 42.6591 | <.0001 |
| 43 | Growth/Development deficit | -1.5931 | 0.4040 | 15.5529 | <.0001 |
| 45 | Anxiety | -0.4901 | 0.1401 | 12.2464 | 0.0005 |
| 51 | Altered family process | -0.8548 | 0.2324 | 13.5227 | 0.0002 |
| 52 | Altered parenting | -1.7321 | 0.5709 | 9.2055 | 0.0024 |

While some of the nursing diagnoses left in the model were also present in Table 4.2.1, some other nursing diagnoses included in the model do not seem to be nursing diagnoses that the literature associates with patients with primary diagnosis of type 2 diabetes mellitus. These nursing diagnoses are presumed to be less prevalent with patients with T2DM and are shown with negative betas on Table 4.2.2. Examples of these nursing diagnoses are *instability*, *bleeding*, *activity intolerance*, *ineffective airway clearance*, *decreased cardiac output*, and altered parenting among others. Although demographic variables such as age and race/ethnicity were withheld from the model as the intent of this inquiry was to see the effect of a list of nursing diagnoses on the T2DM status of hospitalized patients, it is recognized that patient race/ethnicity socioeconomic status, and age are variables generally considered in the discussion of type 2 diabetes mellitus care and treatment.

Five of the 8 nursing diagnoses common to both Table 4.2.1 and Table 4.2.2 were also identified to follow the trend of higher rate of occurrence and higher relative importance for PrimDx group versus other patient groups in Table 4.2.1. These five nursing diagnoses were Noncompliance, Prolonged disease/disability, Nutrition more than required, Nutrition, potential for excess, and Knowledge deficit.

In summary, research question 2 was able to identify and confirm 8 nursing diagnoses hypothesized based on current diabetes literature to be important in the care of the patient hospitalized with complications related to type 2 diabetes mellitus yet another 34 nursing diagnoses were identified by assigned nurses as present and significant in the 445 T2DM cases. This pattern reinforces the perspective identified in addressing Question 1, above. In caring for their patients, nurses are taught to use a holistic approach and provide care for their patients based on the nursing needs of each patient rather than a disease label that might not be sensitive to all the health needs of the patient.

## Research Question 3

Question 3 was, “What is the magnitude and direction of the correlation between the number of nursing diagnoses and of length of stay and intensive care unit days among hospitalized patients with primary diagnosis of type 2 diabetes mellitus?”

The aim of research question 3 was to examine the relationship between the number of nursing diagnoses and the length of stay among patients hospitalized with primary diagnosis of type 2 diabetes mellitus. This query examined general stay in the hospital as well as stay in the Intensive Care Unit (ICU) where applicable. This question was answered in steps using three different statistical tests: (a) examination of the correlation between the number of nursing diagnosis and patients’ length of stay using Pearson correlation, (b) identification of other patient variables that might affect length of stay while at the same time checking for multicollinearity using multiple regression models, and (c) fit models with statistically significant variables and examine interaction terms for significance using general linear models (GLM).

Patients with primary diagnosis of type 2 diabetes mellitus ($n$ = 445) constituted the core group for this analysis. Table 4.3.1 show that the average age of this group was 57.2 ($SD$ = 16.7) with considerable variance in age. Average hospital length of stay was over 9 days, which seem long for a diabetes diagnosis necessitating admission to the hospital. This is however not unexpected considering this population had on average over 19 nursing diagnoses.

Table 4.3.1

*Mean Age Length of Stay and Nursing Diagnoses*

| Variables | N | Mean | Median | Mode | STD | Variance | Min | Max |
|---|---|---|---|---|---|---|---|---|
| Age | 445 | 57.19 | 59.00 | 64.0 | 16.70 | 278.91 | 1.0 | 101.0 |
| Length of Stay | 445 | 9.42 | 6.0 | 4.0 | 10.94 | 119.74 | 1.0 | 105.0 |
| Nursing Diagnoses | 445 | 19.47 | 16.00 | 12.0 | 12.31 | 151.56 | 1.0 | 58.0 |

Independent *t*-test to compare average length of stay (LOS) of patients with primary diagnosis of type 2 diabetes mellitus across marital status, gender, and insurance types was performed. The folded *F*-statistic to assess the equality of variances indicates the population are unequal across marital status (*F*-value = 1.8, $p < .001$), and gender (*F*-value = 1.45, $p = .009$) therefore, the Satterthwaite method for unequal variances was used to examine the *t*-test for the mean length of stay across groups. The first analysis produced a non-significant *t* value ($t_{(397)} = 1.78$, $p = .08$) at the .05 significance level for marital status. Thus, length of stay averages for married and unmarried patients were not significantly different. Average length of stay was however significantly different across these groups at the .10 alpha level. Married patients stayed on average, 8.3 days compared to 10.0 days for unmarried patients (see Table 4.3.2). Regarding gender, the second *t*-test result also yielded a non-significant *t value* ($t_{(381)} = -.33$, $p = .74$). An examination of the means however revealed that females had a slightly longer average length of stay (9.5 days) than males (9.2 days).

Table 4.3.2

*Length of Stay across Subgroups of Patients with Primary Diagnosis of Type 2 Diabetes Mellitus*

| Patient Factors | Groups | *n* (%) | Mean LOS (*SD*) | *P*-value |
|---|---|---|---|---|
| Marital Status | Married | 155 (34.8) | 8.3 (8.9) | .0752 |
| | Not Married | 290 (65.2) | 10.0 (11.9) | ($t$ = 1.78) |
| Gender | Female | 285(64.0) | 9.5 (11.6) | .7426 |
| | Male | 160 (36.0) | 9.2 (9.6) | ($t$ = -0.33) |
| Insurance | Private/HMO | 117 (23.53) | 6.9 (6.9) | .0065 |
| | Medicare/Other | 215 (41.63) | 10.5 (13.2) | ($F$ = 5.09) |
| | Medicaid/Welfare | 169 (34.84) | 8.4 (8.3) | |

Analysis of variance (ANOVA) was used to compare this patient population across three levels of insurance classification- Private/HMO, Medicare/Other, and Medicaid/Welfare. Table 4.3.3 shows the classification of sources of insurance or guarantors into the three financial classes.

Table 4.3.3

*Classification of Insurance Types by Financial Class*

| **Financial Class** | **Insurance Type** | ***n* (%)** |
|---|---|---|
| **Private/HMO** | Blue Cross (including Cincinnati Blue Cross)<br>Commercial<br>Industrial Commission/Workman's Compensation<br>University Hospital Employee<br>Health Management Organizations (HMO)<br>Research | 104 (23.5) |
| **Medicare/Other** | Miscellaneous<br>Medicare (Part A and Part B)<br>PPO | 184 (41.6) |
| **Medicaid/Welfare** | Crippled Child<br>Medicaid (including Out-of-State Medicaid)<br>County Welfare- Adult<br>County Welfare Child<br>Pending or Self pay<br>Delinquent pay | 154 (34.9) |
| **Total** | | **442 (100.0)** |

Analysis of the general model result (*F* value = 5.09, *p* = .0065) indicated that differences in the mean length of stay for patients across insurance groups are statistically significant at the .05 alpha level (see Table 4.3.2). Based on the Levene's test of homogeneity (or equality of variances between the groups), the variances for the groups are not equal (*F* value =2.66, *p* = .07) using 0.1 significance level. Based on the Tukey test for pairwise comparison, mean length of stay for patients with Medicare/Other insurance was different from that of patients with Private/HMO. This was the only pairwise comparison of statistical significance at the 0.05 alpha level. In general, patients with private insurance or members of health management organizations (HMOs) tended to have the shortest average length of stay (see Table 4.3.2). Patients on Medicare or other forms of non-private pay insurance had the longest average length of stay.

*Pearson Correlation between Variables*

Of the 505 patients admitted with primary diagnosis of T2DM sixty had missing values and were thus excluded from this analysis, resulting in a sample of 445 patients. The correlation between the number of nursing diagnoses and length of stay among patients with primary diagnosis of T2DM was positive, strong, and statistically significant ($r$ = .67, $p$ <.0001). See

Table 4.3.4

*Pearson Correlation Coefficients of Variables*

| | **Length of Stay** | **Num. of Nsg. dx.** | **ICU days** |
|---|---|---|---|
| **Number of Nursing dx.** | 0.66652<br><.0001 | | |
| **ICU days** | 0.33254<br><.0001 | 0.38581<br><.0001 | |
| **Age** | 0.16492<br>0.0005 | 0.19852<br><.0001 | 0.10492<br>0.0269 |

The coefficient of determination ($r^2$ = .44) revealed that 44% of the variance in hospital length of stay was explained by patients' number of nursing diagnoses. The number of nursing diagnoses also had a positive but relatively weak correlation ($r$ = .39) with the number of days spent in the ICU. A coefficient of determination ($r^2$ = .145) accounted for approximately 15% of the variation in ICU length of stay. There were also positive, but weaker correlations between patient's age, length of hospital stay, the number of nursing diagnoses, and ICU days. Finally, spending time in the ICU seems to be associated with longer length of stay. This is because there exists a statistically significant correlation between ICU days and length of stay ($r$ = .33, $p$ < .0001) with a coefficient of ($r^2$ = .11). All correlations were statistically significant at the .05 alpha level. Figure 10 is a scatter plot showing relationship between patient length of stay and the number of nursing diagnoses for patients with primary diagnosis of T2DM. From the figure, it is evident that length of stay is increased as the number of nursing diagnoses increased.

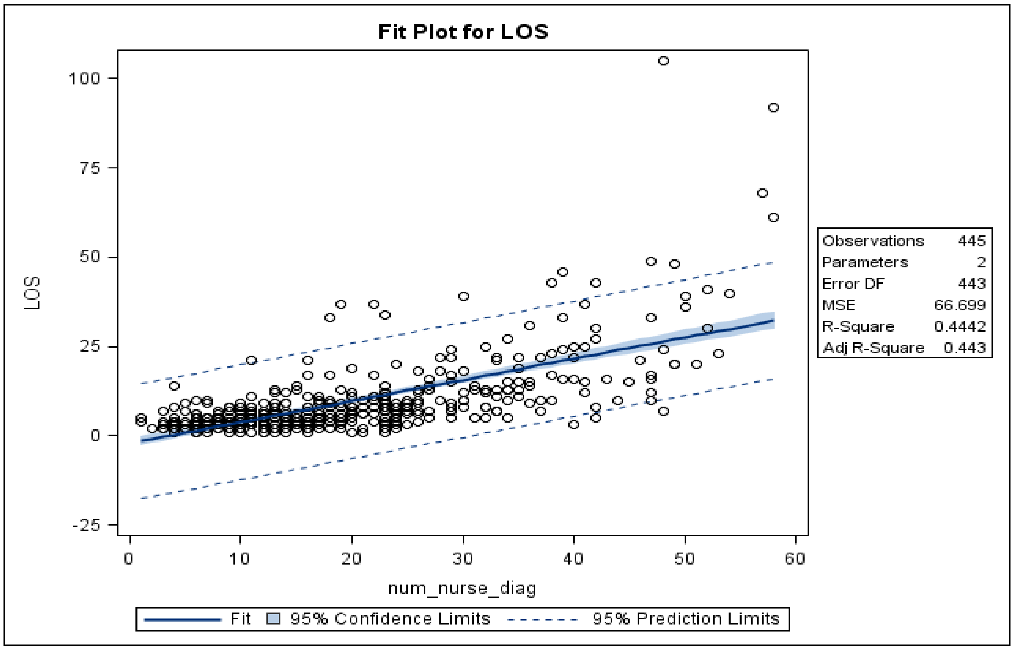


*Figure 10.* Correlation of Length of Stay and Number of Nursing Diagnoses in Patients with Primary Diagnosis of Type 2 Diabetes Mellitus.

*Multiple Regression Models*

A multiple regression model was constructed to identify the independent effects of these patient factors and the number of nursing diagnoses on length of stay. Patient age, gender, marital status, and type of insurance (Blue Cross/HMO, Commercial/Workman's Compensation, Medicare, Medicaid, Welfare or Self-pay, etc.) and number of nursing diagnoses were put in a single model for length of stay. Together, these predictor variables accounted for 44% ($r^2$ = .4413) (See Table 4.3.5) of the variance in hospital length of stay among patients with primary diagnosis of T2DM. However, only one variable –number of nursing diagnoses- was a significant predictor of length of stay (see Table 4.3.6). Number of nursing diagnoses ($\beta$ = .59, $p$

< .0001) was positively associated with length of stay. Age ($\beta$ = .03, $p$ = 0.35), gender ($\beta$ = -1.2, $p$ = 0.18), marital status ($\beta$ = -.62, p = 0.4922), private/HMO ($\beta$ = -.57, $p$ = 0.61), and Medicare/other ($\beta$ = -.26, $p$ = 0.82) were not statistically significantly associated with length of stay (see table 4.3.6) with other variables controlled for in the model. Whereas for every one additional nursing diagnosis, length of stay increased by .59 days, but for every additional year in age, length of stay only increased by .03 days. Being female was associated with 1.2 days decrease in length of stay ($p$ < .05). Being married was predicted to result in .64 days reduction in length of stay and having private insurance or being a member of a health management organization (HMO) was associated with .47 fewer days in length of stay. However, these variables were not statistically significant (see Table 4.3.6).

Table 4.3.5

*Multiple Regression Summary*

| Root MSE | Dependent Mean | Coefficient of Variation | R-Square | Adjusted R-Square |
|---|---|---|---|---|
| 8.20152 | 9.43891 | 86.89052 | 0.4489 | 0.4413 |

Table 4.3.6

*Parameter Estimates of Variables Affecting Length of Stay*

| Variable | Label | DF | Parameter Estimate | *t* value | *p* value | 95% Confidence Limit | |
|---|---|---|---|---|---|---|---|
| Intercept | Medicaid/Welfare | 1 | -2.42411 | -1.43 | 0.1530 | -5.75272 | 0.90450 |
| Nursing dx. | Number of Nsg. dx. | 1 | 0.58604 | 18.02 | <.0001 | 0.52211 | 0.64996 |
| Age | Patient Age | 1 | 0.02906 | 0.93 | 0.3508 | -0.03209 | 0.09022 |
| Female | Gender | 1 | -1.15556 | -1.36 | 0.1746 | -2.82564 | 0.51453 |
| Married | Marital Status | 1 | -0.62162 | -0.69 | 0.4922 | -2.39917 | 1.15592 |
| Insurance 1 | Private/HMOs | 1 | -0.57592 | -0.52 | 0.6048 | -2.76156 | 1.60971 |
| Insurance 2 | Medicare/Other | 1 | -0.25806 | -0.23 | 0.8212 | -2.50118 | 1.98505 |

*General Linear Models with Interaction Terms*

Patient age is often considered in the evaluation of a patient's ability to recover from illness and thus an important variable in health outcome of the hospitalized patient (Kirkland & Sinclair, 2011; Scott, 2003). For this reason age was also examined for a potential interaction effect. In the full model that included number of nursing diagnoses, age gender, marital status, insurance type and the interaction between number of nursing diagnoses and patient age, interaction was found to be significant (*F* value = 11.94, $p$ = .0006). Table 4.3.7 displays results from the GLM full model. When age was deconstructed into two groups: patients 35 years of age or younger and patients over 35 years of age, number of nursing diagnoses was found to have a significant effect on length of stay for patients 35 years of age and younger (*t* value = 7.33, $p <$ .0001) and an even stronger effect among patients age 35 and older (*t* value = 18.52, $p < .0001$). This full GLM model ($R^2$ = .463643) accounted for 46% of the variance in length of stay among patients with primary diagnosis of T2DM.

Table 4.3.7

*General Linear Model Result for Length of Stay*

| Variables | *F* Values | *P* Value |
|---|---|---|
| Number of nursing diagnoses | 2.76 | 0.0976 |
| Age | 4.23 | 0.0403 |
| Gender | 2.13 | 0.1450 |
| Marital Status | 0.58 | 0.4486 |
| Insurance | 0.05 | 0.9516 |
| Number nursing diagnoses*Age | 11.94 | 0.0006 |

In summary, the result of this analysis demonstrates that patients' number of nursing diagnoses is a strong predictor of length of stay. This finding suggests that nursing diagnoses nurses use in the care of their patients are more sensitive predictors of patient health outcome when length of stay is used as a proxy measure for patient outcome in a regression model that include patient age, marital status, gender and type of insurance. Age by itself is not a strong predictor of patient length of stay. However when age, particularly in older patients is considered along with number of nursing diagnoses then patient age becomes an important patient variable in explaining the variance in patient length of stay. These findings, like findings in research question 1 also suggest that nurses, in caring for their patients, use a holistic approach and provide care for their patients based on the nursing needs of each patient rather than a disease label or on demographic characteristics that might not be sensitive to all the health needs of the patient.

## Research Question 4

Question 4 was, "Which of the 61 nursing diagnoses are most influential in explaining the variances in the length of stay among patients with primary diagnosis of type 2 diabetes mellitus?"

For this analysis, nursing diagnoses use pattern was examined across three patient populations: patients with primary diagnosis of T2DM, patients with secondary diagnosis of T2DM, and patients with neither form of diabetes in either as a primary or secondary diagnosis. This analysis is premised on the axiom that use pattern of nursing diagnosis should be different for different groups of patient and ought to be sensitive to patients' health conditions. Alternatively, the absence of use pattern might be indicative of the uniqueness of patients from the perspective of nurses in patient health outcome versus the medical model that is associated with patient illnesses and diseases.

Research question 4 aimed to identify a subset of nursing diagnoses from the 61 nursing diagnoses that are most influential in explaining the variance in patient length of stay among patients hospitalized with primary diagnosis of type 2 diabetes mellitus. Determining which nursing diagnoses are most predictive of patient length of stay in patients with type 2 diabetes as primary diagnosis involved the use of a regression procedure and a stepwise selection technique. The use of automated model selection in regression model fitting has been praised for their ability to manage large numbers of variables while at the same time criticized for their instability in terms of replication (Sauerbrei & Schumacher, 2007). For these reasons, it is important for the researcher to have a priori knowledge of the subject matter and be able to adjust the automated model selection process by manually removing or adding variables to the model. The stepwise method was chosen in this over other methods (i.e. forward selection, backward elimination, and maximum R technique) because it is a more dynamic selection method that continuously evaluates the contribution and significance of each variable already in the model as new variables are added to the model. Variables already in the model may be removed as their significance change based on the addition of other variables (SAS, 2013). Along with this automated method of fitting a model, variables were also manually added to the model based on a priori knowledge of the population of interest from current literature. Researcher's knowledge of the data to guide the model selection process even when automated procedures are used is good practice (Elliott, 2010) that enhances the validity of the final model. The approach to research question four involved analysis of two different models: (a) an automated selection model and (b) a combined automated and manually selected model. Multicollinearity of all variables was assessed using the *Collin VIF Tol* options in SAS.

Collin refers to the test of collinearity or multicollinearity of variables within a model. The TOL option requests the tolerance values for the parameter estimates. Tol refers to tolerance values for the estimates. The tolerance for a variable is defined as $I/R^2$ where $R^2$ is obtained from the regression of a particular variable on all other variables in the model. VIF refers to variance inflation factors of the parameter estimates. These factors measure the inflation in the variances of the parameter estimates due to collinearities that exist among the independent variables (SAS, 2013).

Variables were included in this automated model selection process using the significance level of 0.1(Slentry = 0.1) Because the stepwise method continuously evaluates the contribution and significance of each variable already in the model a significance level condition is required to keep variables in the model. In this analysis an alpha significance level of 0.15 (Slstay = 0.15) was set as a condition to keep variables in the model. These predetermined levels of significance are intended to be more conservative than the usual SAS default levels of .5 because a more parsimonious final model is desired. The first automated model selection for the patient group with primary diagnosis of T2DM yielded 8 variables plus the intercept. Table 4.4.1 is a summary of the initial regression model. These 8 nursing diagnoses accounted for 26.6% of the variance in patient length of stay.

Table 4.4.1

*Group Summary of Model Selection*

| Groups | n | # of Variables included | Selection Steps | R-Square | Adjusted $R^2$ |
|---|---|---|---|---|---|
| Primary diagnosis of T2DM | 445 | 8 | 8 | 0.2776 | 0.2643 |

Table 4.4.2 offers a list of variables included in the final model. Inexplicably, this model included two variables - Constipation and Sexual dysfunction that seem out of place based on their *p*-values and partial *R*-squares that borders on statistical insignificance at the .5 alpha level. These variables were removed from the model and the regression re-ran to see if appreciable information was lost based on the new model R-square. The new model without the variables of sexual dysfunction and constipation was an improved model with an adjusted R-square of 0.2552 (F-value = 26.35, P< .0001). Thus, 25.5 % of variance in patient length of stay is explained by only 6 nursing diagnoses.

Table 4.4.2

*List of Variables Affecting Variance in Length of Stay*

| **Variables** | **Partial R-Square** | **Model R-Square** | ***F*-Value** | ***p*-Value** |
|---|---|---|---|---|
| 33. Impaired Mobility | 0.1669 | 0.1669 | 88.78 | <.0001 |
| 37. Pain | 0.0377 | 0.2046 | 20.94 | <.0001 |
| 47. Depression | 0.0210 | 0.2256 | 11.96 | 0.0006 |
| 16. Skin Impairment | 0.0195 | 0.2451 | 11.35 | 0.0008 |
| 34. Self-Care Deficit | 0.0121 | 0.2573 | 7.18 | 0.0077 |
| 22. Constipation | 0.0082 | 0.2654 | 4.86 | 0.0280 |
| 8. Sociocultural Econ | 0.0075 | 0.2729 | 4.51 | 0.0343 |
| 56. Sexual Dysfunction | 0.0047 | 0.2776 | 2.81 | 0.0946 |

Also of interest in this analysis was the role of patient demographic variables such as age, marital status, and insurance type in determining patient length of stay. It was also important to see if other patient variables were more influential in explaining the variance in length of stay among patients with primary diagnosis of T2DM. For this inquiry, the above demographic variables were added to the model and forced to stay using the include option in SAS. Table 4.4.3 is a summary of the final model (*F*-value= 14.33, $p < .0001$).

Table 4.4.3

*Group Summary of Model Selection with Demographic Patient Variables*

| Groups | *n* | # of Variables included | Selection Steps | R-Square | Adjusted $R^2$ |
|---|---|---|---|---|---|
| Primary diagnosis of T2DM | 445 | 12 | 7 | 0.2861 | 0.2661 |

The regression model did not improve substantially with the inclusion of patient demographic variables. Only one of the demographic variables- marital status, had a statistically significant impact on the model at the .05 alpha level. Table 4.4.4 lists the variables and their *p*-values along with the 95% confidence limits. Seven Nursing diagnoses variables were included in this model. Sexual dysfunction is replaced by diversional activity deficit and the variable constipation was again included in this model.

Table 4.4.4

*List of Variables Related to Patient Length of Stay*

| Variable | Estimates | Std. error | *t*-value | *p*-value | 95% Confidence Limit | |
|---|---|---|---|---|---|---|
| Intercept (Medicaid)* | 0.07808 | 2.01651 | 0.04 | 0.9691 | -3.88539 | 4.04154 |
| Age* | 0.05824 | 0.03703 | 1.57 | 0.1165 | -0.01454 | 0.13102 |
| Private/HMO* | -0.51481 | 1.28512 | -0.40 | 0.6889 | -3.04073 | 2.01110 |
| Medicare/Other* | -1.17186 | 1.32273 | -0.89 | 0.3761 | -3.77169 | 1.42797 |
| Gender (Female)* | 0.35782 | 1.00088 | 0.36 | 0.7209 | -1.60942 | 2.32506 |
| Marital Status (Married)* | -2.13397 | 1.03897 | -2.05 | 0.0406 | -4.17607 | -0.09186 |
| 16. Skin Impairment | 5.09924 | 1.31372 | 3.88 | 0.0001 | 2.51711 | 7.68138 |
| 22. Constipation | 5.42657 | 2.57066 | 2.11 | 0.0354 | 0.37392 | 10.47922 |
| 31. Diversional Activity Deficit | 3.06837 | 1.55910 | 1.97 | 0.0497 | 0.00394 | 6.13280 |
| 33. Impaired Mobility | 2.97288 | 1.69163 | 1.76 | 0.0796 | -0.35205 | 6.29780 |
| 34. Self-Care Deficit | 3.71357 | 1.59754 | 2.32 | 0.0206 | 0.57358 | 6.85356 |
| 37. Pain | 5.93970 | 1.86063 | 3.19 | 0.0015 | 2.28263 | 9.59678 |
| 47. Depression | 7.63027 | 2.49134 | 3.06 | 0.0023 | 2.73352 | 12.52702 |

* Forced into the model by the INCLUDE = option

In summary, patient variables of age, gender, marital status, and financial class were not as important in predicting patient length of stay as nursing diagnoses. This inquiry confirms findings in research question 3 where the number of nursing diagnoses was also the most important predictor of patient length of stay given that other patient demographic variables were included in regression models. Being married seemed to have a reductive effect on the average length of stay. This finding confirms information gleaned from the review of the literature that suggests the support of a spouse or family was determinant of discharge disposition.

## Research Question 5

Question 5 was, "What is the relationship between patients' discharge disposition (Home, Rehabilitation facility, nursing home, death, etc.) and patients' age gender, race/ethnicity, marital status, and payer type?"

Research question 5 examines the relationship between patients' discharge disposition (discharge to home, discharge to other facility, discharge to nursing home/rehabilitation facility, and discharge to home with home healthcare) and patients' factors of age, gender, race/ethnicity, marital status and insurance type. The aim was to highlight the influence of these patient variables on patient discharge disposition. In this inquiry, the dependent variable- discharge disposition was collapsed from 14 categories to four categories based on the type of nursing care needs of patients at discharge, also included, is a fifth category of patients recorded as died. The five categories included 1) discharge to own home, 2) discharge to own home with home health services, 3) discharge to extended healthcare facilities including nursing homes and rehabilitation centers, 4) discharge to other health care facilities not including nursing homes or rehabilitation center, and 5) died. Tables 4.5.1 gives the frequency distributions of discharge disposition for all patients.

Table 4.5.1

*Discharge Disposition for all Patients*

<table>
<tr><th>Discharge Disposition</th><th>Frequency</th><th>Percent</th><th>N</th><th>Percent</th></tr>
<tr><td>Discharged Home</td><td>74371</td><td>89.50</td><td>74371</td><td>89.50</td></tr>
<tr><td>Discharged to a home care services</td><td>3295</td><td>3.97</td><td>3295</td><td>3.97</td></tr>
<tr><td>Discharged to extended care facility</td><td>1828</td><td>2.20</td><td rowspan="2">2,423</td><td rowspan="2">2.92</td></tr>
<tr><td>Discharged to Rehab facility</td><td>595</td><td>0.72</td></tr>
<tr><td>Discharged to another acute care</td><td>347</td><td>0.42</td><td rowspan="6">910</td><td rowspan="6">1.11</td></tr>
<tr><td>Discharged against medical advice</td><td>237</td><td>0.29</td></tr>
<tr><td>Unknown discharge destination</td><td>82</td><td>0.1</td></tr>
<tr><td>Discharged to another UH facility</td><td>200</td><td>0.24</td></tr>
<tr><td>Discharged to Psychiatric facility</td><td>38</td><td>0.05</td></tr>
<tr><td>Discharged to a hospice</td><td>6</td><td>0.01</td></tr>
<tr><td>Died</td><td>2093</td><td>2.52</td><td>2,093</td><td>2.52</td></tr>
<tr><td>Total</td><td>83,092</td><td>100</td><td>83,092</td><td>100</td></tr>
</table>

Insurance type was used in this analysis as a proxy measure for financial class. Health resources for example, the availability and access to health insurance coverage has been linked to socioeconomic status and has been shown to be predictive of health status and desired health outcomes (Kim & Richardson, 2012). In the current study, the type of patient health insurance coverage was used to determine patients' financial class. Consequently, financial class was categorized based on the socioeconomic status theoretically associated with the various insurance types and their providers or guarantors. Health insurance type was reduced from 19 categories to 3 major categories: Private/HMO insurance, Medicare/Other insurance, and Medicaid/welfare. Table 4.5.2 is a summary of the classification of the various insurance types into three main financial classes.

Table 4.5.2

*Insurance Type and Class*

| **Financial Class** | **Insurance Type** |
|---|---|
| **Private/HMO** | Blue Cross (including Cincinnati Blue Cross)<br>Commercial<br>Industrial Commission/Workman's Compensation<br>University Hospital Employee<br>Health Management Organizations (HMO)<br>Research |
| **Medicare/Other** | Miscellaneous<br>Medicare (Part A and Part B)<br>PPO |
| **Medicaid/Welfare** | Crippled Child<br>Medicaid (including Out-of-State Medicaid)<br>County Welfare- Adult<br>County Welfare Child<br>Pending or Self pay<br>Delinquent pay |

Table 4.5.3 gives a distribution of health insurance type by patient race. This table shows that Medicaid/Welfare recipients were 22.4% for Blacks compared to 6.4% for White patients. In contrast, private health insurance holders or HMO members were mostly Whites at 34.7% compared to 9.3% for Black patients. It is important to note that patients often present with more than one form of insurance coverage, for example a patient might have Medicaid and supplemented by private insurance or vice versa with Medicaid as the supplemental health insurance coverage. Medicaid is a means-tested health insurance program for families and individuals with low income and resources. Medicare guarantees health insurance for Americans ages 65 and older and younger people with disabilities, Medicare offers a choice between an open-network single payer health care plan (traditional Medicare) and a network plan (Medicare Advantage, or Medicare Part C), where the federal government pays for private health coverage

(Medicare.gov, 2013). In the current study, wherever more than one insurance type is reported, the first reported primary source of health insurance is used for classification purposes.

Table 4.5.3

*Distribution of Insurance Type by Race*

| Insurance Type | Race: Black vs. White/Other | | | | All Races | |
|---|---|---|---|---|---|---|
| | Blacks | | Whites/Others | | | |
| | Count | Percent | Count | Percent | Count | Percent |
| Medicaid/Welfare | 18,479 | 22.4% | 5,164 | 6.2% | 23,643 | 28.7% |
| Medicare/Other | 7,291 | 8.8% | 14,951 | 18.1% | 22,242 | 27.0% |
| Private/HMO | 7,624 | 9.2% | 28,654 | 34.8% | 36,278 | 44.1% |
| All Insurance Type | 33,394 | 40.6% | 48,769 | 59.3% | 82,163 | 100.0% |

Tables 4.5.4 and 4.5.5 gives a breakdown of patient discharge disposition by gender and race respectively. In both tables, the majority of the patients were discharged home (89.3%). A higher percentage of females than males were discharged to extended care facilities and home health. This is probably due to the higher percentage of females (60.6%) compared to men (39.3%) in the general population of patients.

Table 4.5.4

*Discharge Disposition by Gender*

| Discharge Disposition | SEX | | | | Both Genders | |
|---|---|---|---|---|---|---|
| | Female | | Male | | | |
| | Count | Percent | Count | Percent | Count | Percent |
| 1:Discharged home | 45111 | 54.2% | 29260 | 35.2% | 74371 | 89.5% |
| 2:Home health | 2111 | 2.5% | 1184 | 1.4% | 3295 | 3.9% |
| 3:ECF/Rehabilitation | 1592 | 1.9% | 831 | 1.0% | 2423 | 2.9% |
| 4:Discharged to Other | 453 | 0.5% | 456 | 0.5% | 909 | 1.0% |
| 5:Died | 1127 | 1.3% | 966 | 1.1% | 2093 | 2.5% |
| All Discharge Disposition | 50394 | 60.6% | 32697 | 39.3% | 83091 | 100.0% |

Of interest in this analysis is the percentage of Black patients with a desired discharge disposition –discharge to home rather than to a nursing home. Table 4.5.5 shows a trend that is somewhat consistent with the percentage of each race. Blacks made up about 40% of this entire patient population and they accounted for about 36% of discharges to home.

Table 4.5.5

*Discharge Disposition by Race*

| Discharge Disposition | Race: Black vs. White/Other | | | | Blacks and Whites/Other | |
|---|---|---|---|---|---|---|
| | Blacks | | Whites/Others | | | |
| | Count | Percent | Count | Percent | Count | Percent |
| 1:Discharged home | 29905 | 35.9% | 44464 | 53.5% | 74369 | 89.5% |
| 2:Home health | 1716 | 2.0% | 1579 | 1.9% | 3295 | 3.9% |
| 3:ECF/Rehabilitation | 913 | 1.0% | 1510 | 1.8% | 2423 | 2.9% |
| 4:Discharged to Other | 416 | 0.5% | 493 | 0.5% | 909 | 1.0% |
| 5:Died | 706 | 0.8% | 1387 | 1.6% | 2093 | 2.5% |
| All Discharge Disposition | 33656 | 40.5% | 49433 | 59.4% | 83089 | 100.0% |

Table 4.5.6 is the breakdown of patient discharge disposition by insurance type. A vast majority of the patients were discharged to home (76753 or 89.2%), with a higher proportion of patients with private insurance or HMO as a single group being home bound at almost 42%. Almost 11% (10.8% or 9,245) of the entire patient population included in the analysis were discharged to other destinations or to home with home health services. 3,805 of these 9,245 patients were discharged to an extended care facility or other types of facilities. Of this group, 81.7% were recipients of Medicaid/Welfare or Medicare/Other insurance coverage.

Table 4.5.6

*Discharge Disposition by Insurance Categories*

| Discharge Disposition | Insurance Categories | | | | | | All Insurance Type | |
|---|---|---|---|---|---|---|---|---|
| | Medicaid/Welfare | | Medicare/Other | | Private/HMO | | | |
| 1:Discharged home | 21911 | 26.6% | 17066 | 20.7% | 34518 | 42.0% | 73495 | 89.4% |
| 2:Home health | 668 | 0.8% | 2010 | 2.4% | 597 | 0.7% | 3275 | 3.9% |
| 3:ECF/Rehabilitation | 415 | 0.5% | 1744 | 2.1% | 256 | 0.3% | 2415 | 2.9% |
| 4:Discharged to Other | 338 | 0.4% | 264 | 0.3% | 298 | 0.3% | 900 | 1.0% |
| 5:Died | 311 | 0.3% | 1159 | 1.4% | 609 | 0.7% | 2079 | 2.5% |
| All Discharge Disposition | 23643 | 28.7% | 22243 | 27.0% | 36278 | 44.1% | 82164 | 100.0% |

To get a better sense of the effects of patient variables on discharge disposition a logistic regression analysis was conducted. The predictor (independent) variables were age, gender (male or female), race/ethnicity (Blacks, Whites, and Other), marital status was converted to a dichotomous variable (married and not married) from five categories- divorced, married, separated, widowed, and unknown. Table 4.5.7 is a summary of parameter estimate for the logistic regression.

Table 4.5.7

*Parameter Estimates of Variables Affecting Discharge Disposition*

| | Discharged home vs. to other facility | Discharged home vs. to ECF/Rehab | Discharged home vs. to Home health |
|---|---|---|---|
| Intercept | -4.34** | -5.05** | -5.16** |
| Age | 0.01** | 0.04** | 0.04** |
| Female | -0.20** | -0.05** | 0.02 |
| Black | -0.03 | -0.09** | 0.34** |
| Married | -0.58** | -1.14** | -0.29** |
| Medicaid/Welfare | 0.21** | 0.20** | 0.14** |
| Medicare/Other | -0.02 | 0.51** | 0.16** |

*p < .05, **p < .01, ECF = Extended Care Facility

The intercept value refers to the logit estimate for discharge to other facility relative to discharge to home is -4.33 when the other predictor variables in the model (gender, race, marital status, and insurance type) are evaluated at zero. Regarding age, the logit estimate for discharge to other facility relative to discharge to home is .01 for every one year increase in age given that the other variables in the model are held constant. In other words, for every one year increase in patient age, the multinomial log-odds for discharge to other facility rather than to own home is .01unit while holding all other variables in the model constant. Of note is the effect of race on the multinomial log-odds of discharge to own home. The multinomial log-odds of discharge to other facility rather than to own home is decreased by .03units if the patient was Black given that the other variables in the model are held constant. Likewise, the log-odds of being discharged to an extended care facility (a nursing home) or a rehabilitation center rather than to own home is reduced by.08 units for a Black patient given the other variables in the model are held constant. Perhaps the most interesting result in this analysis is the effect of marital status on discharge disposition. From Table 4.5.7 note that the log-odds of discharge to a nursing home or to a rehabilitation center decreased by 1.14 units for married patients given the other variables in the model are held constant. Of more informative value than the above table is the information provided in Table 4.5.8 that relates a desired outcome to some other outcome while comparing one patient group to another patient group.

Table 4.5.8

*Odds Ratio Estimates for Effects of Patient Variables on Discharge Disposition*

| Odds Ratio Estimates | | | | | |
|---|---|---|---|---|---|
| Effect | | Discharge disposition | Point Estimate | 95% Wald Confidence Limits | |
| Age | | 4:DCOTHER | 1.010 | 1.006 | 1.013 |
| Age | | 3:ECF_REHAB | 1.038 | 1.035 | 1.040 |
| Age | | 2:HOMEHLT | 1.043 | 1.040 | 1.046 |
| Sex | Female versus Males | 4:DCOTHER | 0.665 | 0.591 | 0.747 |
| Sex | Female versus Males | 3:ECF_REHAB | 0.905 | 0.828 | 0.988 |
| Sex | Female versus Males | 2:HOMEHLT | 1.014 | 0.939 | 1.095 |
| Race | Black versus White/Other | 4:DCOTHER | 0.941 | 0.822 | 1.078 |
| Race | Black versus White/Other | 3:ECF_REHAB | 0.839 | 0.766 | 0.920 |
| Race | Black versus White/Other | 2:HOMEHLT | 1.970 | 1.820 | 2.133 |
| Married | | 4:DCOTHER | 0.560 | 0.484 | 0.648 |
| Married | | 3:ECF_REHAB | 0.321 | 0.290 | 0.356 |
| Married | | 2:HOMEHLT | 0.751 | 0.692 | 0.817 |
| Insurance | Medicaid/Welfare versus Private/HMO | 4:DCOTHER | 1.504 | 1.282 | 1.765 |
| Insurance | Medicaid/Welfare versus Private/HMO | 3:ECF_REHAB | 2.479 | 2.109 | 2.913 |
| Insurance | Medicaid/Welfare versus Private/HMO | 2:HOMEHLT | 1.546 | 1.365 | 1.751 |
| Insurance | Medicare/Other versus Private/HMO | 4:DCOTHER | 1.191 | 0.984 | 1.442 |
| Insurance | Medicare/Other versus Private/HMO | 3:ECF_REHAB | 3.382 | 2.890 | 3.958 |
| Insurance | Medicare/Other versus Private/HMO | 2:HOMEHLT | 1.571 | 1.395 | 1.770 |

Information regarding patient race as presented in Table 4.5.8 indicate that the patient variables of marital status had lesser influence on the odds of discharge disposition of patients than expected. For patient race, the odds ratio of a Black patient being discharged to other health care facility rather than to own home (conditional on not being discharged to home health services or nursing home) is .94 times the odds for White patients. Similarly, the odds of a Black patient being discharged to a nursing home rather than to own home (conditional on not being discharged to other healthcare facility or home health services) is .84 times the odds for White patients. Interestingly, the odds of a Black patient being discharged to home with home health services rather than to own home (conditional on not being discharged to other healthcare facility or just to home) is 1.97 times the odds for White patients.

This shows that patient race does matter in discharge disposition particularly, in light of the present finding that Blacks with the primary diagnosis of type 2 diabetes mellitus are disproportionately admitted to hospital for treatment yet neither the disease treatment nor the pattern of nursing diagnoses seems to be associated with differing end results of hospital care. An unanswered question raised here is, does the epidemiology of the disease lead to the disproportion in admissions or does the need for holistic care or the disparate outpatient care for Blacks lead to the increased rate of admissions? Findings from addressing Questions 1-3 here suggest the latter.

Patient age also seem to play some role in determining discharge disposition. For every one year increase in patient age, the odds of being discharged to an extended care facility rather than to home are increased by about 1.038 times. Similar odds are seen for discharge to other facility rather than to home (1.010) and discharge to home with home health services rather than to own home (1.043). For marital status, the odds of a married patient being discharged to an extended care facility or rehabilitation center rather to own home are .32 times the odds of unmarried or single patients. The odds of a discharge to home with home health services rather than just to own home is higher at .75 times in relation to unmarried patients.

Patient gender also had a small influence on patient discharge disposition. For example, the odds of a female patient being discharged to an extended care facility (conditional on not being discharged to home health or other types of care facility) are .91 times the odds for male patients. Further, the odds of a female patient going home with home health services rather than an outright discharge to home, are almost twice (1.970) the odds for male patients.

Patients with Medicaid or on welfare and patients with Medicare or covered by other type of insurance other than private/HMO are more likely to be discharged to an extended care facility such as a nursing home rather than to home. From Table 4.5.8 we note that a patient who is on Medicare or on welfare has higher odds of discharge to nursing home compared to a patient who has private insurance or who is a member of a Health Management Organization (HMO). For example, the odds of a patient with Medicaid/welfare being discharged to an extended care facility rather than to own home are 2.479 times the odds for those patients with private insurance or those with HMO type of health insurance. A patient with Medicare also has similar odds of being discharged to an extended care facility rather than to own home. Here, the odds are 3.382 times the odds of patients with private insurance/HMO of being discharged to a nursing home rather to own home.

In summary patient factors such as age, marital status, race, gender, and insurance type does seem to play some role in determining discharge disposition. All the odds ratio estimates are significant as they are all within 95% confidence limits. In all but three instances, these confidence limits did not include value of 1, thus for these variables, the null hypothesis is not rejected. The null hypothesis is that a particular regression coefficient equals zero and the odds ratio equals one, given the other predictors are in the model. The three instances where the value of 1 is included in the lower and upper confidence limits involved patient gender as it affected discharge to home with home health services rather than to home, patient race as it affected discharge to other healthcare facility rather than to home, and Medicare/Other as it affected discharge to other healthcare facility rather than to home.

# CHAPTER 5

# DISCUSSION

This study examined: (a) how well nursing diagnoses use pattern is able to distinguish one patient group from another using the International Classification of Diseases codes as a guide, (b) the relationship of nursing diagnoses use pattern, number of nursing diagnoses and variations in patient outcomes of length of stay, and (c) the effects of patient demographic variables on patient discharge disposition. This study was a secondary analysis of data collected over a three-year period by nurses in the care of their hospitalized patients. The structure, process, and outcome model provided the conceptual framework for this study. This chapter presents discussion of the major findings, comparisons of the results with previous studies, limitations, suggestions for future studies, and implications.

## Major Findings

The findings of the current study provide evidence for asserting that nursing care is based on a holistic patient approach rather than a disease or illness approach. Patient information gathered by nurses is qualitative in nature, allowing the nurse to view the patient more as an individual rather than as a function of a disease label. The current study failed to prove the hypothesized notion that nursing diagnoses use pattern might be used to categorize patients into different groups using the International Classification of Diseases (ICD) categorized illnesses. This is because nurses assess and diagnose their patients and provide care based on patient healthcare needs that are different from, and independent of the ICD codes standards. It appears that the lack of a distinct nursing diagnoses use pattern in this sample of hospitalized patients is more related to the situational patient factors directing nursing care rather than a distinction of patient groups along the lines of disease labels as dictated by ICD codes.

While some nursing diagnoses might be more important in specific situations affecting certain patient groups, these situations do not define the patient groups along the lines of disease types. For example, the nursing diagnoses of *knowledge deficit* might define the care needs of patients with a new diagnosis of a disease condition. Thus, the incidence of knowledge deficit might be high among several groups of patients such as those newly diagnosed with heart disease, diabetes mellitus, stroke, kidney disease or cancer. Likewise, the nursing diagnoses of *sociocultural-economic* considerations might not just define the patients of racial minority groups or patients of low economic means, but might also define a group of patients with disease conditions that have severe financial and economic implications both to the rich and the poor, the patients covered by private medical insurance and patients on Medicaid or Medicare health coverage.

This point is clearly illustrated in the list of patient health problems (Appendix F) comparing the relative importance of the nursing diagnoses across the three patient groups where the relative importance of nursing diagnoses were not consistently demonstrated according to expectations for each group . The relative importance of sociocultural economic considerations for example, is highest among the general population of patients at .1025, this is a more diverse patient group compared to patients with secondary diagnosis of type 2 diabetes (.0653) and the patient with primary diagnosis of type 2 diabetes group (.0845), the most homogenous group where patients of racial minority comprise 68.5% of the population.

Another instance where the relative importance of a nursing diagnosis was expected to be distinctively different across groups was in the nursing diagnoses of *potential fluid volume deficit*. The relative importance of this nursing diagnosis was .2580 for the general patient population, .2037 for patients with secondary diagnosis of T2DM and .2102 for patients with primary diagnosis of T2DM. These figures appear not to be distinctively different even across distinctively different patient groups. Potential fluid volume deficit was expected to be of more significance for patients for whom issues related to type 2 diabetes was the main reason for admission due to polyuria (excessive urination) and polydipsia (excessive thirst) that is often characteristic of many patients with type 2 diabetes. Also, pain particularly that associated with vascular disease or neuropathy might be expected to be a significant stressor for the patient with late stage diabetes mellitus. But interestingly, the nursing diagnoses of *pain* and *discomfort* had the smallest relative importance values and incidence in the primary diabetes diagnoses group compared to the other two patient groups.

In the examination of patient length of stay alone we see considerable variability among a homogenous group (patient with primary diagnosis of T2DM) that is not explained by the ICD-based categorization of these patients, but rather by the description of the care needs of these patients as postulated by their nurses. This suggests that when the disease is known and the ICD/DRG is assigned, we still do not fully know the nursing needs of patients. For if we did, then there would be minimal variability in patient outcomes. This point is highlighted by Halloran (2009) when he said people acted more alike near death than as members of their respective disease groups. This point explains the finding with the nursing diagnosis of knowledge deficit that seem to transcend disease-based categorization of patients but is related to patients' situational experiences.

The argument is thus supported that nursing diagnoses labels are words that define human needs. These labels have been used by others to classify the needs of patients, Henderson most prominently (See Appendix C). Abdellah's list of 21 problems is another example (See Appendix D). At the center of these opposing views- patient classification by disease types versus classification of patient human needs, are two Yale nurses espousing two different types of lists: John Thompson known principally as the finder of the DRGs, a list emphasizing disease classification (Halloran, 2009) and Virginia Henderson, a proponent of the classification of human needs. According to Thompson's logic, all institutional nursing flowed from disease specificity – when the disease was known and the treatment started, and DRG assigned, the nursing care (and payment for it) was standardized (Halloran, 2009). In contrast, Henderson's perspective of the patient was more holistic. To her, human needs were fundamental, and needs were always affected by social and developmental factors and only sometimes modified by pathological states (Halloran, 2009).This holistic patient view or Henderson's perspective is what seems to have emerged from the current study.

The issue of nursing diagnosis labeling versus medical diagnosis labeling is not an either/or proposition – both are needed. Patients need information about their human functions as expressed in the present study by nursing diagnoses. Patients also need information about their disease(s) and how it can be managed. Nurses need to know how to help people with human functions that are considered 'normal' when they lack strength, will or knowledge to perform them by themselves. Some of the education nurses provide patients will be derived from medical disease management literature (example: take your insulin every day). But just as nurses need both types of patient information, medical and functional, doctors need functional information as feedback on how well patients under their care are progressing. Functional improvement is an objective of both medical and nursing care.

Another finding from this study is the emergence of five nursing diagnoses with high relative importance values for the patients with primary diagnosis of type 2 diabetes mellitus compared to other patients. As the foregoing discussion has shown, these five nursing diagnoses might also be relevant to a different group of patients with different diseases. These five nursing diagnoses were:

1. Noncompliance
2. Prolonged disease and disability
3. Nutrition, more than required
4. Nutrition, potential for excess and
5. Knowledge deficit

This list of nursing diagnoses arguably could also be very relevant to patients diagnosed with obesity and may be very significant in the nursing care of these patients. Because nurses view each patient as an individual with unique healthcare needs, there is a blurring of the artificial lines created by disease labels that are designed to categorize patients in the medicine model of healthcare. This is because, as identified by Burns (1993), medical diagnoses are for physiologic problems (disease) and nurses use nursing diagnoses to label the psychosocial and human needs problems they encounter. The implication is that specific list of nursing diagnoses may not consistently define a patient's health care needs based on the dictates of the diagnoses related groups (DRG) or ICD codes. This finding is similar to that of an earlier study (Halloran et al., 1988) where nursing diagnoses were shown to be independent of medical diagnoses.

While no discernible nursing diagnoses use pattern was found across patient groups, the number of nursing diagnoses assigned to a patient by the nurse in the process of providing care was shown to be related to patient length of stay. In other words, patients with a greater number of different nursing diagnoses tended to have longer average length of stay. The correlation between the number of nursing diagnoses and hospital stay among patients with primary diagnosis of T2DM was positive, strong, and statistically significant (*r* = .67, $p < .0001$). 44% of the variation in length of stay was explained by the number of nursing diagnoses alone. In a regression model fitted with other patient variables of gender, age, marital status and insurance type 44% of the variation in length of stay was also accounted for by the model. However, these other patient variables were not significant factors at .05 alpha. Patient age as an interactive term with number of nursing diagnosis in a model that included patient gender, marital status, and financial class only marginally improved the *R*-square to .463643. Thus 46% of the variation in length of stay is explained by the new model.

It is worthwhile to note that the addition of the patient variable of age did not improve the explanation of the variability of length of stay in this group of patients with primary diagnosis of type 2 diabetes mellitus. However, when a distinction was made between younger patients (age < 35 years based on the well documented premise that younger patient are saddled with a lesser number of chronic disease) and older patients (age > 35 years) then age became a significant explanatory variable of variation in length of stay in the regression model with other fitted variables. This finding suggests that older patients experience longer average length of stay in hospitals compared to younger patients. The longer length of stay associated with older patients only highlight the significance of the finding that the number of nursing diagnoses is an important factor in the length of stay in hospitalized patients. It is noteworthy that even after controlling for patient age, the number of nursing diagnoses remained the most significant explanatory variable of the variance in length of stay. The fact that this finding was among a group of patients with primary diagnosis of type 2 diabetes confirms studies (Ahern & Hendryx, 2007; Kirkland & Sinclair, 2011; Scott, 2003) that have listed type 2 diabetes patients as patients with many comorbidities and increased healthcare resource utilization.

Another major finding in the current study was the identification of a list of nursing diagnoses that are associated with longer length of stay. Specifically, 7 nursing diagnoses were identified in a regression model to account for 26% variation in length of stay among the group of patients with primary diagnosis of type 2 diabetes. These nursing diagnoses include:

1. Impaired mobility
2. Pain
3. Depression
4. Skin impairment
5. Self-care deficit
6. Socio-cultural/economic considerations and inexplicably
7. Constipation

Not surprisingly, five of these nursing diagnoses are related to patient health conditions that might point to the presence of a prolonged disease state. For example, impaired mobility might define the patient with very limited mobility as might be obtainable in cases of limb amputation resulting from complications of diabetic peripheral neuropathy. Impaired mobility might also define the patient with prolonged infirmed state that is bedridden.

Depression, particularly *major depression* in the context of a psychiatric diagnosis necessitating in-hospital medical treatment might also lead to prolonged length of stay. Sociocultural economic consideration is another nursing diagnosis that might be relevant to a situation of prolonged length of stay. This situation might arise in instance where a patient with a chronic illness or a patient with an acute illness made worse by other complications has exhausted available resources, and thus has no more medical care resources to allow for placement in a long-term health care facility or specialty hospital. Inexplicably, the nursing diagnoses of constipation and sexual dysfunction were included in the model. These two variables seemed far-fetched as variables that might be thought to be relevant to prolonged hospital stay. Rather than presenting as a source of contradiction, the inclusion of these two variables in the model speaks to the unique patient situation and experiences that guides the nurse's assignment of nursing diagnoses. In the case of the nursing diagnoses of constipation for example, it might be in the context of a gastrointestinal complication resulting in surgical intervention might constipation be thought to be explanatory of a prolonged hospital stay.

In the final analysis, patient discharge disposition was examined and found to be most influenced by insurance type in a multinomial logistic model that included other patient variables such as age, gender, marital status, and race. Patients on Medicaid or on welfare were more likely to be discharged to an extended care facility such as nursing home or a rehabilitation center rather than to home compared to patients who had private insurance or belonged to a Health Management Organization (HMO) for health insurance. The analysis also showed that the odds of a Black patient being discharged to a nursing home rather than to own home were .839 times the odds for White patients. While race by itself did not seem to be a major determinant of patient discharge disposition, insurance type as a proxy for socioeconomic position was an important determinant of discharge disposition. Thus, the odds of discharge to a nursing home rather than to own home by virtue of being a Medicare or Medicaid recipient (which was high among Black patients) combined with the odds of being discharged to nursing home rather than to own home by virtue of being a Black patient compared to White patients seem to result in a severe disadvantage for the Black patient. Just over 35% of Black patients were discharged to own home compared to 53% of White patients, and 22.4% of Black patients were Medicaid/Welfare recipients compared to 6.4% of White patients. It is important to point out that these figures come from the general population of the hospitalized patients and not from the subgroup of patients with type 2 diabetes mellitus where the natural high incidence of this disease might predispose the Black patients to such disparate outcomes. With these numbers one is curious to know the source of such disparities. One is inclined to conclude that at the minimum, patient race and socioeconomic position converge to affect patient discharge disposition.

## Limitations

The current study has several limitations. First, the data is relatively old, having been collected in the period spanning 1986-1989. The treatment of type 2 diabetes has evolved over the last three decades. Patients with diabetes now have more options such as insulin pens and glucose monitoring meters are more affordable. These tools help the patient with diabetes achieve better control of their serum glucose. Because of these advances, nurses today most likely face different types of patients with different types of barriers in disease management. As a consequence, a different set of nursing diagnoses might be required by nurses in the care of their patients. Furthermore, in the three decades since the data in the current study were collected using a list of 61 nursing diagnoses, the list of approved nursing diagnoses by the North American Nursing Diagnosis of Association (NANDA) has grown to over 200 nursing diagnoses (Carpenito, 1991; Potter, 2013).

Second, because this is a secondary data analysis, the selection of variables was limited. In particular, because of the lack of information on patient hemoglobin $A_{1c}$, blood pressure and weight, the variations across groups in patient health status related to these variables could not be assessed. As a result, the study was unable to examine the relationship between patient diabetes status and patient weight. Another variable that could not be examined pertained to the number of nursing diagnoses at admission and the number of nursing diagnoses at discharge. This information might have been useful in analyses examining patient length of stay and health outcome.

Third, the relatively small sample size for patients with primary diagnosis of type 2 diabetes mellitus limited the comparison of this group of patients to the other patient groups. Missing information about nursing diagnoses meant exclusion of the affected subjects from some analyses.

Lastly, generalization of these results to a wider population which is related to external validity is hampered first by the dated nature of the data, and secondly by the fact that the data were collected primarily for administrative purposes. The sample of patients came from a large Midwestern state, although from a diverse area, it remains that data collection was limited to one geographical area.

## Recommendations for Further Research

Several recommendations can be suggested based on the results of this study. Findings from this study confirmed that the nursing model of holistic patient approach differs from the disease and illnesses model and further, the nursing model explains variation in length of stay, a variable used to create the DRG Medicare prospective payment system. These results are consistent with findings from decades of international research that compared the inputs of nurses with those of physicians to determine how long patients stay in hospital (Halloran & Kiley, 1987; O'Brien-Pallas, Irvine, Peereboom, & Murray, 1997; Rosenthal et al., 1995; Van den Heede, Clarke, Sermeus, Vleugels, & Aiken, 2007). This implies that the manner in which nurses interact with their patients results in access to quality patient information. This manner of interaction is aided by the use of nursing diagnoses in obtaining a more comprehensive understanding of the patient. But in spite of this unique value, the use of nursing diagnosis is not widespread, some have argued that this is due to deficiencies in clinical application (Junttila, Hupli, & Salantera, 2010) and reliance on predetermined categorization (Lützén & Tishelman, 1996). A future study might examine the issues faced by today's nurses in incorporating nursing diagnoses, or a more attractive alternative such as the International Council of Nurses' Nurse-Patient Summary, or the closely related World Health Organization's International Classification of Function, Disability and Health (WHO, 2001) into daily patient care.

Another suggestion for further research is an inquiry that might closely link nursing diagnoses to patient health outcomes. Because this data was primarily collected for administrative purposes, it was difficult to more precisely link nursing diagnoses to patient health outcomes. Although the current study was able to establish a correlative relationship between the number of patient nursing diagnoses and patient length of stay, a more direct link might have been made with difference in number of nursing diagnoses between admission and at discharge to length of stay.

Finally, nursing data, which is information on patients gathered by nurses, has been shown in this and previous studies to be an invaluable tool in understanding patient healthcare needs. The use of nursing diagnoses or their alternatives in future research might not only highlight the importance of nursing diagnosis in the human needs of patient but also demonstrate the utility of nursing data in the realm of quality improvement as measured by patient satisfaction levels, nursing staff management, implementation of dynamic policies and procedures, and the installation of a responsive hospital administrative culture.

Several additional research questions are raised:

1. How can the data from nurses be more closely linked to patient outcome?
2. Is there a need for a development of weighted system for the patient data from nurses to accurately document patient care needs? And might this weighted system be more able to predict outcomes such as length of stay and discharge disposition?
3. What is the distinction between nursing diagnoses as patient labeling and nursing diagnoses as identification of patient healthcare needs?

These are some potential research questions that emerged from this current study.

## Implication for Practice

The findings from the current study suggest that nurses do not consistently label their patients such that they can be categorized by disease types. A holistic perspective was observed – not all patients with T2DM had a knowledge deficit yet many did. Also, while the issue of treatment noncompliance was high among high among patients with type 2 diabetes, this issue was relatively important for other groups of patients as well. The uniqueness of data collected by nurses in explaining variations in patient outcomes where medical diagnoses have proved inadequate makes a strong argument for the inclusion of the nursing minimum data set (NMDS) in the uniform hospital discharge data set (UHDDS).

## Conclusions

This study examined patient information gathered by nurses in the routine care of their patients. The aim of this study was to evaluate the importance of this information in predicting or explaining key patient outcomes. Examining nursing diagnoses use pattern and the ability of this important nursing tool to group patients into disease categories was an overarching goal of this study. Also of interest was whether there is a subset of nursing diagnoses that are particularly associated with patients with type 2 diabetes mellitus, a disease that disproportionately affects Black Americans. The study was also concerned with patient length of stay and how this is affected first by the number of nursing diagnoses and second by the subset of nursing diagnoses that explains the variation of patient length of stay. Finally, patient discharge disposition was examined in relation to the patient variables of age, gender, race/ethnicity, marital status and health insurance type (socioeconomic status), and all these variables were found to be relevant in planning patient discharge.

Nursing diagnoses use pattern did not discriminate patients by ICD groups. However, a subset of nursing diagnoses was demonstrated to be more applicable in several situational events that defined patient health status. For example, knowledge deficit was high in all patient groups, but highest among patients with type 2 diabetes mellitus as primary diagnosis. While this is an interesting finding, it was hardly unexpected. The author admits that such finding might be true of any patient groups diagnosed with any other chronic and complex illness. Knowledge deficit is high among patients with T2DM not because the disease in question is diabetes mellitus but rather because of the chronic nature and the complexity of the disease. This has significance particularly to those with an aversion to nursing’s perceived attempt at categorizing patients along disease labels using nursing diagnoses. To these people, the answers to the following questions might be helpful in framing the findings of this inquiry:

If you know the nursing needs (pattern of nursing diagnoses) of patients, do you know their medical diagnosis?

If you know the medical diagnoses of hospital patients, do you also know their nursing needs?

The answers to these questions is no. This is because human needs are not synonymous with diseases. Indeed, the significance of this finding only symbolizes the caring model that nursing has long embodied as defined by Virginia Henderson:

> "Nurses help people, sick or well, in the performance of those activities contributing to health, its recovery (or to a peaceful death), that they would perform unaided if they had the necessary strength, will or knowledge. Nurses help people gain independence as rapidly as possible."

The study also highlighted a subset of nursing diagnoses associated with longer average length of stay. Very closely related to this inquiry, is the confirmation of findings from previous studies that patient length of stay is related to patient nursing needs (nurse intensity) as evidenced by the number of nursing diagnoses. Nursing diagnoses proved to be the most important predictor of patient length of stay even when considered along with other patient variables such as age, sex, marital status and insurance type. Even in a very homogeneous group (patients with primary diagnosis of T2DM), unexplained variation in length of stay was explained by the pattern of nursing diagnoses. The significance of these findings is clear; the predictive power of nursing diagnoses speaks to the uniqueness of nurses' actions even in an interdependent and collaborative clinical environment. These actions cannot be performed by any other healthcare personnel including the nursing assistant (nurses' aide). Patients need nurses and access to patients by nurses will continue to improve care and patient outcome.

Although the healthcare delivery system is based on the medical model of diagnosing and treating diseases, nurses' impact in addressing the list that really matters, a list that emphasizes disease prevention and helping patients regain independence is even more significant even if not fully appreciated in the patient discharge summary. Giving nurses access to patients and allowing them to provide those human needs to their patients seem a sure path to quality patient care and way to stem the spiraling cost of care even if this approach is grounded on the abiding works and writings of Virginia Henderson.

# APPENDICES

## APPENDIX A: Nurse/Patient Summary Sheet

### UNIVERSITY HOSPITALS OF CLEVELAND
#### NURSE/PATIENT SUMMARY

| | RN Code Number | Other Code Number | Consultant Code Number |
|---|---|---|---|
| TODAY | | | |
| LAST NIGHT | | | |
| LAST EVENING | | | |

Primary Nurse Code Number ____________

NAME

HOSP. NO. DATE

SERVICE

SEX AGE

DIVISION ROOM NO.

Date Today ____________

**DIRECTIONS: Check the items below if Actually or Potentially Present.**

**HEALTH PERCEPTION-MANAGEMENT**

Potential for Injury . . . . . . . . . . ______ 001
Noncompliance . . . . . . . . . . ______ 002
Infection/Contagion . . . . . . . . . . ______ 003
Prolonged Disease/Disability . . . . . . . . . . ______ 004
Instability . . . . . . . . . . ______ 005
Impaired Life Support Systems . . . . . . . . . . ______ 006
Sanitation Deficit . . . . . . . . . . ______ 007
Socio-cultural-economic Considerations . . . . . . ______ 008

**NUTRITIONAL-METABOLIC**

**Fluid**

Excess Volume . . . . . . . . . . ______ 009
Volume Deficit . . . . . . . . . . ______ 010
Potential Volume Deficit . . . . . . . . . . ______ 011
Bleeding . . . . . . . . . . ______ 012

**Nutrition**

Less Nutrition than Required . . . . . . . . . . ______ 013
More Nutrition than Required . . . . . . . . . . ______ 014
Potential for Excess . . . . . . . . . . ______ 015

**Skin Integrity**

Actual Skin Impairment . . . . . . . . . . ______ 016
Potential Skin Impairment . . . . . . . . . . ______ 017
Alterations in Oral Mucous Membrane . . . ______ 018

Altered Body Temperature . . . . . . . . . . ______ 019

**ELIMINATION**

**Urinary**

Incontinence . . . . . . . . . . ______ 020
Other Altered Urinary Elim. Pattern . . . . . . ______ 021

**Bowel**

Constipation . . . . . . . . . . ______ 022
Diarrhea . . . . . . . . . . ______ 023
Incontinence . . . . . . . . . . ______ 024

**ACTIVITY-EXERCISE**

Activity Intolerance . . . . . . . . . . ______ 025
Ineffective Airway Clearance . . . . . . . . . . ______ 026
Altered Breathing Pattern . . . . . . . . . . ______ 027
Impaired Gas Exchange . . . . . . . . . . ______ 028
Altered Tissue Perfusion . . . . . . . . . . ______ 029
Decreased Cardiac Output . . . . . . . . . . ______ 030
Diversional Activity Deficit . . . . . . . . . . ______ 031
Altered Health Maintenance . . . . . . . . . . ______ 032
Impaired Mobility . . . . . . . . . . ______ 033
Self-Care Deficit . . . . . . . . . . ______ 034
Impaired Home Maintenance Mgmt. . . . . . . . . . ______ 035

**COGNITION-PERCEPTION**

**Altered Comfort**

Discomfort . . . . . . . . . . ______ 036
Pain . . . . . . . . . . ______ 037

Altered Level of Consciousness . . . . . . . . . . ______ 038
Altered Thought Process . . . . . . . . . . ______ 039
Impulsivity/Hyperactivity . . . . . . . . . . ______ 040
Altered Sensory Perception . . . . . . . . . . ______ 041
Knowledge Deficit . . . . . . . . . . ______ 042
Growth and Development Deficit . . . . . . . . . . ______ 043

**SLEEP-REST**

Sleep Disturbance . . . . . . . . . . ______ 044

**SELF-PERCEPTION/SELF-CONCEPT**

Anxiety . . . . . . . . . . ______ 045
Disturbed Self-Concept . . . . . . . . . . ______ 046
Depression . . . . . . . . . . ______ 047
Fear . . . . . . . . . . ______ 048
Powerlessness . . . . . . . . . . ______ 049

**ROLE RELATIONSHIPS**

Grieving . . . . . . . . . . ______ 050
Altered Family Process . . . . . . . . . . ______ 051
Altered Parenting . . . . . . . . . . ______ 052
Social Isolation . . . . . . . . . . ______ 053
Impaired Verbal Communication . . . . . . . . . . ______ 054
Potential for Violence . . . . . . . . . . ______ 055

**SEXUALITY-REPRODUCTION**

Sexual Dysfunction . . . . . . . . . . ______ 056
Rape - Trauma Syndrome . . . . . . . . . . ______ 057

**COPING-STRESS TOLERANCE**

Ineffective Individual Coping . . . . . . . . . . ______ 058
Ineffective Family Coping . . . . . . . . . . ______ 059
Potential for Growth in Family Coping . . . . . . ______ 060

**VALUE-BELIEF**

Spiritual Distress . . . . . . . . . . ______ 061

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APPENDIX B: List of Nursing Problems

**List of 21 Nursing Problems**

1. To maintain good hygiene and physical comfort.
2. To promote optimal activity; exercise, rest, and sleep.
3. To promote safety through prevention of accident, injury, or other trauma and through prevention of the spread of infection.
4. To maintain good body mechanics and prevent and correct deformities
5. To facilitate the maintenance of a supply of oxygen to all body cells.
6. To facilitate the maintenance of nutrition of all body cells.
7. To facilitate the maintenance of elimination.
8. To facilitate the maintenance of fluid and electrolyte balance.
9. To recognize the physiological responses of the body to disease conditions-pathological, physiological, and compensatory.
10. To facilitate the maintenance of regulatory mechanisms and functions.
11. To facilitate the maintenance of sensory function.
12. To identify and accept positive and negative expressions, feelings, and reactions.
13. To identify and accept the interrelatedness of emotions and organic illness.
14. To facilitate the maintenance of effective verbal and nonverbal communication.
15. To promote the development of productive interpersonal relationships.
16. To facilitate progress toward achievement of personal spiritual goals.
17. To create and/or maintain a therapeutic environment.
18. To facilitate awareness of self as an individual with varying physical, emotional, and developmental needs.
19. To accept the optimum possible goals in the light of limitations, physical and emotional.
20. To use community resources as an aid in resolving problems arising from illness.
21. To understand the role of social problems as influencing factors in the cause of illness.

-(Abdellah, Beland, Martin, & Matheney, 1960)

APPENDIX C: Needs of All Patients Usually met by Nurses

| **Components of Basic Nursing** | **Conditions always Present that Affect Basic Needs** | **Pathological States (as contrasted with Specific Diseases) that Modify Basic Needs** |
|---|---|---|
| 1. Breathe normally<br>2. Eat and drink adequately<br>3. Eliminate by all avenues of elimination<br>4. Move and maintain desirable posture (walking, sitting, lying and changing from one to the other)<br>5. Sleep and rest<br>6. Select suitable clothing, dress and undress<br>7. Maintain body temperature within normal range by adjusting clothing and modifying the environment<br>8. Keep the body clean and well groomed and protect the integument<br>9. Avoid dangers in the environment<br>10. Communicate with others in expressing emotions, needs, fears, etc.<br>11. Worship according to the patient's faith.<br>12. Work at something that provides a sense of accomplishment<br>13. Play, or participate in various forms of recreation<br>14. Learn, discover, or satisfy the curiosity that leads to "normal" development and health | 1. Age: new born, child, youth, adult, middle aged, aged, and dying<br>2. Temperament, emotional state, or passing mood:<br>a) "normal" or<br>b) euphoric and hyperactive<br>c) anxious, fearful, agitated or hyperactive<br>d) depressed and hypoactive<br>3. Social or cultural status: A member of a family unit with friends and status, or a person relatively alone and/or maladjusted destitute<br>4. Physical and intellectual capacity:<br>a) normal weight<br>b) underweight<br>c) overweight<br>d) normal mentality<br>e) sub-normal mentality<br>f) gifted mentality<br>g) normal sense of hearing, sight, equilibrium and touch<br>h) loss of special sense<br>i) normal motor power<br>j) loss of motor power | 1. Marked disturbances of fluid and electrolyte balance including starvation states, pernicious vomiting, and diarrhea<br>2. Acute oxygen want<br>3. Shock (including "collapse" and hemorrhage)<br>4. Disturbances of consciousness fainting, coma, delirium<br>5. Exposure to cold and heat causing markedly abnormal body temperatures<br>6. Acute febrile states (all causes)<br>7. A local injury, wound and/or infection<br>8. A communicable condition<br>9. Pre-operative state<br>10. Post-operative state<br>11. Immobilization from disease or prescribed as treatment<br>12. Persistent or intractable pain |

From Basic Principles of Nursing Care, Virginia Henderson- International Council of Nursing

APPENDIX D: Descriptive List of Variables

| List of Variables in Creation Order | | | | | |
|---|---|---|---|---|---|
| **#** | **Variables** | **Type** | **Len** | **Format** | **Label** |
| 1 | PATNUM | Char | 9 | | Patient number |
| 2 | DISDTE | Num | 8 | MMDDYY | Discharge date |
| 3 | SUMX1 | Num | 8 | | Potential for Injury |
| 4 | SUMX2 | Num | 8 | | Noncompliance |
| 5 | SUMX3 | Num | 8 | | Infection/Contagion |
| 6 | SUMX4 | Num | 8 | | Prolonged Disease/Disability |
| 7 | SUMX5 | Num | 8 | | Instability |
| 8 | SUMX6 | Num | 8 | | Impaired Life Support System |
| 9 | SUMX7 | Num | 8 | | Sanitation Deficit |
| 10 | SUMX8 | Num | 8 | | Socio-cultural-economic Considerations |
| 11 | SUMX9 | Num | 8 | | Excess Fluid Volume |
| 12 | SUMX10 | Num | 8 | | Fluid Volume Deficit |
| 13 | SUMX11 | Num | 8 | | Potential Fluid Volume Deficit |
| 14 | SUMX12 | Num | 8 | | Bleeding |
| 15 | SUMX13 | Num | 8 | | Less Nutrition than Required |
| 16 | SUMX14 | Num | 8 | | More Nutrition than Required |
| 17 | SUMX15 | Num | 8 | | Potential for Excess Nutrition |
| 18 | SUMX16 | Num | 8 | | Actual Skin Impairment |
| 19 | SUMX17 | Num | 8 | | Potential Skin Impairment |
| 20 | SUMX18 | Num | 8 | | Alterations in Oral Mucous Membrane |
| 21 | SUMX19 | Num | 8 | | Altered Body Temperature |
| 22 | SUMX20 | Num | 8 | | Urinary Incontinent |
| 23 | SUMX21 | Num | 8 | | Other Altered Urinary Elimination Pattern |
| 24 | SUMX22 | Num | 8 | | Constipation |
| 25 | SUMX23 | Num | 8 | | Diarrhea |
| 26 | SUMX24 | Num | 8 | | Bowel Incontinence |
| 27 | SUMX25 | Num | 8 | | Activity Intolerance |
| 28 | SUMX26 | Num | 8 | | Impaired Airway |
| 29 | SUMX27 | Num | 8 | | Altered Breathing Pattern |
| 30 | SUMX28 | Num | 8 | | Impaired Gas Exchange |
| 31 | SUMX29 | Num | 8 | | Altered Tissue Perfusion |
| 32 | SUMX30 | Num | 8 | | Decreased Cardiac Output |
| 33 | SUMX31 | Num | 8 | | Diversional Activity Deficit |
| 34 | SUMX32 | Num | 8 | | Altered Health Maintenance |
| 35 | SUMX33 | Num | 8 | | Impaired Mobility |
| 36 | SUMX34 | Num | 8 | | Self-Care Deficit |
| 37 | SUMX35 | Num | 8 | | Impaired Home Maintenance Management |
| 38 | SUMX36 | Num | 8 | | Discomfort |
| 39 | SUMX37 | Num | 8 | | Pain |
| 40 | SUMX38 | Num | 8 | | Altered Level of Consciousness |
| 41 | SUMX39 | Num | 8 | | Altered Thought Process |
| 42 | SUMX40 | Num | 8 | | Impulsivity/Hyperactivity |
| 43 | SUMX41 | Num | 8 | | Altered Sensory Perception |
| 44 | SUMX42 | Num | 8 | | Knowledge Deficit |
| 45 | SUMX43 | Num | 8 | | Growth and Development Deficit |
| 46 | SUMX44 | Num | 8 | | Sleep Disturbance |
| 47 | SUMX45 | Num | 8 | | Anxiety |
| 48 | SUMX46 | Num | 8 | | Disturbed Self-Concept |

| | | | | | |
|---|---|---|---|---|---|
| 49 | SUMX47 | Num | 8 | | Depression |
| 50 | SUMX48 | Num | 8 | | Fear |
| 51 | SUMX49 | Num | 8 | | Powerlessness |
| 52 | SUMX50 | Num | 8 | | Grieving |
| 53 | SUMX51 | Num | 8 | | Altered Family Process |
| 54 | SUMX52 | Num | 8 | | Altered Parenting |
| 55 | SUMX53 | Num | 8 | | Social Isolation |
| 56 | SUMX54 | Num | 8 | | Impaired Verbal Communication |
| 57 | SUMX55 | Num | 8 | | Potential for Violence |
| 58 | SUMX56 | Num | 8 | | Sexual Dysfunction |
| 59 | SUMX57 | Num | 8 | | Rape Trauma Syndrome |
| 60 | SUMX58 | Num | 8 | | Ineffective Individual Coping |
| 61 | SUMX59 | Num | 8 | | Ineffective Family Coping |
| 62 | SUMX60 | Num | 8 | | Potential for Growth in Family Coping |
| 63 | SUMX61 | Num | 8 | | Spiritual Distress |
| 64 | SUMDAYS | Num | 8 | | Sum of days each patient was rated by assigned nurse |
| 65 | JENCNTR | Char | 18 | | Patient number/Account suffix/date of admission |
| 66 | ACCTSFIX | Char | 3 | | Account # suffix (001 = 1st admission) |
| 67 | ADMDATE | Num | 8 | MMDDYY | Date of patient admission |
| 68 | ADMMDNO | Char | 5 | | Admitting MD identification number |
| 69 | ADMDX | Char | 7 | | Admitting diagnoses |
| 70 | ADMSORCE | Char | 2 | | Source of admission |
| 71 | ANCHARGE | Num | 8 | | Ancillary patient charge |
| 72 | ATTENDMD | Char | 5 | | Attending MD |
| 73 | COMPLICA | Char | 1 | | Complication of patient health during stay |
| 74 | PREOPDAY | Num | 8 | | Pre-operative day |
| 75 | ICUDAYS | Num | 8 | | Number of days spent in ICU |
| 76 | LOS | Num | 8 | | Length of stay |
| 77 | DRGWGT | Char | 7 | | DRG weight |
| 78 | OUTLIER | Char | 1 | | Outlier values |
| 79 | DRGPAYMT | Num | 8 | | DRG payment |
| 80 | DRGFINAL | Char | 4 | | Final DRG at patient discharge |
| 81 | OUTLIER1 | Char | 1 | | Other outlier value |
| 82 | DRGCHARG | Num | 8 | | DRG charge |
| 83 | DRGLOS | Num | 8 | | DRG length of stay |
| 84 | DISHDISP | Char | 3 | | Discharge disposition |
| 85 | GUARNZIP | Char | 5 | | Guarantor’s listed zip code |
| 86 | FINCLASS | Char | 2 | | Financial class (primary insurance type) |
| 87 | FINCLAS2 | Char | 2 | | Financial class 2 (secondary insurance type) |
| 88 | PRCDCLAS | Char | 1 | | Procedure class |
| 89 | MEDCAID | Char | 12 | | Medicaid health insurance |
| 90 | ANCHG | Num | 8 | | Ancillary charge |
| 91 | CONSLT | Num | 8 | | Consults/Consultation |
| 92 | PROD | Num | 8 | | Procedure performed |
| 93 | DX2 | Num | 8 | | Secondary medical diagnoses |
| 94 | PATCODE | Char | 8 | | Patient code |
| 95 | DX1CODE | Char | 7 | | Primary medical diagnosis code |
| 96 | DX1NAME | Char | 30 | | Primary medical diagnosis name |
| 97 | PROCODE | Char | 7 | | Procedure performed code |
| 98 | PROCNAME | Char | 30 | | Procedure performed name |
| 99 | PROCDMD | Char | 5 | | Procedure MD identification code |
| 100 | AGE | Num | 8 | | Patient age |

| | | | | | |
|---|---|---|---|---|---|
| 101 | BIRTHDAY | Num | 8 | MMDDYY | Patient date of birth |
| 102 | MARSTATE | Char | 1 | | Patient marital status |
| 103 | RACE | Char | 1 | | Patient race |
| 104 | RELIGION | Char | 3 | | Patient religion |
| 105 | SEX | Char | 1 | | Patient sex |
| 106 | ZIPCODE | Char | 5 | | Patient address zip code |
| 107 | REFERFAC | Char | 6 | | Referring |
| 108 | ANCCOST | Num | 8 | | Ancillary cost |
| 109 | ANCCHRGE | Num | 8 | | Ancillary charge |
| 110 | COST | Num | 8 | | Cost |
| 111-129 | DXCODE2 | Char | 7 | | Secondary diagnoses codes (2-20) |
| 130-148 | PRCODE2 | Char | 7 | | Secondary procedure codes (2-20) |
| 149 | INSPLAN | Char | 1 | | Insurance plan |
| 150 | dx1first3_num | Num | 8 | | First 3 digits of primary diagnosis |
| 151 | dx1code_name | Char | 38 | | Name of primary diagnosis |
| 152 | insurance | Char | 18 | | FINCLASS category |
| 153 | discharge | Char | 15 | | Discharge Status |
| 154 | rrace | Char | 10 | | Race: White, Black, Other |
| 155 | race2 | Char | 10 | | Race: Black vs. White/Other |
| 156 | married | Num | 8 | | Marital Status |
| 157 | ins1 | Num | 8 | | Private/HMO |
| 158 | ins2 | Num | 8 | | Medicare/Other |
| 159 | ins3 | Num | 8 | | Medicaid/Welfare |
| 160 | female | Num | 8 | | Female |
| 161 | type2_prim | Num | 8 | | Has Type 2 as primary DX |
| 162 | type1_prim | Num | 8 | | Has Type 1 as primary DX |
| 163 | type2_sec | Num | 8 | | Has Type 2 as secondary (but not primary) DX |
| 164 | type1_sec | Num | 8 | | Has Type 1 as secondary (but not primary) DX |
| 165 | diabetes_status | Char | 20 | | Patient Diabetes status |
| 166 | type1_all | Num | 8 | | Has Type 1 as either secondary or primary DX |
| 167 | type2_all | Num | 8 | | Has Type 2 as either secondary or primary DX |
| 168-228 | pctx1 | Num | 8 | | Percentage of nursing diagnosis (pctx1-pctx61) |
| 229-289 | ndx1 | Num | 8 | | Nursing diagnoses (ndx1-ndx61) |
| 290 | ndxmean1 | Num | 8 | | Potential for Inj (mean number of nursing diagnosis) |
| 291 | ndxmean2 | Num | 8 | | Noncompliance |
| 292 | ndxmean3 | Num | 8 | | Infection/Contagion |
| 293 | ndxmean4 | Num | 8 | | Prolonged disease/disab |
| 294 | ndxmean5 | Num | 8 | | Instability |
| 295 | ndxmean6 | Num | 8 | | Impaired Life supt syst |
| 296 | ndxmean7 | Num | 8 | | Sanitation deficit |
| 297 | ndxmean8 | Num | 8 | | Sociocultural Econ |
| 298 | ndxmean9 | Num | 8 | | Fluid Vol Exce |
| 299 | ndxmean10 | Num | 8 | | Fluid Vol Defi |
| 300 | ndxmean11 | Num | 8 | | Potential Vol Defic |
| 301 | ndxmean12 | Num | 8 | | Bleeding |
| 302 | ndxmean13 | Num | 8 | | Nutrition less req |
| 303 | ndxmean14 | Num | 8 | | Nutrition more req |
| 304 | ndxmean15 | Num | 8 | | Nutrition Potentl Exc |
| 305 | ndxmean16 | Num | 8 | | Skin Impairment |
| 306 | ndxmean17 | Num | 8 | | Potential Skin Impairmt |
| 307 | ndxmean18 | Num | 8 | | Altera Mucous Memb |
| 308 | ndxmean19 | Num | 8 | | Altered Body Temp |

| | | | | | |
|---|---|---|---|---|---|
| 309 | ndxmean20 | Num | 8 | | Urinary Inconti |
| 310 | ndxmean21 | Num | 8 | | Other Altered Urin Elim |
| 311 | ndxmean22 | Num | 8 | | Constipation |
| 312 | ndxmean23 | Num | 8 | | Diarrhea |
| 313 | ndxmean24 | Num | 8 | | Bowl Incont |
| 314 | ndxmean25 | Num | 8 | | Activity Intol |
| 315 | ndxmean26 | Num | 8 | | Ineffect Airway Clr |
| 316 | ndxmean27 | Num | 8 | | Altered Breath Pattn |
| 317 | ndxmean28 | Num | 8 | | Impaired Gas Exng |
| 318 | ndxmean29 | Num | 8 | | Altered Tissue Perf |
| 319 | ndxmean30 | Num | 8 | | Decreased CO |
| 320 | ndxmean31 | Num | 8 | | Diversl Activity Defic |
| 321 | ndxmean32 | Num | 8 | | Altered Hlt Maintn |
| 322 | ndxmean33 | Num | 8 | | Impaired Mobility |
| 323 | ndxmean34 | Num | 8 | | SelfCare Deficit |
| 324 | ndxmean35 | Num | 8 | | Impaired Home Maint Mgmt |
| 325 | ndxmean36 | Num | 8 | | Discomfort |
| 326 | ndxmean37 | Num | 8 | | Pain |
| 327 | ndxmean38 | Num | 8 | | Altered Level Cons |
| 328 | ndxmean39 | Num | 8 | | Altered Thogt Process |
| 329 | ndxmean40 | Num | 8 | | Impulsive/Hyperactive |
| 330 | ndxmean41 | Num | 8 | | Altered Sensory Percptn |
| 331 | ndxmean42 | Num | 8 | | Knowledge Defic |
| 332 | ndxmean43 | Num | 8 | | Growth/Dev Defic |
| 333 | ndxmean44 | Num | 8 | | Sleep Disturbance |
| 334 | ndxmean45 | Num | 8 | | Anxiety |
| 335 | ndxmean46 | Num | 8 | | Disturbed Self Concpt |
| 336 | ndxmean47 | Num | 8 | | Depression |
| 337 | ndxmean48 | Num | 8 | | Fear |
| 338 | ndxmean49 | Num | 8 | | Powerlessness |
| 339 | ndxmean50 | Num | 8 | | Grieving |
| 340 | ndxmean51 | Num | 8 | | Altered Fam Process |
| 341 | ndxmean52 | Num | 8 | | Altered Parenting |
| 342 | ndxmean53 | Num | 8 | | Social Isolation |
| 343 | ndxmean54 | Num | 8 | | Impaired Verbal Comm |
| 344 | ndxmean55 | Num | 8 | | Potential for Violence |
| 345 | ndxmean56 | Num | 8 | | Sexual Dysfunct |
| 346 | ndxmean57 | Num | 8 | | Rape Trauma Synd |
| 347 | ndxmean58 | Num | 8 | | Ineffective Individ Copg |
| 348 | ndxmean59 | Num | 8 | | Ineffective Family Copg |
| 349 | ndxmean60 | Num | 8 | | Potential Growth Fam Copg |
| 350 | ndxmean61 | Num | 8 | | Spiritual Distress |
| 351 | num_nurse_diag | Num | 8 | | Number of nursing diagnoses |
| 352 | drgwgtfl | Num | 8 | | Final DRG weight |
| 353 | Staydays | Num | 8 | | Total number of stay days (excluding day of admission) |

SUMX refers to the number of days during the length of stay that a specific nursing diagnosis was checked by a nurse as applicable to each patient. For example, a patient with LOS of 9 and SUMX1 with value of 5 indicates that the nursing diagnosis of “potential for injury” (SUMX1) was applicable in his care 5 days during the 9 days of his hospital stay.

APPENDIX E: Descriptive Statistics of Data Set Including Subsets of Diabetes Patients

| Variables | STATISTIC | ALL PATIENTS (HIFX4) | ALL DIABETES CASES | DIABETES PRIMARY DX | DIABETES SECONDARY DX | DIABETES TYPE 1 (<21YR) |
|---|---|---|---|---|---|---|
| | N | 123,241 | 9,516 | 1,492 | 8,024 | 453 |
| **LOS** | MEAN | 7.3 | 8.7 | 7.9 | 8.8 | 5.8 |
| | MEDIAN | 4.0 | 5.0 | 5.0 | 6.0 | 4 |
| | MODE | 2.0 | 2.0 | 3.0 | 2.0 | 2 |
| | STDV | 13.0 | 10.9 | 10.8 | 10.9 | 8.8 |
| | VARIANCE | 170.2 | 118.6 | 116.7 | 118.9 | 77 |
| **AGE** | MEAN | 33.1 | 56.7 | 38.6 | 60.0 | 12.3 |
| | MEDIAN | 29.0 | 61.0 | 38.0 | 63.0 | 13 |
| | MODE | 0.0 | 66.0 | 13.0 | 66.0 | 13 |
| | STDV | 27.6 | 19.48 | 22.9 | 16.8 | 4.6 |
| | VARIANCE | 761.4 | 379.7 | 522.3 | 281.1 | 21 |
| **GENDER** | Female | 51209 | 3890 | 549 | 3341 | 291 (64.24) |
| | Male | 71929 | 5626 | 943 | 4683 | 162 (35.76) |
| **RACE** | White | 69373 | 4868 | 595 | 5273 | 218 |
| | Black | 52975 | 4596 | 891 | 3705 | 233 |
| | Other | 890 | 52 | 7 | 46 | 2 |
| **RACE by SEX** | | *n* ( %) | *n* (%) | *n* (%) | *n* (%) | *n* (%) |
| | 0 Unknown | 1 (0.0) | NA | NA | NA | NA |
| | 1 White Female | 31184 (25.3) | 2321 (24.39) | 240 (16.09) | 2081 (25.93) | 91 |
| | 2 White Male | 38189 (40.0) | 2547 (26.77) | 355 (23.79) | 2192 (27.32) | 127 |
| | 3 Other Female | 399 (0.32) | 26 (0.27) | 1 (0.07) | 25 (0.31) | 0 |
| | 4 Other Male | 491 (0.40) | 26 (0.27) | 5 (0.34) | 21 (0.26) | 2 |
| | 5 Black Female | 19626 (15.93) | 1543 (16.21) | 308 (20.64) | 1235 (15.39) | 71 |
| | 6 Black Male | 33349 (27.06) | 3053 (32.08) | 583 (39.08) | 2470 (30.78) | 162 |
| **ADMIT SOURCE** | UH ER | 35165 (28.75) | 4269 (45.25) | 857 (57.68) | 3412 (42.93) | |
| | UH OPD | 5675(4.65) | 193 (2.05) | 26 (1.75) | 167 (2.10) | |
| | MD Office | 70723 (57.82) | 4434 (47.0) | 528 (35.51) | 3906 (49.15) | |
| | Jail/Law Enforc. | 3 (0.0) | | | | |
| | ER other Hosp. | 23 (0.02) | | | | |
| | ECF | 235 (0.19) | 31 (0.33) | 2 (0.13) | | |
| | Other acute Hosp. | 8090 (6.61) | 443 (4.70) | | 376 (4.73) | |
| | Other UH Hosp. | 2048 (1.67) | 34 (0.36) | 67 (4.51) | 32 (0.40) | |
| | Psych Transf. | 28 (0.02) | 1 (0.01) | 2 (0.13) | 1 (0.01) | |
| | Rehab Hosp. | 127 (0.10) | 1 (0.01) | | 1 (0.01) | |
| | Other | 192 (0.16) | 28 (0.30) | 5 (0.34) | 23 (0.29) | |
| **DISCHARGE DISPOSITION** | Discharged home | 108764 (88.25) | 7669 (80.59) | 1207 (80.90) | 6462 (80.53) | |
| | Against Med Adv. | 454 (0.37) | 45 (0.47) | 9 (0.60) | 36 (0.45) | |
| | Home care serv. | 3957 (3.21) | 906 (9.52) | 192 (12.87) | 714 (8.90) | |
| | Anothe acute care | 819 (0.66) | 55 (0.58) | 10 (0.67) | 45 (0.56) | |
| | Other | 4 (0.00) | | | | |
| | Extend care facilit | 2243 (1.82) | 380 (3.99) | 35 (2.35) | 345 (4.30) | |
| | Unknown | 971 (0.79) | 13 (0.14) | 2 (0.13) | 11 (0.14) | |
| | Other UH facility | 1919 (1.56) | 31 (0.33) | 6 (0.40) | 25 (0.31) | |
| | Psychiatric facility | 87 (0.07) | 4 (0.04) | 1 (0.07) | 3 (0.04) | |
| | Rehab facility | 800 (0.65) | 79 (0.83) | 13 (0.87) | 66 (0.82) | |
| | Specialty hospital | 1 (0.00) | | | | |
| | Hospice | 6 | 2 (0.02) | | 2 (0.02) | |
| | Died | 167 | 14 (0.15) | | 14 (0.17) | |
| | Died, autopsy unk | 3044 (2.47) | 318 (3.34) | 17 (1.14) | 301 (3.75) | |
| **NsgDxIndx** | MEAN | 0.18 | 0.14 | 0.13 | 0.14 | |
| | MEDIAN | 0.00 | 0.00 | 0.00 | 0.00 | |
| **(Sumx1-61)/LOS** | MODE | 0.00 | 0.00 | 0.00 | 0.00 | |
| | STDV | 0.42 | 0.30 | 0.27 | 0.30 | |
| | VARIANCE | 0.18 | 0.09 | 0.07 | 0.09 | |

## APPENDIX F: Nursing Diagnoses Use Pattern in Three Patient Groups

| Nursing Diagnoses | All Patients* (*n*=74,818) | | | | Secondary diag. of T2DM (*n*=5,163) | | | | Primary diag. of T2DM (*n*=445) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Freq (sumdays)** | **Pct. (Ndx)** | **Mean (Sumx)** | **Relative import.** | **Freq (sumdays)** | **Pct. (Ndx)** | **Mean (Sumx)** | **Relative import.** | **Freq (sumdays)** | **Pct. (Ndx)** | **Mean (Sumx)** | **Relative import.** |
| 1. Potential for Injury | 209430 | 0.69 | 2.80 | 0.4738 | 17007 | 0.70 | 3.29 | 0.4402 | 1537 | 0.62 | 3.45 | 0.3728 |
| 2. Noncompliance | 26403 | 0.15 | 0.35 | 0.0531 | 3216 | 0.24 | 0.62 | 0.0814 | 434 | 0.35 | 0.98 | 0.1347 |
| 3. Infection/Contagion | 160792 | 0.55 | 2.15 | 0.3541 | 11137 | 0.50 | 2.16 | 0.2519 | 1196 | 0.54 | 2.69 | 0.2705 |
| 4. Prolonged disease/disability | 263378 | 0.68 | 3.52 | 0.5412 | 27369 | 0.92 | 5.30 | 0.7779 | 2648 | 0.95 | 5.95 | 0.8218 |
| 5. Instability | 55080 | 0.27 | 0.74 | 0.1160 | 5105 | 0.36 | 0.99 | 0.1486 | 222 | 0.21 | 0.50 | 0.0678 |
| 6. Impaired Life support system | 25043 | 0.11 | 0.33 | 0.0378 | 2588 | 0.17 | 0.50 | 0.0590 | 100 | 0.09 | 0.22 | 0.0250 |
| 7. Sanitation deficit | 9955 | 0.06 | 0.13 | 0.0187 | 709 | 0.08 | 0.14 | 0.0171 | 82 | 0.08 | 0.18 | 0.0167 |
| 8. Sociocultural Econ | 40859 | 0.22 | 0.55 | 0.1010 | 2344 | 0.21 | 0.45 | 0.0637 | 350 | 0.26 | 0.79 | 0.0845 |
| 9. Fluid Volume Excess | 65643 | 0.27 | 0.88 | 0.1224 | 10279 | 0.50 | 1.99 | 0.2740 | 682 | 0.39 | 1.53 | 0.1749 |
| 10. Fluid Volume Deficit | 31540 | 0.20 | 0.42 | 0.0695 | 2041 | 0.20 | 0.40 | 0.0559 | 230 | 0.26 | 0.52 | 0.0763 |
| 11. Potential Volume Deficit | 114766 | 0.53 | 1.53 | 0.2660 | 7836 | 0.51 | 1.52 | 0.2057 | 724 | 0.53 | 1.63 | 0.2102 |
| 12. Bleeding | 100178 | 0.46 | 1.34 | 0.2695 | 5297 | 0.38 | 1.03 | 0.1501 | 365 | 0.24 | 0.82 | 0.0748 |
| 13. Nutrition less than required | 166277 | 0.57 | 2.22 | 0.3423 | 11423 | 0.54 | 2.21 | 0.2790 | 959 | 0.51 | 2.16 | 0.2495 |
| 14. Nutrition more than required | 12845 | 0.08 | 0.17 | 0.0298 | 2803 | 0.23 | 0.54 | 0.0871 | 401 | 0.38 | 0.90 | 0.1585 |
| 15. Nutrition Potential Excess | 9151 | 0.06 | 0.12 | 0.0181 | 2276 | 0.21 | 0.44 | 0.0658 | 408 | 0.40 | 0.92 | 0.1471 |
| 16. Skin Impairment | 237357 | 0.70 | 3.17 | 0.5361 | 17993 | 0.63 | 3.48 | 0.4352 | 1690 | 0.52 | 3.80 | 0.3701 |
| 17. Potential Skin Impairment | 188754 | 0.62 | 2.52 | 0.3863 | 16463 | 0.67 | 3.19 | 0.3976 | 1506 | 0.64 | 3.38 | 0.3648 |
| 18. Altera Mucous Membrane | 44993 | 0.20 | 0.60 | 0.0781 | 3097 | 0.22 | 0.60 | 0.0648 | 223 | 0.16 | 0.50 | 0.0457 |
| 19. Altered Body Temp | 54348 | 0.28 | 0.73 | 0.1111 | 2921 | 0.23 | 0.57 | 0.0680 | 216 | 0.17 | 0.49 | 0.0416 |
| 20. Urinary Incontinence | 26227 | 0.11 | 0.35 | 0.0453 | 2898 | 0.16 | 0.56 | 0.0658 | 220 | 0.13 | 0.49 | 0.0497 |
| 21. Other Altered Urine Elimination | 68391 | 0.30 | 0.91 | 0.1358 | 6995 | 0.39 | 1.35 | 0.1732 | 516 | 0.32 | 1.16 | 0.1224 |

| Nursing Diagnoses | All Patients* (*n*=74,818) | | | | Secondary diag. of T2DM (*n*=5,163) | | | | Primary diag. of T2DM (*n*=445) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Freq (sumdays)** | **Pct. (Ndx)** | **Mean (Sumx)** | **Relative import.** | **Freq (sumdays)** | **Pct. (Ndx)** | **Mean (Sumx)** | **Relative import.** | **Freq (sumdays)** | **Pct. (Ndx)** | **Mean (Sumx)** | **Relative import.** |
| 22. Constipation | 80706 | 0.37 | 1.08 | 0.1848 | 5453 | 0.36 | 1.06 | 0.1268 | 398 | 0.25 | 0.89 | 0.0825 |
| 23. Diarrhea | 29804 | 0.13 | 0.40 | 0.0467 | 2861 | 0.19 | 0.55 | 0.0598 | 193 | 0.16 | 0.43 | 0.0433 |
| 24. Bowl Incontinence | 24143 | 0.09 | 0.32 | 0.0348 | 2854 | 0.14 | 0.55 | 0.0552 | 211 | 0.13 | 0.47 | 0.0482 |
| 25. Activity Intolerance | 200085 | 0.65 | 2.67 | 0.4194 | 17460 | 0.73 | 3.38 | 0.4606 | 1303 | 0.57 | 2.93 | 0.3097 |
| 26. Ineffective Airway Clearance | 69923 | 0.27 | 0.93 | 0.1385 | 5109 | 0.31 | 0.99 | 0.1252 | 189 | 0.15 | 0.42 | 0.0399 |
| 27. Altered Breath Pattern | 76475 | 0.31 | 1.02 | 0.1598 | 5918 | 0.36 | 1.15 | 0.1597 | 232 | 0.19 | 0.52 | 0.0569 |
| 28. Impaired Gas Exchange | 56423 | 0.23 | 0.75 | 0.1074 | 4602 | 0.30 | 0.89 | 0.1213 | 175 | 0.16 | 0.39 | 0.0459 |
| 29. Altered Tissue Perfusion | 64894 | 0.31 | 0.87 | 0.1328 | 7553 | 0.48 | 1.46 | 0.2043 | 727 | 0.43 | 1.63 | 0.1745 |
| 30. Decreased CO | 29578 | 0.15 | 0.40 | 0.0616 | 4261 | 0.33 | 0.83 | 0.1322 | 195 | 0.18 | 0.44 | 0.0610 |
| 31. Diversional Activity Deficit | 138538 | 0.53 | 1.85 | 0.2986 | 10495 | 0.60 | 2.03 | 0.2858 | 924 | 0.56 | 2.08 | 0.2497 |
| 32. Altered Health Maintenance | 77333 | 0.37 | 1.03 | 0.1718 | 6222 | 0.42 | 1.21 | 0.1613 | 675 | 0.49 | 1.52 | 0.1945 |
| 33. Impaired Mobility | 197597 | 0.59 | 2.64 | 0.3879 | 18223 | 0.68 | 3.53 | 0.4413 | 1810 | 0.57 | 4.07 | 0.3960 |
| 34. Self-Care Deficit | 200891 | 0.61 | 2.69 | 0.3971 | 17979 | 0.66 | 3.48 | 0.4273 | 1523 | 0.54 | 3.42 | 0.3323 |
| 35. Impaired Home Maint/Magment. | 110638 | 0.41 | 1.48 | 0.2136 | 10795 | 0.56 | 2.09 | 0.2895 | 1015 | 0.62 | 2.28 | 0.3080 |
| 36. Discomfort | 267332 | 0.83 | 3.57 | 0.6408 | 20311 | 0.83 | 3.93 | 0.5654 | 1653 | 0.69 | 3.71 | 0.4337 |
| 37. Pain | 159126 | 0.58 | 2.13 | 0.3649 | 10581 | 0.52 | 2.05 | 0.2703 | 883 | 0.39 | 1.98 | 0.1692 |
| 38. Altered Level Cons | 32737 | 0.17 | 0.44 | 0.0650 | 2857 | 0.18 | 0.55 | 0.0632 | 194 | 0.14 | 0.44 | 0.0425 |
| 39. Altered Thought Process | 30756 | 0.14 | 0.41 | 0.0557 | 3392 | 0.20 | 0.66 | 0.0754 | 281 | 0.19 | 0.63 | 0.0782 |
| 40. Impulsive/Hyperactive | 14037 | 0.09 | 0.19 | 0.0275 | 1048 | 0.09 | 0.20 | 0.0213 | 71 | 0.08 | 0.16 | 0.0161 |
| 41. Altered Sensory Perception | 55620 | 0.24 | 0.74 | 0.1055 | 6671 | 0.38 | 1.29 | 0.1653 | 565 | 0.34 | 1.27 | 0.1391 |
| 42. Knowledge Deficit | 262267 | 0.84 | 3.51 | 0.6435 | 22348 | 0.90 | 4.33 | 0.6706 | 2194 | 0.91 | 4.93 | 0.7310 |
| 43. Growth/Development Deficit | 39947 | 0.17 | 0.53 | 0.0808 | 958 | 0.10 | 0.19 | 0.0272 | 92 | 0.11 | 0.21 | 0.0264 |
| 44. Sleep Disturbance | 125404 | 0.52 | 1.68 | 0.3020 | 6936 | 0.45 | 1.34 | 0.1793 | 488 | 0.37 | 1.10 | 0.1287 |

| Nursing Diagnoses | All Patients* ($n$=74,818) | | | | Secondary diag. of T2DM ($n$=5,163) | | | | Primary diag. of T2DM ($n$=445) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Freq (sumdays) | Pct. (Ndx) | Mean (Sumx) | Relative import. | Freq (sumdays) | Pct. (Ndx) | Mean (Sumx) | Relative import. | Freq (sumdays) | Pct. (Ndx) | Mean (Sumx) | Relative import. |
| 45. Anxiety | 207571 | 0.74 | 2.77 | 0.4942 | 13745 | 0.70 | 2.66 | 0.3867 | 1095 | 0.63 | 2.46 | 0.3148 |
| 46. Disturbed Self Concept | 55892 | 0.25 | 0.75 | 0.0971 | 3821 | 0.27 | 0.74 | 0.0865 | 375 | 0.22 | 0.84 | 0.0702 |
| 47. Depression | 57593 | 0.24 | 0.77 | 0.0938 | 4838 | 0.31 | 0.94 | 0.1025 | 448 | 0.24 | 1.01 | 0.0842 |
| 48. Fear | 99461 | 0.42 | 1.33 | 0.2015 | 6092 | 0.41 | 1.18 | 0.1497 | 472 | 0.30 | 1.06 | 0.1088 |
| 49. Powerlessness | 139286 | 0.50 | 1.86 | 0.2676 | 10612 | 0.56 | 2.06 | 0.2581 | 888 | 0.45 | 2.00 | 0.1959 |
| 50. Grieving | 30189 | 0.14 | 0.40 | 0.0543 | 1774 | 0.14 | 0.34 | 0.0374 | 203 | 0.12 | 0.46 | 0.0349 |
| 51. Altered Family Process | 113750 | 0.47 | 1.52 | 0.2895 | 4061 | 0.29 | 0.79 | 0.0976 | 324 | 0.28 | 0.73 | 0.0873 |
| 52. Altered Parenting | 42574 | 0.21 | 0.57 | 0.1030 | 779 | 0.07 | 0.15 | 0.0182 | 66 | 0.06 | 0.15 | 0.0157 |
| 53. Social Isolation | 41527 | 0.20 | 0.56 | 0.0737 | 3590 | 0.27 | 0.70 | 0.0860 | 287 | 0.20 | 0.64 | 0.0649 |
| 54. Impaired Verbal Communication | 32660 | 0.12 | 0.44 | 0.0488 | 3358 | 0.17 | 0.65 | 0.0640 | 157 | 0.11 | 0.35 | 0.0360 |
| 55. Potential for Violence | 3713 | 0.02 | 0.05 | 0.0072 | 192 | 0.02 | 0.04 | 0.0056 | 20 | 0.02 | 0.04 | 0.0044 |
| 56. Sexual Dysfunction | 10843 | 0.05 | 0.14 | 0.0197 | 393 | 0.04 | 0.08 | 0.0101 | 10 | 0.01 | 0.02 | 0.0045 |
| 57. Rape Trauma Syndrome | 670 | 0.00 | 0.01 | 0.0016 | 12 | 0.00 | 0.00 | 0.0002 | 0 | 0.00 | 0.00 | 0.0000 |
| 58. Ineffective Individual Coping | 37023 | 0.18 | 0.49 | 0.0695 | 2958 | 0.23 | 0.57 | 0.0716 | 301 | 0.25 | 0.68 | 0.0770 |
| 59. Ineffective Family Coping | 21303 | 0.11 | 0.28 | 0.0370 | 1108 | 0.09 | 0.21 | 0.0235 | 110 | 0.10 | 0.25 | 0.0248 |
| 60. Potential Growth Family Coping | 149890 | 0.56 | 2.00 | 0.3845 | 6394 | 0.42 | 1.24 | 0.1719 | 630 | 0.42 | 1.42 | 0.1737 |
| 61. Spiritual Distress | 23615 | 0.11 | 0.32 | 0.0425 | 1234 | 0.12 | 0.24 | 0.0308 | 87 | 0.09 | 0.20 | 0.0188 |

## REFRENCES


Abdellah, F.G., Beland, I.L., Martin, A., & Matheney, R.V. (1960). *Patient-centered approaches to nursing*. New York: Macmillan.

ADA. (2010). Diagnosis and Classification of Diabetes Mellitus. *Diabetes Care*, *33*(S1), S62-S69.

ADA. (2012a). Diabetes basics: Type 1. from [http://www.diabetes.org/diabetes-basics/type-1/?loc=HomePage-type1-tdt&](http://www.diabetes.org/diabetes-basics/type-1/?loc=HomePage-type1-tdt&)

ADA. (2012b). Standards of Medical Care in Diabetes—2012. *Diabetes Care*, *35*(Supplement 1), S11-S63. doi: 10.2337/dc12-s011

ADA. (2013). Economic Costs of Diabetes in the U.S. in 2012. *Diabetes Care*, *36*(4), 1033-1046. doi: 10.2337/dc12-2625

Ahern, M. M., & Hendryx, M. (2007). Avoidable hospitalizations for diabetes: comorbidity risks. *Disease Management, 10*(6), 347-355.

Ahluwalia, Indu B., Tessaro, Irene, Greenlund, Kurt J., & Ford, Earl S. (2010). Factors associated with control of hypertension, hypercholesterolemia, and diabetes among low-income women in West Virginia. *Journal of Women's Health, 19*(3), 417-424. doi: 10.1089/jwh.2009.1590

Alberti, K., & Zimmet, PZ. (1998). Definition, diagnosis and classification of diabetes mellitus and its complications. Part 1: diagnosis and classification of diabetes mellitus. Provisional report of a WHO consultation. *Diabetic medicine, 15*(7), 539-553.

Allison, P. D. (1999). *Multiple regression: A primer*. Thousand Oaks, California, USA.: Pine Forge Press.

Anderson, J. H. (2007). The impact of using nursing presence in a community heart failure program. *Journal of Cardiovascular Nursing*, *22*(2), 89-98.

Aschemeier, B., Lange, K., Kordonouri, O., & Danne, T. (2008). Paediatric obesity and type 2 diabetes: strategies for prevention and treatment. *Practical Diabetes International, 25*(9), 368-375.

Bailey, D. M. (1997). *Research for the health professional: a practical guide* (2 ed.). Philadelphia: F. A. Davis Company.

Balsa, A.I., & McGuire, T.G. (2003). Prejudice, clinical uncertainty and stereotyping as sources of health disparities. *Journal of Health Economics, 22*(1), 89-116.

Barr, C.C. (2001). Retinopathy and nephropathy in patients with type 1 diabetes four years after a trial of intensive insulin therapy, by The Diabetes Control and Complications Trial/Epidemiology of Diabetes Interventions and Complications Research Group. N. Engl. J. Med 342: 381-9, 2000. *Survey of ophthalmology, 45*(5), 459.

Beckwith, S. (2010). Diagnosing type 2 diabetes in children and young people. *British Journal of School Nursing, 5*(1), 15-19.

Black, S. A. (2002). Diabetes, diversity, and disparity: what do we do with the evidence? *Am J Public Health, 92*(4), 543-548.

Blank, M. B., Hanrahan, N. P., Fishbein, M., Wu, E. S., Tennille, J. A., Ten Have, T. R., . . . Aiken, L. H. (2011). A Randomized Trial of a Nursing Intervention for HIV Disease Management Among Persons With Serious Mental Illness. *Psychiatric Services, 62*(11), 1318-1324.

Blegen, M.A., Goode, C.J., Spetz, J., Vaughn, T., & Park, S.H. (2011). Nurse Staffing Effects on Patient Outcomes: Safety-Net and Non-Safety-Net Hospitals. *Medical Care, 49*(4), 406.

Brink, P. J., & Wood, M.J. (1998). *Advanced design in nursing research* (2 ed.). Thousand Oaks, California: Sage Publications, Inc.

Brookhart, M. A., Stürmer, T., Glynn, R. J., Rassen, J., & Schneeweiss, S. (2010). Confounding control in healthcare database research: challenges and potential approaches. *Medical Care, 48*(6 Suppl), S114-120. doi: 10.1097/MLR.0b013e3181dbebe3

Brooten, D., & Naylor, M.D. (1995). Nurses' effect on changing patient outcomes. *Journal of Nursing Scholarship, 27*(2), 95-99.

Buell, C., Kermah, D., & Davidson, M.B. (2007). Utility of A1C for diabetes screening in the 1999–2004 NHANES population. *Diabetes Care, 30*(9), 2233-2235.

Burgess, S., Geddes, J., Hawton, K., Townsend, E., Jamison, K., & Goodwin, G. (2001). Lithium for maintenance treatment of mood disorders. *Cochrane Database Syst Rev, 3*.

Burns, C. (1993). Using a comprehensive taxonomy of diagnoses to describe the practice of pediatric nurse practitioners: findings of a field study. *Journal of Pediatric Healthcare, 7*(3), 115-121.

Campbell, M., Grimshaw, J., & Elbourne, D. (2004). Intracluster correlation coefficients in cluster randomized trials: empirical insights into how should they be reported. *BMC Medical research methodology, 4*(1), 9.

Carpenito-Moyet, L.J. (2006). *Nursing diagnosis: Application to clinical practice*: Lippincott Williams & Wilkins.

Carpenito, L. J. (1991). The NANDA definition of nursing diagnosis. In R. M. Carroll-Johnson (Ed.), *Classification of Nursing Diagnoses: Proceedings of the ninth conference 1990* (pp. 65-71). Philadelphia J. B. Lippincott.

CDC. (2011a). *National Dabetes Fact Sheet: national estimates and general information on diabetes and prediabetes in the United States*. Atlanta, GA.

CDC. (2011b). *National diabetes fact sheet: national estimates and general information on diabetes and prediabetes in the United States*. Atlanta, Georgia: Centers for Disease Control and Prevention Retrieved from http://www.cdc.gov/diabetes/pubs/pdf/ndfs_2011.pdf.

Chiu, C. W., & Wong, F. K. Y. (2010). Effects of 8 weeks sustained follow-up after a nurse consultation on hypertension: A randomised trial. *International Journal of Nursing Studies, 47*(11), 1374-1382. doi: 10.1016/j.ijnurstu.2010.03.018

Chung, J. H., Voss, K. J., Caughey, A. B., Wing, D. A., Henderson, E. J., & Major, C. A. (2006). Role of patient education level in predicting macrosomia among women with gestational diabetes mellitus. *Journal of Perinatology, 26*(6), 328-332.

Clark, N.G., Fox, K.M., & Grandy, S. (2007). Symptoms of diabetes and their association with the risk and presence of diabetes. *Diabetes Care, 30*(11), 2868.

Clay, O.J., Roth, D.L., Safford, M.M., Sawyer, P.L., & Allman, R.M. (2011). Predictors of Overnight Hospital Admission in Older African American and Caucasian Medicare Beneficiaries. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences, 66*(8), 910-916.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). Mahwah, New Jersey, USA.: Lawrence Erlbaum Associates, Publishers.

Courtney, M., Edwards, H., Chang, A., Parker, A., Finlayson, K., & Hamilton, K. (2009). Fewer emergency readmissions and better quality of life for older adults at risk of hospital readmission: a randomized controlled trial to determine the effectiveness of a 24-week exercise and telephone follow-up program. *Journal of the American Geriatrics Society, 57*(3), 395-402. doi: 10.1111/j.1532-5415.2009.02138.x

Davidson, M. B., & Schriger, D. L. (2010). Effect of age and race/ethnicity on HbA1c levels in people without known diabetes mellitus: implications for the diagnosis of diabetes. *Diabetes Research & Clinical Practice, 87*(3), 415-421.

Davidson, M.B., Schriger, D.L., Peters, A.L., & Lorber, B. (1999). Relationship between fasting plasma glucose and glycosylated hemoglobin. *JAMA: the journal of the American Medical Association, 281*(13), 1203.

DeCoster, V. A., & Cummings, S. (2004). Coping with type 2 diabetes: do race and gender matter? *Social Work in Health Care, 40*(2), 37-53.

DeFronzo, RA. (1988). Lilly lecture 1987. The triumvirate: beta-cell, muscle, liver. A collusion responsible for NIDDM. *Diabetes, 37*(6), 667-687.

Donabedian, A. (1968). Promoting quality through evaluating the process of patient care. *Medical Care, 6*(3), 181-202.

Donabedian, A. (1969). Quality of care: problems of measurement. II. Some issues in evaluating the quality of nursing care. *American Journal of Public Health, 59*(10), 1833.

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

Dunlop, D. D., Manheim, L. M., Sohn, M., Liu, X., & Chang, R. W. (2002). Incidence of functional limitation in older adults: the impact of gender, race, and chronic conditions. *Archives of Physical Medicine & Rehabilitation, 83*(7), 964-971.

Elliott, A. C., & Woodward, W. A. (2010). *SAS essentials: Mastering SAS for research*. San Francisco, California, USA: Jossey-Bass.

Emanuele, N., Sacks, J., Klein, R., Reda, D., Anderson, R., Duckworth, W., & Abraira, C. (2005). Ethnicity, race, and baseline retinopathy correlates in the veterans affairs diabetes trial. *Diabetes Care, 28*(8), 1954.

Faris, P.D., Ghali, W.A., Brant, R., Norris, C.M., Galbraith, P.D., & Knudtson, M.L. (2002). Multiple imputation versus data enhancement for dealing with missing data in observational health care outcome analyses. *Journal of clinical epidemiology, 55*(2), 184-191.

Fehring, R.J. (1987). Methods to validate nursing diagnoses. *Nursing Faculty Research and Publications*, 27.

Fitzpatrick, J. J., Halloran, E. J., & Algase, D. L. (1987). An experiment in nursing revisited: changes in progress on the Frances Payne Bolton/University Hospitals of Cleveland collaboration model. *Nursing Outlook, 35*(1), 29-33.

Fitzpatrick, J.J., Kerr, M.E., Saba, V.K., Hoskins, L.M., Hurley, M.E., Mills, W.C., . . . Carpenito, L.J. (1989). Nursing diagnosis: Translating nursing diagnosis into ICD Code. *The American Journal of Nursing, 89*(4), 493-495.

Fraze, T. K., Jiang, H. J., & Burgess, J. (2010). Hospital stays for patients with diabetes, 2008. *Healthcare Cost and Utilization Project H-CUP Statistical Brief #93*. Rockville, MD: Agency for Healthcare Research and Quality.

Fry, Vera S. (1953). The Creative Approach to Nursing. *The American Journal of Nursing, 53*(3), 301-302.

Gæde, Peter, Lund-Andersen, Henrik, Parving, Hans-Henrik, & Pedersen, Oluf. (2008). Effect of a Multifactorial Intervention on Mortality in Type 2 Diabetes. *New England Journal of Medicine, 358*(6), 580-591. doi: doi:10.1056/NEJMoa0706245

Gazmararian, J.A., Williams, M.V., Peel, J., & Baker, D.W. (2003). Health literacy and knowledge of chronic disease. *Patient education and counseling, 51*(3), 267-275.

Gebbie, K., & Lavin, M.A. (1974). Classifying nursing diagnoses. *The American Journal of Nursing*, 250-253.

Gerich, J.E. (1998). The genetic basis of type 2 diabetes mellitus: impaired insulin secretion versus impaired insulin sensitivity. *Endocrine Reviews, 19*(4), 491-503.

Gordon, M. . (1987). *Nursing diagnosis: process and application.* . New York: McGraw-Hill.

Grimes, D.A., & Schulz, K.F. (2002). Bias and causal associations in observational research. *The Lancet, 359*(9302), 248-252.

Guttmann, A., Nakhla, M., Henderson, M., To, T., Daneman, D., Cauch-Dudek, K., . . . Hux, J. (2010). Validation of a health administrative data algorithm for assessing the epidemiology of diabetes in Canadian children. *Pediatric Diabetes, 11*(2), 122-128.

Halloran, E. J. (1988). Computerized nurse assessments. *Nurs Health Care, 9*(9), 497-499.

Halloran, E. J. (2009). Women hold up half the sky. *Int Nurs Rev, 56*(4), 410-415. doi: INR781 [pii] 10.1111/j.1466-7657.2009.00781.x [doi]

Halloran, E. J., & Kiley, M. (1985). The nurses' role and length of stay. *Med Care, 23*(9), 1122-1126.

Halloran, E. J., & Kiley, M. (1987). Nursing dependency, diagnosis-related groups, and length of hospital stay. *Health Care Financ Rev, 8*(3), 27-36.

Halloran, E. J., Kiley, M., & England, M. (1988). Nursing diagnosis, DRGs, and length of stay. *Applied Nursing Research, 1*(1), 22-26.

Halloran, E. J., Patterson, C., & Kiley, M. (1987). Case-mix: matching patient need with nursing resource. *Nurs Manage, 18*(3), 27-30, 32, 36 passim.

Han, H. R., Kim, J., Kim, K. B., Jeong, S., Levine, D., Li, C., . . . Kim, M. T. (2010). Implementation and success of nurse telephone counseling in linguistically isolated Korean American patients with high blood pressure. *Patient Education & Counseling, 80*(1), 130-134. doi: 10.1016/j.pec.2009.10.012

Harrison, T.A., Hindorff, L.A., Kim, H., Wines, R., Bowen, D.J., McGrath, B.B., & Edwards, K.L. (2003). Family history of diabetes as a potential public health tool. *American Journal of Preventive Medicine, 24*(2), 152-159.

Henderson, V. (1960). *ICN basic principles of nursing care*. New York: International council of nurses.

Henderson, V., & Nite, G. (1978). *Principles and practice of nursing* (6 ed.). New York: Macmillan Publishing Co., Inc.

Hernán, M.A., Hernández-Díaz, S., Werler, M.M., & Mitchell, A.A. (2002). Causal knowledge as a prerequisite for confounding evaluation: an application to birth defects epidemiology. *American Journal of Epidemiology, 155*(2), 176-184.

Heron, M. (2012). *Deaths: Leading causes for 2008*. Hyattsville, Maryland: National Vital Statistics Report

Higashi, T., Wenger, N.S., Adams, J.L., Fung, C., Roland, M., McGlynn, E.A., . . . Shekelle, P.G. (2007). Relationship between number of medical conditions and quality of care. *New England Journal of Medicine*, *356*(24), 2496-2504.

Hiss, R. G., Armbruster, B. A., Gillard, M. L., & McClure, L. A. (2007). Nurse care manager collaboration with community-based physicians providing diabetes care: a randomized controlled trial. *Diabetes Educator, 33*(3), 493-502.

Huang, E.S., Basu, A., O'Grady, M., & Capretta, J.C. (2009). Projecting the future diabetes population size and related costs for the US. *Diabetes Care, 32*(12), 2225.

Huang, E.S., Brown, S.E.S., Thakur, N., Carlisle, L., Foley, E., Ewigman, B., & Meltzer, D.O. (2009). Racial/ethnic differences in concerns about current and future medications among patients with type 2 diabetes. *Diabetes Care, 32*(2), 311.

Huang, T. T., & Goran, M. I. (2003). Prevention of type 2 diabetes in young people: a theoretical perspective. *Pediatr Diabetes, 4*(1), 38-56. doi: 10.1034/j.1399-5448.2003.00022.x PDI022 [pii]

Iezzoni, L.I. (1997). Assessing quality using administrative data. *Annals of Internal Medicine, 127*(8 Part 2), 666.

Jaeger, T. F. (2008). Categorical data analysis: away from ANOVAs (transformation or not) and towards logit mixed models. *Journal of Memory & Language, 59*(4), 434-446.

Jager, K. J., Zoccali, C., MacLeod, A., & Dekker, F. W. (2008). Confounding: What it is and how to deal with it. *Kidney International, 73*(3), 256-260.

Jelinek, R., & Pierce, F. (1982). A Nursing Systems Approach: Productivity and Quality of Care. *Public Productivity Review*, 223-240.

Jenum, A. K., Holme, I., Graff-Iversen, S., & Birkeland, K. I. (2005). Ethnicity and sex are strong determinants of diabetes in an urban Western society: implications for prevention. *Diabetologia, 48*(3), 435-439. doi: 10.1007/s00125-005-1668-8

Jeppesen, K. M., Coyle, J. D., & Miser, W. F. (2009). Screening questions to predict limited health literacy: a cross-sectional study of patients with diabetes mellitus. *Annals of Family Medicine, 7*(1), 24-31. doi: 10.1370/afm.919

Jiang, H. Joanna, Andrews, Roxanne, Stryer, Daniel, & Friedman, Bernard. (2005). Racial/Ethnic Disparities in Potentially Preventable Readmissions: The Case of Diabetes. *American Journal of Public Health, 95*(9), 1561-1567. doi: 10.2105/ajph.2004.044222

Jiang, H.J., Stryer, D., Friedman, B., & Andrews, R. (2003). Multiple hospitalizations for patients with diabetes. *Diabetes Care, 26*(5), 1421.

Jovanovic, L., & Pettitt, D.J. (2001). Gestational diabetes mellitus. *JAMA: the journal of the American Medical Association, 286*(20), 2516.

Junttila, K., Hupli, M., & Salantera, S. (2010). The use of nursing diagnoses in perioperative documentation. *International Journal of Nursing Terminologies & Classifications, 21*(2), 57-68. doi: 10.1111/j.1744-618X.2010.01147.x

Kiley, M., Halloran, E. J., Monahan, J. L., Nosek, L., & Patterson, C. (1986). A nursing information system using nursing diagnosis. *Ohio Nurses Rev, 61*(5), 7-8.

Kim, C., Newton, K.M., & Knopp, R.H. (2002). Gestational diabetes and the incidence of type 2 diabetes. *Diabetes Care, 25*(10), 1862.

Kirkland, Fiona, & Sinclair, Alan. (2011). Barriers to the delivery of high-quality care for care home residents with diabetes. *Journal of Diabetes Nursing, 15*(3), 102.

Kleinbaum, David G., Kupper, Lawrence L., Miller, Keith E., & Nizam, Azhar. (1998). *Applied regression analysis and other multivariable methods* (3rd ed.). New York: Brooks/Cole Publishing Company.

Kronman, A. C., Freund, K. M., Hanchate, A., Emanuel, E. J., & Ash, A. S. (2010). Nursing home residence confounds gender differences in Medicare utilization an example of Simpson's paradox. *Women's Health Issues, 20*(2), 105-113. doi: 10.1016/j.whi.2009.11.016

Lanting, L.C., Joung, I., Mackenbach, J.P., Lamberts, S.W.J., & Bootsma, A.H. (2005). Ethnic differences in mortality, end-stage complications, and quality of care among diabetic patients. *Diabetes Care, 28*(9), 2280.

Lee, R.V., Jampol, L.M., & Brown, W.V. (1971). Nephrogenic diabetes insipidus and lithium intoxication—complications of lithium carbonate therapy. *New England Journal of Medicine, 284*(2), 93-94.

Leff, B., Reider, L., Frick, K. D., Scharfstein, D. O., Boyd, C. M., Frey, K., . . . Boult, C. (2009). Guided care and the cost of complex healthcare: a preliminary report. *American Journal of Managed Care*, *15*(8), 555-559.

Levin, R. F. (1984). *Yesterday, today and tomorrow: Nursing diagnosis research*. Paper presented at the First Mid-Atlantic Regional Conference on Nursing Diagnosis, Philadelphia, PA.

Levin, R. F., Krainovitch, B. C., Bahrenburg, E., & Mitchell, C. A. (1989). Diagnostic content validity of nursing diagnoses. *Image: Journal of Nursing Scholarship, 21*(1), 40-44.

Levin, R. F., Lunney, M., & Krainovich-Miller, B. (2004). Improving Diagnostic Accuracy Using an Evidence Based Nursing Model. *International Journal of Nursing Terminologies and Classifications, 15*(4), 114-122.

Little, R.R. (2003). Glycated hemoglobin standardization–National Glycohemoglobin Standardization Program (NGSP) perspective. *Clinical chemistry and laboratory medicine, 41*(9), 1191-1198.

Little, R.R., Rohlfing, C.L., Wiedmeyer, H.M., Myers, G.L., Sacks, D.B., & Goldstein, D.E. (2001). The national glycohemoglobin standardization program: a five-year progress report. *Clinical Chemistry, 47*(11), 1985.

Lubitz, J.D., & Riley, G.F. (1993). Trends in Medicare payments in the last year of life. *New England Journal of Medicine*, *328*(15), 1092-1096.

Luger, S., & Chabanuk, A. J. (2009). Management of type 2 diabetes: implications for the home healthcare clinician. *Home Healthcare Nurse, 27*(2), 92-103.

Lundbaek, K. (1962). Intravenous glucose tolerance as a tool in definition and diagnosis of diabetes mellitus. *British medical journal, 1*(5291), 1507.

Lunney, M. (2003). Critical thinking and accuracy of nurses' diagnoses. *International Journal of Nursing Terminologies and Classifications, 14*(3), 96-107.

Lunney, Margaret, Delaney, Connie, Duffy, Mary, Moorhead, Sue, & Welton, John. (2005). Advocating for Standardized Nursing Languages in Electronic Health Records. *Journal of Nursing Administration, 35*(1), 1-3.

Luttik, M. L., Jaarsma, T., Veeger, N., & van Veldhuisen, D. J. (2006). Marital status, quality of life, and clinical outcome in patients with heart failure. *Heart & Lung, 35*(1), 3-8.

Lützén, Kim, & Tishelman, Carol. (1996). Nursing diagnosis: a critical analysis of underlying assumptions. *International Journal of Nursing Studies, 33*(2), 190-200.

Mahler, R.J., & Adler, M.L. (1999). Type 2 diabetes mellitus: update on diagnosis, pathophysiology, and treatment. *Journal of Clinical Endocrinology & Metabolism, 84*(4), 1165.

Manley, S. (2003). Haemoglobin A1c–a marker for complications of type 2 diabetes: the experience from the UK Prospective Diabetes Study (UKPDS). *Clinical chemistry and laboratory medicine, 41*(9), 1182-1190.

Martikainen, P., Moustgaard, H., Murphy, M., Einiö, E. K., Koskinen, S., Martelin, T., & Noro, A. (2009). Gender, living arrangements, and social circumstances as determinants of entry into and exit from long-term institutional care at older ages: a 6-year follow-up study of older Finns. *Gerontologist, 49*(1), 34-45. doi: 10.1093/geront/gnp013

McCarthy, M.I., & Zeggini, E. (2009). Genome-wide association studies in type 2 diabetes. *Current diabetes reports, 9*(2), 164-171.

McHugh, Matthew D., Margo, & Kang, Xiao L. (2010). Medicare Readmissions Policies and Racial and Ethnic Health Disparities: A Cautionary Tale. *Policy, Politics & Nursing Practice, 11*(4), 309-316.

Medicare.gov. (2013). What Medicare covers. 2013, from http://www.medicare.gov/what-medicare-covers/index.html

Medpac. (2010). Medicare beneficiary demographics.A data book: Healtcare spending and the Medicare program: http://www.medpac.gov/chapters/Jun10DataBookSec2.pdf.

Metzger, B.E., Buchanan, T.A., Coustan, D.R., de Leiva, A., Dunger, D.B., Hadden, D.R., . . . Oats, J.N. (2007). Summary and recommendations of the fifth international workshop-conference on gestational diabetes mellitus. *Diabetes Care, 30*(Supplement 2), S251-S260.

Micek, W. T., Berry, L., Gilski, D., Kallenbach, A., Link, D., & Scharer, K. (1996). Patient outcomes: the link between nursing diagnoses and interventions. *Journal of Nursing Administration, 26*(11), 29-35.

Miech, R.A., Kim, J., McConnell, C., & Hamman, R.F. (2009). A Growing Disparity in Diabetes-Related Mortality:: US Trends, 1989-2005. *American Journal of Preventive Medicine, 36*(2), 126-132.

Molinaro, R. J. (2011). Diabetes cases on the rise: current diagnosis guidelines and research efforts for a cure. *MLO: Medical Laboratory Observer, 43*(2), 8-15.

Montgomery, Douglas C., Peck, Elizabeth A., & Vining, G. Geoffrey. (2006). *Introduction to linear regression analysis*. New Jersey: John Wiley & Sons Inc.

Müller-Staub, M. (2009). Evaluation of the implementation of nursing diagnoses, interventions, and outcomes. *International Journal of Nursing Terminologies & Classifications, 20*(1), 9-15. doi: 10.1111/j.1744-618X.2008.01108.x

Müller Staub, M., Needham, I., Odenbreit, M., Ann Lavin, M., & Van Achterberg, T. (2007). Improved quality of nursing documentation: results of a nursing diagnoses, interventions, and outcomes implementation study. *International Journal of Nursing Terminologies and Classifications, 18*(1), 5-17.

Nair, M. (2007). Diabetes management. Nursing management of the person with diabetes mellitus. Part 2. *British Journal of Nursing (BJN), 16*(4), 232-235.

Nathan, D. M. (1993). Long-Term Complications of Diabetes Mellitus. *New England Journal of Medicine, 328*(23), 1676-1685. doi: doi:10.1056/NEJM199306103282306

Nathan, D. M. (2009). International Expert Committee report on the role of the A1C assay in the diagnosis of diabetes. *Diabetes Care*, *32*(12), e160.

Nelson, A. (2002). Unequal treatment: Confronting racial and ethnic disparities in health care. *Journal of the National Medical Association*, *94*(8), 666.

Nelson, A. (2003). Unequal treatment: report of the Institute of Medicine on racial and ethnic disparities in healthcare. *The Annals of thoracic surgery*, *76*(4), S1377.

Norris, K., & Nissenson, A.R. (2008). Race, gender, and socioeconomic disparities in CKD in the United States. *Journal of the American Society of Nephrology, 19*(7), 1261-1270.

Nosek, L. J. (1986). *Explanation of hospital stay by nursing diagnoses, medical diagnoses, and social postition* (Thesis (Ph. D.)--Case Western Reserve University. 1986), Case Western Reserve University Frances Payne Bolton School of Nursing. May 1986, Frances Payne Bolton School of Nursing, Ohio.

O'Brien-Pallas, Linda, Irvine, Diane, Peereboom, Elisabeth, & Murray, Michael. (1997). Measuring nursing workload: understanding the variability. *Nursing Economics*, *15*(4), 171-182.

Ollerton, R.L., Playle, R., Ahmed, K., Dunstan, F.D., Luzio, S.D., & Owens, D.R. (1999). Day-to-day variability of fasting plasma glucose in newly diagnosed type 2 diabetic subjects. *Diabetes Care*, *22*(3), 394-398.

Paasche-Orlow, M.K., & Wolf, M.S. (2007). The causal pathways linking health literacy to health outcomes. *American Journal of Health Behavior, 31*(Supplement 1), S19-S26.

Paradis, P. E., Nemis-White, J., Meilleur, M., Ginn, M., Cox, J., & Montague, T. (2010). Icons. Managing care and costs: the sustained cost impact of reduced hospitalizations in a partnership-measurement model of disease management. *Healthcare Quarterly, 13*(4), 30-39.

Peek, M.E., Cargill, A., & Huang, E.S. (2007). Diabetes health disparities: a systematic review of health care interventions. *Medical care research and review: MCRR, 64*(5 Suppl), 101S.

Penny, K.I., & Atkinson, I. (2011). Approaches for dealing with missing data in health care studies. *Journal of Clinical Nursing*.

Persell, S.D., Osborn, C.Y., Richard, R., Skripkauskas, S., & Wolf, M.S. (2007). Limited health literacy is a barrier to medication reconciliation in ambulatory care. *Journal of general internal medicine, 22*(11), 1523-1526.

Peters, A.L., Davidson, M.B., Schriger, D.L., & Hasselblad, V. (1996). A clinical approach for the diagnosis of diabetes mellitus. *JAMA: the journal of the American Medical Association, 276*(15), 1246.

PHA, Commission. (1974). Length of Stay in PAS Hospitals (C. o. P. a. H. Actvities, Trans.). Ann Arbor, MI: Commission on Professional and Hospital Actvities.

Potter, P. A., Perry, A. G., Stockert, P. A., & Hall, A. M. (2013). *Fundamentals of nursing* (8 ed.). St. Louis, Missouri: Elsevier-Mosby.

Quan, H., Li, B., Duncan Saunders, L., Parsons, G.A., Nilsson, C.I., Alibhai, A., & Ghali, W.A. (2008). Assessing Validity of ICD-9-CM and ICD-10 Administrative Data in Recording Clinical Conditions in a Unique Dually Coded Database. *Health services research, 43*(4), 1424-1441.

Quan, H., Parsons, G.A., & Ghali, W.A. (2004). Validity of procedure codes in International Classification of Diseases, 9th revision, clinical modification administrative data. *Medical Care, 42*(8), 801.

Rapley, P., O'Connell, B., & Lunney, M. (1997). Responding to accuracy... Nursing Diagnosis, 7(2), p.80... the issue of determining accuracy of nursing diagnosis. *Nursing Diagnosis, 8*(1), 40-42.

Rathore, S.S., Foody, J.A.M., Wang, Y., Smith, G.L., Herrin, J., Masoudi, F.A., . . . Krumholz, H.M. (2003). Race, quality of care, and outcomes of elderly patients hospitalized with heart failure. *JAMA: the journal of the American Medical Association, 289*(19), 2517.

Renpenning, K. M., SozWiss, G. B., Denyes, M. J., Orem, D. E., & Taylor, S. G. (2011). Explication of the Nature and Meaning of Nursing Diagnosis. *Nursing Science Quarterly, 24*(2), 130-136.

Richardson, L.D., & Norris, M. (2010). Access to health and health care: how race and ethnicity matter. *Mount Sinai Journal of Medicine: A Journal of Translational and Personalized Medicine, 77*(2), 166-177.

Riley, A. A., McEntee, M. L., Gerson, L., & Dennison, C. R. (2009). Depression as a comorbidity to diabetes: implications for management. *Journal for Nurse Practitioners, 5*(7), 523-535.

Rodkey, G.V., & Itani, K.M.F. (2009). Evaluation of healthcare quality: a tale of three giants. *The American Journal of Surgery, 198*(5), S3-S8.

Roe-Prior, P. (2007). Sociodemographic variables predicting poor post-discharge outcomes for hospitalized elders with heart failure. *MEDSURG Nursing, 16*(5), 317-321.

Rohlfing, C.L., Wiedmeyer, H.M., Little, R.R., England, J.D., Tennill, A., & Goldstein, D.E. (2002). Defining the relationship between plasma glucose and HbA1c. *Diabetes Care, 25*(2), 275.

Rosenthal, G. E., Halloran, E. J., Kiley, M., & Landefeld, C. S. (1995). Predictive validity of the Nursing Severity Index in patients with musculoskeletal disease. Nurses of University Hospitals of Cleveland. *J Clin Epidemiol, 48*(2), 179-188. doi: 089543569400142D [pii]

Rosenthal, G. E., Halloran, E. J., Kiley, M., Pinkley, C., & Landefeld, C. S. (1992). Development and validation of the Nursing Severity Index. A new method for measuring severity of illness using nursing diagnoses. Nurses of University Hospitals of Cleveland. *Med Care, 30*(12), 1127-1141.

Sacks, D.B. (2005). Global harmonization of hemoglobin A1c. *Clinical Chemistry, 51*(4), 681.

Sargeant, LA, Wareham, NJ, & Khaw, KT. (2000). Family history of diabetes identifies a group at increased risk for the metabolic consequences of obesity and physical inactivity in EPIC-Norfolk: a population-based study. *International Journal of Obesity, 24*(10), 1333-1339.

SAS. (2013). SAS Documentation. *SAS User's Guide.* 2. Retrieved January 29, 2013, 2013, from http://support.sas.com/documentation/cdl/en/statug/63033/HTML/default/viewer.htm#statug_reg_sect030.htm

Saudek, C. D., & Golden, S. H. (1999). Feasibility and outcomes of insulin therapy in elderly patients with diabetes mellitus. *Drugs & Aging, 14*(5), 375-385.

Saudek, C. D., Herman, W. H., Sacks, D. B., Bergenstal, R. M., Edelman, D., & Davidson, M. B. (2008). A new look at screening and diagnosing diabetes mellitus. *Journal of Clinical Endocrinology & Metabolism, 93*(7), 2447.

Sauerbrei, Willi, & Schumacher, Martin. (2007). A bootstrap resampling procedure for model building: application to the Cox regression model. *Statistics in medicine, 11*(16), 2093-2109.

Scheffer, J. (2002). Dealing with missing data. *Research letters in the information and mathematical sciences, 3*(1), 153-160.

Schlotfeldt, Rozella M., & MacPhail, Jannetta. (1969). An Experiment in Nursing: Introducing Planned Change. *The American Journal of Nursing, 69*(6), 1247-1251.

Schneeweiss, S., & Avorn, J. (2005). A review of uses of health care utilization databases for epidemiologic research on therapeutics. *Journal of clinical epidemiology, 58*(4), 323-337.

Scott, I. A. (2003). Determinants of quality of in-hospital care for patients with acute coronary syndromes. *Disease Management & Health Outcomes, 11*(12), 801-816.

Shadish, W. R., Cook, T. D., & Campbell, D. T. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Boston: Houghton Mifflin Company.

Shin, Y. . (1977). Variation of hospital cost and product heterogeneity (E. a. W. U.S Department of Health, Trans.) *Health insurance studies contract research series (77-11 722)*. Washington, DC: U.S Department of Health, Education and Welfare.

Silverthorn, D.U. (2007). *Human Physiology: An Integrated Approach* (4th ed.). San Francisco: Pearson-Benjamin Cummings.

Smeulders, E. S. T., van Haastregt, J. C. M., Ambergen, T., Uszko-Lencer, N. H. K., Janssen-Boyne, J. J. J., Gorgels, A. P. M., . . . Kempen, G. I. J. (2010). Nurse-led self-management group programme for patients with congestive heart failure: randomized controlled trial. *Journal of Advanced Nursing, 66*(7), 1487-1499. doi: 10.1111/j.1365-2648.2010.05318.x

Smith, E. R., & Stevens, A. B. (2009). Predictors of discharges to a nursing home in a hospital-based cohort. *Journal of the American Medical Directors Association, 10*(9), 623-629. doi: 10.1016/j.jamda.2009.06.003

Stuart, C.A., Neelon, F.A., & Lebovitz, H.E. (1980). Disordered control of thirst in hypothalamic-pituitary sarcoidosis. *New England Journal of Medicine, 303*(19), 1078-1082.

Tabachnick, Barbara G., & Fidell, Linda S. (2001). *Using multivariate statistics* (4th ed.). Boston: Allyn and Bacon.

Tesfaye, S, Vileikyte, L, Rayman, G, Sindrup, Søren Hein, Perkins, BA, Baconja, M, . . . Boulton, AJM. (2011). Painful diabetic peripheral neuropathy: consensus recommendations on diagnosis, assessment and management. *Diabetes/metabolism research and reviews, 27*(7), 629-638.

Tomlin, A. M., Dovey, S. M., & Tilyard, M. W. (2008). Risk factors for hospitalization due to diabetes complications. *Diabetes Research & Clinical Practice, 80*(2), 244-252.

Troisi, R.J., Cowie, C.C., & Harris, M.I. (2000). Diurnal variation in fasting plasma glucose. *JAMA: the journal of the American Medical Association, 284*(24), 3157.

Urdan, T. C. (2010). *Statistics in plain English*. New York, NY. USA.: Routledge Taylor and Francis Group.

Utz, S.W., Williams, I.C., Jones, R., Hinton, I., Alexander, G., Yan, G., . . . Oliver, M.N. (2008). Culturally tailored intervention for rural African Americans with type 2 diabetes. *The Diabetes Educator, 34*(5), 854-865.

Van den Heede, Koen, Clarke, Sean P, Sermeus, Walter, Vleugels, Arthur, & Aiken, Linda H. (2007). International experts' perspectives on the state of the nurse staffing and patient outcomes literature. *Journal of Nursing Scholarship, 39*(4), 290-297.

Van Ryn, M., & Burke, J. (2000). The effect of patient race and socio-economic status on physicians' perceptions of patients. *Social Science & Medicine, 50*(6), 813-828.

Vasquez, M. S. (2009). Preventing rehospitalization through effective home health nursing care. *Professional Case Management, 14*(1), 32-38. doi: 10.1097/01.PCAMA.0000343145.81635.e3

Vincent, Karen G., & Coler, Marga S. (1990). A Unified Nursing Diagnostic Model. *Journal of Nursing Scholarship, 22*(2), 93-95. doi: 10.1111/j.1547-5069.1990.tb00182.x

Von Krogh, Gunn, Dale, Cecilie, & Nåden, Dagfinn. (2005). A Framework for Integrating NANDA, NIC, and NOC Terminology in Electronic Patient Records. *Journal of Nursing Scholarship, 37*(3), 275-281. doi: 10.1111/j.1547-5069.2005.00047.x

Welch, Verna L., Oster, Natalia Vukshich, Gazmararian, Julie A., Rask, Kimberly, Schild, Laura, Cutler, Charles, . . . Reardon, Michael. (2006). Impact of a Diabetes Disease

Management Program by Race and Ethnicity. *Disease Management & Health Outcomes, 14*(4), 245-252. doi: 10.2165/00115677-200614040-00007

Welton, J. M. (1999). *A comparison of patient hospital outcomes using medical diagnosis and nursing diagnosis.* (PhD Dissertation), University of North Carolina, Chapel Hill, North Carolina.

Welton, J. M., & Halloran, E. J. (1999). A comparison of nursing and medical diagnoses in predicting hospital outcomes. *Proc AMIA Symp*, 171-175. doi: D005355 [pii]

Welton, J. M., & Halloran, E. J. (2005). Nursing diagnoses, diagnosis-related group, and hospital outcomes. *J Nurs Adm, 35*(12), 541-549. doi: 00005110-200512000-00008 [pii]

Werley, H. H., & Lang, N. M. (Eds.). (1988). *Identifcation of the nursing minimum data set*. New York, NY. USA.: Springer Publishing Company.

Whitson, H.E., Hastings, S.N., Landerman, L.R., Fillenbaum, G.G., Cohen, H.J., & Johnson, K.S. (2011). Black–White Disparity in Disability: The Role of Medical Conditions. *Journal of the American Geriatrics Society, 59*(5), 844-850.

WHO. (1999). Definition, diagnosis and classification of diabetes mellitus and its complications. *Diagnosis and classification of diabetes mellitus, 99*(2).

WHO. (2001). International Classification of Functioning, Disability and Health (ICF). *Classifications.* Retrieved April 15, 2012, 2012, from http://www.who.int/classifications/icf/en/

Wong, E. (2008). Coining and defining novel nursing terminology. Part 1: critical incident nursing diagnosis. *International Journal of Nursing Terminologies & Classifications, 19*(3), 89-94.

Zielstorff, R. D., Tronni, C., Basque, J., Griffin, L. R., & Welebob, E. M. (1998). Mapping nursing diagnosis nomenclatures for coordinated care. *Image: Journal of Nursing Scholarship, 30*(4), 369-373.