TESTING A THEORETICAL MODEL FOR SEVERE MEDICATION ERRORS

by

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ABSTRACT

YUNKYUNG CHANG: Testing a Theoretical Model for Severe Medication Errors
(Under the direction of Barbara Mark)

There were three purposes of this dissertation. The first was to develop a theoretical framework for severe medication errors in acute care hospitals by integrating the human error model and the organizational learning model. The second purpose was to examine direct effects between nursing units’ error-producing conditions and severe medication errors. The third purpose was to test the moderating role of learning climate in the relationships between error-producing conditions and severe medication errors in acute care hospitals. The human error model guided the identification of error-producing conditions, which included work environment factors, team factors, person factors, patient factors and medication-related support services. The organizational learning model was used to introduce the concept of learning climate and hypothesize its moderating role between error-producing conditions and medication errors. It was hypothesized that when learning climate was positive, the relationship between error-producing conditions and medication errors would be weaker, and when learning climate was negative the relationship between error-producing conditions and medication errors would be stronger.

Using data derived from the Outcomes Research in Nursing Administration II study, which included 286 nursing units at 146 hospitals across the U.S., results supported a positive relationship between RN hours and medication error rates and an asymptotic relationship between nursing education levels and medication error rates such that nursing
units with 40-50% of BSN-prepared nurses had the lowest rate of severe medication errors. The study also found that nursing units with a positive learning climate had higher rates of severe medication errors than those with a negative learning climate, implying potential under-reporting and under-detection of medication errors.

These results suggest several policy and practice implications. From a policy perspective, 40-50% of BSN-prepared nurses at the nursing unit may be the optimal proportion to minimize severe medication errors. Further, development of a better measurement of medication errors, which is free from under-reporting or under-detecting problems, is warranted. From a practice perspective, nursing units should identify error-producing conditions present on their units that contribute to medication errors and make an effort to create a positive learning climate by emphasizing open communication, revealing and thinking about medication errors.
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Attention to patient safety has never been greater than in recent years, fueled mostly by the publication in 2000 of the Institute of Medicine’s (IOM) report “To Err is Human: Building a Safer Health System.” In particular, the eye-opening figures on medical errors reported in this book were alarming enough to prompt a number of legislative and regulatory initiatives designed to document errors and begin the search for solutions (Kohn, Corrigan, & Donaldson, 2000; Shojania, Duncan, McDonald, & Wachter, 2001). In terms of medication errors, for example, thousands of publications ensued since the IOM report in 2000: While only 1,018 papers were published on this topic during the six-year period from 1994 to 1999, more than 2,456 papers (more than a two-fold increase) were published during the comparable six-year period from 2000 to 2005 (Figure 1).

Although the focus of this dissertation is on hospital settings, evidence of medication error problems has been demonstrated in outpatient settings (e.g., Gandhi et al., 2000), nursing homes and small hospitals (e.g., Barker, Mikeal, Pearson, Illig, & Morse, 1982), and pediatric settings (e.g., West et al., 1994). Teaching hospitals are not exceptions (e.g., Lesar, Lomaestro, & Pohl, 1997), and the situation is similar in countries other than the United States (e.g., Dean, Allan, Barber, & Barker, 1995). For these reasons, the United States Congress provided the Agency for Health Research and Quality (AHRQ) $50 million for
Figure 1. Trends of the Number of Publications
safety research in 2002. Although it is less than half of 1% of the National Institutes of Health budget that funds research for technical and other important medical advances, it is a first step in patient safety becoming one of the most crucial issues in the U. S. healthcare system (Leape, Berwick, & Bates, 2002).

Prevalence

What most captures both the public and health care providers’ attention is probably the prevalence of medication errors. Medication errors are commonplace. According to the Harvard Medical Practice Study in 1991, adverse drug events (ADEs), defined as injuries resulting from medical interventions related to a drug, were the single most frequent cause of all types of adverse events, accounting for 19.4% of all disabling adverse events (Bates, Boyle, Vander Vliet, Schneider, & Leape, 1995; Brennan et al., 1991; Leape et al., 1991). Specifically, in 1995, Bates, Boyle et al. reported that 2 to 14% of patients experienced at least one medication error during hospitalization, which is equivalent to 0.3 errors per patient-day. Eleven years later, the Institute of Medicine (2006) reported that at least one medication error occurs every day for every hospitalized patient, implying that the error rate has not abated over the last decade. In the case of medication administration errors committed by nurses, one observational study found that one of every five doses administered by nurses was in error (Barker, Flynn, Pepper, Bates, & Mikeal, 2002). Consequently, continued research to better understand factors that contribute to the prevention of medication errors remains a priority.

While it is true that most of these errors do not result in injury, it is also true that as many as 1.5 million people annually experience harmful sequelae from a medication error (Institute of Medicine, 2006) and preventable medication errors account for 7,000 deaths per
year (Kohn et al., 2000). In fact, the increased risk of death associated with ADEs is almost
twofold compared to that not associated with ADEs, and researchers have estimated adverse
drug reactions (ADRs) to be responsible for more than 100,000 deaths nationwide each year
(Classen, Pestotnik, Evans, Lloyd, & Burke, 1997; Lazarou, Pomeranz, & Corey, 1998).
Furthermore, ADEs rank fifth, after congestive heart failure, breast cancer, hypertension, and
pneumonia, among the leading causes of preventable threats to the health of older Americans
(Fink, Siu, Brook, Park, & Solomon, 1987).

Cost

In addition to prevalence, the costs associated with medication errors are also of concern. Almost ten years ago, the Adverse Drug Events Prevention Study Group at Harvard and researchers at Latter Day Saint hospital reported that ADEs lengthened hospital stay by 1.91-2.2 days and that the estimated excess costs of hospitalization were $2,013-2,595 (Bates et al., 1997; Classen et al., 1997). Similarly, drug-related morbidity and mortality in the U.S. have been estimated at $76.6-$136 billion annually, a figure far greater than the cost of all diabetes care, $45.2 billion (Johnson & Bootman, 1995). These costs do not include the psychological costs (e.g., pain, suffering, grief, and loss) or the damage to an organization’s reputation that might influence recruiting and other efforts negatively. Further, they do not include malpractice claim costs or the costs of injury to the patient, which often account for the highest total expenditure of any type of procedure-related injury. Rothschild and colleagues (2002) estimated that the mean costs of defending malpractice claims due to ADEs were $376,500 for preventable inpatient ADEs and $64,700-74,200 for non-preventable inpatient and outpatient ADEs and preventable outpatient ADEs. In short, the total costs of medication errors are enormous (National Association of Insurance
Continued growth in the number of medication errors is expected due to an aging population, the complexity of the current health care system, and seemingly ironically, advanced technology. First, although some studies have not found a link between age and medication errors, in general, the elderly have more ADEs than other age groups because they consume the greatest quantity of medications and their exposure to a greater number of medications provides more opportunities for medication errors and drug-drug interactions. In fact, they have the highest rate of death from medication errors followed by patients between birth and two years of age (Phillips et al., 2001). Since the elderly population continues to increase in number, the number of medication errors and ADEs may also continue to increase (Leape et al., 1991).

In addition, modern hospitals and other health care settings are becoming more complex than ever and the complex systems provide multiple opportunities for errors. For example, a multi-stage process of ordering, transcribing, verifying, and transmitting medication orders from order book to pharmacy offers several opportunities for error. Moreover, complex, tightly-coupled systems have increasingly become so opaque to the people who manage, maintain, and operate them that these people may not know what is happening or may not understand what the system can do (Perrow, 1984; Reason, 1990). As such, the causes of failures in complex systems are sometimes not apparent to frontline workers, who may therefore be unable to take corrective action.

Finally, technology, originally designed to reduce human errors, may actually increase errors. In the case of the computerized physician order entry systems (CPOE), while most
studies have found support for the effectiveness of CPOE in error reduction, others reported that implementation of CPOE often facilitated medication error risks and high rates of ADEs (Nebeker, Hoffman, Weir, Bennett, & Hurdle, 2005). For example, CPOE may provide the dosages based on the pharmacy’s warehousing and purchasing decisions, not clinical guidelines, and house staff often rely on CPOE displays for normal dosage ranges (Koppel et al., 2005). In a different way, while technology renders diseases that previously were not able to be diagnosed or cured, curable now, new procedures and approaches may create the possibility of errors. Similarly, technological advances have increased the number and potency of drug products being developed and used. Therefore, the chance for medication errors has increased.

Actually, medication errors are not a new problem. Literature on this topic has been published for more than 40 years, and the current health care system is safer than ever. In particular, well-publicized reports about medication errors, mostly published since 1995, and the IOM reports have increased the public’s understanding about the limitations of medical science as well as health care professionals’ awareness of the significance of the problem. Such a new insight into errors may have contributed to the shattering of a “perfection myth,” in which medicine was traditionally expected to be “perfect” both by the public and medical professionals. From the public side, for example, medication errors are unacceptable because they are an “error” and potentially preventable. While medical professionals are taught to “do no harm” as the first Hippocratic Oath, what people expect from health care professionals in reality is to “do good,” far from doing harm and making errors. Meanwhile, the inclination toward perfection has made health care providers unable to see, or sometimes not to want to see, their flaws (Berwick, 2003). As a result, getting rid of the “bad apples” has been
considered as the quick and correct approach to error management. Now, with a growing understanding of human fallibility and the limitations of medical science, a need for new approaches to error management has arisen.

Definition of Medication Errors

The three terms most frequently used in the literature to denote drug related mishaps are medication errors, adverse drug reactions (ADRs), and adverse drug events (ADEs). The relationship among the three terms is depicted in Figure 2.

Medication error is the broadest concept among the three. The National Coordinating Council for Medication Error Reporting and Prevention (NCC MERP, 1998) defines a medication error as follows:

A medication error is any preventable event that may cause or lead to inappropriate medication use or patient harm while the medication is in the control of the healthcare professional, patient, or consumer. Such events may be related to professional practice, healthcare products, procedures, and systems, including prescribing; order communication; product labeling, packaging, and nomenclature; compounding; dispensing; administration; education; monitoring; and use.

Similarly, Bates, Boyle et al. (1995) defined medication error as an error in the process of ordering or delivering a medication, regardless of whether an injury occurred or the potential for injury was present. Although this definition encompasses all stages of medication errors occurring from prescribing to administration, some researchers do not distinguish these stages and use the term medication error when they actually mean medication administration error (e.g., Barker, Flynn, Pepper et al., 2002). In addition to these
Figure 2. Relationship between ADEs, ADRs, and medication errors
definitions, some have further classified medication errors by two types: errors of commission and errors of omission, each of which can be subdivided into intentional and unintentional errors. For example, while errors of omission involve failing to give the prescribed medication, errors of commission involve wrong drug, wrong patient, wrong medication, wrong dose, or wrong route, etc (Wolf, 1989).

Meanwhile, the World Health Organization defines an ADR as “noxious and unintended, and which occurs at doses used in man for prophylaxis, diagnosis, therapy, or modification of physiologic function” (Classen, Pestotnik, Evans, & Burke, 1991). On the other hand, the ADE Prevention Study Group defines an ADE as an injury resulting from medical intervention related to drugs (Bates, Cullen et al., 1995). The difference between ADRs and ADEs is that while ADRs include only the appropriate use of drugs (excluding therapeutic failures, poisonings, and intentional overdoses), ADEs embrace both appropriate and inappropriate use of drugs. In other words, ADRs are non-preventable (Morimoto, Gandhi, Seger, Hsieh, & Bates, 2004). While ADEs and medication errors overlap to a very small extent, ADRs and medication errors are mutually exclusive because all ADRs have a detrimental effect resulting from properly used medications. Although ADEs and ADRs have different meanings, researchers have used them interchangeably (e.g., Classen et al., 1991; 2003).

In addition to these three terms, the literature reports studies of events without harm and near misses. An event without harm is one in which an act of omission or commission may have had the potential for harm but, through luck or a robust physiology, had no detrimental effect on the patient. A near miss is an act of commission or omission that could have harmed the patient but was prevented from being completed through a planned or
unplanned recovery. These two terms provide a rich source of useful information. The importance of including events without harm and near misses within an error classification scheme derives from their similarity to, and greater frequency than, events that cause harm. Specifically, near-miss events are conducive to learning about why something did not happen and providing a means to study human recovery. In addition, they are conducive to knowing what actions were taken to prevent harm or to prevent the event from escalating to the point of harm (Kaplan & Fastman, 2003).

Research Problems

As shown in Figure 1, the literature on medication errors is abundant. Extensive discussions regarding the organizational variables that might have affected patient safety have existed, and researchers and practitioners have advocated the systems approach as the ideal way of error prevention. Yet, as pointed out by Hoff, Jameson, Hannan, and Flink (2004), despite numerous publications, only a handful of articles are empirical and use medication errors as a dependent variable. Specifically, most studies are descriptive case studies (e.g., Benjamin, 2003; Joiner, 1994; Meisel, Sershon, & White, 1998), non-experimental pre-post comparison studies (e.g., Cordero, Kuehn, Kumar, & Mekhjian, 2004; Kuperman, Teich, Gandhi, Bates et al., 2001), or retrospective chart review studies (e.g., Bates, Boyle et al., 1995; Bates, Leape, & Petrycki, 1993; Jha et al., 1998), frequently investigated in a single organization. Few have investigated the interrelationships of different organizational variables or tested a multilevel model of organizational factors on the prevention and management of medication errors (see, e.g., Gold et al., 1992; Roseman & Booker, 1995; Taunton, Kleinbeck, Stafford, Woods, & Bott, 1994). Consequently, despite the current emphasis on organizational variables such as teams and leadership in reducing
errors and enhancing patient safety, little empirical evidence has tested the effectiveness of such variables. Above all, what is most important is the lack of studies employing a theoretical approach (e.g., Anderson & Ellis, 1999; Ansari, Collopy, & Brosi, 1995; Gilliand, Stanislav, Constantin, & Schwinghammer, 1992; Kuperman, Teich, Gandhi, & Bates, 2001). Without a theoretical framework, researchers are unable to make predictions a priori or provide explanations of the effects of selected organizational variables on medication errors. In what follows, therefore, I will describe several theoretical models and discuss which framework will best serve the understanding of medication errors.

*Theoretical Models on Safety*

The health care literature reports several schools of thought in the relationship between organizational safety and medical errors. Although all are concerned with human failures in organization, they originated from different disciplines and their target organizational failure is often distinct. For example, normal accident theory and high-reliability organization theory have been good sources of explaining why errors occur and suggesting what safe organizations should be like (Perrow, 1984; Roberts, 1990). These theories are particularly interested in catastrophic disasters occurring in high-hazard industries such as nuclear power generation plants, chemical processing plants, and commercial aircraft companies. Because of such exclusive interest in catastrophic disasters, however, applications of these theories to the patient safety literature have been often limited to rare sentinel events, which usually result in death or deadly results.

There is another research camp on safety issues in the organization psychology literature. Unlike normal accident theory or high-reliability organization theory, which originated from high-hazard industries, this research stream is more interested in small
safety-related problems than in errors and has a specific focus on violations, defined as deliberate deviations from acceptable and necessary practices (Hofmann & Stetzer, 1996; Zohar, 2000). Despite its concentration on organizational safety, however, this stream of research has not been adopted in the health care literature. This may be due to health care researchers’ assumption that, rather than violating rules or procedures they are supposed to follow, individuals try to do the right thing but, for various reasons, simply do not do it successfully. In other words, it has been thought that patient safety issues are more likely to be the result of errors, rather than violations.

Independently but not mutually exclusively, an error-oriented research effort has been developed along with the safety-oriented research stream. Contrary to the safety-oriented literature, the error-oriented research camp is interested in unintended but failed actions due to a mistakenly faulty plan or a miscue in the execution of the correct plan (Heimbeck, Frese, Sonnentag, & Keith, 2003; Van Dyck, Frese, Baer, & Sonnentag, 2005). This approach seems more accepted in the medication error research than the safety-oriented, violation-focused approach and many medication errors are actually viewed as “errors” because health care providers are not likely to intentionally try to harm the patient. Still, some medication errors do result from violating rules or standard protocols (i.e., violating the rule that requires double-checking before administrating a high-alert drug) and a thorough understanding of medication errors should need consideration of both safety-oriented and error-oriented approaches. However, due to the complexity of investigating the role of both safety climate and error climate, the current study focuses only on the error-oriented approach, the one more suitable to understanding why medication errors occur and how they can be reduced.

Although it is not always easy to distinguish one from the other, there are two foci
within the error-oriented approach. One focuses in the prevention of errors, the other is in the management of errors after they have occurred. Along with the IOM report’s (Kohn et al., 2000) emphasis on finding and correcting system failures, health care researchers have preferred the prevention-oriented approach. Specifically, Reason’s human error model (1990; 2000) that stresses the prevention of errors by using a systems-based approach has dominated the discussion of patient safety and particularly of medication errors. In contrast, patient safety research has paid little attention to the management-oriented approach, although it has been actively developed in the organizational-psychology literature including the organizational learning model. In what follows, typical models of prevention-oriented and management-oriented approaches will be briefly introduced, and why none of them is sufficient and how they complement to each other will be discussed.

*Human Error Model*

The human error model is the most commonly used prevention-oriented framework. An underlying assumption of the human error model is that errors can be prevented by creating error-proof working environments. This model acknowledges that, although individuals make errors, characteristics of the systems within which they work can make errors more likely and also more difficult to detect and correct (Leape et al., 1995). Specifically, the systems-based approach suggests that errors should be managed, and in turn patient safety ensured, by shifting the focus of interventions from the individual to the system. Rather than blaming individuals who made errors, therefore, this model identifies human factors and system failures as the causes of errors. Further, the human error model has also facilitated the implementation of error prevention strategies, which use structural and technological factors like computerized physician order entry systems.
Despite broad applications of the human error model to medication error research, previous studies have not addressed several important issues. First, as noted previously, the human error model pays relatively less attention to post-hoc error management than to error prevention. Errors occur even in the best organizations employing the most advanced error-proof technological innovations. Hence, strategies for coping with errors are also needed. Second, although Reason’s later work (1998; 2000) acknowledges that effective error management depends crucially on establishing a reporting culture and, in turn, trust as key elements of a reporting culture, he did not show how trust and a reporting culture would be incorporated within his pre-existing human error model. Finally, despite abundant discussion about the human error model, few studies have attempted to test this model or examine causal relationships between system factors and medication errors. As a result, not enough evidence has been accumulated to provide a solid explanation of which human or system factors will contribute most to error prevention. Rather, essentially what this model has contributed is to identify latent system factors retrospectively that might have caused an error.

Organizational Learning Model

The error management approach assumes that human errors can never be completely prevented; thus it is necessary to ask the question of what can be done after an error has occurred (Van Dyck et al., 2005). The organizational learning model can be considered as a prototype of the error management approach in the sense that its premise is that organizational learning is a way to contribute to error management. Argyris and Schön (1978), gurus of the organizational learning model, argue that learning is detection and correction of error. Specifically, they distinguish single-loop learning, which is detecting error without questioning underlying policies, from double-loop learning, which involves
questioning and changing governing conditions. Problem-solving strategies resulting from single-loop learning typically create new problems in the long run because they allow work to continue but do nothing to prevent a similar problem from occurring. Such approaches to the problem prevent an organization from learning because short-term success reduces both an organization’s ability to take corrective action to detect and its motivation to remove underlying causes of recurring problems (Tucker, Edmondson, & Spear, 2002). In contrast, second-order problem solving employing double-loop learning investigates and seeks to change underlying causes. The organizational learning model suggests that, if an organization is to benefit consistently from learning, the critical issue is not how to solve a particular problem but how to create conditions that facilitate people’s ability to detect and correct problems (Lipshitz, 2000).

While applications of the organizational learning model reported in health care studies have been limited, several distinct features of this model may complement the human error model. First, while the human error model tends to focus on accidents with consequential results, Edmondson (2004) suggests that an important part of learning from failure in complex organizations such as hospitals, is attention to small, everyday process failure rather than only to sentinel events and formal investigations. She further argues that an organization’s ability to learn from failures is measured by how it deals with both large and small failures rather than just by how it handles major, highly visible events. Second, the organizational learning model proposes that the quality of organizational learning primarily depends on the quality of interaction between members within an organization (Lipshitz & Popper, 2000). For example, Tucker et al. (2002) found that organizational learning was limited by a lack of communication about problems, and this finding suggests that for
organizational learning to be successful, familiarity among group members is critical because it facilitates effective interaction and coordination (Edmondson, 1999). Third, with regard to effective interpersonal interactions, the organizational learning model argues that leaders play a crucial role in shaping a safety climate. For example, in certain groups, leaders establish a climate of openness that facilitates discussion of error, which is likely to have an important influence on detected error rates (Edmondson, 1996). Similarly, leaders have an essential role in providing support for members who speak up and attempt to improve their work systems and in valuing them as motivated employees (Tucker & Edmondson, 2003).

Summary and Study Purposes

As reviewed previously, both models introduced in this section may have the benefit of accounting for different types of errors and management strategies. For example, the human error model can be particularly conducive to the prevention of errors by correcting for poor work conditions or faulty system design because it is primarily interested in identifying system factors that may result in errors. In contrast, the organizational learning model has the benefit of allowing people to learn from errors and eventually to prevent the same error from reoccurring by creating a learning climate in which people are not afraid of sharing information about their errors.

Second, the organizational learning model may supplement the human error model by suggesting how a learning climate should play a role in error management. According to the organizational learning model, by creating a climate that values safety over productivity or efficiency, people do not have to resort to finding an unsafe “short-cut” to get work done. Although the human error model implies the importance of culture, suggesting that a safety climate can be strengthened by trust and a just climate as necessary conditions for a safety
culture, it does not fully explore the role of safety culture within its theoretical framework. As a result, little is known about how a safety culture plays a role in various organizational conditions.

Therefore, the purpose of the dissertation is to develop and test a theoretical model integrating the human error model and the organizational learning model. In doing so, it will seek to examine the conditions under which the effectiveness of strategies for error prevention and management can be maximized. Specifically, the current study only focuses on severe medication errors to minimize potential under-reporting problems that are inherent in most medication error studies, because severe medication errors may be less likely to go unnoticed and unreported. Severe medication errors were defined in this study as those resulting in increased nursing observation, increased technical monitoring, laboratory testing, radiographic testing, medical intervention, or transfer of the patient to another unit. The specific questions to be answered are as follows:

1. What nursing unit characteristics are associated with a higher likelihood of severe medication errors?
2. How does a learning climate moderate the relationship between error producing conditions and severe medication errors?

Dissertation Organization

The dissertation is organized as follows. In Chapter 2, a literature review on medication errors focuses on the three most frequently investigated topics (i.e., classification, etiology, and management strategies). In addition, the literature on the human error model and the organizational learning model will be thoroughly reviewed from a position of error prevention and management. In Chapter 3, based on the premises of both the human error
model and the organizational learning model, a new integrated theoretical framework will be suggested and hypotheses will be proposed. Chapter 4 and 5 respectively will describe the methodology and the results of the study. Finally, Chapter 6 will present a discussion and the conclusion drawn from the results of the study.
Chapter 2

REVIEW OF THE LITERATURE

This chapter presents a review of the literature on medication errors, the human error model, and the organizational learning model. The medication error section is organized into three sub-sections according to the topics that are studied most commonly and considered most important in the medication error literature: 1) the classification of medication errors, 2) the etiology of medication errors, and 3) prevention and management strategies. Complexity and the wide scope of medication errors have led early researchers to concentrate on the issue of error classification, such as definition, prevalence, preventability, potentiality, stages, or types (e.g., Bates, Cullen et al., 1995). However, the different methods each study employs (i.e., settings, error types and definitions, unit of measurement, and sources of data) make it difficult to compare results across studies. In the first sub-section, therefore, several classical studies are selected and their study settings, type of incidents of interest, unit of measurement, and the source of data will be reviewed and compared. Through the review of contributing factors to medication errors, the following sub-section on etiology seeks to answer the question of why and under what circumstances medication errors occur. This sub-section is followed by a discussion of strategies that are most commonly used in hospital settings as a way to prevent or manage medication errors.

The second section, on the human error model, begins with documentation of two basic premises (human fallibility and the systems approach) and several key concepts from the original model Reason (1990) proposed. The first part is followed by the discussion on the
evolution of the human error model that Reason and other researchers have suggested. This section closes with a discussion on limitations particularly focusing on the lack of research on the role of safety culture.

The final section of this chapter begins with the introduction of the organizational learning model. Instead of aiming to grasp the whole picture of the model, the literature review will be made around several key constructs that health care researchers have found most useful. In the last part of this section, I will discuss the organizational learning model as an error management approach.

Medication Errors

*Classification of Medication Errors*

The two most significant motivators that have fueled medical error research for the last 15 years are the Harvard Medical Practice Study (Brennan et al., 1991; Leape et al., 1991) and the Utah and Colorado Medical Practice Study (Classen et al., 1997; Thomas, Studdert et al., 2000). One common result from these two distinct studies is the recognition that medication errors are the most prevalent type of medical error in hospitals. Such a result has prompted a series of medication error studies, particularly those performed on adult patients in acute care hospitals. Specifically, the most frequent type of early research in this field was a series of descriptive studies assessing the incidence and classification of medication errors (e.g., Barker, Flynn, Pepper et al., 2002; Bates et al., 1993; Classen et al., 1997; Kopp, Erstad, Allen, Theodorou, & Priestley, 2006; Lesar, Lomaestro et al., 1997). These studies have concluded that although most medication errors do not result in injury, they occur more frequently than expected. Yet there are large discrepancies among the studies in the way in which medication errors were defined, how they were reported, and what method of
investigation was used, and such methodological variation makes it difficult to compare study results and draw a single conclusion on what type of errors occur in what frequency. Therefore, the purpose of this sub-section is to review several classic studies on medication errors performed in acute care settings and compare their study settings, type of incidents, unit of measurement, and sources of data.

The method guiding this literature review is similar to that used by Hoff, Jameson, Hanna, and Flink (2004) and Kellogg and Havens (2003). Questions explored through this review concern 1) what kinds of settings are studied, 2) what terms are used to denote medication errors and how they are defined, 3) what unit of measurement is used, and 4) what sources of data are used to study medication errors. In the selection of the articles, a general content analytic approach was used in perusing both abstracts and articles for pertinent information. Only data-based empirical studies published from 1990 to 2006 were selected by electronically searching the Medline database. Additionally, a manual search of the reference lists of the articles selected in the review was conducted. For the purpose of the review, studies included should at least identify the prevalence, unit of measurement, and the source of data. Additional criteria for the review are that the studies 1) focused on medication errors, adverse drug events, or adverse drug reactions, 2) were conducted on adult population in acute care hospitals, 3) were published in a refereed medical, health services, or nursing journal, and 4) were written in English. Studies performed in a pediatric, obstetric, geriatric, or psychiatric setting were excluded. A total of 17 studies were chosen according to these criteria. Table 1 summarizes the distinguishing features of those selected articles.
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<td>Barker, Flynn, Pepper, Bates, and Mikeal (2002)</td>
<td>Medication administration errors</td>
<td>19% of the doses are in error; 7% of the errors are potential ADEs</td>
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<td>Bates, Cullen et al. (1995)</td>
<td>ADEs</td>
<td>6.5 preventable ADEs/100 admission; 5.5 potential ADEs/100 admission</td>
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<td>Bates, Leape, and Petrycki (1993)</td>
<td>ADEs</td>
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<td>Solicited reporting by nurses and pharmacists is inferior to chart review for identifying ADEs, but was effective for identifying potential ADEs</td>
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<td>Classen et al. (1991)</td>
<td>ADEs (ADRks)</td>
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<td>Medication errors (all stages)</td>
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<td>Administering errors are most common; one fourth of the errors are from wrong dose</td>
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<td>Jha et al. (1998)</td>
<td>ADEs</td>
<td>21 ADEs/1,000 patient days</td>
<td>Computer: “rules,” chart review, voluntary reporting</td>
<td>Chart review identified ADEs the most frequently; ADEs identified by computer monitor were more likely to be “severe” than those identified by chart review</td>
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<td>Lesar et al. (2002)</td>
<td>Prescribing errors involving medication dosage form</td>
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<td>Nebeker et al. (2005)</td>
<td>ADEs (ADRks)</td>
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<td>CPOE</td>
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<td>Rolland (2004)</td>
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<td>Rozich et al. (2003)</td>
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<td>Dean et al. (1995)</td>
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<td>IV administration errors</td>
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* N.S: not specified; All: all error stages included; A: administration; P: prescription; PACU: Peri-anesthesia care unit
Study Setting

Although the selected studies were all performed in acute care hospitals, some varied in terms of unit types. When the primary purpose of the study was to investigate the overall incidence of medication errors in a hospital, data were usually collected from all available units regardless of their types. However, when the study was performed in a particular type of unit, intensive care units (ICUs) were the most popular settings, used in seven of the studies. This may be because that ICUs were expected to have more medication errors than other units because they administer more medications due to the gravity of patient conditions, more high-risk medications, and a greater variety in the types of medications, so the chance of identifying errors in ICUs was greater (Bates, Cullen et al., 1995).

Although the absolute number of medication error events was higher in ICUs than non-ICUs, such an association did not always hold true for adjusted error rates that took account of the number of medications prescribed. For example, Bates, Leape, and Petrycki (1993) found that ADE rates were significantly higher in coronary intensive care units than in medical or surgical units even after controlling for the number of drugs ordered. Bates, Cullen, and colleagues (1995) substantiated this result two years later, showing that ADE rates were highest in medical ICUs among 11 ICUs and non-ICUs after controlling for the number of drugs ordered. In a study performed by those authors two years later, however, Cullen et al. (1997) found no difference in ADE rates between ICUs and non-ICUs after controlling for the number of drugs ordered. These results imply that, although no definite conclusions were made about the influence of unit type on medication errors, adjusting factors that may contribute to the occurrence of ADEs (i.e., number of medications ordered or administered) is important when performing a study investigating ADE rates among
different unit types, and possibly different hospital types.

Compared to the number of studies on unit types, few studies on inter-hospital comparisons have been performed and only one study compared error rates among a sample of hospitals. Barker, Flynn, Pepper, Bates, and Mikeal (2002) examined 36 health care facilities including both Joint Commission on Accreditation of Healthcare Organizations (JCAHO) accredited and non-accredited hospitals and skilled nursing facilities and found no difference among these facilities. Similarly, although some studies examined error rates across countries, most of them used very rudimentary methodologies, for example, sampling only one hospital from each country (e.g., Cousins, Sabatier, Begue, Schmitt, & Hoppe-Tichy, 2005; Dean et al., 1995). Inter-country studies especially should take into account of the possible effect of different health care systems.

Incidents

Overall, ADEs, ADRs, and medication errors are the most frequently investigated types of incidents. As noted in the first chapter, studies use the terms ADEs and ADRs interchangeably, even when they denote different types of incidents. Specifically, several studies used the definition of an ADR yet designated it an ADE (e.g., Classen et al., 1991; Nebeker et al., 2005; Rozich et al., 2003). Such interchangeable use of terms may cause one to think that results from the studies employing different types of incidence are comparable, when they actually are not because all ADRs are a detrimental effect resulting from properly used medications and thus are not preventable whereas ADEs are sum of both medication errors and ADRs.

While ADEs and ADRs are consequence-based terms, the studies investigating them usually included incidents from all medication stages from prescription to administration, and
some studies focused on a specific stage of medication errors. Unlike the studies on ADEs and ADRs that involved retrospective methods of data collection, with some exceptions (e.g., Hicks, Becker, Krenzischeck, & Beyea, 2004; Rolland, 2004), these stage-specific studies commonly used prospective data collection methods such as observation (e.g., Barker, Flynn, Pepper et al., 2002; Cousins et al., 2005; Tissot et al., 1999; van den Bemt et al., 2002) or pharmacists’ review (Lesar, 2002). Studies focusing on administration errors were most common, possibly because administration of drugs is a critical step, the chance of correcting errors at this stage is limited and errors at this level may directly harm the patient (van den Bemt et al., 2002).

**Unit of Measurement**

The measurement of medication errors varies also across studies. No single measure predominated and sometimes such inconsistent usage caused researchers to report several different measures of medication errors, allowing the comparison of results across studies. The unit of measurement has been used to standardize the incidence of medication errors and compare the incidence in a “fair” way across studies by taking into account the volume of patient admission/discharge, number of drugs administered, or the length of stay, which all are expected to be associated with the number of medication errors.

Although the number of medications prescribed or administered would be most closely associated with medication error rates and thus most accurately reflect standardized error rates, few hospitals have a system to track down such data. In fact, only small scale studies such as in a single nursing unit (e.g., Kopp et al., 2006) or in a single hospital (e.g., Lesar, 2002) used the number of medications ordered as their measurement unit. For these reasons, when conducted in several different settings, studies often used patient days, such as the
incidence per 1,000 patient days, because this measure is easy to calculate and also
influences the number of medications used (e.g., Cullen et al., 1997; Jha et al., 1998; Lesar,
2002; Nebeker et al., 2005; Rothschild et al., 2005). Examples of other measures are the
percentage of incidents of admitted patients (e.g., Classen et al., 1991); number of incidents
per 100 admissions (e.g., Bates, Cullen et al., 1995; Lesar, 2002; Nebeker et al., 2005); and
percentage of medication errors from all observed events (e.g., Hicks, Becker et al., 2004;
Rolland, 2004; Tissot et al., 1999; van den Bemt et al., 2002).

Sources of Data

The studies selected used four sources of data -- computer programs, chart reviews,
observation, and reporting systems -- and depending on the data source the incidence of
medication errors varies a great deal. Because each source of data has advantages to a
particular type of research study, no single method can be said to be better than the others.
This section describes each data source and reviews the potential strengths and weaknesses
of each.

Computer Programs

Three studies used electronic medical records or computerized surveillance programs,
and the method each study employed differed slightly from the others. For example, Classen
et al. (1991) used computer-aided algorithms using various “signals,” created for automated
detection of candidate ADRs. Signals included discontinuation of medications, decreases in
dosages, ordering of known antidotes, ordering of specific laboratory tests, and specific
laboratory test abnormalities. Revising Classen et al.’s signals, Jha et al. (1998) developed
ADE detection “rules,” the combination of simple medical conditions and medication orders
associated with changes in laboratory values over time. Another type of computer-aided
method was the use of multiple computerized medication ordering and administration systems. For example, Nebeker, Hoffman, Weir, Bennett, and Hurdle (2005) performed a prospective daily review of electronic medical records using CPOE systems and bar code-controlled medication deliveries.

While computer-aided methods can markedly increase detection of ADEs or ADRs compared to traditional voluntary reporting systems, they have several weaknesses. First, computer programs have the problem of a high number of false-positive values. Often, therefore, as Classen and colleagues (1991) did, a clinical pharmacist is needed to review the potential ADEs detected by the computer programs and determine causality by reviewing medical charts, contacting physicians and nurses, and interviewing the patient. The false-positive value problem can be also resolved to some extent by making signals or rules more sensitive to practice guidelines, but because each hospital has different practice guidelines, it is difficult to cross-compare the results from different hospitals. Second, because of the lack of a clear “gold standard” for comparison, little is known about the validity of the number of events detected (Classen et al.). In fact, Nebeker et al. (2005) argued that most errors detected by their computer program were actually ADEs that would have been caught had more sophisticated methods been used previously, implying that the validity of the errors caught before the computer program was implemented is questionable. Further, and most importantly, due to its high cost, the utility of computer-aided methods is still limited and only a small number of hospitals actually use computer programs to detect medication incidents.

*Chart Review*

Chart review usually involves multiple steps (i.e., trained nurses’ preliminary
reviewing and physicians’ confirming), and depending on thoroughness, it can use screening of medication orders and certain laboratory values to identify possible ADEs (e.g., Bates, Cullen et al., 1995; Cullen et al., 1997; Jha et al., 1998). Compared to computer programs, chart review methods have fewer false-positive values and show increased sensitivity (Classen et al.). Further, intensive chart review is more effective than computer programs in finding ADEs. For example, Jha et al. found more ADEs using chart review (65%) than the computer monitoring they created (45%)

In spite of increased sensitivity and effectiveness, however, chart review is extremely time- and labor-intensive. Jha and colleagues (1998) reported that, for example, while the computer program required 11 person-hours per week, chart review required 55 person-hours per week, suggesting that chart review is not suitable when the number of patients to review is large. Further, because more than two reviewers are often involved, checking the degree of consensus and confidence among the reviewers is critical in chart review. For these reasons, chart review has been used mostly for studies performed in a single hospital.

Observation

Observational methods have been used specifically when medication administration errors are the target incidents (e.g., Barker, Flynn, Pepper et al., 2002; Cousins et al., 2005; Tissot et al., 1999; van den Bemt et al., 2002). These methods require trained observers to record what the subject (i.e., a nurse) did, including all details about the medication, and to witness the administration to the patient within limited time.

Detecting medication errors using direct observation has several advantages compared to either chart review or incident reporting. First, observational methods are more efficient and accurate than chart review and incident reports. For example, Flynn, Barker, Pepper,
Bates, and Mikeal (2002) reported that direct observation was more successful in identifying erroneous doses and produced more accurate results in terms of identifying the actual number of medication errors than chart review or incident reporting systems. Similar results are also found in Kopp, Erstad, Allen, Theodorou, and Priestley’s study (2006). In a direct observation study performed in ICU settings, these authors found a higher incidence of ADEs compared with that reported by the ADE Prevention Study, which was also performed in ICUs but used chart review methods (Cullen et al., 1997). Further, observation methods are particularly advantageous when identifying the causes of medication errors (Barker, Flynn, & Pepper, 2002). For example, observers can collect data on factors that may contribute to errors, such as poor work environment (i.e., interruptions, distractions, insufficient light, and noise) and the unavailability of drugs or equipment.

Despite such well-known advantages of direct observation, the practicality of this method seems limited because observational methods are only suitable for small-scale studies due to their high cost. Further, there are concerns about the validity of observational data in relation to the potential effect of the research on the individuals observed (Dean & Barber, 2001). For example, people may be more cautious about their behavior than at other times when they know they are being studied (i.e., Hawthorne effect), and their caution may result in fewer events being observed. However, Dean and Barber argue that disguised-observation techniques in which nurses are aware of the observation but unaware of its true purpose may reduce such problems.

*Incident Reporting System*

Incident reporting systems are by far the most common method of collecting medication error data. Despite their wide usage, researchers have cautioned that reporting
bias (e.g., a gap between the number of actual and reported errors) is an important concern when using incident reports or voluntary reporting systems only. For example, in a study investigating the utility of a computerized ADR monitor they developed, Classen et al. (1991) reported that nine ADRs were reported through the traditional voluntary reporting system while the computer monitoring detected 641 ADRs in the same period. Similarly, Jha et al. (1998) found 26 times more errors by either computer rules or chart review than by voluntary report. In fact, except for Rolland’s study (2004), none of the studies depended only on reporting systems in collecting data. Despite such low sensitivity, however, Jha et al. found that voluntary reporting systems were much more effective at detecting potential ADEs than either computer programs or chart review, suggesting that, if implemented well, voluntary reporting systems will be the most useful in identifying near misses.

Summary

Overall, the most frequently occurring problem regarding classification of medication errors is that there is no single agreed-upon measure for classification. Studies use several terms for medication errors interchangeably, different units of prevalence, and various sources of data. Among all, however, collecting data from various sources is most problematic because both prevalence and the type of errors caught vary considerably depending on the sources of data. In fact, Jha et al. (1998) found surprisingly little overlap among the ADEs identified by chart review and computer programs, suggesting that neither is sufficient alone. In addition, they reported that the characteristics of ADEs detected by computer programs were different from those detected by chart review. To illustrate, chart review was more effective than the computer program at detecting events manifested primarily by symptoms. Conversely, the computer program was more reliable in identifying
events associated with changes in laboratory values, such as renal failure and hypoglycemia.

Unlike ADEs that can be easily identified by chart reviews or computer programs, potential medication errors or errors with minimal harm may not be detected with such methods because these errors usually do not show evident symptoms that chart reviews or computer programs can detect. While reporting systems do better at identifying such errors than chart review or computer programs (e.g., Jha et al., 1998), they are not sufficient either because potential errors can go unnoticed, and thus they are less likely to be reported. In a study examining the opinions of hospital leaders about state reporting systems, for example, Weissman et al. (2005) found that while hospital leaders generally favored the disclosure of patient safety incidents to the involved patients, fewer would disclose incidents involving moderate or minor injury to state reporting systems. In fact, potential medication errors or errors with minimal harm can be best identified by direct observation, but this method is only possible in a small scale study because of the reasons discussed earlier. As such, there is no single best source of data collection, and each method serves a different purpose. Also, while researchers can choose the method of data collection depending on their research interest (i.e., ADEs vs. potential ADEs), they need to be cautious when comparing study results employing different sources of data.

Etiology of Medication Errors

One way to categorize the causes of medication errors is to sort them into following error-producing conditions as Dean, Schachter, Vincent, and Barber suggested (2002): work environment factors, team factors, person factors, and patient-specific factors. Although Dean et al. also noted task factors, because of a dearth of literature, the current discussion excludes them.
**Work Environment**

**Distractions**

Nurses believe that distractions and interruptions during medication administration are the primary causes that increase the risk of medication errors, followed by inadequate staffing and high nurse-patient ratios (Cohen, Robinson, & Mandrack, 2003). Empirical evidence has shown that, together with heavy workload, distractions accounted for over 60% of contributing factors to medication errors in post-anesthesia care units (Hicks, Becker et al., 2004). Similarly, distractions resulting from heavy workload when nurses are carrying out several tasks at the same time have also been reported as a frequent cause of intravenous (IV) errors (Taxis & Barber, 2003).

**Workload**

Along with distractions, heavy workload is more likely to lead to errors. Nurses’ medication errors increase with the number of patient days per month, and nurses who work a variety of shifts are twice as likely to make medication errors (Gold et al., 1992; Roseman & Booker, 1995). Similarly, a survey study performed by Seki and Yamazaki (2006) found that when nursing care was delayed longer because of workload, IV errors occurred at a significantly higher frequency. Workload has been reported as the main cause of prescribing errors as well. Using multivariate regression, for example, Kralewski et al. (2005) found that seeing more patients per clinic hour was strongly associated with more prescribing errors among physicians in a medical group practice. Similarly, Landrigan and colleagues (2004) reported that interns made substantially more serious medication errors when they worked frequent shifts of 24 hours or more than when they worked shorter shifts.

Yet, some studies have not found significant relationships between workload and
medication errors. For example, Taunton, Kleinbeck, Stafford, Woods, and Bott (1994) explored the possible relationships between medication errors and workload, measured as required nursing hours based on patient need divided by actual available nursing hours, and found no association between them. They argued that such contrasting results occurred because, as Leape (1994a) argued, errors can also occur when workload is too low, which suggests non-linear relationships between workload and medication errors.

**Staffing**

Insufficient or inadequate staffing has been shown to be related to medication errors. Nursing researchers have often found an inverse relationship between nursing staffing and medication errors (e.g., Whitman, Kim, Davidson, Wolf, & Wang, 2002). For example, McGillis Hall, Doran, and Pink (2004) reported that a higher proportion of RNs in the staff mix was associated with lower rates of medication errors on medical and surgical units. Similarly, Blegen and Vaughn (1998) argued that the relationship between the proportion of RNs in the staff mix and medication administration errors was non-linear, as the proportion of RNs on a unit increased from 50% to 85% the rate of errors declined, but as the RN proportion increased from 85% to 100% the rate of errors increased. Studies using RN hours, measured as hours of care delivered by RNs, as a staffing variable, have yielded similar results. In a study of failure to rescue, Seago, Williamson, and Atwood (2006) reported that failure to rescue from medication errors increased as the non-RN hours of care per patient day increased. Blegen, Goode, and Reed (1998) also found an inverse relationship between RN hours and rates of medication errors, after controlling for patient acuity.

The addition of certain types of personnel, however, has been shown to reduce medication errors. For example, in an observational study performed in ICUs, van den Bemt
et al. (2002) found that administration errors were less likely to occur when full-time specialized intensive care physicians were available on the unit. Similarly, Kralewski, Dowd, Heaton, and Kaissi (2005) reported that having a case manager program was strongly related to fewer prescribing errors in medical group practices. Most of all, clinical pharmacist services have shown rather consistent effects on reducing medication errors. Clinical pharmacists contribute to the reduction of medication errors by interacting with the health care team on patient rounds, interviewing patients, reconciling medications, providing patient discharge counseling and follow-up services (e.g., Kaboli, Hoth, Mcclimon, & Schnipper, 2006; Kucukarslan, Peters, Mlynarek, & Nafziger, 2003; Leape et al., 1999; Scarsi, Fotis, & Noskin, 2002). For example, Schnipper et al. (2006) found that pharmacists’ medication review, patient counseling, and telephone follow-up were associated with a lower rate of preventable ADEs 30 days after hospital discharge. Pharmacists who are physically stationed in nursing units can improve consistency of services as well as communication between pharmacy and nursing personnel, creating opportunities to clarify unique administration issues (Kopp et al., 2006). In this vein, the American Hospital Association (AHA) recommended that hospitals institute 24-hour pharmacy services to facilitate medication distribution after hours so that they ensure access to consultation with a pharmacist if a pharmacist is not available on-site (American Hospital Association, 2002).

Team Factors

Team factors include poor communication, inadequate supervision, insufficient responsibility and low morale. Communication problems encompass misinterpretation of orders, both oral and written, or incorrect interaction with other services. In particular, the National Coordinating Council for Medication Error Reporting and Prevention (NCC MERP)
Taxonomy of Medication Errors reported that oral and written miscommunications among care providers are the top factors leading to medication errors (Hoff, Pohl, & Bartfield, 2005). Similarly, Phillips et al. (2001) found that transcription and handwriting errors, examples of written miscommunication, were likely responsible for fatal overdoses associated with medication errors. Additionally, Taxis and Barber (2003) reported that 16% of medications were omitted because of failures in communication.

Although inadequate supervision or responsibility has not been studied rigorously, a qualitative study that investigated causes of prescribing errors discussed several examples in which junior doctors felt that supervision was inadequate and that responsibilities between teams were overlapping and not clearly defined (Dean et al., 2002). For example, a senior doctor asked a junior doctor to prescribe a drug, who did so without asking questions, assuming that to do so was correct. Some junior doctors were often unclear about whose responsibility prescription of drugs was in such instances, and they felt that if a problem occurred, responsibility would rest with the senior doctor.

In a study that analyzed the causes of IV errors, Taxis and Barber (2003) found a lack of perceived risk and poor role models as system failures. They argued that the cultural context condoning unsafe drug use and the failure to teach practical aspects of drug handling were underlying problems resulting in IV errors. Fogarty and McKeon (2006) also found similar results. These authors argue that when the organizational climate is positive (i.e., when nurses receive supportive leadership, are involved in decision making, and are able to participate in professional development), nurses are less likely to participate in unsafe behavior when administering medications. On the other hand, nurses are more likely to violate regulations regarding medication administration when there are high expectations.
from physicians for nurses to work outside the scope of practice (McKeon, Fogarty, & Hegney, 2006).

**Personal Factors**

Insufficient knowledge and performance deficits have been reported as personal factors contributing to medication errors. Studies have found lack of knowledge of the drug as the most common proximal cause both in prescription and administration stages, accounting for 15-22% of errors (Leape et al., 1995; Phillips et al., 2001). In terms of prescribing errors, for example, together with insufficient knowledge about the patient, a lack of knowledge or appreciation of drug therapy issues such as misapplication of drug therapy rules accounted for 60% of prescribing errors (Lesar, Briceland, & Stein, 1997). Similarly, lack of knowledge of preparation or administration procedures is a frequent cause in medication administration errors and IV medication errors (Taxis & Barber, 2003; Tissot et al., 1999). Lack of information about the patient is second in frequency, accounting for 14% of errors (Leape et al., 1995). For example, insufficient information about the patient could lead nurses to administer drugs to a patient known to be allergic to them.

Similar to knowledge deficits, performance deficits have also been found to be a significant personal factor contributing to error. Performance deficit means that the person involved in the error does not have requisite skills and working knowledge to perform the duty safely (Hicks, Becker et al., 2004). In a review of fatal medication errors, Phillips et al. (2001) reported that human factors such as performance or knowledge deficits accounted for 65.2% of such medication errors. In terms of prescribing errors, Lesar, Briceland, and Stein (1997) found that more than one in six prescribing errors involved miscalculation of medication doses, wrong decimal point placement, incorrect expression of unit of
measurement or concentration, or an incorrect medication administration rate. Rowe, Koren, and Koren (1998) also reported that a substantial proportion of pediatric trainees made mistakes while calculating drug doses. In a similar vein, numerous studies have suggested that nurses lack the ability to calculate drug doses accurately (Bayne & Bindler, 1988; Worrell & Hodson, 1989).

In the nursing literature, knowledge and performance deficits have often been studied in relation to nurses’ education and experience. While it is intuitively appealing to suggest that nurses’ education and experience are linked to medication errors, study results have been inconclusive. For example, Ives, Hodge, Bullock, and Marriott (1996) found that newly registered nurses had an inadequate knowledge of pharmacology but that longer experience as an RN and participation in a graduate program were associated with higher scores in both self-rated and tested knowledge of pharmacology, suggesting that nurses continually accumulate and update medication-related knowledge as they gain experience and education. Blegen, Vaughn, and Goode (2001) also found that, although nursing unit-level education, defined as the proportion of BSN-prepared nurses on the unit, was not significant, nursing units staffed with more experienced nurses had significantly fewer medication errors.

In contrast, other studies reported that educational preparation and years of experience did not significantly influence nurses’ drug knowledge or ability to calculate drug dosages (e.g., Ashby, 1997; Bayne & Bindler, 1988; Grandell-Niemi, Hupli, Puukka, & Leino-Kilpi, 2006; Markowitz, Pearson, Kay, & Loewenstein, 1981). Such counter-intuitive findings can be explained by the so-called “competence trap,” (Levitt & March, 1988) in which complacency with and commitment to the skills that make experienced nurses successful prevent growth and change. In fact, Reason (1990) argued that skilled individuals are more
likely than the less-skilled to make their errors in “strong-but-wrong” forms. In other words, as shown in Perlstein, Callison, White, Barnes, and Edwards’s study (1979), experienced nurses tended to be more certain, although wrong, in their judgment of the appropriateness of the drug dose ordered, while the overall error rate was not different for experienced or inexperienced nurses.

Patient Factors

Patient-specific factors include patients’ age, gender, the number of drugs they are taking, and their comorbid conditions. Although it seems reasonable to assume that older people are more likely to experience ADEs because of their fragile health conditions, evidence has shown it is not always the case. For example, while Lesar, Briceland et al. (1997) found that older patients were at risk of having ADEs, Evans, Lloyd, Stoddard, Nebeker, and Samore (2005) reported that age was not statistically associated with higher risk of ADEs for any drug class. Such opposite results are also found in Bates, Miller et al.’s study (1999) that incorporated two different analysis methods (i.e., a cohort analysis and a case-control study). Bates, Miller et al. argued that old age was a significant factor in the increase of risk of ADEs in the cohort analysis, but due to lack of predictive power, its effects became insignificant in the multivariate studies when both cases and controls were included. They concluded that the effect of old age could be modest at best and the magnitude of its risk was probably smaller than had been suggested in the literature.

Regarding gender, Evans et al. (2005) found that females had 1.2-1.7 higher odds than males to have ADEs while others found no such relationship. In terms of the number of drugs, van den Bemt et al. (2002) reported that the number of drugs or doses per patient per day was not significantly associated with the occurrence of an error ADEs. Somewhat differently,
Bates, Miller et al. (1999) found a borderline association between the number of drugs received and risk of an ADE. Regarding comorbidities, Evans et al. (2005) found an association between the number of patient comorbidities and an increased risk of all ADEs, and the association was strongest for severe ADEs. However, no other study has found similar results to what Evans and colleagues reported. Overall, partly because of the small number of studies, none of the patient factors has shown consistent results.

Summary

Two important points regarding etiology can be drawn from this sub-section. First, no single factor can explain a medication error sufficiently because most medication errors involve multiple factors and often there are interactions between the factors, such as workload and staffing. Practitioners and researchers have long believed that a retrospective investigation will allow finding a single root cause, even though in fact the very idea of a “root cause” is misleading because most errors result from a complex interaction among a varied set of elements, including human behavior, technological aspects of the system, socio-cultural factors and a range of organizational and procedural weaknesses (Department of Health, 2000). Thus, what they believe as causes are often multiple possible “suspects.” For example, Hicks et al. (2004) found that 610 out of 645 medication errors were associated with at least one cause of error. This finding illustrates that one type of error can result from several proximal causes, and, at the same time, a single proximal cause can result in a variety of types of errors.

Second, although the term “conditions” was used in this sub-section, in most cases the literature reviewed used the term “cause” even when a causal relationship between a presumed cause and a presumed effect was not made sufficiently. Descriptive studies using
chart review or retrospective case studies, dominant study designs for medication error research, are not suitable for making causal relationships. Further, in relation to the first point, having multiple proximal causes does not allow examining a causal relationship between a cause and an effect. For example, although physicians’ illegible prescriptions have been identified as proximal causes for medication errors, it may not be correct to assume that poor handwriting causes an error because an error happens only when such a case is misinterpreted and not corrected.

Despite a substantial body of research on error-producing conditions, the understanding of medication errors is still limited. With the exception of isolated correlational and case-control studies (e.g., Bates et al., 1998; Bates, Miller et al., 1999; Rowe et al., 1998; Thomas, Orav, & Brennan, 2000; van den Bemt et al., 2002), the current state of knowledge is limited to the results from descriptive studies and, as a consequence, not many factors have been identified as necessary conditions for error occurrence. In addition, multiple factors can always simultaneously contribute to errors, and therefore the impact of some factors can be cancelled out (i.e., staffing and workload). Few researchers have investigated a set of error-producing conditions in a single study and examined the relative effect of each factor in the occurrence of medication errors. Further, little effort has been made to test error-producing conditions from multi-level perspectives incorporating individual to team to organizational levels. Because no single factor is free from being affected by higher-level conditions, consideration of multi-level features is critical. With these points in mind, I will extend the discussion to prevention and management strategies in the next section.

Prevention and Management Strategies

This section presents a review of technological strategies that health care researchers
and practitioners have often recommended to reduce medication errors and ensure patient safety.

**Unit-Dose Systems**

Unit dosing is a major systems change that has significantly reduced medication dosing errors since it was introduced (Kohn et al., 2000; Simborg & Derewicz, 1975). Research over the years continues to support the effectiveness of unit dosing systems for reducing medication errors, particularly errors occurring during dispensing and administration processes (Fontan, Maneglier, Nguyen, Loirat, & Brion, 2003; The Massachusetts Coalition for the Prevention of Medical Errors, 2001). If used with CPOE, in particular, unit dose drug dispensing systems can decrease prescription and administration error rates significantly.

Unit-dose systems contribute to the reduction of medication errors by simplifying and standardizing the complex medication process. In a traditional ward stock distribution system, nurses needed to measure out each dose, a situation that created substantial risk for nurse error. However, unit-dose systems reduce such risk by eliminating the need for calculation, measurement, preparation, and handling in the nursing unit; providing individually packaged medications by the pharmacy in the exact dose needed; and delivering them to the point of administration (Kohn et al., 2000; The Massachusetts Coalition for the Prevention of Medical Errors, 2001). Experts advise that, although traditional unit-dose systems provide only packaging, future systems should also include methods for labeling and order screening. Further, organizations should maintain and systematically use unit-dose distribution systems that have been either prepared by the manufacturer or repackaged by a pharmacy for all non-emergency medications (American Hospital Association, 2002).

**Computerized Physician Order Entry Systems**
CPOE systems have shown the strongest evidence of effectiveness for reducing medication errors (Leape et al., 2002). Originally, CPOE systems aimed to reduce medication errors resulting from misinterpretation of physicians’ poor handwriting by using pre-set standardized terminology. Now, however, CPOE systems can also function as buffers that prevent physicians from making erroneous orders. Such broadened usage may be due to the realization that medication errors most commonly occur at the drug-prescribing stage (Bates, Cullen et al., 1995; Bates et al., 1993; Leape et al., 1995).

In addition to eliminating prescribing errors, the literature has shown that CPOE systems have the potential to prevent most medication errors and are useful at all stages of the medication process (Bates, Boyle et al., 1995; Evans et al., 1998). First, CPOE systems provide immediate access to patient and drug information at the time of ordering, thus reducing errors resulting from a lack of knowledge about drugs and the patient; errors of this type account for 60% of all prescription errors (Leape et al., 1995). Second, CPOE systems reduce the number of choices to be made by the physician by showing only acceptable doses and frequencies. Such limited choices decrease the potential for physicians selecting the wrong drug, dose, route, or frequency (Cordero et al., 2004). Third, even if an error is made, CPOE systems, if fully implemented, can screen for drug interactions, contradictions, adverse side effects, and allergies. For instance, although the dose prescribed might be acceptable for people in general, if it is not appropriate for the patient’s kidney or liver function, CPOE systems will raise a red flag (Kohn et al., 2000; Schiff & Rucker, 1998; The Massachusetts Coalition for the Prevention of Medical Errors, 2001).

Altogether, CPOE systems standardize the medication process and establish redundant checks so that even if errors happen they can be caught in time. In other words, CPOE
systems can “error-proof” so that a physician cannot enter an order for a lethal overdose of a
drug or prescribe a medication to which a patient is known to be allergic (Leape, 1994a).
CPOE systems can yield the most benefit when linked with decision support systems
including laboratory and radiology databases (Kaushal, Shojania, & Bates, 2003). Such links
allow CPOE systems to provide information about drug-laboratory problems and result in
sizable reductions of error at all stages (Bates et al., 1998; Kohn et al., 2000; Leapfrog Group,
2003). In short, CPOE systems decrease the likelihood that an error will occur and increase
the chances of intercepting errors that do occur (Leape et al., 1995).

Despite all the promising advantages experts have proposed, however, the literature on
the effectiveness of CPOE systems has been controversial. Bates, Boyle, et al. (1995)
suggested that physicians were responsible for 81% of non-missing dose errors and argued
that 84% of these non-missing dose errors were preventable by CPOE systems. Another
study showed that CPOE systems decreased the number of medication errors with potential
for harm by more than half (Bates et al., 1998), suggesting that CPOE systems can augment
providers’ capacity to catch near misses. When CPOE systems were used with decision-
support features such as drug-allergy and drug-drug interaction warnings, the non-missed
dose medication error rate fell more than 80% (Bates, Teich et al., 1999).

On the other hand, some researchers have reported a downside of CPOE systems
(Berger & Kichak, 2004; McNutt, Abrams, & Arons, 2002). A recent study shows that CPOE
systems can actually facilitate 22 types of medication errors, primarily information errors
generated by fragmentation and systems integration failure and human-machine interface
flaws (Koppel et al., 2005). For example, while CPOE systems require discontinuing the
current dose when new or modifying existing medications are ordered, physicians may
change medication doses without doing so and thus might accidentally prescribe a double total dose. Thus, some argue that a CPOE system alone is not enough to reduce ADEs unless accompanied by proper decision support functions (Nebeker et al., 2005). In sum, although the literature has shown more advantages of CPOE systems than disadvantages, future studies should carefully evaluate potential problems that might be facilitated by the use of CPOE systems.

Implementing CPOE systems is not a simple matter; it requires a substantial period of time and money (American Hospital Association, 2002; Richardson & Briere, 2001; The Massachusetts Coalition for the Prevention of Medical Errors, 2001). However, as the AHA suggests, CPOE systems and pharmacy dispensing processes are prerequisites for patient safety because many other longer-term changes rely on computerization of these two systems. In support of this suggestion, the Leapfrog Group (2003) promoted CPOE systems as one of three "leaps" to improve patient safety in urban hospitals. The Leapfrog Group projects that if implemented in all urban hospitals in the U.S., the three leaps—CPOE systems, intensive care unit physician staffing, and evidence-based hospital referral—could each year save up to 65,341 lives, prevent as many as 907,600 serious medication errors, and save $41.5 billion. Altogether, it is recommended that CPOE systems should be applied more extensively to various types and sizes of hospitals and other health care settings.

Other Support Services

In addition to the two system changes just discussed, other technological innovations such as bar coding (e.g., Chester & Zilz, 1989; Meyer et al., 1991) and intelligent IV infusion pumps (e.g., Rothschild, Keohane, Thompson, & Bates, 2003) have also been reported to be effective in reducing medication errors. For example, medication administration errors may
occur more frequently in a floor stock system than in a system in which a pharmacy
dispenses a substantial portion of the drugs because in a floor stock system nurses have to
pick the correct drugs from the stock before preparing and administering them (van den Bemt
et al., 2002). In addition, the AHA and the Massachusetts Coalition for the Prevention of
Medical Errors (American Hospital Association, 2002; The Massachusetts Coalition for the
Prevention of Medical Errors, 2001) recommend practices such as instituting a 24-hour
pharmacy service, educating practitioners and patients, and actively involving leadership in
creating a safety culture.

Summary

Despite the potential benefit of technology described earlier, there is still insufficient
evidence to prove the effectiveness of using technology to reduce medication errors. With
some exceptions, empirical studies investigating the effectiveness of these technologies were
performed in a single organization (e.g., Cordero et al., 2004; Fontan et al., 2003) and their
results were often controversial (e.g., Bates et al., 1998; Koppel et al., 2005). As a result,
little is known about when and under what circumstances such technology is more likely to
be effective.

This chapter provided an overview of the literature on the classification, etiology, and
management strategies of medication errors. Despite the burgeoning research on medication
errors, most studies are atheoretical and such limitation continues to impede understanding of
how to reduce the occurrence of medication errors. Because no single theoretical model is
comprehensive, incorporating extant models that have specific advantages can overcome
such limitations. The next section, using what was discussed in this chapter as a guide, will
review two theoretical models – the human error and organizational learning models -- that
can be used to explain why medication errors occur and will discuss why neither of them is sufficient alone.

Human Error Model

Reason’s human error model (1990) was originally developed for use in complex, high-hazard organizations such as nuclear power generation plants, chemical processing plants, and commercial aircraft companies to understand the relationships between the various factors causing accidents and to identify methods of accident prevention (Stanhope, Vincent, Taylor-Adams, O'Connor, & Beard, 1997). It examines the chain of events that leads to an accident or adverse outcome, including the actions of those involved and then, crucially, looks further back at the conditions in which staff were working and the organizational context in which the incident occurred (Vincent, Stanhope, & Taylor-Adams, 2000).

With the increased attention to patient safety, the model has been quickly adapted to health care fields and it is one of the most frequently used models in the patient safety realm. In particular, two basic premises of this model, human fallibility and the systems approach, have appealed to researchers and practitioners the most and they are considered the crux of most patient safety initiatives. Beginning with these two premises, a literature review of the key concepts of this model – active failures, latent conditions, and defensive barriers – will follow.

Basic Premises

Human Fallibility

An underlying assumption of the human error model is that humans are fallible. In his book, *Human Error* (1990), Reason explicates the types of human errors and the conditions that precede their occurrence in great detail. After an extensive account of the nature and
form of human errors, he concludes that the psychological antecedents of unsafe acts such as
distraction, momentary inattention, and forgetting are extremely difficult to control because
they are entirely natural human reactions to work environments. In other words, it is rarely
possible to predict the occurrence of individual unsafe acts because of these inevitable
psychological antecedents. Thus he concludes that humans are fallible and this conclusion
leads him to introduce the systems approach, which he considers the answer for imperfect
humans.

*Systems approach*

The basic premise of the systems approach regarding errors is that humans are fallible
and errors are to be expected, even in the best organization. It recognizes that many of the
problems facing organizations are complex, and ill-defined, and result from the interaction of
a number of factors. Yet, two important facts about human error have often been overlooked:
First, the best people can make the worst mistakes; second, far from being random, errors fall
into recurrent patterns (Department of Health, 2000; Reason, 1990). These facts suggest that
a person-centered approach focusing on the control of psychological precursors of error (i.e.,
inattention, forgetfulness and carelessness) and using the control paradigm of management
(i.e., disciplinary measures, writing more procedures to guide individual behavior, or blaming,
naming and shaming) is doomed to fail. Thus, Reason argues that error management should
shift from individual-focused remedies towards system-focused intervention and the key to
effective safety management strategy is to manage the manageable (Reason, 1990, 2000).

This approach recognizes that accidents common in low-risk yet high-hazard systems
are usually organizational accidents that involve multiple causes whose origins can be traced
to decisions taken some time before an accident occurs. In this vein, the human error model
regards errors as consequences rather than causes of system failures, having their origins not so much in the perversity of human nature as in “upstream” systemic factors, which include the organization’s strategy, its culture, and the approach of management towards risk and uncertainty (Reason, 2000). In other words, errors made by workers at the “sharp” end – i.e., those who actually provide care for patients -- are symptomatic of underlying organizational failings as well as human fallibility, and the people at the sharp end are the inheritors rather than the instigators of an accident sequence (Reason, 1995). As such, the systems approach concentrates on the conditions under which individuals work and tries to build system defenses to avert errors or mitigate their effects.

Despite the well-known importance of system factors, however, it is challenging to find and assess the influence of these multi-level factors on patient outcomes in empirical studies and in fact, research on the effect of these upstream factors on clinical practice is minimal (Vincent, Taylor-Adams, & Stanhope, 1998). It is partly because, with few exceptions, there are often too many system factors involved – and, in fact, a chain of systems factors -- so that it is difficult to isolate only one or two factors as the “cause.” For example, the Australian Incident Monitoring Study found that system factors were implicated in 90% of the incidents excluding those resulting from human factors (Runciman, Webb, Lee, & Holland, 1993). In such situations, to single out the most relevant system factors and test their influence is not an easy matter. In addition, many quality and safety initiatives often rely on only one level of intervention (e.g., staff training or tightening protocols) and give insufficient attention to other factors that influence clinical practice (Vincent et al.). Safe practice can only come from acknowledging the potential for error and building in error reduction strategies at every stage of clinical practice (Leape, 1994a).
Key Concepts

Active Failures

Active failures are unsafe acts committed by people at the sharp end (i.e., surgeons, nurses, anesthetists, etc.) who are in direct contact with patients in system, so their actions can have immediate and adverse consequences. Although there is no single taxonomy for categorizing these active failures, in general errors and violations have been considered the two most frequent types of failures in health care. In what follows, definitions and comparison of errors and violations will be reviewed.

Errors versus Violations

Error has been defined as “the failure of planned actions to achieve their desired ends” (Reason, 1990). There are three elements to this definition: a plan or intention that incorporates both the goal and the means to achieve it, a sequence of actions initiated by that plan, and the extent to which these actions are successful in achieving their purpose. In other words, it is important to emphasize that the actors were attempting to achieve the desired outcome using a correct strategy, but they failed either to identify or enact the correct strategy or they failed to execute the correctly chosen strategy. In short, individuals were trying to do the right thing, but they simply did not do it successfully because of a mistakenly faulty plan or a miscue in the execution of the correct plan (Hofmann & Mark, 2006). Reason qualified the failure by excluding those brought about by chance. For example, he did not consider a power failure that prevented a planned action from achieving the intended results as an error because it is brought about by chance. Violations, in contrast, are deviations from safe operating practices, procedures, standards or rules (Reason, Parker, & Lawton, 1998). Violations can have two important consequences: They can increase the probability of a
subsequent error, and they can also increase the likelihood that it will have a bad outcome\textsuperscript{1}.

Violations differ from errors in several ways. First, whereas errors arise primarily from informational problems (e.g., forgetting, inattention, incomplete knowledge, etc), violations are more often associated with motivational problems such as low morale, poor supervision from senior staff, perceived lack of concern, the failure to reward compliance, and inadequate management generally. Second, errors can be explained by what goes on in the mind of an individual, but violations occur in a regulated social context. For example, safe operating procedures are continually being amended to prohibit actions that have been implicated in some recent accident or incident. These additions become increasingly restrictive over time, often reducing the range of permitted actions to less than those necessary to get the job done under normal conditions. Similarly, such additions also result in procedural over-specification that may ultimately create violations. Third, errors can be reduced by improving the quality and delivery of the necessary information within the workplace. In short, violations generally require motivational and organizational remedies.

\textit{Latent Failures}

The identification of latent failures is well depicted in Figure 3 (Reason, 1990, p 202). The framework shows that latent failures consist of several stages of human contributions to the breakdown of complex systems. The accident sequence begins with fallible decisions made by designers and high-level managerial decision makers. The consequences of such fallible decisions can be further exacerbated by the extremely complex interaction between line management deficiencies and the imperfect psychological precursors of unsafe acts.

\textsuperscript{1} Not every violation leads to bad outcomes. For example, nurses may choose to bend rules to “save” a patient’s life by initiating an action that is not authorized by hospital protocols in an emergency situation. For more discussion, see Hughes (2007).
Figure 3. Reason’s (1990) Stages in the Development of an Organizational Accident

- Management Decisions, organizational processes, corporate culture
- Error-producing conditions, Violation-producing conditions
- Errors, Violations
- Bad Outcome: Accidents
- Latent failure pathway
As such, latent failures provide the conditions in which unsafe acts occur, and for this reason some have suggested the use of the term “latent conditions” rather than “latent failures” (Department of Health, 2000). Human errors occur at each stage and are considered latent because they are not obvious until accidents happen. These latent conditions lead to weaknesses in the organization’s defenses, thus increasing the likelihood that when active failures occur they combine with existing preconditions, breach the system’s defenses, and result in organizational accidents. Reason argues that even in the best-run organizations a significant number of influential decisions will subsequently prove to be mistaken.

Latent conditions possess two important properties: First, their effects are usually longer lasting than those created by active failures; second, they are present within the system prior to an adverse event and can be detected and repaired before they cause harm (Reason, 2004). These properties imply that, although latent conditions are deep-rooted in the organization and thus are hard to change, they are manageable and finding and correcting them is what the systems approach pursues.

Latent conditions that can lead to accidents include introducing rapid change within an organization without adequate preparation, incompatible goals or conflicts between finance and clinical need, inadequate systems of communication, and inadequate maintenance of equipment and facilities (Vincent et al., 1998). For example, Dean and colleagues (2002) found physicians’ inadequate education and training on medication doses before starting their practice a latent failure contributing to prescribing errors. In addition, a hierarchical culture in medical teams and resulting self-denial or low self-awareness of making errors have also been found to be latent conditions.

*System Defenses*
Because latent failures are an inevitable part of the design and management process, the human error model suggests that questions should focus on how to ensure detecting and correcting adverse consequences from errors before they harm patients rather than how to prevent them from occurring. In fact, while many unsafe acts resulting from latent failures are likely to be committed, only very few penetrate the systems defenses and come to be accidents. For example, less than one percent of medication errors actually become ADEs (Bates, Boyle et al., 1995). This gap is due to system defenses health care organizations have built such as standardized work processes, high quality providers, favorable work environments, and a positive organizational climate.

System defenses can be either “hard” (i.e., physical containment, automation or engineered safety features) or “soft” (i.e., the procedures, protocols, administrative controls and people at the sharp end) (Department of Health, 2000). In many hazardous domains in which the operations are relatively stable and predictable (i.e., nuclear power generation, chemical process plants, and commercial aircraft), a great deal of reliance is placed on engineered safety devices and procedural controls. In health care, in contrast, the nature and variety of defenses varies widely from one activity to the next and doctors and nurses have to rely heavily on their own skills to protect patients from harm. In other words, in many areas of health care, people at the sharp end constitute the primary defense (Reason, 2004). For example, one study (Dean et al., 2002) has shown that pharmacists were the main source of defense, identifying and rectifying all the prescribing errors doctors did not notice.

Compared to the amount of discussion on what system defenses are, little discussion has occurred on what would comprise system defenses. For example, the human error model describes anything from top-level managerial decisions to front-line worker’s lapse to turn
down the pump can be system defenses. Further, the human error model does not draw a clear line between system defenses and latent factors. For example, while work environment contributing to medication errors is considered as an error-producing condition, it can also function as a system defense in that favorable work environment can prevent medication errors. Similarly, while an organization climate that values patient safety and promotes the use of safe procedures is a matter of organizational-level managerial decisions, at the same time it is also regarded as a system defense in that a positive safety climate is more likely to close out the “holes” in latent failures that occurred in a previous stage.

Summary

One of the contributions of the human error model to patient safety research is the introduction of the concepts of latent factors and the systems approach. Rather than focusing on proximal causes and instant solutions to human errors, studies using this model have focused on identifying often long-term and rarely obvious system failures. For example, numerous studies have found system factors contributing to medication errors at the team and organization level (e.g., workload, poor work conditions, and lack of productive communication) as well as the individual (e.g., inadequate knowledge and skills) and patient level (e.g., old age and severity). In addition, in accordance with Reason’s arguments about building redundancy as system barriers, studies have suggested that technology, if used properly, is the best error prevention strategy to enhance patient safety by standardizing and simplifying work processes and reducing human errors. Examples of such technological implements that have been shown to be effective in medication error reduction are CPOE with decision support systems, automated unit-dose dispensing systems, and automated medication administration system (Bates et al., 1998; Berger & Kichak, 2004; Fontan et al., 2005).
Yet, despite the current state of knowledge on medication errors and system factors, our understanding of medication errors is still limited because previous research efforts adopting the human error model tend to focus on structural aspects and pay relatively little attention to patient safety culture. While continuous efforts to identify the impact of structural aspects and technology are essential, they should be accompanied by supportive behavioral, system, and environmental changes because structural changes themselves are insufficient to achieve patient safety (Hoff et al., 2005). In the aviation industry, for example, the variation of safety culture among different carriers has shown to make a difference in the risk to passengers, even when airlines operate globally with similar equipment, training, and licensing (Reason, 1997). Despite the extensive discussions on the role of safety culture on medication errors (Firth-Cozens, 2001; Kohn et al., 2000; Mohr, Abelson, & Barach, 2002; Pronovost et al., 2003; Singer et al., 2003), research studies on safety culture have been performed in a single organization, usually in the form of case studies. As a result, there is limited understanding of when or under what safety culture the impact of the technology is most effective. For example, even if two nursing units possess the same level of error reduction technologies, their error rates may differ depending on their safety culture (i.e., positive or negative).

Although Reason (1998; 2000) alluded to the importance of safety culture in health care, his arguments on safety culture have not been fully developed or tested in patient safety studies. For example, he argues that a just culture in which the line between acceptable and unacceptable behavior is clearly drawn and understood is a prerequisite for a safe culture. Further, he suggests high reliability organizations, systems operating in hazardous conditions that have fewer than their fair share of adverse events, are the prime examples of the systems
approach because they are not immune to adverse events, but over time they have learned how to convert accidents into enhanced resilience of the system. However, because he failed to specify how safety culture could be integrated into the human error model, safety culture remains one of the most often discussed yet least often investigated or understood areas of the patient safety literature. In this sense, the organizational learning model can supplement the human error model because it does address a learning climate, a specific aspect of safety culture, as a way of introducing error management strategies. The next section, therefore, will include a brief description of safety culture, safety climate and learning climate, followed by a discussion of the organizational learning model.

Safety Culture, Safety Climate, and Learning Climate

Before moving to the next section, it is necessary to clarify the terms that have been mixed in the literature. Researchers tend to have used the terms “safety culture” and “safety climate” with little conceptual distinction. Such a tendency is not only in the health literature but also in the business and psychology literature. Denison (1996) argues that culture refers to the deep structure of organizations, which is rooted in the values, beliefs, and assumptions held by organizational members. Climate, in contrast, portrays organizational environments as being rooted in the organization’s value system, but tends to present these environments in relatively static terms, describing them in terms of a fixed set of dimensions. Thus, climate is often considered as relatively temporary, subject to direct control, and largely limited to those aspects of the social environment that are consciously perceived by organizational members. Another difference between culture and climate is that culture studies often require qualitative research methods and an appreciation for the unique aspects of individual social settings. In contrast, climate studies prefer quantitative methods and the assumption that
generalization across social settings not only is warranted but also is the primary objective of
the research.

A learning climate, as used in the current study, is a dimension of nursing unit work
environment perceived by the nurses on the unit and, therefore, closer to climate than to
culture. Using questionnaires and quantitative methods, it measures observable practices and
procedures that each nursing unit requires nurses to perform and follow, which are closer to
the surface of organizational life (Denison, 1996). It is a learning climate because, unlike
safety climate that emphasizes compliance with protocols and procedures as an error
prevention strategy, it is more concerned with what to do after an error has occurred.
Therefore, from now on I will use the term learning climate unless I need to follow the
original term the authors used.

Organizational Learning Model

Most organizational learning literature has its foundation in Argyris and Schön’s book
(1978) *Organizational Learning: A Theory of Action Perspective*. The fundamental idea of
this book is that cognitive and interpersonal factors facilitate learning behavior and
eventually give rise to organizational effectiveness (Levitt & March, 1988; Edmondson,
1999; Starbuck, 1992). Although the organizational learning model is rather new to health
care researchers, it has recently received increased attention particularly in the area of patient
safety research. This increased interest may be due to the fact that what healthcare
researchers have envisioned as an ideal safety culture is similar to the organizational learning
culture (e.g., Department of Health, 2000).

The organizational learning model has often been suggested as the prime example of an
error management strategy in occupational psychology (Sitkin & Sutcliffe, 1994; Van Dyck
et al., 2005). With escalating attention to medical errors and especially to safety culture, health care researchers have found the notion of organizational learning beneficial in creating an error-reducing environment. While research guided by the organizational learning model is quite extensive (Cohen & Sproull, 1991; Crossan, 2003; Easterby-Smith, 1997) and its application has been primarily in management science rather than in health care, the scope of discussion in this dissertation will be confined mostly to learning from failures and organizational learning as an error management strategy.

In the first section, two key concepts of the organizational learning model, learning from failure and single-loop and double-loop learning, are reviewed. This section is followed by the introduction of the error-management approach, which calls upon the ideas of the organizational learning model and learning climate.

**Key Concepts**

*Learning from Failure*

Some argue that failure, deviation from expected and desired results (Cannon & Edmondson, 2001), is more important than success for organizational learning and that organizations in which failure is tolerated and discussed are expected to perform better in the long run than those in which failure is covered up (Sitkin, 1992). While learning from failure entails activities similar to the usual form of learning as feedback seeking or asking for help, it has a unique feature that makes learning from failure difficult. Learning from failure requires an individual to take an interpersonal and career risk because the process of admitting, identifying, discussing and analyzing failures may undermine one’s self-esteem and put the individual at risk for punishment or discipline. Further, fear of being ridiculed or blamed or fear that others will use knowledge of their failures against them keeps people...
from discussing their failures or disagreements (Cannon & Edmondson, 2001). To illustrate, admitting an error or asking for help may raise stress and anxiety because an individual may appear incompetent or experience low self-esteem. In such a situation, therefore, people tend to avoid facing the situation or to act in ways that inhibit learning (Staw, Sandelands, & Dutton, 1981).

In health care, most patient outcome indicators such as failure to rescue, unexpected complications, and adverse events are examples of “failures.” Because these failures are all interpersonally threatening issues when openly discussed, psychological responses and the pattern of behavior toward them often impede learning (Argyris & Schon, 1978). This is particularly true with regard to medication errors. In her study of medication errors in eight nursing units, for example, Edmondson (1996) found that reported error rates were strongly associated with higher scores on perceived unit performance, which was opposite to her initial expectation. If we assume that reported errors are indicative of failures, the study results do not make sense. However, as she explained, the results could have been contaminated because the reported error rates she used did not necessarily reflect actual errors. In other words, it is plausible that the nursing units in which nurses felt less threatened report more errors and thus may appear to have more errors, when, in fact, they do not. According to the organizational learning model, such nursing units are in a superior position in future performance. This is due to their positive learning climate, in which they facilitate learning behavior of their nurses by alleviating their excessive concern about others’ reaction to their failures. Therefore, the nurses on these units eventually learn when and how they make errors and try to prevent them at a minimal cost of guilty feelings (Edmondson, 1999).

**Single-Loop vs. Double-Loop Learning**
One of the most important concepts in the organizational learning model is single-loop and double-loop learning. The usual way for an organization to learn is either through the inherited knowledge of its members or by recruiting new members with external knowledge not previously possessed by the organization (Simon, 1991). More important, however, is the potential of the organization to learn through feedback on the consequences of its previous actions (Easterby-Smith, 1997). Argyris and Schön (1978; 1996, p 20) define learning as detection and correction of error and distinguish single-loop learning, which is detecting error without questioning underlying policies, from double-loop learning, which involves questioning and changing governing conditions. Stable solutions to organizational problems through single-loop learning typically create new problems in the long run because this type of learning does not engage in identifying and correcting the actual cause of the problem, thus a similar problem may occur again in the future. Therefore, if an organization is to benefit consistently from learning, the critical issue is not how to solve a particular problem but how to create conditions that facilitate people’s ability to detect and correct problems (Lipshitz, 2000).

The idea of single- and double-loop learning has been extended to the notion of first-order (i.e., fixing problems) and second-order problem solutions (i.e., diagnosing and altering underlying causes to prevent recurrence) (Tucker et al., 2002). First-order problem solving allows work to continue but does not help to prevent a similar problem from occurring again. Second-order problem solving, in contrast, investigates and seeks to change underlying causes. Problem-solving behaviors that focus solely on remedying or overcoming immediate obstacles prevent the organization from learning because short-term success reduces both an organization’s ability to detect and its motivation to remove underlying causes of recurring
problems and take corrective action (Tucker et al.). Moreover, such behaviors keep communication of problems isolated so that they do not surface as collective learning opportunities (Edmondson, 2004). Tucker, Edmondson, and Spear (2002) found that nurses frequently use first-order problem-solving patterns in their daily work and argued that health care organizations actually encouraged and rewarded such “quick fixes” in the name of autonomy and professionalism.

The Error Management Approach and a Learning Climate

One of the most common applications of the organizational learning model is to the error-management approach. Unlike the error-prevention approach, which forms the basis of the human error model and suggests that errors can be prevented and minimized through pre-established system defenses, the error-management approach assumes that human errors per se can never be completely prevented. Further, error management researchers argue that the exclusive emphasis on error prevention has its limits because a pure error-prevention approach reduces the chances of learning from errors and minimizes the possibility of benefiting from the potential long-term positive consequences of errors (Van Dyck et al., 2005).

In essence, the error management approach distinguishes errors from their consequences (Van Dyck et al., 2005). Specifically, whereas the error-prevention approach aims at avoiding negative error consequences by avoiding the error altogether, the error-management approach focuses on reducing negative error consequences and increasing potentially positive consequences. In other words, it does not attempt to do away with errors completely but rather attempts to deal with errors and their consequences after an error has occurred. Further, error management ensures that errors are quickly reported and detected,
that negative error consequences are effectively handled and minimized, and that learning occurs. Outside of health care, research has been performed on how organizations manage errors after they occur and how error management influences organizational performance (Helmreich, 2000; Keith & Frese, 2005; Sitkin, 1992; Van Dyck et al.).

The error-management approach is particularly interested in the learning climate, or the ways in which learning from errors is fostered in organizations. Error-management researchers suggest that learning takes place when people are encouraged to learn from errors (Heimbeck et al., 2003), when they think about errors thoroughly (e.g., planning, monitoring, and evaluating one’s actions), and when the negative emotional impact of errors is abated (Keith & Frese, 2005). They value organizational practices related to communicating about errors, sharing error knowledge, helping in error situations, and quickly detecting and handling errors (Van Dyck et al., 2005). In fact, accepting errors as a natural part of work and communicating about them should encourage individuals to explore and experiment and finally learn from their errors (Edmondson, 1999; March, 1991).

A positive learning climate in which open evaluation of the potential causes of medication errors takes place should facilitate improved learning about the errors and, as a result, be associated with fewer medication errors over time (Hofmann & Mark, 2006). Evidence from aviation supports an association between a culture of safety and better error management (Sexton & Klinect, 2001). Further, Firth-Cozens (2001) argues that the reasons why organizational learning often fails to occur are bureaucracy, a lack of clear purpose or feedback mechanisms, poor communication, and cultural issues involving a lack of openness, centralized authority, and blame when errors are seen as indicating incompetence. Unfortunately, however, much of the evidence for using a positive organizational approach to
errors is still anecdotal and needs to be empirically validated (Van Dyck et al., 2005).

Summary

The organizational learning model can supplement the human error model in that, whereas the human error model is essentially an error-prevention approach focusing on identifying latent failures and building system defenses, the organizational learning model is an error-management approach that pays more attention to correcting what went wrong after the fact. In reality, although errors can be minimized they will never be completely eliminated, particularly when high volumes of activity occur. It has been estimated, for example, that a 600-bed teaching hospital with 99.9% error free drug ordering, dispensing, and administration will still experience 4,000 drug errors a year (Leape, 1994b).

Moreover, as discussed previously, while the human error model only implies that safety climate may function as a system defense, it does not explicitly show how to incorporate the concept into the model. In contrast, the organizational learning model and the error management approach hint that, depending on the learning climate, some organizations will be more effective at managing errors than others. For example, even in the most eventful circumstances, some organizations are more successful in compensating for their errors than others because, rather than making their systems immune to organizational accidents, they improve the reliability of people at the sharp end (de Leval, Carthey, Wright, Farewell, & Reason, 2000; Reason, 2004). Therefore, using a learning climate as a bridge to connect the two models, in the next chapter I will develop a conceptual framework integrating the constructs of both human error model and the organizational learning model.
Chapter 3

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

The goal of this chapter is to develop a conceptual framework examining the occurrence of medication errors by incorporating the constructs derived both from the human error model and the organizational learning model. Because no single cause explains medication errors sufficiently, the current study examined an array of error producing conditions. These error producing conditions are considered to be consistent with what the human error model calls system factors. Further, the organizational learning model is used to investigate the moderating effect of a learning climate in the relationship between the error producing conditions and medication errors.

In the first part of this section, I will develop hypotheses on the direct relationship between the error-producing conditions discussed in the second chapter and medication errors. The second part of this section will discuss learning climate as a system defense and will develop hypotheses on the moderating effect of a learning climate.

Error-Producing Conditions

Work Environment

A favorable work environment has been shown to reduce medication errors. As presented in the second chapter, researchers have identified distractions, workload, staffing, and work conditions as contributing factors to medication errors (Hicks, Becker et al., 2004; Taxis & Barber, 2003). In general, a poor work environment characterized by heavy workload, chaotic work situations, and short staffing increases medication errors (Kralewski
et al., 2005; Seki & Yamazaki, 2006). To illustrate, on a nursing unit that cares for mostly severely ill patients, its care complexity increases and nurses often simultaneously organize and reorganize priorities and manage changing clinical information for multiple patients (Wolf et al., 2006). In such an environment, nurses constantly shift their attention from patient to patient and often have to carry out several tasks simultaneously. Such an environment may lead nurses to rush to accomplish tasks in a timely fashion and the possibility for the nurse to make an error is likely to increase. Similarly, stressful work dynamics, featured as frequent changes of orders, care plans, and procedures, may cause nurses to become confused and distracted and may result in errors. Further, nurses may not always be able to keep up with the updated information in patient care (Cohen et al., 2003).

Staffing issues also have been shown to be inversely related to medication errors, with a higher proportion of RNs in the staff mix and RN hours leading to fewer medication errors (Blegen et al., 1998; McGillis Hall et al., 2004). For an organization, such as a hospital, in which people are the core competency, excess workers, to some extent, are one of the most important slack resources, and increasing levels of slack have been associated with improved performance (Bourgeois, 1981; Lawson, 2001). In a nursing unit staffed with many RNs, those “extra” RNs, up to a certain point, can function as a slack workforce. They build heightened levels of redundancy in the surveillance and supervision of each other’s performance and thus leave less chance for the error. For example, with the increased spare time resulting from “extra” staff, nurses now may have time to take a careful look at prescriptions and consider possible drug interactions and side effects. The following hypotheses were thus derived from prior research regarding complexity and work dynamics of the nursing work environment, nurse staffing, and errors.
Hypothesis 1A (H1A): Higher levels of care complexity on nursing units are associated with higher medication error rates.

Hypothesis 1B (H1B): Higher levels of work dynamics on nursing units are associated with higher medication error rates.

Hypothesis 1C (H1C): A higher proportion of RNs among nursing staff on nursing units is associated with lower medication error rates.

Hypothesis 1D (H1D): A greater number of RN hours on nursing units is associated with lower medication error rates.

Team Factors

Although the definition of “team” or the decision about who is on the team can be made in several ways depending on the context, for the sake of simplicity, it is herein defined as a workgroup comprised of nurses, physicians, and pharmacists, all of whom are involved in various stages of potential medication errors. This team is a grouping of professionals all practicing independently, yet trying to achieve a common goal.

Communication among health care providers has been positively associated with high quality of patient care (Arford, 2005; McMahan, Hoffman, & McGee, 1994; Shortell et al., 1995). In a prospective study performed in nine ICUs, for example, Zimmerman et al. (1993) reported that death rates were lower in hospitals that showed higher quality physician-nurse communication. Similarly, other researchers have also found that nurses’ reports of physician-nurse collaboration and the frequency, timeliness, and accuracy of communication among health care providers were associated with the quality of care (Baggs et al., 1999; Gittell et al., 2000).

In relation to medication errors, specifically, the quality of nurse-physician and nurse-
Pharmacist communication has shown a positive relationship with the quality of drug use, evaluated as proper drug selection and the presence of polymedicine (i.e., concurrent use of three or more psychotropic drugs) (Schmidt & Svarstad, 2002). For example, in a prospective, direct observation study, Kopp, Erstad, Allen, Theodorou, and Priestley (2006) found that pharmacists’ participation on rounds and physical stationing in nursing units yielded more opportunities to clarify unique medication administration issues that nurses raised and thus led to fewer medication errors. In contrast, failures of communication, particularly those that result from inadequate “hand offs” between care providers, have been found to be the most common factors contributing to the occurrence of adverse events (Bates & Gawande, 2003). Particularly, inadequate or insufficient communication such as misinterpretation of orders, oral and written miscommunication, or incorrect interaction with other services increases medication errors (Kohn et al., 2000; Leape, 1994a; Phillips et al., 2001; Taxis & Barber, 2003).

**Hypothesis 2A (H2A):** Better nurse-physician communication on nursing units is associated with lower medication error rates.

**Hypothesis 2B (H2B):** Better nurse-pharmacist communication on nursing units is associated with lower medication error rates.

In addition to communication among health care providers, nurses’ expertise and commitment to care have also been found to be associated with patient outcomes. Nurses’ expertise is the ability to recognize potentially ominous events early. The earliest changes in a patient’s condition can be very subtle and difficult to describe, and only nurses who possess clinical expertise can recognize the first indication of a change based on careful monitoring of a patient (Minick & Harvey, 2003). Because expert nurses know under what circumstances
errors occur and often anticipate one, they prevent near misses from becoming accidents. Although a nurse can detect the decline in a patient’s condition, taking corrective actions, either independently or in consultation with physicians, requires a commitment to care, defined as the ability of the nurse to initiate appropriate actions in response to patient problems. Because nurses who possess clinical expertise and are highly committed to their job are vigilant in recognizing changes in a patient’s condition and take action in a timely manner, a nursing unit staffed with such nurses will experience fewer medication errors.

*Hypothesis 2C (H2C):* Higher levels of nursing expertise on nursing units are associated with lower medication error rates.

*Hypothesis 2D (H2D):* Higher levels of commitment to care on nursing units are associated with lower medication error rates.

*Person Factors*

As noted in Chapter 2, despite the number of studies investigating the link between nurses’ education and experience and patient outcomes, few researchers have studied the direct effect of such variables on medication errors. Further, study results often have been inconclusive and some studies have reported a non-linear relationship among those variables. For example, studies on seniority, defined as the length of tenure on the current job, and job performance have consistently found that seniority has a linear effect on job performance up to a certain point (e.g., five years) but beyond that point the relationship appears to plateau (Jacobs, Hofmann, & Kriska, 1990; McDaniel, Schmidt, & Hunter, 1988; Schmidt, Hunter, & Outerbridge, 1986). In other words, there is a trend of increasing levels of expected performance through the first several years on the job but after this initial learning period, the additional amount of seniority accrued does not significantly impact job performance.
Psychologists argue that expertise alters one’s level of cognitive regulation (Rasmussen, 2003; Reason, 1990). With increasing expertise, the primary focus of control moves from knowledge-based towards skill-based levels. Particularly in skilled problem solving, for example, experts and novices use different levels and complexities of their knowledge representation and rules (Reason, 1990). In general, experts are more likely to represent the problem space at a more abstract level and novices are more likely to focus on the surface features of the problem. As they gain expertise through education and experience, novices accumulate a large stock of appropriate routines to deal with a wide variety of contingencies and have a large collection of problem-solving rules. This means that experts can establish a close relationship between the predictability of error and the degree of expertise or they may not have to resort to the knowledge-based mode of problem solving. It also means that the more skilled an individual is in carrying out a particular task, the more likely it is that his or her errors will take “strong-but-wrong” forms at the skill-based and rule-based levels of performance.

Take an error as an example of job performance. Newly graduated nurses are more likely to make errors because of insufficient skills and inadequate knowledge of pharmacology. They accumulate medication-related knowledge as they gain experience as an RN and education through participation in a graduate program (Ives et al., 1996). However, the effect of better education and more experience is not likely to continue to increase at the same rate because, once they are confident with their knowledge and skills, they may not be attentive to the procedures they have performed over and over again and find their own way, which may not be necessarily safe, to get things done. These actions of experienced and educated nurses are more likely to result in errors that are “strong-but-wrong” (Perlstein et al.,
In this study, individual expertise is conceptualized as the level of education and experience. Therefore, it is herein argued that the relationship between nurses’ experience and education and medication errors is linear up to certain point followed by a plateau.

**Hypothesis 3A (H3A):** Educational preparation of the nursing workgroup will have an initially linear then asymptotic function with medication error rates.

**Hypothesis 3B (H3B):** Experience of the nursing workgroup will have an initially linear then asymptotic function with medication error rates.

**Patient Factors**

Patient characteristics such as age, health status, and previous hospitalization are likely to increase the possibility of medication errors. Although some researchers have found no relationship between patient age and ADEs (e.g., Bates, Miller et al., 1999; Evans et al., 2005), in general, the literature has suggested that patient age is positively related to medication errors (e.g., Lesar, Briceland et al., 1997). While health status and previous hospitalization have not been directly linked to medication errors, they are considered as proxy measures of patient co-morbidities, which have been found to be associated with increased risk of ADEs (Evans et al.).

**Hypothesis 4 (H4):** Nursing units with patients of older age, poorer health status, and previous hospitalization are associated with higher medication error rates.

**Support Services**

A nursing unit in which various types of medication-related support services are available is less likely to experience medication errors. Such support services include both high-tech (i.e., CPOE, unit-dose medication systems, automated medication administration
systems) and low-tech services (i.e., transcribing orders and placing information in patient charts, IV team services, medication and IV fluid delivery services, pharmacist consultation). While a number of studies have found the link between some of these services such as unit-dose systems, CPOE, or pharmacists consultation and fewer medication errors (e.g., Bates et al., 1998; Fontan et al., 2003; Kaushal et al., 2003; Kopp et al., 2006), few studies have evaluated the impact of the other services in relation to medication errors (Oren, Shaffer, & Guglielmo, 2003). Because these medication-related services are designed to standardize and simplify the medication procedure nurses use, they can minimize the possibility of human error at every point of the medication process. Therefore, it is theorized that a nursing unit on which a greater number of medication-related support services is available, is less likely to have medication errors.

**Hypothesis 5 (H5):** Nursing units with greater availability of medication-related support services are associated with lower medication error rates.

**Learning Climate as a Moderator**

A positive learning climate prevents medication errors by closing the holes in the defensive layer resulting both from latent and active errors that occurred in the previous stage of the medication process. According to Reason (2000), each defensive layer in an organization looks like a slice of Swiss cheese in that it has many holes (Figure 4). Unlike in the cheese, however, these holes are continually opening, shutting, and shifting their location. When a learning climate is positive, nurses are more likely to be aware of errors because they communicate and think about errors frequently. In other words, they anticipate errors. Nurses working in a positive learning climate will be encouraged to actively engage in such error management activities as fixing error-prone work situations or intercepting near misses so
Figure 4. Swiss Cheese Model by Reason (2000)
that even if an error occurred in a previous stage, it cannot come through to subsequent stage. In other words, nurses in a positive learning climate are empowered to close holes in the defensive layer in the medication process. When a learning climate is negative, however, it not only discourages nurses from acting, but it opens gaps and weaknesses, and most importantly, it can allow them to remain uncorrected. In such a situation, nurses are not encouraged or allowed to deal proactively with known deficiencies in system defenses and when the holes in latent failures momentarily line up, an accident occurs. In the following section, I will discuss how a learning climate moderates some of the relationships reviewed in the previous section and develop hypotheses.

*Learning Climate and Work Environment*

While most health care researchers have only examined a negative linear association between unfavorable work environment factors and medication errors, some have suggested that, depending on an organization’s emphasis on safety climate, the degree of the negative relationship between work environment and safety outcomes can be either attenuated or intensified (e.g., Probst, 2004). In other words, a safety climate functions as a moderator in the relationship between work environment and safety outcomes. In a work environment in which performance and productivity are stressed over safety (i.e., a negative learning climate), workers are less likely to be concerned about following safety protocols and more likely to undertake their jobs in an “efficient” way. For example, in fast paced nursing units in which a majority of patients expect immediate responses and nurses are interrupted frequently by patients’ requests for assistance, it is challenging to engage in second-order problem solving because it takes time (Tucker, Edmondson, & Spear, 2001). In such situations, nurses feel that they need to meet a patient’s needs first and engage in first-order
problem solving because it is the way to get a job done quickly and get procedures going smoothly again. However, because the root cause of a problem is not fixed or eliminated, such first-order problem solving, which may not always be safe, can cause an accident to occur at some point in the future. In contrast, if a nursing unit places patient safety as its priority and encourages nurses to have open channels of communication (i.e., a positive learning climate), the negative impact of the work environment can be mitigated because, in the long run, a positive safety climate fosters the creation of work environments that make it easier for nurses to comply with required safe work practices (DeJoy, Gershon, & Schaffer, 2004).

Although the discussions above have been made relative to safety climate, a similar argument can also be made for a learning climate and its influence on error management. In a nursing unit that has a supportive learning climate (i.e., encourages frequent communications and open discussions about errors), nurses will be more likely to be aware of the possibility of committing errors and more cautious in taking care of patients. Such tendencies may be augmented when nurses’ workloads are heavy resulting from increased patients’ needs (i.e., higher levels of care complexity) or frequent changes of care processes (i.e., higher levels of work complexity). Then these nurses, who are aware of the possibility of errors in such a situation, will pay special attention to patient care in order to prevent errors (Zhao & Olivera, 2006). Similarly, when nursing units are staffed with an adequate number of nurses to take care of patients, these nurses, who anticipate errors, will build heightened levels of redundancy in the surveillance system and look over each other’s work. In other words, a positive learning climate can mitigate the negative effect of poor work environment on error occurrence because nurses actively engage in surveillance of others’ work.
In contrast, in a nursing unit in which communication among workers is rare or unidirectional and admitting one’s mistakes is not valued, the negative effect of a deficient work environment on error occurrence will be accelerated and the positive effect of a good work environment will be attenuated. For example, in a nursing unit in which work is often delayed due to high volumes of patients and resulting frequent changes of care plans and physical and personnel resources to take care patients are insufficient (i.e., short staff), nurses may feel that their job priority is to keep patients alive at any cost, and they may be more likely to engage in short-cuts to get the work finished quickly. In some situations, such first-order problem solving is actually encouraged and nurses who are good at it can be regarded as professional or autonomous because they know how to resolve problems without others’ help and do not leave their work unfinished (Tucker et al., 2002). Thus, double checking and documenting will be reduced and actions may be carried out less attentively, resulting in reduced monitoring and sometimes leading to error (Elfering, Semmer, & Grebner, 2006). Therefore, the following hypothesis is suggested.

Hypothesis 6A (H6): Learning climate will moderate the relationship between work environment factors (i.e., care complexity, work dynamics, RN proportion, and RN hours) and medication error rates. Specifically, the relationships will be weaker when learning climate is positive and stronger when learning climate is negative.

Learning Climate and Team Factors

Good communication among health care providers is directly related to better patient outcomes, and such a relationship can be either fostered by a positive learning climate or mitigated by a negative learning climate. First, in a positive learning climate, a channel of communication can be expanded above and beyond its usual form because talking about an
error and thinking about how to prevent it, which may not take place under a negative learning climate, are now everyday activities. In other words, because people talk freely about their errors in a positive learning climate, they help each other develop a shared meaning of specific situations, and subsequently develop a mutual understanding of high-risk situations (i.e., error traps) and strategies for effectively preventing errors. Further, a positive learning climate should also facilitate the quick detection and handling of errors. In such a situation, nurses may feel it easier and safer to monitor each others’ performance to ensure that they are following procedures and providing feedback when necessary (McIntyre & Salas, 1995). Hence, they can talk freely about safety- and error-related matters without great concern. When a medication order does not seem right for a patient, for example, a nurse can speak up and raise a question about the prescription immediately without feeling afraid or intimidated so that unnecessary delay in patient care does not occur. Finally, communication under a positive learning climate is usually accurate. For example, when a prescription is not clear to a nurse, the nurse can ask and clarify it, rather than assuming it right and following the prescription. Therefore, open communication about errors, a shared understanding of potential error situations, being able to help others in such situations, and fast error detection should allow for quick, smooth, and well-coordinated error handling, reducing the potential negative error consequences frequently associated with errors (Sitkin, 1996).

In contrast, when a learning climate is not positive, the channels of communication become narrow and the possible types of communication become fewer. In a recent survey study, for example, physicians and nurses reported that impaired communication resulting from their disruptive behavior, defined as any inappropriate behavior, confrontation, or conflict, increased medical errors (Rosenstein & O'Daniel, 2005). For example, if a learning
climate is negative and the communication pattern is unsound, nurses may not raise a question or may delay clarification even when a medication order they receive looks suspicious because getting involved with physicians is stressful and they may be afraid of challenging physicians. Similarly, nurses may not report a change in a patient’s condition in order for a physician to alter care plans, which they would have done had their communication pattern been healthy. Without question, less frequent, inaccurate, and often delayed communication patterns among health care providers can affect the quality of care and unnecessary patient deterioration may occur.

Compared to the two contrasting situations discussed above, poor communication patterns in a positive learning climate or good communication patterns in a negative learning climate are not likely to happen because communication is a part of a learning climate. In fact, communication has been considered as one of the most important features of a learning climate and a safety climate (e.g., DeJoy et al., 2004; Van Dyck et al., 2005). For example, van Dyck et al. argue that open error communication, a basic attribute of a high-error management culture, is the best way to learn from others’ errors and share knowledge of different error situations. They also assert that without communication employees are only able to benefit from their own errors, so organizational learning will not occur. In fact, a learning climate itself has such organizational features as communicating about errors, sharing error knowledge, helping in error situations, and quickly detecting and handling errors.

Hypothesis 7 (H7): Learning climate will moderate the relationship between nurse-physician communication and medication error rates and nurse-pharmacist communication and medication error rates. Specifically, the relationships will be weaker when learning
climate is positive and stronger when learning climate is negative.

A learning climate can also moderate the relationship between nurses’ expertise and commitment to care and medication errors. In a nursing unit in which learning from error is valued and emphasized, nurses who possess clinical expertise and are highly committed to patient care will tend to define their job obligations in a broad and flexible manner and extend their role definitions above and beyond their formal job responsibilities to patient safety issues, which may not be required by normal roles (i.e., organizational citizenship behaviors). According to organizational behavior researchers, commitment causes employees to define their job responsibilities more broadly and organizations with such employees will experience increased organizational effectiveness in the long run (Morrison, 1994; O'Reilly & Chatman, 1986; Podsakoff, MacKenzie, Paine, & Bachrach, 2000). Within a positive learning climate in which learning from errors is strongly encouraged, nurses who are clinical experts and highly committed to care are more likely to view error-related behaviors as part of their formal role responsibilities and initiate change consistent with the climate of the organization (Hofmann, Morgeson, & Gerras, 2003). Therefore, they will not only perform job duties that are expected of them by others but voluntarily participate in learning activities that are not required by their normal roles such as reporting their errors voluntarily, thinking about how to rectify them, and sharing the information on errors, participation that is strongly influenced by involvement in and commitment to the work.

In contrast, in a nursing unit in which a learning climate is negative, the chance of errors is likely to increase because asking for help raises stress and anxiety and nurses will be overly concerned about whether their self-esteem will be undermined (Cannon & Edmondson, 2001). Thus, they may hesitate to ask another nurse for help when they do not
quite understand what to do regarding a medication order prescribed because such behavior may make them look incompetent. Such behavior may yield an unnecessary delay in patient care and may eventually lead to medication errors that could have been prevented. In addition, nurses within a negative learning climate are discouraged from admitting or disclosing their errors. In other words, nurses may feel that the potential costs of reporting (such as effort, fear of reprisal, and damaged reputations) are far greater than potential benefits such as learning and preventing negative consequences (Zhao & Olivera, 2006). Because errors are covered up, nurses will not engage in such error-related activities as asking for help before or after they make mistakes, sharing information, or openly discussing errors. They may use a quick fix when they encounter an error, but because such experience is not shared it cannot prevent other nurses from making the same mistake in the future. In short, second-order problem solving, which goes beyond simply fixing a situation at hand, is not likely to occur.

Hypothesis 8 (H8): Learning climate will moderate the relationship between nurses’ expertise and medication error rates and commitment to care and medication error rates. Specifically, the relationships will be weaker when learning climate is positive and stronger when learning climate is negative.

Summary

This chapter drew hypotheses from a direct link between various error producing conditions and medication errors and an indirect link through a potential moderator (i.e., a learning climate). Based on the hypotheses developed in this chapter, Figure 5 illustrates the proposed framework for this dissertation. The next chapter addresses the research methodology utilized to evaluate the hypotheses.
Figure 5. Theoretical Framework and Proposed Hypotheses

**Error-Producing Conditions**
- Work Environment
  - Technology
  - Work Complexity
  - RN hour
  - RN Proportion
- Team Factors
  - Nurse-physician Communication
  - Nurse-pharmacist Communication
  - Commitment
  - Expertise
- Person Factors
  - Education
  - Unit Experience
- Support Services
  - Unit-dose system
  - CPOE
  - Transcribing orders
  - Automated med adm.
  - IV team services
- Patient Factors
  - Age
  - Health status
  - Previous hospitalization

**Accidents**
- Learning Climate
- Medication Errors
Chapter 4

RESEARCH METHODOLOGY

The overall purpose of this dissertation research was to develop and test a model integrating the human error model and the organizational learning model (Figure 5). Specifically, the research questions proposed in the first chapter are as follows:

1. What nursing unit characteristics contribute to medication errors?
2. How does a learning climate moderate the relationship between the selected error producing conditions and medication errors?

The current chapter outlines the research methodology to answer these questions.

Because the data for the current study were derived from the Outcomes Research in Nursing Administration Project (ORNA II), the first section of this chapter begins with an overview of the parent study, including a description of the study and the study purpose, research design, sample, data, and data collection procedures. The second section describes the current dissertation study. The next section delineates the justification for and procedures of model building and the final section describes issues related to analysis.

ORN II Study

The ORNA II study is a federally-funded research study by the National Institute of Nursing Research (grant number 2R01NR03149) and is officially titled “A Model of Patient and Nursing Administrative Outcomes” (P.I. Barbara A. Mark, 2001). The ORNA II study uses structural contingency theory (SCT) as its theoretical grounding, which assumes that organizational effectiveness depends on the way work is structured and the extent to which
work is compatible with the organizational environment and the task an organization seeks to accomplish. The study design of the ORNA project permits the investigation of relationships among organizational context (characteristics of the external, hospital, and nursing unit environments), structure (unit capacity, work engagement, and work conditions), and effectiveness (organizational and patient outcomes) (Figure 6).

Research Design

The ORNA II study uses a non-experimental, longitudinal causal modeling research design, with the nursing unit as the unit of analysis. It is non-experimental because it does not involve three essential characteristics of experimental designs (i.e., manipulation, control, and randomization) (Brink & Wood, 1998). Manipulation is the process of maneuvering the independent variable so that its effect on the dependent variable can be observed. The ORNA II study measured variables as they existed and therefore it is non-experimental. Randomization means that participants are assigned by chance to either the experimental group or the control group. Because there was no manipulation, having two groups (i.e., experimental and control) was unnecessary and randomization of the sample was not required. Such randomization is distinguished from random selection of samples: Although the ORNA II study randomly selected the participating hospitals from across the U.S., it did not randomly distribute the sample into the experimental and the control groups.

The ORNA II study design is longitudinal because the nursing unit measures were repeated at intervals during a six-month period. One of the strengths of a longitudinal design is that by measuring the same group of participants repeatedly over time it can avoid many of the confounding factors inherent in cross-sectional design. Therefore, a researcher can be more confident that the independent variable of interest is more responsible for the dependent
Figure 6. Outcomes Research in Nursing Administration Conceptual Framework

- External Environmental Characteristics
- Hospital Characteristics
- Nursing Unit Characteristics

Context → Structure → Effectiveness

Staffing Adequacy → Administrative Outcomes
Work Conditions → Patient Outcomes
variable than confounding variables (Menard, 1991; Pedhazur & Schmelkin, 1991).

A causal modeling design study must meet three basic requirements for testing causality: 1) association between the independent and the dependent variable, 2) temporal ordering when the cause unambiguously precedes an effect, and 3) isolation of the effect ruling out extraneous variables (Bollen, 1989; Bullock, Harlow, & Mulaik, 1994). As depicted in Figure 6, the ORNA II study proposed the context variables being related to the structure variables, and, in turn, the structure variables being related to the effectiveness variables. This proposition can be tested simply by examining whether these variables are correlated with each other. Regarding temporal ordering when the cause must precede an effect, the ORNA II study collected data in a way that the data on the context variables (i.e., external environmental, hospital, and nursing unit characteristics) were collected prior to those on the structure variables (i.e., staffing adequacy and work conditions), and the data on the structure variables prior to those on the effectiveness variables (i.e., patient and nursing administrative outcomes). More details on data collection follow in the data collection procedure section and Table 2. Unlike a cross-sectional design, a longitudinal design minimizes the effect of extraneous variables in explaining the dependent variable. As such, the ORNA II study possessed some features that enable the examination of causality (Davis, 1985). However, it is noteworthy that only in true experimental designs can plausible alternative explanations for observed relationships be eliminated or discredited (Brink & Wood, 1998).

Sample

Hospitals were invited to participate in the study if they were non-federal, not-for-profit, non-psychiatric, and JCAHO-accredited acute care facilities with at least 99 licensed
beds. Because the focus of interest was on the nursing unit, each hospital selected two nursing units from which the data were collected. If a hospital had only two eligible units, both participated; if a hospital had more than two eligible units, an on-site study coordinator selected the units that participated. Inclusion criteria for nursing units were “general” medical-surgical or medical-surgical specialty units (i.e., orthopedic, neurology, telemetry, step-down). Critical care, operating room, pediatric, obstetric, and psychiatric units were excluded. Nurses eligible to participate in the study were RNs employed on their unit for not less than three months. Patients eligible to participate were 18 or older, able to speak English, hospitalized on the unit for at least 48 hours, and not scheduled for discharge the day the questionnaire was completed.

Data

The data for the ORNA II study consisted of four levels: community/market, hospital, nursing unit, and individual. Community/market level data representing a hospital’s external environment included geographic region, managed care penetration, and urban/rural designation. Hospital level data contained information on the hospital’s general characteristics such as the number of licensed and maintained beds, the number of admissions and discharges, inpatient days, magnet hospital status, and teaching status.

Data on the nursing unit level were three-fold: personnel, outcomes, and financial data. The personnel data contained variables such as the number of full-time and part-time nursing personnel (i.e., RNs, licensed practice nurses or LPNs, and nurse aids), nursing care hours delivered by each type of nursing personnel, the number of vacant positions, the type of services the nursing unit provided, and the number of patient days and discharges. The outcomes data contained information on the number of medication doses administered,
medication errors, severe medication errors, patient falls, urinary tract infections. The financial data contained information on total operating budget (i.e., revenues and expenses), salaries for personnel (i.e., projected and budgeted), fringe benefit rates, productive time, non-productive time, and overtime.

At the individual level, the ORNA II study obtained data both from staff nurses and patients. Administering questionnaires at three different rounds, staff nurses provided information on their demographics as well as their perception of nursing practice on their unit such as the complexity of patient care, work dynamics, clinical expertise, commitment to care, autonomy, and job satisfaction. Patients were asked to what extent they were satisfied with the nursing care and symptom management they received during hospitalization.

Because the purpose of the ORNA II study is to test a theoretical model examining relationships among organizational context, structure, and effectiveness (Figure 6), an adequate sample size was needed, based on the power to differentiate between a good fitting model (RMSEA < .05) and a poor fitting model (RMSEA > .08) (MacCallum, Browne, & Sugawara, 1996). The original sampling frame for the ORNA II study calculated by this condition consisted of 320 nursing units from 160 hospitals. Because of dropouts common in longitudinal design studies, the final sample for the study consisted of 286 nursing units from 146 hospitals (Figure 7).

Data Collection Procedure

To avoid the complexity of dealing with an enormous amount of data, the ORNA II research team randomly divided hospitals by state into two groups and collected data from one group per year: Data were collected from the first group of hospitals from January to June 2003, and from the other group during the same period in 2004. The post-hoc analysis
<table>
<thead>
<tr>
<th>Category</th>
<th>No. of Eligible Sample</th>
<th>No. of Actual Sample (Response Rate)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospitals</td>
<td>160</td>
<td>146</td>
</tr>
<tr>
<td>Nursing Units</td>
<td>320</td>
<td>286</td>
</tr>
<tr>
<td>Time 1 Nurse Survey</td>
<td>6562</td>
<td>4954 (75%)</td>
</tr>
<tr>
<td>Time 2 Nurse Survey</td>
<td>6389</td>
<td>3718 (58%)</td>
</tr>
<tr>
<td>Time 3 Nurse Survey</td>
<td>6144</td>
<td>3293 (54%)</td>
</tr>
<tr>
<td>Patient Survey</td>
<td>2991</td>
<td>2722 (91%)</td>
</tr>
</tbody>
</table>
revealed no significant difference between the two groups in any aspect.

To meet proper time ordering of the independent variable and the dependent variable, data collection was completed in a sequential manner such that the data on hospital and nursing unit characteristics (i.e., unit size, support services availability, work complexity) were collected prior to the nurse and patient outcomes data (Table 2).

Each hospital appointed a study coordinator who was in charge of distributing and collecting questionnaires and obtaining administrative data. Study coordinators held various positions in the hospital such as staff nurse, nurse manager, educator, director, vice president, chief nurse executive, or nurse researcher. To enhance consistency in data collection procedures and data integrity, study coordinators participated in a 1 ½ day training session conducted by the ORNA II research team. The purposes of the training were to introduce the study, present the study aims and goals, review and clarify conceptual and operational definitions for the key data elements, describe detailed procedures for data collection, and share successful strategies in collecting data. Information presented in the training was incorporated into a hard-copy procedure manual given to each study coordinator. Members of the research team kept in touch with study coordinators through the entire data collection period and promptly answered any inquiries regarding the study.

During the data collection period, members of the research team reviewed all data to ensure data integrity and contacted study coordinators by phone, fax, or e-mail to resolve data discrepancies. Further, the research team completed calculations required for the measurement of selected variables to ensure that each hospital used the same formulae and corrected calculation errors.
Table 2. Calendar for Data Collection

<table>
<thead>
<tr>
<th>Name of Questionnaire</th>
<th>January</th>
<th>February</th>
<th>March</th>
<th>April</th>
<th>May</th>
<th>June</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospital Questionnaire</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Outcomes Questionnaire</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time 1</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time 2</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Financial Questionnaire</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Personnel Questionnaire</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time 1</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time 2</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Staff Nurse Questionnaire</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time 1</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time 2</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Time 3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Patient Questionnaire</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
</tr>
</tbody>
</table>

* Hospital characteristics from Hospital questionnaire; nursing unit characteristics from Time 1 Personnel and Time 1 Staff Nurse questionnaires; nurse and patient outcomes from Time 3 Staff Nurse and Patient questionnaires.
In order to ensure the highest response rates in this mail survey study, the ORNA II study implemented Dillman’s (1978) Total Design Method for the individual nurse questionnaires. The purpose of this method was to provide information about the survey in a cover letter to participants and emphasize the importance of their participation to the success of the study. During each data collection round, staff nurses received a study questionnaire followed in two weeks by a duplicate questionnaire and a letter reminding them about the importance of participation. Two weeks later, they received a second reminder letter, followed in another two weeks by a third reminder letter. The staff nurse response rates with the use of this method were 75% at the first round (ranging from 13.3% to 100%), 58% at the second round (ranging from 0% to 100%), and 54% at the third round (ranging from 0% to 100%).

In terms of the patient data, study coordinators selected 10 patients at random from each nursing unit and the patients provided data during the final month of data collection. Patients provided data on their demographics, perceived health status, and the history of previous hospitalization. The total number of eligible patients was 2,991, and the response rate was 91% (Figure 7).

Current Study

Although the ORNA II study was designed as a longitudinal study and collected data in a sequential manner for six months, the current study employed a descriptive, cross-sectional study design because most of the variables except for two (i.e., medication errors and RN hours) were measured at only once.

Table 3 illustrates the sources of the selected variables for the current study. This study only focused on the characteristics of nursing units so the hospital level data were omitted
Table 3. Sources of Selected Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Information Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Error-producing conditions</strong></td>
<td></td>
</tr>
<tr>
<td>Work Environment Factors</td>
<td></td>
</tr>
<tr>
<td>Care Complexity</td>
<td>Time 1 Staff Nurse Questionnaire</td>
</tr>
<tr>
<td>Work Dynamics</td>
<td>Time 1 Staff Nurse Questionnaire</td>
</tr>
<tr>
<td>RN Proportion</td>
<td>Personnel Questionnaire</td>
</tr>
<tr>
<td>RN hours</td>
<td>Personnel Questionnaire</td>
</tr>
<tr>
<td><strong>Team Factors</strong></td>
<td></td>
</tr>
<tr>
<td>Communication with Physicians</td>
<td>Time 2 Staff Nurse Questionnaire</td>
</tr>
<tr>
<td>Communication with Pharmacists</td>
<td>Time 2 Staff Nurse Questionnaire</td>
</tr>
<tr>
<td>Expertise</td>
<td>Time 1 Staff Nurse Questionnaire</td>
</tr>
<tr>
<td>Commitment to Care</td>
<td>Time 1 Staff Nurse Questionnaire</td>
</tr>
<tr>
<td><strong>Person Factors</strong></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>Time 1 Staff Nurse Questionnaire</td>
</tr>
<tr>
<td>Unit Experience</td>
<td>Time 1 Staff Nurse Questionnaire</td>
</tr>
<tr>
<td><strong>Support Services Availability</strong></td>
<td></td>
</tr>
<tr>
<td>Unit-dose system</td>
<td>Time 1 Staff Nurse Questionnaire</td>
</tr>
<tr>
<td>CPOE</td>
<td>Time 1 Staff Nurse Questionnaire</td>
</tr>
<tr>
<td>Automated medication administration system</td>
<td>Time 1 Staff Nurse Questionnaire</td>
</tr>
<tr>
<td>IV team services</td>
<td>Time 1 Staff Nurse Questionnaire</td>
</tr>
<tr>
<td>Transcribing orders</td>
<td>Time 1 Staff Nurse Questionnaire</td>
</tr>
<tr>
<td>Pharmacist consultation</td>
<td>Time 1 Staff Nurse Questionnaire</td>
</tr>
<tr>
<td><strong>Patient Factors</strong></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>Patient Questionnaire</td>
</tr>
<tr>
<td>Health Status</td>
<td>Patient Questionnaire</td>
</tr>
<tr>
<td>Previous Hospitalization</td>
<td>Patient Questionnaire</td>
</tr>
<tr>
<td><strong>Learning Climate</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Accidents</strong></td>
<td></td>
</tr>
<tr>
<td>Medication Errors</td>
<td>Outcomes Questionnaire</td>
</tr>
</tbody>
</table>
from the analysis. Likewise, financial data and Time 3 staff nurse survey data were not used. Although the ORNA II data included 286 nursing units, the final dataset for the dissertation consists of 279 nursing units due to missing values for the selected variables (Figure 8).

Measures

This section discusses the definition and measurement of the selected variables in the current study. Table 4 provides a summary of the variables.

Medication Errors

The variable medication error was a count of medication errors over the six months reported by the nursing unit. A medication error was defined as the wrong dose, wrong patient, wrong time, wrong drug, wrong route, or an error of omission (for example, the patient did not receive the ordered medication). Among the medication errors reported, the current study specifically examined severe medication errors because they are more clinically significant and are believed to have a decreased likelihood of reporting bias. Severe medication errors were defined as those resulting in increased nursing observation, increased technical monitoring, laboratory testing, radiographic testing, medical intervention, or transfer of the patient to another unit.

Under usual circumstances, one can capture the variation in medication error data over time by using monthly data instead of an aggregate measure, and consequently better explain how the trend of medication errors changes over the period. However, when the variation in medication error data is minimal, as is the case with ORNA II data, and the trend itself is not the issue of interest, an aggregate measure has the benefit of reducing measurement error and still keep high levels of stability because error of measurement is likely to be high and temporal reliability low when findings are derived from single observations (Epstein, 1979).
Figure 8. Creation of Sample

Time 1 Nurse Survey

Time 2 Nurse Survey

Patient Survey

Personnel Data

Outcomes Data

286 units

285 units

285 units

283 units

283 units

279 units

286 units

286 units

286 units
Table 4. Definitions and Measurement of Selected Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Measurement</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accidents</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medication Errors</td>
<td>Number of medication errors (wrong dose, wrong patient, wrong time, wrong drug, wrong route, or an error of omission) on the unit over six months that required increased observation, technical monitoring, laboratory testing, medical intervention or treatment, or transfer of the patient to another unit, as reported on unit incident reports.</td>
<td>Sum of medication errors reported on the unit during a 6-month period divided by patient days over the same period.</td>
</tr>
<tr>
<td><strong>Error-producing conditions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Work Environment Factors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Care Complexity</td>
<td>Nurses’ perceptions of the proportion of patients on each unit who have had complex problems</td>
<td>Average unit score of 14-item scale developed by Overton, Schneck and Hazlett (1977), Mark (1992), and Mark et al. (2004).</td>
</tr>
<tr>
<td>Work Dynamics</td>
<td>Nurses’ perceptions of the extent to which a nursing unit was characterized by frequent interruptions or unanticipated events</td>
<td>Average unit score of 7-item scale developed by Salyer (1996)</td>
</tr>
<tr>
<td>RN Proportion</td>
<td>Proportion of RNs</td>
<td></td>
</tr>
<tr>
<td>RN hour</td>
<td>Proportion of nursing care hours delivered by RNs</td>
<td></td>
</tr>
<tr>
<td>Team Factors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Communication with</td>
<td>Nurses’ perceptions of the degree of communication between nurses and physicians in terms of frequency, timeliness, and accuracy</td>
<td>Average unit score of 3-item scale developed by Gittel (2000)</td>
</tr>
<tr>
<td>Physicians</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Communication with</td>
<td>Nurses’ perceptions of the degree of communication between nurses and pharmacists in terms of frequency, timeliness, and accuracy</td>
<td>Average unit score of 3-item scale developed by Gittel (2000)</td>
</tr>
<tr>
<td>Pharmacists</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expertise</td>
<td>Nurses’ perceptions of clinical expertise of a nursing workgroup in terms of recognizing critical patient</td>
<td>Average unit score of 8-items scale developed by Minick et al.</td>
</tr>
<tr>
<td>Category</td>
<td>Description</td>
<td>Source/Description</td>
</tr>
<tr>
<td>------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td><strong>Commitment to Care</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Person Factors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>Proportion of nurses with BSN or higher</td>
<td>Proportion of nurses with BSN or higher</td>
</tr>
<tr>
<td>Unit Experience</td>
<td>Nurses’ unit experience in months</td>
<td>Average nurses’ tenure on the unit in months</td>
</tr>
<tr>
<td>Support Services Availability</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unit-dose system</td>
<td>Nurses’ perceptions of the degree of availability of each service (not available, inconsistently available, consistently available)</td>
<td>Ditto…</td>
</tr>
<tr>
<td>CPOE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Automated medication</td>
<td></td>
<td></td>
</tr>
<tr>
<td>administration system</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IV team services</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transcribing orders</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pharmacist consultation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Patient Factors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>Age in years as reported by patients</td>
<td>Average of the reported age obtained from all patients</td>
</tr>
<tr>
<td>Health Status</td>
<td>Patients’ perceptions of their health status, rated on a scale from 1-5 (with 1 being very poor and 5 being very good)</td>
<td>Average of patients’ reported health status</td>
</tr>
<tr>
<td>Previous Hospitalization</td>
<td>Patients’ reporting of whether they had been hospitalized in the past year (yes or no)</td>
<td>Average of patients’ reported hospitalizations</td>
</tr>
<tr>
<td>Learning Climate</td>
<td>Shared perceptions of nurses about their unit’s approaches to error management</td>
<td>Average unit score on the Error orientation scale developed by Rybowiak et al. (1999)</td>
</tr>
<tr>
<td>Patient Days</td>
<td>Total patient days for six months</td>
<td></td>
</tr>
</tbody>
</table>
In other words, by averaging over occasions, errors of measurement can be reduced and temporal reliability increased. Therefore, instead of using repeated data for six months, the current study used the total count of medication errors over the six months.

While it is true that medication errors should be related to the number of medication doses administered, this information was not available in many nursing units either because the units did not have a system to track the doses administered or because they only had a tracking system for the whole hospital, not for each nursing unit. Instead, because medication errors increase with the number of patient days (Roseman & Booker, 1995), the number of medication errors was adjusted for by the patient days over the same period of time.

**Error-Producing Conditions**

**Work Environment Factors**

**Care Complexity**

Care complexity (see Appendix 1) was measured using a 14-item Likert-type questionnaire developed by Overton, Schneck and Hazlett (1977) and twice revised by Mark (1992; 2003). Nurses were asked to estimate the proportion of patients on their unit who had complex problems (e.g., how many patients required the use of technical equipment, medications through central venous lines, or frequent monitoring). Items on this scale were anchored by five response options ranging from “a few (< 20%)” to “most (> 80%)” with higher scores indicative of higher patient acuity. The possible range of scores for this scale is 14 to 70. Cronbach’s alpha in the current study was 0.82.

**Work Dynamics**

This variable was measured by a seven-item Likert-type questionnaire that asked nurses about the extent to which their unit was characterized by frequent interruptions or
unanticipated events (Salyer, 1996). A sample item from the scale is “frequent movement of patients on and off the unit for diagnostic studies, procedures, etc., makes it difficult for nurses on this unit to do a good job” (see Appendix 2). Items on this scale were anchored by six response options ranging from “strongly disagree” to “strongly agree” with higher scores indicative of greater work dynamics. A possible range of scores for this scale is 7 to 42. This scale has a Cronbach’s alpha of 0.85 indicating strong internal consistency reliability.

**RN Proportion**

RN proportion was defined as the proportion of RNs on a unit, relative to all nursing personnel on the unit including LPNs, unlicensed nursing personnel, and other direct patient care staff. These RNs were agency, float, and per diem RNs as well as permanent RNs. To better reflect the number of RNs actually serving nursing care, RN proportion was measured by full time equivalents (FTEs) instead of the number of people. Further, RNs who spent less than 50% time in direct patient care were excluded.

**RN Hours**

RN hours were defined as the percentage of nursing care hours delivered by RNs (i.e., permanent, float and per diem, and agency RNs) relative to the care hours delivered by all nursing personnel (all types of RNs, LPNs, and unlicensed nursing personnel). RN hours ranged from zero to 100 percent.

**Team Factors**

*Communication with Physicians and Communication with Pharmacists*

These two variables were measured by using the Relational Coordination Scale (Gittell et al., 2000). The original Relational Coordination Scale is a five-point Likert-type scale asking health care providers in various disciplines to assess the quality of their collaboration
with each of eight other disciplines regarding four communication dimensions (frequency, timeliness, accuracy, and problem-solving) and three relationship dimensions (shared goals, shared knowledge, and mutual respect). The included disciplines were attending MDs, physical therapy, respiratory therapy, lab, case manager, pharmacy, radiology, and dietary. Gittell (2000) reported Cronbach’s alpha of .85 for the total scale.

Because of its focus on nurses, the ORNA II study asked nurses to evaluate their relational coordination with other health care providers. Among all, only physicians’ and pharmacists’ data were used for the current study because they are the two disciplines most frequently involved in medication errors along with nurses. Items on the four communication dimensions were anchored to response options ranging from “always” to “never” with higher scores indicative of better communication. Items on three relationship dimensions were anchored to response options ranging from “completely” to “not at all” or “everything” to “not at all,” with higher scores indicative of better relationship. A possible range of scores for these two seven-item scales is 7 to 35 and they had Cronbach’s alphas of 0.82 and 0.81, respectively.

**Expertise**

Nursing expertise was measured with eight items from the Nursing Expertise and Commitment to Care Scale (Minick, Dilorio, Mitchell, & Dudley, 2000). RNs were asked to rate the expertise of their nursing workgroup in terms of recognizing critical patient problems. A sample item from this scale was “Nurses on this unit act on the basis of their clinical understanding to get needed tests and/or implement immediate intervention when there is a decline in patient status.” Items were anchored to response options ranging from “strongly agree” to “strongly disagree,” with higher scores indicative of greater expertise. A possible
range of scores for this scale is 8 to 48. Cronbach’s alpha was 0.92 indicating strong internal reliability consistency.

Commitment to Care

Commitment to care was measured by using another eight items from the Nursing Expertise and Commitment to Care Scale (Minick et al., 2000) that asked RNs to evaluate the ability of nurses on their unit to initiate actions independently in response to patient problems. A sample item from this scale was “Nurses on this unit do not hesitate to ask another nurse when they do not understand what to do.” Items were anchored to response options ranging from “strongly agree” to “strongly disagree,” with higher scores indicative of greater commitment to care. A possible range of scores for this scale is 8-48. Cronbach’s alpha for the current study was 0.82.

Person Factors

Education Level

Education level was defined as the proportion of nurses on each unit whose highest education level was a bachelor’s degree or higher. Recall that the Hypotheses 3A and 3B (see p. 72) proposed an asymptotic relationship between education levels and medication errors, specifically a linear relationship followed by a plateau. While it was clear that the relationship was non-linear, the modeling method that would best represent the relationship was not obvious. In other words, because an asymptotic relationship can be exemplified by curvilinear, spline, or log models, the current study examined all three modeling methods to find the best fit model among them.

First, both linear and squared terms were used for the curvilinear model. To reduce a potential multicollinearity problem between the linear and squared terms, education level was
centered to the mean. The second method was to fit a linear spline to the data. A linear spline is a continuous piecewise linear function, which is a continuous function composed of straight lines. The motivation for using the linear spline is that any continuous regression function can be approximated arbitrarily well by a piecewise linear function (Horowitz, Loughran, & Savin, 1996). To determine the location of knots that define the cutoffs for the separate linear lines, bivariate plots between education levels and medication errors were examined. The plot looked a J-shape that had two separate linear lines and the lines met around 40% of education level. Thus, 40% was used as a knot and two variables were created to represent the two separate linear lines. Finally, to develop a log model, log values of education level were created. Because there were five nursing units that had zero proportion of BSN-prepared nurses, a minimal number (0.01) was added to the actual value of education level so that none of the observations were missed.

Unit Tenure

Unit tenure was defined as the average of each nurse’s experience on the current unit in months. Similar to the variable education level, unit tenure was also expected to have a non-linear relationship with medication errors. All three methods used for education level were also applied. First, centered values of linear and squared terms were used for a curvilinear model. The location of knots from a bivariate plot of experience and medication errors was less apparent than the education plot so the location of knots could not be identified from the plot. However, the literature on seniority has identified five years of job experience as a turning point of productivity (Jacobs et al., 1990): a significant linear contribution for the less than 5 years of experience group and a non-significant relationship between the more than 5 years of seniority group and their performance. Such literature implies that the 5-year point
may be a turning point in becoming an “expert” (Benner, 1982). Therefore, 60-months of experience was chosen as a knot. Finally, the log value of unit tenure was also calculated to test the log model.

Patient Factors

Age

Patient age was defined as the average age of patients who completed the questionnaire on each unit.

Health Status

This variable measured patients’ perception of their health status. Patients were asked to rate their health status in five categories from “very poor” to “very good.”

Previous Hospitalization

This was a dichotomous variable asking whether the patient had been hospitalized in the past year. “Yes” was coded as 1.

Support Services Availability

This variable was measured by using a sum of scores on the checklist in which nurses rated six medication-related support services as not available, inconsistently available, or consistently available. The original scale from which this scale was derived has 27 items including services from specimen pick up to social work services (alpha = .85) (Mark, 1992; Mark et al., 2003). This study only utilized data derived from six items on the following services: transcribing orders and placing information in patient charts, CPOE, unit-dose medication system, automated medication administration system, intravenous team services, and pharmacist consultation. Higher scores are indicative of greater availability of these services. A possible range of scores for this scale is 0 to 14.
Learning Climate

This variable was measured by using 13 items from the Error Orientation Scale developed by Rybowiak, Garst, Frese, and Batinic (1999). As discussed in the second chapter, the basic ideas of the error management approach are very similar to those of the organizational learning model. Although this scale was originally developed to measure the degree of error-oriented climate in a workplace, not a learning climate, because the items on the scale reflect learning climate dimensions such as employee willingness to reveal errors, degree of open communication about errors, and extent to which employees actively think about and diagnose the sources of errors, this scale was taken to represent the learning climate. This scale was entered as an interaction term to examine moderating effects of a learning climate. Items on this 5-point Likert-type scale were anchored by response options ranging from “strongly disagree” to “strongly agree,” with higher scores indicative of a stronger learning climate. A possible range of scores for the variables is 13 to 65. Cronbach’s alpha for this scale was 0.92 indicating strong internal reliability consistency.

Model Building

Recall that the variables hypothesized in Chapter 3 were selected because they have been identified as error-producing conditions in the literature review, and thus each is presumed to be a valid covariate in explaining medication errors independently. However, no studies have tested these variables collectively with a conceptual framework in a single study, and little is known about whether their distinct effects on medication errors would change when other covariates were in the model concurrently. In other words, because such covariates are expected to be correlated with one another to some degree, some may become insignificant when others are accounted for. Further, although there are no criteria regarding
the appropriate number of covariates, too many covariates compared to sample size may yield unstable, and thus less valid, coefficient estimates.

In the current study, the sample comprised of 279 nursing units. However, each of these units did not contribute independent information because they were clustered within 146 hospitals. That is, if the within-hospital correlation is moderate to high, the effective sample size is actually closer to 146, rather than 279. Further, the hospitals that had zero medication errors contributed less information than those that had some errors. In fact, 30% of sample nursing units had zero medication errors, and this lack of medication errors further decreased the effective sample size. One way to obtain stable and valid coefficient estimates with such a small sample size is to find the model containing the “best” set of variables that can maximize the explanatory power. The procedures and criteria used to arrive at the best-fitting, most parsimonious statistical model will be described in the next chapter.

Data Analysis

This section discusses the attributes of the data that should be considered for data analysis. Beginning with the issue of the unit of analysis, this section addresses two issues regarding the data (Poisson distribution and violation of independence assumption), followed by the plan of statistical analysis.

Unit of Analysis and Approaches to Data Aggregation

As in the ORNA II study, the unit of analysis of the current study was also at the nursing unit level. While most organizational outcomes studies have used a hospital as the unit of analysis, such studies cannot account for possible variation in work groups within the hospital. However, the literature on work groups suggests that each work group possesses a distinctive fashion of work processes that yield different levels of performance (Hackman,
1993). Even in a hospital, for example, nurse managers’ leadership styles play a distinctive role in shaping nurses’ willingness to report their medication errors (Edmondson, 1996), and head physicians’ leadership styles can either promote or hinder organizational learning (Lipshitz & Popper, 2000).

Several variables in this study (e.g., work environment factors, team factors, learning climate) were measured at the individual level using data from self-administered questionnaires and needed to be aggregated to the unit level to represent measurement at the nursing unit level. Theoretical justification for data aggregation was met because these variables were measured by asking staff nurses to respond to items referenced to their nursing unit. For example, rather than asking what individual nurses do or think, the items asked what nurses on their unit would do or think.

Statistical justification for data aggregation was based on the degree of agreement about the variables among nurses on each nursing unit. Klein, Dansereau, and Hall (1994) argue that to establish agreement, it is necessary to demonstrate that responses from group members (i.e., staff nurses) are more similar to each other than would be expected by chance. According to Bliese (2000), two approaches have been used to define “greater than chance similarity.” First, observed group variances were contrasted to some theoretical expected random variance by using estimates of agreement, $r_{wg}$. Second, within-group variance was contrasted to between-group variance by estimating the intraclass correlation coefficient or ICC(1). Each of these procedures provides an assessment of the extent to which lower level data are homogeneous within units, and neither is sufficient alone (Klein & Kozlowski, 2000a, 2000b).

$R_{wg}$ Statistics
The \( r_{wg} \) statistics, originally developed by James, Demaree, and Wolf (1984; 1993), are measures of interrater agreement within a single unit for a single measure, which indicate the extent to which different judges (i.e., individual nurses on a unit) tend to make exactly the same judgments about the rated subject (Tinsley & Weiss, 1975). Although James et al. designed two types of \( r_{wg} \) statistics, \( r_{wg} \) for a single-item scale and \( r_{wg}(J) \) for a multi-item scale, I will refer to both indices as the \( r_{wg} \) for simplicity. The \( r_{wg} \) is calculated by comparing an observed group variance to an expected random variance, which is observed if responses from group members form a uniform (i.e., rectangular) distribution (James et al., 1984). If the variability within a unit is substantially smaller than the variability expected by chance, then the resulting \( r_{wg} \) value suggests that it is justifiable to aggregate lower level data to the unit level of analysis (Klein & Kozlowski, 2000a). Although there is no agreement on the desirable \( r_{wg} \) values, the popular rule-of-thumb is that \( r_{wg} \) values equal to or greater than .70 demonstrate high consistency within groups and justify the aggregation within the group (Klein & Kozlowski, 2000a). As summarized in Table 5, the mean \( r_{wg} \) scores for the selected variables were over the 0.70 threshold, ranging from .80 to .96, and therefore indicated adequate within-unit agreement.

**Intraclass Correlation**

Reliability of the aggregated data was evaluated by the proportion of variance explained by group membership using the intraclass correlation coefficient or ICC(1) and mean rater reliability of the aggregated data using ICC(2). Both forms of the ICC are calculated from a one-way random-effect ANOVA in which the variable of interest is the dependent variable and group membership is the independent variable (Bliese, 2000). ICC(1) provides an estimate of the proportion of the total variance of a measure explained by unit
Table 5. Statistics for Data Aggregation

<table>
<thead>
<tr>
<th>Variable</th>
<th>r_wg</th>
<th>ICC(1)</th>
<th>ICC(2)</th>
<th>Eta-squared</th>
</tr>
</thead>
<tbody>
<tr>
<td>Care Complexiry</td>
<td>.9248</td>
<td>.1244</td>
<td>.7110</td>
<td>.1700</td>
</tr>
<tr>
<td>Work Dynamics</td>
<td>.7973</td>
<td>.1686</td>
<td>.7784</td>
<td>.2111</td>
</tr>
<tr>
<td>Communication with Physicians</td>
<td>.9491</td>
<td>.3551</td>
<td>.8779</td>
<td>.3302</td>
</tr>
<tr>
<td>Communication with Pharmacists</td>
<td>.9493</td>
<td>.3276</td>
<td>.8641</td>
<td>.3075</td>
</tr>
<tr>
<td>Expertise</td>
<td>.9563</td>
<td>.0872</td>
<td>.6233</td>
<td>.1361</td>
</tr>
<tr>
<td>Commitment to Care</td>
<td>.9210</td>
<td>.0853</td>
<td>.6176</td>
<td>.1343</td>
</tr>
<tr>
<td>Support Services Availability</td>
<td>.8367</td>
<td>.2623</td>
<td>.8603</td>
<td>.2984</td>
</tr>
<tr>
<td>Learning Climate</td>
<td>.9523</td>
<td>.2340</td>
<td>.7995</td>
<td>.2718</td>
</tr>
</tbody>
</table>
membership. Although there is no agreement upon target for the ICC(1), it is generally accepted that the larger the ICC(1), the greater the similarity among raters (James, 1982).

ICC(2) provides an estimate of the reliability of the group means within a sample (Bryk & Raudenbush, 1992; James, 1982; Klein & Kozlowski, 2000a). Other things being equal, the larger the group size, the larger the ICC(2) because group means based on many people per group are more stable and thus more reliable measures of group properties than are group means based on fewer people per group (Klein & Kozlowski, 2000a). ICC(2) values of .70 or higher indicate adequate group-level reliability.

As shown in Table 5, when compared to the rest of the variables, expertise and commitment to care have a relatively low ICC(1) (.0872 and .0853, respectively) and the ICC(2) for both variables is below .70 (.6233 and .6176, respectively). While such low reliability statistics may indicate low group membership or small between-group variability of those variables, and provide insufficient justification for aggregation, because there is no agreement upon desirable value for the ICC(1) additional steps were needed to make this determination. Klein and Kozlowski (2000a) pointed out that researchers usually have concluded that aggregation is justified when the \( F \) test for ICC(1) values is significant, which it is in this study. Further, low values for ICC(2) may well have been caused by small group sizes in the sample because the average number of nurses on nursing units was 17.32, less than 25, the cut point for large sample (Bliese, 2000; Klein & Kozlowski, 2000a).

**Eta-Squared**

The eta-squared value provides an estimate of the extent to which individual-level variability on a given measure is explained by higher level units. For example, an eta-squared value of .25 suggests that 25% of the variance in the measure is between-groups whereas the
remaining 75% of the variance is within groups (Klein & Kozlowski, 2000a). Eta-squared, like ICC(1), is calculated from a one-way random-effects ANOVA, in which group membership is the independent variable and the construct of interest (e.g., medication errors) is the dependent variable (Bliese, 2000).

The magnitude of eta-squared values and their significance of F test are highly dependent on the size of the groups in the sample. When group sizes are large, eta-squared values are more likely to be statistically significant and equivalent to ICC(1) values. However, when group sizes are small, usually less than 25 people per group, ICC(1) values and eta-squared values differ with eta-squared values showing significant inflation relative to the ICC(1) (Bliese, 2000). In this study, although the average number of nurses on nursing units was small at 17.32 so that the eta-squared values in Table 5 might have been inflated, ICC(1) values and eta-squared values were not dramatically different from one another and thus can be considered valid and stable values.

Poisson Distribution

Medication error data typically have a positively skewed distribution, with a substantial proportion of zero errors, gradually trailing off toward higher values. Such data often follow a Poisson distribution, a specific type of distribution in which scores take the form of a non-negative whole number or integer values (Hutchinson & Holtman, 2005). The use of ordinary least squares (OLS) estimation for this type of count data is problematic because OLS regression assumes normality in the distribution of error terms and thus in the dependent variable. Hence, OLS regression would yield biased and inefficient coefficients if count data are used without being transformed to address the effects of the positive skew (Wooldridge, 2000). One possible alternative approach to modeling medication errors is to apply Poisson
regression. Poisson regression models, a family of generalized linear models (GLMs), have “log” as the link function and Poisson distributed errors (Stokes, Davis, & Koch, 2001). A Poisson model uses a maximum likelihood estimation technique.

A true Poisson model assumes that the distribution of the dependent variable has a mean equal to its variance. In most practical circumstances, however, the observed variance is usually greater than the mean, which is known as overdispersion. When overdispersion is present, statistical corrections must be incorporated into the model to account for the overdispersion so that the Poisson model can still be used with corrected standard errors or a Poisson mixture model like the negative binomial distribution can be used. While the negative binomial model with log link from a generalized linear mixed model (GLMM) construction is possible, which is the model chosen for the current study, the GLMM with normal random effect has the advantage, relative to the negative binomial model, of providing a way of permitting multiple random effects and multilevel models (Agresti, Booth, Hobert, & Caffo, 2000). In the current study, overdispersion was accounted for by introducing a dispersion parameter $\phi$ into the relationship between the variance and the mean as follows:

$$\text{Var}(Y_i) = \phi \mu$$

where $\phi = 1$ is an ordinary Poisson model, and $\phi > 1$ is an overdispersed Poisson model (Pedan, 2001).

Violation of Independence Assumption

Another issue regarding the ORNA data is that, because nursing units, the unit of analysis in this study, are nested within hospitals, the assumption of independence cannot be guaranteed. In other words, because observations on subjects (i.e., nursing units) in the same
analyses of such data must take intracluster correlation into account rather than assuming independence among all observations. The standard errors will be incorrect unless this correlation is accounted for. In the case of a positive correlation as is the one between two nursing units within a hospital, the standard errors for regression coefficients will be underestimated and, therefore, statistical inferences using the underestimated standard errors will yield more significant results than they would using correct standard errors (Wooldridge, 2000).

When the sampling scheme uses a random sample of clusters (i.e., hospitals) with independent observations (i.e., nursing units) within each cluster, as was the case in the ORNA II study, one can account for the clustering by using random effects for the clusters (Agresti et al., 2000). Therefore, the current study employed random effects models, which allowed a separate intercept for each hospital in the study, under the constraint that these hospital-specific intercepts were normally distributed. In doing so, random effects models allow an unobserved effect for each hospital that is common to and influences each nursing unit in the given hospital (Sashegyi, Stephen Brown, & Farrell, 2000).

Statistical Analysis

To account for the issues addressed previously (i.e., Poisson distribution with overdispersion and non-independence), the current study employed a random effects Poisson model, a class of generalized linear mixed models (GLMMs) (Littell, Milliken, Stroup, & Wolfinger, 1996). The GLMM is an extension of ordinary linear models and permits both fixed and random effects in the predictor rather than only fixed effects (Agresti et al., 2000). While GLMMs are similar to generalized linear models (GLMs) in that they both deal with
categorical data, only GLMMs allow for several types of random effects (e.g., clustered or longitudinal data) in the linear predictor (Hedeker, 2005). The inclusion of random effects in the linear predictor reflects the idea that there is natural heterogeneity across clusters in their regression coefficients (Szyszkowicz, 2006). In the absence of random effects, GLMMs yield the same results as GLMs. GLMMs are also similar to mixed models in that they both can deal with multiple random effects, but only GLMMs can be used for categorical data.

GLMMs have several advantages especially related to this study because the data display 1) non-normality of the dependent variable, 2) correlation resulting from shared random effects due to clustering, and 3) overdispersion. To model the GLMMs, the current study employed the GLIMMIX procedure using SAS version 9.13 ("The GLIMMIX Procedure," Nov. 2005; SAS Institute, 2006). The modeling procedure required two considerations. First, medication errors needed to be standardized in a way to best reflect actual medication error rates. To do this, the model included the natural logarithm of the variable patient days as an offset variable so that the interpretation of the dependent variable could be made as rates, rather than counts, of medication errors. Second, two random effects were used in the model to account for clustering and overdispersion: Clustering of nursing units within the hospitals was accounted for by using “class” and “random” statements, and overdispersion of the medication error data was accounted for by adding a multiplicative overdispersion parameter with the “random _residual_” statement.

Summary

This chapter described the specific research methodologies used in this study. It began with an overview of the parent study, the ORNA II study, which included an introduction of the study and study purpose, research design, sample, data, and data-collection procedures.
The chapter continued with a description of the current study, followed by an introduction of the dependent and independent variables and their reliability and validity. It then provided the rationale for model building. Finally, it closed with a summary of the data analysis methods used, which included a discussion of the unit of analysis, Poisson distribution, violation of independence assumption, and proposed statistical analysis. The next chapter reports a summary of the results obtained in this study.
Chapter 5

RESULTS

Recall that the purpose of the current study was to develop and test a model that integrated the human error model with the organizational learning model. Specifically, this study investigated the characteristics of a nursing unit that contribute to medication errors and examined whether a learning climate moderated the relationships between error producing conditions and medication errors. This chapter describes the model building procedures used to reach the final model, presents the results of the statistical analysis, and reports the results of the research hypotheses postulated in Chapter 3.

Description of Study Variables

The current section provides information about the means, standard deviations, observed ranges, and correlations among the variables used in the dissertation study. As summarized in Table 6, nursing units in the current study sample had a very wide range of medication errors (range of 0 to 49 errors) over six months. On average, they had 3.71 medication errors and 4,800 patient days (range of 1,245 to 12,172 patient days) in six months, which is equivalent to 0.78 (range of 0 to 14.13 medication errors per 1,000 patient days) medication errors per 1,000 patient days. The average RN proportion of these nursing units was 59% (range of 23 to 100 percent of RNs) and their average RN hours were 62% (range of 28 to 100 percent of RN hours), meaning that 62% of nursing care hours was provided by RNs. Also, the nursing units employed, on average, a 37% BSN-prepared RN staff (range of 0 to 100 percent of BSN-prepared nurses) among total RNs, and the nurses’
Table 6. Descriptive Statistics and Correlations for Study Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>MEANS</th>
<th>S.D</th>
<th>Min.</th>
<th>Max.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Care Complexity</td>
<td>45.57</td>
<td>3.59</td>
<td>34.50</td>
<td>56.67</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Work Dynamics</td>
<td>26.84</td>
<td>3.50</td>
<td>15.79</td>
<td>37.40</td>
<td>0.17*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. RN Proportion</td>
<td>59.42</td>
<td>13.43</td>
<td>23.26</td>
<td>100.00</td>
<td>-0.02</td>
<td>-0.20*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. RN Hours</td>
<td>62.14</td>
<td>13.74</td>
<td>27.51</td>
<td>100.00</td>
<td>-0.05</td>
<td>-0.19*</td>
<td>0.72*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Comm with Physicians</td>
<td>25.36</td>
<td>2.22</td>
<td>15</td>
<td>30.31</td>
<td>-0.05</td>
<td>-0.34*</td>
<td>0.05</td>
<td>0.08</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Comm with Pharmacists</td>
<td>25.76</td>
<td>1.91</td>
<td>19</td>
<td>30.80</td>
<td>-0.22*</td>
<td>0.12*</td>
<td>0.11</td>
<td>0.44*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Expertise</td>
<td>42.44</td>
<td>2.09</td>
<td>34.28</td>
<td>46.89</td>
<td>-0.17*</td>
<td>0.16*</td>
<td>0.14*</td>
<td>0.27*</td>
<td>0.14*</td>
<td></td>
</tr>
<tr>
<td>8. Commitment</td>
<td>36.59</td>
<td>1.85</td>
<td>29.22</td>
<td>40.87</td>
<td>-0.14*</td>
<td>0.15*</td>
<td>0.14*</td>
<td>0.23*</td>
<td>0.16*</td>
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<tr>
<td>9. Education</td>
<td>36.52</td>
<td>19.36</td>
<td>0</td>
<td>100</td>
<td>0.12*</td>
<td>-0.06</td>
<td>0.21*</td>
<td>0.17*</td>
<td>-0.15*</td>
<td>-0.03</td>
</tr>
<tr>
<td>10. Unit Experience</td>
<td>138.49</td>
<td>45.38</td>
<td>43.57</td>
<td>322.80</td>
<td>-0.08</td>
<td>-0.05</td>
<td>0.03</td>
<td>0.06</td>
<td>0.06</td>
<td>0.00</td>
</tr>
<tr>
<td>11. Patient Age</td>
<td>56.91</td>
<td>7.53</td>
<td>36.71</td>
<td>78.25</td>
<td>0.20*</td>
<td>0.07</td>
<td>0.03</td>
<td>0.05</td>
<td>0.11</td>
<td>-0.02</td>
</tr>
<tr>
<td>12. Health Status</td>
<td>3.46</td>
<td>0.45</td>
<td>2</td>
<td>5</td>
<td>-0.04</td>
<td>-0.03</td>
<td>0.05</td>
<td>0.05</td>
<td>0.10</td>
<td>0.02</td>
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<tr>
<td>13. Previous Hospitalization</td>
<td>0.53</td>
<td>0.21</td>
<td>0</td>
<td>1</td>
<td>0.05</td>
<td>-0.06</td>
<td>0.07</td>
<td>0.08</td>
<td>0.00</td>
<td>0.10</td>
</tr>
<tr>
<td>14. Support Services</td>
<td>8.83</td>
<td>1.20</td>
<td>3.71</td>
<td>11.35</td>
<td>-0.09</td>
<td>-0.04</td>
<td>0.14*</td>
<td>0.12*</td>
<td>0.04</td>
<td>0.08</td>
</tr>
<tr>
<td>15. Learning Climate</td>
<td>48.04</td>
<td>3.94</td>
<td>28.00</td>
<td>56.75</td>
<td>0.00</td>
<td>-0.20*</td>
<td>0.14*</td>
<td>0.17*</td>
<td>0.43*</td>
<td>0.37*</td>
</tr>
<tr>
<td>16. Patient Days</td>
<td>4798.61</td>
<td>1676.31</td>
<td>1,245</td>
<td>12,172</td>
<td>0.08</td>
<td>0.25*</td>
<td>-0.04</td>
<td>0.00</td>
<td>-0.14*</td>
<td>-0.03</td>
</tr>
<tr>
<td>17. Medication Errors</td>
<td>3.71</td>
<td>6.05</td>
<td>0</td>
<td>49</td>
<td>-0.04</td>
<td>0.00</td>
<td>0.03</td>
<td>0.04</td>
<td>0.10</td>
<td>-0.01</td>
</tr>
<tr>
<td>18. Error Rates/1,000 pt days</td>
<td>0.78</td>
<td>1.39</td>
<td>0</td>
<td>14.13</td>
<td>-0.08</td>
<td>-0.11*</td>
<td>0.06</td>
<td>0.08</td>
<td>0.16*</td>
<td>0.01</td>
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Table 6. (continued)

<table>
<thead>
<tr>
<th></th>
<th>7</th>
<th>8</th>
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<th>10</th>
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<th>12</th>
<th>13</th>
<th>14</th>
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<tbody>
<tr>
<td>1. Care Complexity</td>
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<tr>
<td>2. Work Dynamics</td>
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<td>3. RN Proportion</td>
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<tr>
<td>5. Comm with Physicians</td>
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<td>6. Comm with Pharmacists</td>
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<td>8. Commitment</td>
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<td>10. Unit Experience</td>
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<tr>
<td>11. Patient Age</td>
<td>0.00</td>
<td>-0.04</td>
<td>-0.09</td>
<td>0.06</td>
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<tr>
<td>12. Health Status</td>
<td>0.13*</td>
<td>0.08</td>
<td>0.02</td>
<td>0.00</td>
<td>-0.05</td>
<td></td>
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<td>13. Previous Hospitalization</td>
<td>-0.03</td>
<td>-0.05</td>
<td>-0.04</td>
<td>0.03</td>
<td>0.06</td>
<td>-0.41*</td>
<td></td>
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<td>14. Support Services</td>
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<td>-0.04</td>
<td>-0.05</td>
<td>-0.01</td>
<td>0.09</td>
<td>-0.01</td>
<td>0.04</td>
<td></td>
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<tr>
<td>15. Learning Climate</td>
<td>0.42*</td>
<td>0.44*</td>
<td>0.03</td>
<td>0.02</td>
<td>-0.13*</td>
<td>0.05</td>
<td>-0.01</td>
<td>-0.02</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>16. Patient Days</td>
<td>0.00</td>
<td>0.02</td>
<td>0.05</td>
<td>0.01</td>
<td>0.08</td>
<td>0.03</td>
<td>0.01</td>
<td>0.03</td>
<td>-0.02</td>
<td></td>
<td></td>
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<tr>
<td>17. Medication Errors</td>
<td>0.05</td>
<td>0.04</td>
<td>-0.17*</td>
<td>0.05</td>
<td>0.10</td>
<td>-0.03</td>
<td>0.07</td>
<td>-0.04</td>
<td>-0.07</td>
<td>0.18*</td>
<td></td>
</tr>
<tr>
<td>18. Error Rates/1,000 pt days</td>
<td>0.06</td>
<td>0.04</td>
<td>-0.19*</td>
<td>0.06</td>
<td>0.07</td>
<td>-0.05</td>
<td>0.08</td>
<td>-0.07</td>
<td>-0.05</td>
<td>-0.02</td>
<td>0.93*</td>
</tr>
</tbody>
</table>

* Correlations are significant at the .05 level.
average unit tenure was 138 months (range of 44 to 323 months of unit tenure). In terms of patient characteristics, the average age of patients in the sample nursing unit was 57 years old (ranging from 37 to 78 years old), they rated their health status as moderate to good, and 53% (0 to 100) had experienced hospitalizations in the past year.

Table 6 also presents correlation coefficients among the variables. The count of medication errors was significantly correlated with two variables (education, r = -0.17; patient days, r = 0.18). When standardized by using 1,000 patient days, medication error rates were correlated with work complexity (r = -0.11) and communication with physicians (r = 0.18). Education (r = -0.19) still had a significant correlation with medication error rates, but patient days was no longer significant (r = -0.02).

**Multicollinearity**

Multicollinearity refers to the situation in which two or more independent variables are strongly, but not perfectly, correlated (Berry & Feldman, 1991; Fox, 1991). When two independent variables are highly correlated, they both convey essentially the same information so that neither may contribute significantly to the model after the other one is included. Although a high degree of multicollinearity does not violate the assumptions of regression, regression coefficient estimates tend to have larger standard errors than they would have in the absence of multicollinearity, and as a result, the statistical inferences would be wrong (Schroeder, Sjoquist, & Stephan, 1991).

As shown in Table 6, the overall correlations among the independent variables in the current study were below 0.70 except for two correlations: r = 0.72 between RN proportion and RN hours and r = 0.84 between expertise and commitment. Although the magnitude of these correlation coefficients is not greater than 0.90, a cutoff value recommended by
Tabachnick and Fidell (1996), correlations between 0.70 and 0.90 often raise concerns about multicollinearity.

According to Neter, Kutner, Nachtsheim, and Wasserman (1996), one of the indications of multicollinearity is estimated regression coefficients’ having signs opposite to those expected from theoretical considerations or prior experience. In fact, while both RN proportion and RN hours were positively correlated with medication errors, their coefficients yielded opposite signs (RN proportion was positive, while RN hours was negative) in the first run of the model (not presented here). Similarly, both expertise and commitment to care also had positive correlations with medication errors but their coefficient signs were different from each other in the first run of the model (expertise was positive, while commitment was negative). To make a decision on which variables should be removed, three aspects were considered. First, while both RN proportion and RN hours have been used as staffing variables in the literature, RN hours reflect the actual availability of nursing staffing whereas RN proportion reflects capacity of nursing staffing to perform nursing care when needed. In other words, RN hours can better measure actual day-to-day staffing situations than RN proportion. Expertise has been known to be a similar concept to experience and, in fact, expertise was significantly correlated with experience (r = 0.12) in this study (Table 6). Thus, RN proportion and expertise were less favored over RN hours and commitment to care.

Second, these four variables were expected to have a negative sign on medication error rates but RN proportion and expertise had positive signs in the first run of the model. Third, the model including RN hours and commitment to care yielded the best model fit among four models². Therefore, RN proportion and expertise and each of their interaction terms were

---

² Four possible combinations of model were run (RN hours and RN proportion × expertise
excluded from further analysis to prevent potential multicollinearity problems.

Model Building Procedures

The analysis proceeded in several steps before it reached the final model (Figure 9). Although the number of covariates and interaction terms decreased to 21 from 25 after the elimination of four variables (RN proportion and expertise and each of their interaction terms) due to possible multicollinearity, it was difficult to know whether the 25 variables were “appropriate” or whether there were “too many” variables compared to the sample size to yield stable and reliable coefficient estimates. One way to verify the validity of the model was to fit the same model using a GEE with negative binomial regression and examine whether the results of the GEE model were comparable with those of the original GLMM Poisson with random effects model. Although GLMMs are subject-specific (i.e., nursing unit) whereas GEEs are population-average models, in theory, these analyses should be comparable because they both can model count variables and account for overdispersion and clustering. In the first run of the model, the GEE model with negative binomial regression did not converge, implying that the result of the original GLMM with 25 variables may not have been stable and correct.

To reach the best-fitting, most parsimonious model with unbiased and stable coefficients, the next step involving variable reduction employed a backward elimination method. Backward elimination is preferred to forward selection, especially for non-linear models, because forward selection may exclude important covariates of the model and thus yield biased estimates. Backward elimination usually begins with a full model containing all the independent variables of interest, and then, at each step, the variable with the smallest $F$-
Figure 9. Model Building Procedures

25 Variables

→ Multicollinearity (4 variables excluded)
   RN Proportion, Learning Climate×RN Proportion,
   Expertise, Learning Climate×Expertise

21 Variables

→ 1st Reduction (2 variables excluded)
   Patient age
   Patient health status

19 Variables

→ 2nd Reduction (4 variables excluded)
   Commitment, Learning Climate×Commitment,
   Learning Climate×Communication with Physicians,
   Learning Climate×Communication with Pharmacists

15 Variables
statistic is sequentially removed until the $F$ is no higher than the chosen cutoff level. At each step, the full model and the reduced model were iteratively reevaluated to determine whether the reduced model performed better. Although automatic computerized elimination methods are available using statistical packages, such methods treat every variable with equal importance, which is not the case for the current study. In other words, because one of the purposes of this study was to test the moderating effect of a learning climate, this variable should not have been removed from the model even if its $F$-statistic was not significant, as long as at least one of the interaction terms remained significant. For a similar reason, interaction terms should be treated with more weight than direct effect variables to permit the investigation of the moderating effects.

To ensure these two conditions, backward elimination was performed manually with only the main effects of covariates entered first into the model so that potentially important interaction effects would not be eliminated inadvertently. At each iteration, the decision of whether or not to eliminate the least important variable was made based on the evaluation of relative model fit between the two models: the simpler model (reduced model) and the more complex model (full model). In this study, the full model included all the variables and the reduced model excluded variables with the smallest $F$-value.

Model fit was evaluated with two indices: significance of likelihood ratio test (LR test) and the relative size of Akaike Information Criterion (AIC) (Diggle, Heagerty, Liang, & Zeger, 2002). LR tests compare the relative fit of the reduced and the full model. If LR tests are not significant then the reduced model is preferred. The AIC index takes into account both the statistical goodness of fit and the number of parameters that have to be estimated to achieve this particular degree of fit by imposing a penalty for an increase in the number of
parameters. Lower values of the index indicate the preferred model, that is, the one with the fewest parameters that still provides an adequate fit to the data (Everitt, 1998). If the AIC of the reduced model was not greater than that of the full model, then the reduced model was preferred and the variable having the smallest $F$-value was eliminated. This procedure was continued until either the LR test became significant or the AIC of the full model was lower than the reduced model. Two variables (patient age, patient health status) were eliminated from this procedure so the number of the main effect variables decreased to 13 from 15.

The second stage was essentially the same except that the interaction terms were entered into the reduced model already containing 13 main effect variables. The same procedure was taken and two interaction terms (learning climate $\times$ communication with physicians, learning climate $\times$ communication with pharmacists) were eliminated. Further, commitment, which remained in the reduced model through the first stage, became insignificant in this stage when the interaction terms were entered so its main effect and interaction term (learning climate $\times$ commitment) were eliminated. As a result, the final model contained 15 variables, which included 10 main effects and three interaction terms (Figure 9).

Once the final reduced model was selected, three additional models using the three different specifications of education and experience variables (i.e., curvilinear, spline, log model) were evaluated. Model fit indices demonstrated that the curvilinear model using linear and squared terms fit the data better than the log model or the spline model (results not shown). Therefore, the curvilinear model was chosen as the final model.

Model Fit

The fit of the final model was significantly better than the fit of the initial model (LR
test = 0.34, p = .999; AIC for the full model = 946.85, as compared to the AIC for the reduced model = 934.51). Also, when contrast tests between the full and reduced model were performed, the $F$ test validated that the dropped variables were collectively insignificant so that they could be removed ($F = 0.10; \text{df} = 6, 113; p = 0.9964$). In other words, the reduced model performed no worse with fewer variables than the full model. Considering that the general rule of thumb of effective sample size (159 in this study)\(^3\) is to have at least 5 to 10 observations for each covariate, the final reduced model with 15 variables seems appropriate. Further, the GEE results provided sufficient validation of the GLMMIX results, so this final model is reasonable.

The estimate of the variance of the hospital-specific effects was 1.38. That means, 96% of random hospital effects lie between -2.35 to 2.35 ($\pm 2 \times \text{square root (1.38)}$) and the medication error rates spread as much as a 10.5-fold ($\exp^{2.35}$) across hospitals. In other words, as expected, there was significant hospital-to-hospital heterogeneity in medication error rates. Further, the residual covariance parameter was 1.15, indicating that the variability in these data has been properly modeled and that there was only a slight residual overdispersion. Values larger than 1 indicate the presence of overdispersion.

The quality of the fit of the final model was also examined with various plots of studentized residuals. The graph in the left corner of the panel displays studentized residuals against the linear predictor (Figure 10). The graph in the upper right-hand corner of the panel

\(^3\) Although the unit of analysis is at the nursing unit level, because nursing units are nested within the hospitals each nursing unit cannot provide full information independently and the effective sample size is less than 286 (number of nursing units). At the same time, because the nursing units are not perfectly correlated, the effective sample size is greater than 146 (number of hospitals). Although there is no way to calculate effective sample size for a non-linear model specifically, the calculation for a linear model ($n/(1+(m-1)\times\text{ICC}$, where $m$ = the cluster size (2 in the current study)) can provide a good estimation of what the effective sample size for a non-linear model would be. $159 = (286/1+(2-1)\times0.80)$. 

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Figure 10. Residual Plots
shows a histogram with overlaid normal density. A Q-Q plot and a box plot are shown in the lower cells of the panel. Overall, the residual plots indicate that the residuals of the final GLMM were approximately normally distributed and the chosen variance function is appropriate for these data (Figure 10).

Results of the Final Model

The current section summarizes the results of the hypotheses outlined in Chapter 3 that postulated both main effects and moderating effects. These hypotheses were proposed for work environment, team, person, and patient factors as well as medication-related support services. Because of the variables dropped during the model building process, this section discusses the results of only those that remained in the final model, which are 10 main effects and three moderating effects.

Table 7 lists the estimates, standard errors, and incidence rates from the final Poisson random effects model. Incidence rates were calculated by taking the exponents of coefficient estimates (i.e., $e^{\hat{\beta}}$). Incidence rates greater than 1 imply an increase in medication errors, while rates smaller than 1 imply a decrease. For example, if an incidence rate is 2, a one unit increase in the covariate leads to a twofold increase in medication error rates. Similarly, if an incidence rate is 0.5 a one unit increase in the covariate leads to a decrease by half in medication error rates.

When a moderating effect is present (or significant) the interpretation of a variable should be made with regard to the condition of moderator (i.e., high vs. low learning climate) and interpreting the main effect is not appropriate because the main effect holds true only if the moderator effect is not present (i.e., learning climate is zero). Therefore, for the three variables that had both moderating and main effects, if their moderating effect was
Table 7. The Effects of Selected Variables on Medication Errors

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>Standard Error</th>
<th>Incidence Rate</th>
</tr>
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<td>Intercept</td>
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<td>10.4419</td>
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<td>Care Complexity</td>
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<td>0.1875</td>
<td>1.3500</td>
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<td>0.1829</td>
<td>0.7135†</td>
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<td>RN Hours</td>
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<td>0.0542</td>
<td>0.8668*</td>
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<td>Communication with Physician</td>
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<td>0.0394</td>
<td>1.0730†</td>
</tr>
<tr>
<td>Communication with Pharmacist</td>
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<td>0.9629</td>
</tr>
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<td>Education</td>
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<td>0.0001</td>
<td>1.0002†</td>
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<td>Experience</td>
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<td>1.0001</td>
</tr>
<tr>
<td>Experience(^2)</td>
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<td>0.0000</td>
<td>1.0000</td>
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<td>0.9096</td>
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<td>Learning Climate</td>
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<td>0.8969</td>
</tr>
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<td>Care Complexity × Learning Climate</td>
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<td>0.0039</td>
<td>0.9943</td>
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<td>0.0038</td>
<td>1.0068†</td>
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<tr>
<td>RN Hours × Learning Climate</td>
<td>0.0029</td>
<td>0.0011</td>
<td>1.0029*</td>
</tr>
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</table>

* Significant at 0.05 level; † Significant at 0.10 level.
significant, the result of the main effect was not interpreted even if it was significant. Conversely, if a moderating effect was not significant the result of the main effect was reported.

**Work Environment Factors**

*Hypothesis 1A (H1A):* Higher levels of care complexity on nursing units are associated with higher medication error rates.

*Hypothesis 1B (H1B):* Higher levels of work dynamic on nursing units are associated with higher medication error rates.

*Hypothesis 1D (H1D):* Greater RN hours on nursing units are associated with lower medication error rates.

*Hypothesis 6A (H6):* Learning climate will moderate the relationship between work environment factors (i.e., care complexity, work dynamics, RN proportion, and RN hours) and medication error rates. Specifically, the relationships will be weaker when learning climate is positive and stronger when learning climate is negative.

Work environment has been known to contribute to the incidence of medication errors. Nursing units with poor work environments, characterized by high workload, frequent distractions, and short staffing, are likely to have more medication errors. Among the work environment factors, care complexity (H1A) and work dynamic (H1B) specifically represent workload and distractions, respectively. H1C was not examined because RN proportion was eliminated from the analysis because of a potential multicollinearity problem with RN hours. H1D hypothesized the effect of nursing staffing on medication errors.

The results of two hypotheses on care complexity (H1A and H6A) revealed that, while
care complexity was positively related to medication error rates, neither the direct effect nor the moderating role of learning climate in the relationship between care complexity and medication error rates was not statistically significant.

The moderating effects of learning climate were apparent in the relationships between work dynamics and medication error rates and between RN hours and medication error rates ($p = 0.08, p = 0.01$, respectively). In a close look at how a learning climate moderates the relationships, two interaction plots were drawn using the mean for learning climate and one standard deviation above and below the mean to generate regression lines (Aiken & West, 1991). Post hoc tests were performed to determine whether the slope of the simple regression lines significantly differed from zero (Figure 11 and Figure 12).

Figure 11 suggests at least three points. First, nursing units with high learning climates had greater medication error rates than those with average or low learning climates at all levels of work dynamics. Second, the difference in medication error rates between positive and negative learning climates was greater when work dynamics were high than when work dynamics were low. Finally, when learning climate was high, the relationship between work dynamics and medication error rates was positive, which is consistent with prior expectations. However, when learning climate is low or average, the relationship was negative. In other words, when learning climate is either low or average, a nursing unit with high work dynamic levels, i.e., frequent interruptions and distractions, was less likely to have high medication error rates.

A learning climate also moderated the relationship between RN hours and medication error rates. While $\alpha = 0.05$ is frequently used as a cutoff value for significant tests, because the purpose of the current study was to develop and test a model and the model is in the early stages of exploration, I would like to explore the incidence rates when $p < 0.10$. 

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4 While $\alpha = 0.05$ is frequently used as a cutoff value for significant tests, because the purpose of the current study was to develop and test a model and the model is in the early stages of exploration, I would like to explore the incidence rates when $p < 0.10$. 

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error rates, and the results were similar to that found from the moderating effect between work dynamics on medication error rates (Figure 12). First, nursing units with positive learning climates had higher medication error rates than those with average or negative learning climates at all levels of RN hours. In contrast, nursing units with negative learning climates had lower medication error rates than those with average or positive learning climates at all levels of RN hours. In addition, the difference in medication error rates between positive and negative learning climates was far greater when RN hours were high than when RN hours were low. Further, when learning climate was high, the relationship between RN hours and medication error rates was positive, meaning that as nursing units had more RN hours they had greater medication error rates. However, when learning climate is low or average, RN hours was negatively associated with medication error rates.
Figure 11. Moderating Effects of Learning Climate in the Relationship Between Work Dynamics and Medication Errors.
Figure 12. Moderating Effects of Learning Climate in the Relationship Between RN Hours and Medication Errors.
Team Factors

Hypothesis 2A (H2A): Better nurse-physician communication is associated with fewer medication errors.

Hypothesis 2B (H2B): Better nurse-pharmacist communication is associated with fewer medication errors.

Four variables of team factors were originally hypothesized in chapter 3. However, expertise was dropped because of possible multicollinearity with commitment, and commitment was eliminated during the model building process. Hypothesis 2A postulated that better nurse-physician communication would be associated with fewer medication errors. Contrary to what was hypothesized, the level of nurses’ communication with physicians had a positive association with medication error rates, and the relationship was marginally significant (p = .08). In other words, a nursing unit in which nurse-physician communications are more frequent, timely, and accurate is more likely to have high medication error rates. Other things being equal, a one-point increase in the communication with physician scale increased medication errors by 1.07 times. For example, nursing units that have one medication error per 1,000 patient days will experience 1.07 medication errors per 1,000 patient days when they increase the score on the communication with physician scale by one point. Similarly, those that have two medication errors per 1,000 patient days will experience 2.14 (1.07×2) medication errors per 1,000 patient days under the same situation. Communication with pharmacists was negatively related to medication error rates as hypothesized, but this relationship was not significant. Therefore, neither Hypothesis 2A nor 2B was supported.
Person Factors

Hypothesis 3A (H3A): Educational preparation of the nursing workgroup will have an initially linear then asymptotic relationship with medication errors.

Hypothesis 3B (H3B): Experience of the nursing workgroup will have an initially linear then asymptotic relationship with medication errors.

Hypotheses 3A and 3B postulated that nurses’ education and experience would have an asymptotic relationship with medication error rates. As hypothesized, nurses’ education had a negative effect on medication error rates with a diminishing marginal effect, and this relationship was significant (p = .07 for education squared)\(^5\). Specifically, as the level of nurses’ education increased, medication error rates decreased until a nursing unit had 39% of RNs on the unit. After this point, however, this relationship did not continue, and the shape of the curve was almost flat.

Because the relationship is non-linear, the change in medication error rates resulting from the change in education level should be interpreted with regard to the level of education. In other words, a 10% increase in education level when the education level is 30% is different from a 10% increase when the education level is 50%. In detail, when a nursing unit had 20% of RNs on the unit, a 20% increase (20% to 40%) in nurses’ education level decreased medication error rates by 0.93 times\(^6\). To illustrate, if a nursing unit with 20% of RNs increased its RN participation to 40%, their medication error rate would be 0.93 times the initial rate.

\(^5\) When testing a curvilinear relationship using a linear and a quadratic term, regardless of the linear term, it is considered significant as long as the quadratic term is significant.

\(^6\) Because the education variables were centered to the mean, the incidence ratio was calculated using the difference from the mean (e.g., 40%-36.52% (mean of education level) = 3.48 and 20%-36.52% = -13.48) instead of the actual percentage (40% or 20%). 

\[ 0.99893^{3.48-(-13.48)} \times 1.0002^{3.48-2(-13.48)2} = 0.93 \]
BSN-prepared nurses had one medication error per 1,000 patient days, it would experience 0.93 errors per 1,000 patient days when its proportion of BSN-prepared nurses increased by 20%. Similarly, if the nursing unit had two medication errors per 1,000 patient days, it would experience 1.86 (0.93 × 2) errors per 1,000 patient days under the same situation. However, increases in the proportion of BSN-prepared nurses, especially above 39%, did not contribute to a change in medication errors – that is, on units that employed a proportion of BSN-prepared nurses greater than 39% rate, medication error rates actually increased. For example, a 10% increase in nurses’ education level from 40% to 50% increased medication error rates by 1.02 times and a 20% increase from 40% to 60% increased medication error rates by 1.09 times.

In contrast, a 20% decrease in nurses’ education level when a nursing unit had 40% (40% to 20%) increased medication error rates by 1.07 times. To illustrate, if a nursing unit with 40% of BSN-prepared nurses had one medication error per 1,000 patient days, it would experience 1.07 errors per 1,000 patient days when its proportion of BSN-prepared nurses decreased by 20%. However, a 20% decrease from 60% to 40% leads to a decrease in medication error rates by 0.88 times, implying that an appropriate proportion of BSN-prepared nurses in a nursing unit for minimum medication errors may be around 40%.

Nurses’ experience did not have a significant association with medication errors. Therefore, Hypotheses 3A was partially supported and 3B was not supported.

Patient Factors

Hypothesis 4 (H4): Higher age, poorer health status, and previous hospitalizations will be associated with more medication errors.
Age and health status were eliminated from the model in the second stage of variable reduction, so only previous hospitalization was tested in Hypothesis 4. H4 postulated that previous hospitalization of the patient would be positively associated with medication error rates. As hypothesized, the direction of the relationship was positive, and a nursing unit in which a large proportion of patients had experienced a hospitalization in the past year was more likely to have increased medication error rates, but this relationship was not significant. Therefore, Hypothesis H4 was not supported.

Support Services

Hypothesis 5 (H5): Greater availability of medication-related support services will be associated with fewer medication errors.

Hypothesis 5 postulated that nursing units with greater availability of medication-related support services would have fewer medication errors. As hypothesized, the relationship between the availability of medication-related support services and medication error rates was negative, but it was not statistically significant. Therefore, Hypothesis 5 was not supported.

Summary

This chapter described the procedures used to reach the most parsimonious model and described the results of the final model. The final model retained 15 variables (10 main effects and three interaction terms), and the fit of the final model was still as good as the fit of the initial model before the model building process was done. The findings from the final model can be summarized as follows. First, learning climate moderated the relationships between work dynamics and medication errors and between RN hours and medication errors.
Second, nurse-physician communication was positively related to medication error rates.

Third, education had an asymptotic relationship with medication error rates. These findings are summarized in Figure 13. The next chapter discusses the results of the analyses presented in this chapter. Further, it presents the implications of the findings for policy and practice, recommends the direction of future research, and discusses the limitation of the current study.
Figure 13. Summary of Significant Relationships

**Error-Producing Conditions**

- Work Complexity
- RN hours
- Nurse-physician Communication
- Education

**Accidents**

- Medication Errors
- Learning Climate

Relationships:
- Work Complexity to Medication Errors: (+)
- RN hours to Medication Errors: (-)
- Nurse-physician Communication to Medication Errors: (+)
- Education to Learning Climate: (-)
- Medication Errors to Learning Climate: (+)
Chapter 6

DISCUSSION

The purpose of the current study was to test a theoretical model integrating the human error model and the organizational learning model. Specifically, the human error model, which focuses on finding latent and active systems factors, guided the identification of error-producing conditions at the nursing unit level that have been suggested in the previous literature as contributing factors to medication errors. The error-producing conditions examined in this study encompassed work environment factors, team factors, personal factors, patient factors, and medication-related support services. To examine the extent to which these conditions affect medication errors, the current study investigated direct relationships between these factors and medication errors. The organizational learning model was the basis of the investigation for the role of learning climate as an error management strategy. Specifically, the current study explored whether a learning climate moderated the hypothesized relationships between certain error producing conditions and medication errors.

This chapter discusses the findings for the hypotheses presented in the previous chapter. Because some variables were dropped in the model building procedure described in Chapter 5, the current chapter discusses only the hypotheses that remained in the final model. It begins with the discussion of the results of hypotheses testing, followed by theoretical, policy, and practice implications of the findings. It then provides limitations of the study and closes with suggestions for future research.
Hypotheses Testing

The following section discusses results for each of the hypotheses.

Care Complexity

Care complexity was tested for its main and interaction effects on medication errors. Hypothesis 1A, which purported that care complexity was associated with greater medication error rates, was not supported. However, the results indicated that, although not statistically significant, the direction of the relationship (positive) is consistent with findings from previous studies (e.g., Chuo, Lambert, & Hicks, 2007; Hicks, Becker et al., 2004; Hicks, Cousins, & Williams, 2004; Kellogg & Havens, 2006; Tang, Sheu, Yu, Wei, & Chen, 2007; Taxis & Barber, 2003). Hypothesis 6A, which examined the moderating effect of learning climate in the relationship between care complexity and medication errors, was also not supported.

One of the reasons that neither hypothesis was supported may be related to the relatively small contribution of care complexity to medication error rates. In other words, when similar work environment factors (e.g., work dynamics, RN hours) have been accounted for, much of the variance in care complexity may have been explained by these variables. As a result, care complexity may not have enough “independent” explanatory power to predict medication error rates. In fact, care complexity was significantly correlated with work dynamics ($r = 0.17$) and education ($r = 0.12$), both of them a significant predictor of medication error rates, and therefore, these variables may have taken much of the variance of care complexity in medication error rates.

Another possibility may be related to the small variance in this variable across the nursing units. The mean and standard deviation of care complexity were 45.57 and 3.59,
respectively, and the possible range was from 14 to 70. These numbers suggest that, compared to its wide possible range, most nursing units had moderate levels of care complexity with minimal variations and such limited variability may have been insufficient to fully capture the effect of care complexity on medication errors. In fact, the ORNA study collected data only from general medical, surgical units and their specialty units such as neurology, nephrology, or oncology units in order to keep homogeneity in the nature of nursing work. Therefore, limited variance in care complexity may have been an inherent issue from the beginning.

Care complexity, which is reflective of workload, was measured as nurses’ perceptions of the proportion of patients who had complex problems and needed frequent care changes. Under conditions of high patient load, nurses may be required to care for more than one seriously ill patient, increasing stress and the number of tasks to be dealt with, or they may have to do several things at once, all of which can lead to errors in patient identification and, thus, to medication errors (Haw, Dickens, & Stubbs, 2005). In such conditions, nurses may be less attentive to strictly following the “five rights (i.e., right patient, right time, right dose, right route, and right drug)” of medication administration than they would under normal or low patient load conditions. In fact, failure to follow the five rights has been frequently identified as a cause of medication errors and such a tendency is especially likely to occur when nurses have several severely-ill patients to care for or they are behind schedule (Kellogg & Havens, 2006). For example, Cohen and colleagues (2003) found in their survey study that only 57% of 775 nurse respondents answered that they confirmed patients’ identity by checking the ID bracelet before administering any medication. This implies that, once nurses get to know their patients well during a shift, they may feel that they can skip
checking patient identity. These researchers also reported that, even when nurses administer new medications, if they are very busy, they may not check for allergies by asking the patient and checking the patient’s chart, ID bracelet, or medical administration record. Further, when nurses receive an oral or telephone order, they may not write it directly on the patient’s chart. In fact, only 66% of the nurses responded that they write the order directly on the patient’s chart and then read back the name of the drug, dose, and route to the prescriber. Needless to say, orders given orally, either in person or over the telephone, are errors waiting to happen. Therefore, potential for errors will be increased when workload is high and nurses feel time pressure because they may attend to tasks they think are more important than something like ID checking.

Work Dynamics

The results of Hypothesis 1B, which proposed that work dynamics would be positively associated with medication error rates, were unexpected: The direction of this relationship was negative, contrary to what was expected, and it was significant at the $\alpha = 0.10$ level. In other words, as the level of work dynamics increased, a nursing unit had lower reported medication error rates. However, a closer examination of the moderating effect of learning climate in the relationship between work dynamics and medication error rates (Hypothesis 6A) revealed that, when learning climate was positive the relationship between work dynamics and medication errors was also positive, which is consistent with what was originally expected, whereas when learning climate was negative the relationship was negative (see Figure 11, p. 131). The results also showed that medication error rates were higher on nursing units with a positive learning climate than on units with a negative learning climate. Further, the difference in medication error rates between nursing units with positive
learning climate and those with negative learning climate was greater when work dynamics were high than when work dynamics were low.

The reason for these results is not clear. The current study attempted to minimize potential problems of under-reporting by using only severe medication errors -- these errors are less likely go unnoticed or unreported due to their clinical significance – so this approach should have eliminated the possibility of reporting bias problems. However, despite such efforts, unexpected relationships between work dynamics and medication error rates by the level of learning climate seem to suggest that such an approach may not have resolved completely the problem of under-reporting (Figure 11).

The literature has frequently noted the presence of reporting bias when investigating medication errors (e.g., Kellogg & Havens, 2006). In fact, the result that more medication errors were found under positive, rather than negative, learning climate is not new. For example, in a study that explored how group and organizational level factors affect medication errors, Edmondson (1996) found the existence of positive correlations among ADEs, willingness to report errors, and nurses’ perceptions that making a mistake in their nursing unit will not be held against them. In other words, while ADEs are expected to have minimal reporting bias problems because they have harm to patients, they, not to mention non-severe medication errors, are also subject to willingness to report and a nursing unit’s error orientation.

The results may also hint at the possibility of under-detection. Under-detection is not a well-known concept or currently in the literature so that the following discussions are speculative. However, it may help explain the seemingly contradictory results. Under-detection is different from under-reporting in that while the former occurs when an error is
not found or identified, the latter is concerned with an intentional choice not to report an error when there is one. Although the concept of under-detection has not been widely introduced in the health care literature, it is plausible especially because nurses work shifts. For example, if a patient experiences a medical problem due to a medication error but no one, including the nurse who made the error, realizes that an error has been made, it will not be discovered or classified as a medication error.

As an example, consider that a day nurse noticed one of her patients who had had a myocardial infarction felt nauseated at noon. She notified the patient’s doctor and got an order of 12.5 mg of IV phenergan, which is supposed to relieve the patient’s symptom. However, the nurse accidentally gave the patient a vial of the drug, which is 25 mg, without realizing it. After a while, the patient’s symptom subsided and the nurse went off duty with no awareness of her mistake. Since the patient did not complain again about his nausea, the nurse did not communicate this information during change of shift report. By 4 pm, however, when the evening nurse was making rounds, she could not awaken the patient and found the patient’s blood pressure too low - one of the side effects of phenergan. She looked in the patient’s medical chart but nothing appeared out of the ordinary, because the day nurse recorded the 12.5 mg of phenergan she thought she gave rather than the 25 mg she actually gave. Further, the day nurse did not inform the coworker of anything particular from the regular care the patient had received. Because the evening nurse was busy, she did not have enough time to speculate about what might have gone wrong. She did not think about the possibility of medication error and the case was closed without being classified as medication error.

Although it is true that most errors, especially severe errors, will be discovered after
thorough retrospective inspection of what might have gone wrong if a patient shows unexpected but clinically severe symptoms, it is also true that not all errors will be found. For example, in the case of the previous example, nurses on the unit may have investigated the root cause of the event and some nurses may have become suspicious of the day nurse for giving a wrong dose of phenergan. However, because the day nurse did not believe, or even think of the possibility, that she made an error and there was no evidence of her making an error, this event cannot be found as a medication error.

Such a scenario is particularly plausible when work dynamics are highly stressful because, if a nurse’s work is interrupted and she becomes distracted, she may not even realize that she is making an error. The results of Hypothesis 6A actually support the existence of under-detection. When work dynamics are highly stressful, in other words, on nursing units where patients are admitted, discharged, or transferred frequently, nurses may not have enough time to get to know their patients well or learn relevant information about them. Frequent movement of patients on and off the unit for diagnostic studies or procedures will keep nurses busy following up their assignments and nurses may feel that they do not have enough control over the patients or the situation they face. Further, frequent order changes may result in confusion and make it difficult to follow up. Such situations are errors waiting to happen. High work dynamics are more likely to create conditions contributing to errors and, thus, there would be even more errors to detect under stressful work dynamics. However, the extent to which the errors will be found depends on learning climate. In other words, if learning climate is positive nurses will be aware of the possibility of making errors and make an effort to look after potential errors. However, if learning climate is negative, nurses will not take time to reconsider if they may have done something wrong. In contrast, when work
pace is slow and nurses have enough time to complete their work, regardless of learning climate, chances for errors will be low and error-detecting will be less important issues than when work dynamics are high.

The results of Hypothesis 6A also support the existence of under-reporting. When a nursing unit has a positive learning climate, nurses on the unit may not have to worry excessively if their mistakes will be held against them so they are likely to make the effort to report errors. Further, nurses may feel more comfortable talking about others’ as well as their own errors so they may be less hesitant to initiate an incident report when they become aware of another nurse’s mistake. Therefore, reported, rather than actual, error rates may seem higher when a learning climate is positive than when a learning climate is negative. Indeed, nurses’ willingness to report a medication error is an illustration of proactive, learning-oriented behavior, which contributes to the prevention of future errors. However, if a nursing unit has a negative learning climate, even if nurses found their error they may choose not to report it. Similarly, in the case of the previous example, even if the evening nurse caught the day nurse’s mistake she may decide not to report it because she may not want to put the day nurse in trouble, may think that reporting someone else’s error is “not my business,” or does not feel as much obligated to report as when it was her own error. In fact, in a survey asking nurses about medication errors, only 34% of nurses working in hospitals responded that they would initiate an incident report when they caught another nurse’s mistake (Cohen et al., 2003). In short, even when an error was detected there still is a chance of not being reported.

**RN Hours**

The result of Hypothesis 6A indicated that nursing units with a positive learning climate had greater medication error rates than those with average or negative learning
climates at all levels of RN hours. Also, the difference in medication error rates between positive and negative learning climates was far greater when RN hours were high than when RN hours were low. Further, whereas the relationship between RN hours and medication error rates was positive when learning climate was positive, it was negative when learning climate was negative or average (see Figure 12, p. 132).

In addition to the results of work dynamics, these results are also unexpected. Most previous studies have found a negative association, either linear or non-linear, between RN hours and medication errors, implying the more RN hours the fewer errors (e.g., Blegen et al., 1998; Seago et al., 2006). However, the current study results yielded two distinct, positive and negative, results between RN hours and medication error rates depending on the level of learning climate. This may suggest that, without accounting for the role of learning climate, any investigation of the relationship between RN hours and medication errors may be incomplete. In fact, same as other previous studies, the current study also found a negative association when looking at the “overall” relationship (Hypothesis 1D). However, such relationship appears an average of two “true” relationships, which can be either positive or negative, depending on the level of learning climate, suggesting that looking at the “overall” relationship only may mask the “true” relationships between RN hours and medication errors.

The result that more errors occurred under a positive learning climate is related to increased error-reporting and error-detecting. According to organizational learning theory, nursing units in which nurses are actively involved in learning behaviors will eventually experience reduced medication errors. However, such units may find more errors in the short run because nurses are more likely to admit their mistakes and report them instead of keeping the mistakes to themselves. Even when nurses discover others’ mistakes, they may not feel
guilty about filing an incident report so error-reporting rates will be high in the unit with positive learning climate. Further, because these nurses are attentive to the possibility of errors they always anticipate that errors might occur, and their error-detection rates also will be high.

The results also showed that the difference in medication error rates between a positive and negative learning climate was greater when RN hours were high than when RN hours were low. When RN hours are low, nurses’ first priority will be fulfilling patient care needs, regardless of the learning climate on the unit. In other words, nurses may be busy performing what they are assigned to do and they may not have enough time to look back at what they might have done wrong or care for finding others’ errors. On the other hand, in a nursing unit with high RN hours, perhaps due to excess workers, nurses may not have to engage in shortcuts to get the work finished quickly. They may devote their time to close patient care by building heightened levels of redundancy in the surveillance and supervision of each other’s performance. In a positive learning climate, for example, nurses are encouraged to engage in second-order problem solving activities such as frequent communications and open discussion about errors and, thus, their reported and detected error rates may look high. In fact, Blegen (personal communication, June 28, 2007) recently found higher error rates on better staffed nursing units. She also found that nurses on better staffed units were more likely to report the errors and concluded that the higher error rates with higher staffing is most likely an artifact due to higher reporting of errors on better staffed units. In contrast, even on the unit with high RN hours, if a learning climate is negative, nurses may be content with first-order problem solving methods and look for other things to do when they have extra time. Therefore, the difference in “observed” or “detected” medication error rates
between positive and negative learning climate will be large.

**Communication with Physicians/Pharmacists**

Hypotheses 2A and 2B that nursing units with better nurse-physician and nurse-pharmacist communication would have lower medication error rates were not supported. The result of Hypothesis 2A showed a positive, rather than negative, association and it was marginally significant (p = 0.08). That is, better nurse-physician communication was associated with more medication errors. Hypothesis 2B on nurse-pharmacist communication yielded a negative relationship as hypothesized but it was not statistically significant.

One possible explanation for these unexpected findings could be related to how the variables were measured. The scales for nurse-physician and nurse-pharmacist communication each consist of three items asking nurses about the frequency, timeliness, and accuracy of communication with physicians/pharmacists, one item asking physicians/pharmacists’ attitude toward an error, and four items asking the extent to which physicians/pharmacists know about the work of nurses, respect the work of nurses, or share the goals for patients with nurses. As such, these items may represent several constructs that may or may not directly be related to medication errors. For example, while the first three items seem to have a direct relationship to medication errors, the last four items are likely to measure more abstract and overall relational coordination than error-focused communication patterns. To isolate only error-focused communication patterns, a further analysis was performed using only the first three items of frequency, timeliness, and accuracy of communication. However, the results yielded no difference (nurse-physician communication, p = 0.0761 to p = 0.1510; nurse-pharmacist communication, p = 0.4027 to p = 0.3077) and, therefore, the measurement issue should not be a reason for the unexpected results.
Another possible explanation could be related to disparate communication styles between nurses and physicians and nurses and pharmacists. Nurse-physician communication can be very broad. They communicate about almost everything related to patient care such as daily care plans, admissions/discharges, care schedules, procedures, labs, or symptom changes, not just about medications. For this reason, nurses may have rated the perception of their overall communication with physicians, of which medication-related communication is a small portion. Further, even though nurses perceive their communication with physicians to be good, it may not get at the quality of the communications. In contrast, nurse-pharmacist communication is likely to be medication-focused and nurses usually talk with pharmacists only when they have inquiries regarding medications. Such contrasting substance of communication may have resulted in the opposite coefficients in Table 7. For example, although not statistically significant, the negative coefficient on nurse-pharmacist communication may demonstrate the “true” relationship between medication-focused communication and medication error rates, while the positive coefficient on nurse-physician communication may reflect the result of overall communications.

Similar to the previous argument, the investigation of the moderating role of learning climate might have yielded different results. In the original research model prior to the model building, the current study hypothesized moderating effects of learning climate in the relationship among nurse-physician communication, nurse-pharmacist communication, and medication error rates. However, these interaction variables were eliminated through the model building process due to relatively lack of explanatory power compared to other remaining variables. Similar to the role of learning climate in the examples of work dynamics and RN hours, the true association between nurse-physician communication and medication
error rates may be either positive or negative depending on the level of learning climate. Therefore, although the moderating effects were not tested in the study, future study may find different results by testing the moderating effect of learning climate.

Another possible explanation could be that nurse-physician/pharmacist communication is endogenous in a model of medication errors (Kennedy, 2003; Wooldridge, 2000). It is quite possible that, rather than better nurse-physician/pharmacist communication leading to more medication errors, nurses may have more communication with physicians/pharmacists when they encounter a lot of errors. The problem of endogeneity is common in cross-sectional design studies because it is not always possible to make cause and effect inferences in such studies due to ambiguous temporal ordering of cause (Bollen, 1989; Bullock et al., 1994). However, future research can control for endogeneity problems using instrumental variables estimation.

**Education**

Hypothesis 3A, which purported that educational preparation of the nursing workgroup would have a linear but asymptotic relationship with medication errors, was supported at $\alpha = 0.10$ level. Nurses’ education had a negative effect on medication error rates until a nursing unit had 39% of BSN-prepared nurses on the unit, followed by a diminishing marginal effect. If a nursing unit has less than 40% of BSN-prepared nurses, it might be better off increasing the proportion of BSN-prepared nurses to reduce medication error rates. On the contrary, if a nursing unit has greater than 50% of BSN-prepared nurses it would minimize medication error rates by decreasing the proportion down to 40-50%. Consequently, based on this study, 40 to 50% of BSN-prepared nurses appears to be the optimal proportion for a nursing unit to minimize medication error rates.
Although it was significant at the 0.10 level, the current study is the first study that has found empirical evidence suggesting that nurses’ education has an effect on medication errors. In addition, it is also the first study to demonstrate that there are optimal proportions of BSN-prepared nurses to minimize medication errors, rather than the assumption of linearity in which “more” is better. In fact, despite the long-held assumption that BSN-prepared nurses perform better than those without BSN degrees, with the exception of Blegen et al.’s study (2001), few studies have directly examined the effect of nurses’ education on patient safety outcomes at the nursing unit level. Further, Blegen and colleagues found no or positive relationships between BSN-prepared nurses and medication error rates.

Presumably, the contrasting results between the current study and Blegen’s study may have resulted from different study designs, methods, data, and statistical analyses. However, the most important difference is the current study’s examination of non-linear relationships: While Blegen’s study hypothesized a linear relationship between the proportion of BSN-prepared nurses and medication error rates, the current study investigated a curvilinear relationship. In fact, when omitting the squared term from the analysis, the result yielded a negative, non-significant coefficient on education, which is consistent with one of the results that Blegen has found. In short, the results of the current study suggest that testing only a linear relationship may not fully explore the actual relationship between education and medication errors.

Another difference is that, while the current study used only severe medication errors, Blegen’s study used medication errors at all levels of severity. That is to say, an error-reporting bias can be a potentially bigger problem in Blegen’s study than in the current study. As seen from the results of work dynamics and RN hours, even when only severe medication
errors were studied, which are supposed to be less likely to go unreported or unnoticed, under-reporting and under-detecting problems would not disappear. That means that studies for overall medication errors would have a greater possibility of under reporting problems than the current study. In fact, although not statistically significant, Blegen found a positive association between nurses’ education and medication errors from one of her study samples and hinted at the possibility of over-reporting among nursing units with more BSN-prepared nurses such that, the medication errors that increase with BSN nurses may have been the proportion of reported errors rather than the actual medication errors. In other words, by using overall medication errors, Blegen’s study may well have examined nurses’ willingness to report (i.e., behavioral outcomes) rather than patient safety outcomes.

Experience

The findings indicate that experience of the nursing workgroup was not significantly related to medication errors, nor did it have a linear but asymptotic relationship with medication errors. These results also contradict Blegen’s study (2001), which found a significant, negative linear relationship between nurses’ experience level and medication error rates. As discussed previously, the difference may result from the use of different types of medication errors. In other words, it can be hypothesized that, while the proportion of experienced nurses on the nursing unit contributes to fewer “non-severe” or “overall” errors, it may not make any difference in terms of severe medication errors.

A more appealing explanation is that experienced nurses may be less likely to report their errors, especially when the error is non-severe. In fact, most medication errors turn out to be near misses and usually carry inconsequential harm, if any, to patients and, thereby, a significant portion of the medication errors in Blegen’s study may have been “non-severe.”
Because non-severe errors are not obvious and can easily go unnoticed, nurses can use their “discretion” to decide whether or not to report. Such a tendency is likely to be strong for nurses who are confident of their clinical knowledge and experience. For example, when these nurses make an error with no harm occurring to the patient, they know from their experience that the error is not going to leave detrimental effects on the patient so they may choose not to report it because reporting an error is a cumbersome procedure. In some cases, these nurses may consider that the error is not an error at all. In contrast, new nurses are less likely to use their discretion when reporting an error and more likely to report their errors regardless of the clinical significance of the error. Because they are not confident with their clinical skills and knowledge, they usually do not know what impact exactly the error will have on the patient. Thus, they choose to let others know about the error, even if the error looks clinically insignificant to them. By doing so, they can ask for help if needed and do not have to risk taking sole responsibility over the situation.

Previous Hospitalization

The findings for Hypothesis 4 suggest that a nursing unit in which a large proportion of patients has experienced a hospitalization in the past year was more likely to have higher medication error rates, but this relationship was not statistically significant. Although there has been limited empirical evidence that shows a patient’s experience of previous hospitalization does affect medication errors, since previous hospitalization may be considered an indicator of patient’s health status (the variable health status was dropped out from the model building procedure), it is not difficult to assume a positive association from this relationship.

Medication-related Support Services
The findings suggest that the greater the availability of medication-related support services the lower the medication error rate, but this relationship was not statistically significant. One possible explanation could be related to the construct validity of the scale. The scale for medication-related support services measured nurses’ perception of availability of services such as IV teams, medication and IV fluid delivery services, CPOE, unit-dose medication systems, automated medication administration systems, and pharmacist consultation. Thus, it is possible that even though a nursing unit does have such services, for example CPOE, nurses may have rated the availability low if they had felt the CPOE systems were not always helpful or accessible to them when carrying out medication administration. The scale may also have confounded the quality of the services with the mere presence of them. For example, although pharmacist consultation was “usually available,” if nurses often felt that the service was not satisfactory, they may have rated the availability low. As such, what this scale actually measured may be more than just simple availability of the services.

Researchers and practitioners have assumed that technology (i.e., CPOE, unit-dose systems) will decrease medication errors, but the context in which it will be effective or how much it will be useful has not been clearly described. In fact, most studies have only examined the direct relationship between technology and medication errors without consideration of other work environment factors that possibly affect medication errors, and concluded that technology does matter. However, the non-significant relationship found in the current study may suggest that the effect of such technology in reducing medication errors may have been exaggerated and that the independent contributions of technology may be relatively small compared to other types of work conditions such as adequate staffing or skill mix.
Theoretical Implications

In Chapter 2, the current study argued that, while Reason alluded to the importance of safety climate in health care, his arguments on safety climate had not been fully developed or tested within the boundary of the human error model because he did not specify how safety climate could be integrated into the model. The current study further suggested that a learning climate can bridge the gap between the human error model’s error-prevention approach and the organizational learning model’s error-management approach. The motivation of the current study began with the question of how a learning climate could intersect the two models. Specifically, this study suggested a moderating role of learning climate in the relationship between error-producing conditions and medication errors as such that a positive learning climate weakens and a negative learning climate strengthens the relationships between error-producing conditions and medication error rates.

The results of the current study show that, without consideration of a learning climate, the exploration of the role of error-producing conditions on medication errors may be incomplete. For example, without consideration of learning climate, one may conclude that greater RN hours are associated with fewer medication errors, when the true relationships may exist in opposite directions (i.e., positive and negative) depending on learning climate. Additionally, one may be perplexed by the finding that more stressful work dynamics are associated with fewer medication errors, having not thought about the role of a learning climate. In other words, by demonstrating the role of learning climate, the current study suggests that an examination of direct relationships between error-producing conditions and medication errors, a prevailing approach to investigate such relationship, may not be adequate or may even be misleading. Further, it also implies that the human error model may
not be sufficient alone and argues for the importance of integrating the human error model and the organizational learning model, with learning climate as a connecting bridge. All these points together suggest that error management strategies need to consider learning climate.

Another theoretical implication of this study involves finding error-producing factors from multiple organizational levels and testing their relative contributions to the reduction of medication errors. Although there are always too many system factors involved so that it is difficult to label only one or two factors a “cause” of medication errors, most previous studies have examined bivariate relationships with only one candidate factor. Thus, little is known how their independent relationships would change when investigating several factors together. In this regard, the current study tested error-producing factors from four different aspects (nursing unit work environment, team, personal, and patient) as well as medication-related support services. The result implies that, even though all such factors are known as error-producing factors and, thus, are expected to be significantly associated with medication errors, one factor might be more important than another. For example, while care complexity is a common example of a latent system factor, its contribution to medication errors may not be important when staffing or skill mix is adequate. Additionally, although medication-related support services, such as CPOE and unit dose systems, have been emphasized as “must-have” technologies to ensure minimizing errors in every nursing unit, their relative contributions to the reduction of medication errors may be smaller than we have expected, particularly when a nursing unit has an adequate proportion of BSN-prepared nurses. Further, even when an error-producing factor has an impact on medication error rates, its relationship with medication errors may differ depending on the level of learning climate a nursing unit has. These results suggest the exploration of moderating effects or the relative significance
among error-producing factors.

The final theoretical implication relates to the application of the theoretical framework developed in the current study to other types of nursing units or hospitals. Each type of error-producing factor examined in the current study may have differential implications for some nursing units and not for others. Patient characteristics and nursing care needed for the patients differ by type of nursing units and, as a result, error contributing factors in those settings may also be different. For example, patients in intensive care units are more fragile and use more medications than medical surgical patients and, therefore, have a greater risk of adverse outcomes. At the same time, because ICUs usually have better nurse staffing and physician accessibility as well as greater availability of support services than medical surgical units, such factors may be less important than other types of error producing factors (e.g., nurses education or experience) and the relationships between nurse staffing (RN hours) or support service availability and medication errors may be different from the results of this study. Future research should be explored in various settings before a solid conclusion can be made.

Policy Implications

The most important finding of this study from a staffing policy perspective is that the optimal proportion of BSN-prepared nurses for reducing medication errors is at around 40-50%. Along with nurses’ experience, nurses’ education levels have been the continuous target of research interest in relation to patient outcomes. However, empirical evidence showing that nurse education is associated with patient outcomes has been limited. One exception is Aiken, Clarke, Cheung, et al.’s study (Aiken, Clarke, Cheung, Sloane, & Silber, 2003), which found that hospitals with a 10% increase in the proportion of BSN-prepared nurses was
associated with a 5% decrease in 30-day mortality rates and failure-to-rescue rates, after accounting for patient characteristics, hospital characteristics, nurse staffing, as well as nurse experience. The findings from the current study are in keeping with Aiken’s findings, except that the unit of analysis in Aiken’s study was the hospital while the level of analysis in the current study was the nursing unit, and Aiken’s study examined a linear relationship while the current study examined a curvilinear relationship. Partly due to limited evidence of the relationship between nurse education and patient outcomes, the educational composition of the nurse workforce that can yield the best patient outcomes has not received much attention nor become a priority in national nurse workforce policy. The results of the current study, as well as Aiken’s, underscore the importance of altering the educational composition of the future nurse workforce toward an optimal proportion with baccalaureate or higher education as well as ensuring the adequacy of the overall supply.

Another policy implication from this study relates to sources of obtaining medication error data. Despite the effort to minimize reporting bias problems by using only severe medication errors, the results of this study still showed evidence of possible under-reporting and under-detection. It is obvious from the results of this study that, without an appropriate method to detect an error, one cannot be sure whether more medication errors actually mean poor patient outcomes or just a reflection of less reporting bias. One way to eliminate reporting bias problems when investigating medication errors may be, instead of using self-report methods used in the current study, to employ other types of objective methods to detect an error such as observational methods, chart review, or computerized programs, all of which were discussed in Chapter 2. As noted previously, despite high sensitivity and effectiveness, these methods have their own drawbacks and none of them was adequate for a
large scale study because of their high costs. Therefore, designing and utilizing an error
detection method that is sensitive, less likely to be subject to reporting bias problems and not
expensive so that hospitals can afford is required.

Practice Implications

The results of the current study suggest that nurse administrators must develop
strategies to create a positive learning climate that will allow nurses to learn from their errors,
thereby preventing medication errors in the long run. To do so, one must first know under
what work conditions a positive learning climate is likely to be developed. Studies on nursing
work environments have found that some nursing units or hospitals have characteristics that
are conducive to better patient outcomes. For example, magnet accreditation, which is based
on excellence in nursing services, has been noted to promote positive organizational climates
and be associated with positive patient outcomes (Aiken, Smith, & Lake, 1994; Laschinger &
Leiter, 2006). The focus of these studies, however, has been limited to several nursing work
conditions such as nurse experience, educational preparation, and staffing stability. Future
researchers and administrators should work together to identify a broad set of working
conditions that helps create a positive learning climate.

The finding that nursing units with a certain proportion of BSN-prepared nurses are
better at preventing severe medication errors can also provide assistance to nurse
administrators as they seek to develop blueprints for staffing plans that are linked to patient
safety outcomes. In fact, the call for hiring BSN-prepared nurses is not new but there appears
to be a wide gap between the preferences of hospital executives and current staffing patterns.
For example, nurse executives in university teaching hospitals prefer a nurse workforce with
approximately 70% prepared at the baccalaureate level and estimate that actual levels
average 51%. Also, community hospital nurse executives prefer to have 55% of their RNs educated at the baccalaureate level (Goode et al., 2001). Even worse, according to the 2004 National Sample Survey of Registered Nurses ("Preliminary Findings: 2004 National Sample Survey of Registered Nurses," 2004), only 47% of nurses nationally are BSN-prepared. However, considering that almost 18% of currently employed RNs with their initial educational preparation being at either associate’s degree or a diploma receive baccalaureate and master’s degrees later in their career, financial support and incentives by hospital administrators to encourage nurses to pursue higher degrees are required.

Limitations

As with any study, the current study has several limitations. The first limitation relates to measurement issues. To minimize under-reporting problems and maximize homogeneity of data, the current study used severe medication errors only, defined as those that resulted in increased nursing observation, increased technical monitoring, laboratory testing, radiographic testing, medical intervention, or transfer of the patient to another unit. However, some nursing units had a hospital policy that required all medication errors, regardless of their severity, to be treated with increased nursing observation and extra care. In such cases, all medication errors reported to the nursing unit were classified as “severe” per the definition of the ORNA study, and, as a result, the validity of the variable “severe medication errors” may have been threatened. Although the number of nursing units that reported to have such a policy was extremely small (N = 2), there could have been more nursing units that did not tell the study team about such a policy being in practice and this problem may have decreased the validity of the data.

Another limitation relates to the use of incident reports. As discussed in Chapter 2,
incident reporting systems are by far the most commonly used method to collect medication error data. However, studies have found that incident reports have low sensitivity and detect only a very small number of errors compared to chart review or observation methods (Flynn et al., 2002; Jha et al., 1998). One of the reasons for low sensitivity is a potential reporting bias problem and the current study deliberately utilized only severe medication errors in an attempt to minimize this problem. However, incident reporting systems cannot solve the problem of under-detection and, as discussed before, the under-detection issue can be problematic especially when work dynamics is high or a learning climate is negative. One way to address the under-detection issue may be employing observational methods, which are by far more effective and accurate than chart review or incident reports. As discussed in Chapter 2, however, because of their high cost, the use of observation methods has been limited only to small-scale studies.

Errors from violation also need to be considered. The current study started out by examining medication errors only resulting from errors, not from violations, because nurses are not likely to intentionally try to make errors, and thus, most medication errors are believed to be the results of errors. However, because medication error data were collected by incident reports it is impossible to distinguish error-originated medication errors from violation-originated errors. In fact, even though most errors nurses make are likely to be error-originated errors, some medication errors in the current study data may have resulted from violation-originated errors. For example, a nurse may intentionally skip to double-check a high-alert drug with another nurse when she has to according to a medication protocol, simply because she cannot find anyone around at the time she gives a medication or she has administered the drug over and over again on the same patient so she does not feel the need
to double-check the drug. This example is obviously an error resulting from violation because the nurse intentionally violated the rule. In other words, she knew that she had to follow the protocol and double-check the drug but she chose not to. While such instance is not rare in practice settings, the current study was not able to single such violation-originated errors out from the dataset and this limitation may have contributed to the findings.

Another limitation relates to risk adjustment. The current study used several ways to risk-adjust patients. First, it used patients’ age, health status, and previous hospitalizations to reflect the characteristics of the sample patients. However, since patients’ age and health status were eliminated from the model building procedure, only previous hospitalization remained in the final model. Second, care complexity, one of the nursing work condition factors, can function as a risk adjustment variable because it measures how many patients on the unit have complex problems that required complicated nursing care. Third, by collecting data from general medical-surgical or medical-surgical specialty units, the ORNA II study controlled for the type of patients. Despite these approaches, patients’ risk may not have been adjusted well enough so that, even though patient days were controlled for, some nursing units may have administered more medications due to their having sicker patients than others. While using a unit-based patient classification system might be a method to control for patient condition acuity, it may also control for nurse work (e.g., RN proportion, RN hours), which is a target of interest (Seago et al., 2006). Also, because the staffing matrix of medical-surgical units vary based on budget and other factors, most patient classification systems are unit specific and it is often difficult to use them to compare across units or hospitals (Seago et al.).

Another limitation relates to the design of this study. Although the ORNA study
collected the data in a temporal order, enabling some causal arguments, the design does not completely eliminate the possibility of endogeneity problems. For example, it is not clear whether favorable work conditions (i.e., high RN hours, high proportion of BSN-prepared nurses) contribute to fewer medication errors or whether previous history of frequent medication errors has led a nursing unit to change into error-preventing work conditions. Similarly, the current study argued that a nursing unit with a positive learning climate is more likely to report errors. However, it is also possible that nursing units with frequent previous episodes of medication errors decided to be engaged in creating a positive learning climate. Therefore, this study’s inability to provide exact accounts of what might have happened should be viewed as a limitation.

**Future Research**

One of the primary contributions of the current study was the exploration of the role of learning climate in the occurrence of medication errors. The current study found that the way nursing unit work conditions impacts medication error rates depended on the level of learning climate. In other words, without consideration of the role of learning climate, one may get faulty results, particularly when investigating the relationships among work dynamics, RN hours, and medication errors. However, because it is an early exploration of learning climate, the exact roles played by a learning climate are less clear. For example, a positive learning climate may only contribute to the increase in error reporting or it may actually decrease medication errors in the long run. According to the organizational learning model, workers are likely to exercise learning behaviors under a positive learning climate, which, in turn, will contribute to better performance. While such a hypothesis can be examined with a longitudinal study, one must know how long it will take for learning
behaviors to be effective enough to yield decreased error rates. Future research on medication errors, particularly studies employing a longitudinal design, should be able to explore further the function of learning climate.

While the theoretical framework developed in the current study was used to explore severe medication errors, it is not known if it will be useful as the theoretical grounding in the investigation of other types of medication errors such as near misses or non-severe medication errors. While the current study tried to minimize under reporting problems by using only severe medication errors, the results still showed evidence of reporting bias. Considering that near misses and non-severe medication errors will have greater possibilities of under reporting problems than severe errors (i.e., they are less obvious), an investigation of any type of medication errors needs a special consideration of how to deal with such a problem. Further, it is also not known if the framework will be applicable to the exploration of other types of adverse events such as falls, decubitus ulcers, pneumonia, or urinary tract infections. In fact, studies on adverse events have examined several patient safety indicators as targets of interest in a single study, implicitly assuming that all adverse events are the same. However, some adverse events may be more clinically or etiologically closer to each other than other types of adverse events. For example, medication errors may be etiologically close to falls because they both result from errors, while pneumonia is close to urinary tract infection because they both are likely to be clinical care quality issues. Therefore, by examining different types of adverse events with the theoretical framework, one might be able to ascertain whether these patient safety indicators are the same or not.

The last point with regard to future research is that, while many medication error studies have meticulously developed, often complicated, medication error classifications,
none of them is accepted as a standardized, or widely accepted, form. In terms of severity, for example, some studies use four categories for severity such as fatal, life-threatening, serious, and significant (Morimoto et al., 2004), whereas others such as NCC-MERP classified medication errors into 9 categories. However, none of them is a standardized classification and hospitals often develop their own ways of categorizing medication errors by severity, which makes it difficult for researchers to perform an investigation across hospitals. Similarly, while researchers naturally assume that all medication errors are the same and perform a study regardless of error types, some errors may be different from others in terms of clinical significance, hospital management plans, or error prevention and management strategies. Therefore, future studies should further explore classifications of medication errors and find the one that both practitioners and researchers can widely use.
Appendix 1. Care Complexity Scale

Response Options

1. A few (< 20%)
2. Some (21-40%)
3. About half (41-60%)
4. Many (61-80%)
5. Most (80% +)

Items

1. How many patients on your unit require skilled assessment by an RN more than once every hour?
2. How many patients on your unit require the use of technical equipment (e.g., cardiac/telemetry monitor, pulse oximeter, NG suction, Patient Controlled Analgesia, etc.)?
3. How many patients on your unit have emergencies requiring immediate nursing action (e.g. cardiac/respiratory arrest, hemorrhage, seizure)?
4. On an average day, how many patients on your unit require IV medications through a central venous line or port?
5. For what number of patients on your unit does improvement in their condition or prevention of a negative outcome really depend on nurses’ skill and initiative?
6. How many patients on your unit have complex needs that require independent thought and action by nurses rather than just following set procedures or routines?
7. How many patients on your unit have complex problems that are not well understood?
8. How many patients on your unit require assistance with ADL’s like help with ambulation, bathing or feeding, or help to the bedside commode or toilet?
9. How many patients on your unit require frequent monitoring (e.g., daily weights, I&O, vital signs, blood glucose checks)?
10. How many patients on your unit need therapies that require a high level of technical skill (e.g., suctioning, trach care, tube feedings, etc.)?
11. For how many patients on your unit are the needs so complex that it is important to know a detailed health history?
12. For how many patients on your unit does the nursing care change in direct response to the patient’s condition?
13. How many patients on your unit are at high risk for falls or require nursing interventions focused on fall prevention?
14. How many patients on your unit are at high risk for falls or require nursing interventions focused on fall prevention?
Appendix 2. Work Dynamics Scale

Response Options

1. Strongly disagree  
2. Moderately disagree  
3. Slightly disagree  
4. Slightly agree  
5. Moderately agree  
6. Strongly agree

Items

1. Nurses on this unit could do a better job if they had more control over the types of patients they were assigned.  
2. Physicians change their orders so frequently that nurses on this unit have difficulty doing a good job.  
3. Nurses on this unit could do a better job if they had more information about their patients’ condition.  
4. Frequent movement of patients on and off the unit for diagnostic studies, procedures, etc., makes it difficult for nurses on this unit to do a good job.  
5. Frequent discharges from the unit make it difficult for nurses on this unit to do a good job.  
6. Frequent admissions to the unit make it difficult for nurses on this unit to do a good job.  
7. Frequent patient transfers from this unit to another unit, or vice versa, make it difficult for nurses on this unit to do a good job.
Appendix 3. Expertise Scale

Response Options

1. Strongly disagree
2. Moderately disagree
3. Slightly disagree
4. Slightly agree
5. Moderately agree
6. Strongly agree

Items (Nurses on this unit…)

1. Act on the basis of their clinical understanding when there is a decline in patient status to get needed tests and/or immediate intervention.
2. Do a more focused assessment when they have an early warning of patient problems.
3. Notice patterns of changes in patient status which allow them to intervene before critical changes occur.
4. Are able to recognize very subtle changes in patient status
5. Are able to recognize critical changes in patients’ status
6. Use their knowledge of pathophysiology and pharmacology with regard to providing day-to-day nursing care.
7. Consult with the physician when they know that “something’s not right” about the patients’ conditions.
8. Know from experience what is important to observe or notice in the patient
Appendix 4. Commitment Scale

Response Options

1. Strongly disagree
2. Moderately disagree
3. Slightly disagree
4. Slightly agree
5. Moderately agree
6. Strongly agree

Items (Nurses on this unit…)

1. Feel that it is their responsibility to intervene with the patient when sub-standard care is threatening patient safety.
2. Call the physician repeatedly when he/she does not respond appropriately.
3. Will approach and counsel a staff member who is providing sub-standard care.
4. Do not hesitate to ask another nurse when they don’t understand what to do.
5. Really care about the quality of care that they provide to patients.
6. Will continue to seek clarification/question the physician when an order does not quite make sense.
7. Feel that it is important to assist another nurse who asks for help with a patient.
8. Feel free to ask questions at change of shift when “something’s not right.”
Appendix 5. Medication related Support Services Scale

Response Options

1. Consistently available
2. Inconsistently available
3. Not available

Items (Think, in general, about the availability of the support services, and rate them as follows)

1. Transcribing orders and placing information in patient charts
2. Computerized order entry
3. Unit-dose medication system
4. Automated medication administration system
5. Medication and intravenous fluid delivery
6. Intravenous team services
7. Pharmacist consultation
Appendix 6. Communication with Physicians/Pharmacists Scale

Response Options (Item 1-3)

1. Never
2. Rarely
3. Occasionally
4. Often
5. Always

Items

1. How frequently do nurses on your unit communicate with the following groups?
2. Do people in these groups communicate with nurses on your unit in a timely way?
3. Do people in these groups communicate with nurses on your unit accurately about the status of their patients

Response Options (Item 4-7)

1. Only blaming
2. Mostly blaming
3. Blaming/problem-solving
4. Mostly problem solving
5. Only problem-solving

Items

4. When an error has been made regarding a patient, do people in these groups blame others or work on solving problems?
5. How much do people in these groups know about the work of nurses on your unit?
6. How much do people in these groups respect the work of nurses on your unit?
7. To what extent do people in these groups share your goals for patients on your unit?
8. Appendix 7 your unit?
Appendix 8. Learning Climate Scale

Response Options

1. Strongly disagree
2. Disagree
3. No opinion
4. Agree
5. Strongly agree

Items

1. It is advantageous on this unit to openly discuss one’s mistakes.
2. On this unit, it is best to keep my mistakes to myself.
3. Nurses on this unit admit mistakes even when they would go unnoticed.
4. On this unit, it is a bad idea to openly admit one’s mistakes.
5. On this unit, when nurses make mistakes, they tell others about it so the same mistake is not made in the future.
6. On this unit, after a nurse makes a mistake, we think about how it came about and how to prevent the same mistake in the future.
7. On this unit, nurses often think about how they could have prevented mistakes that occur.
8. On this unit, if something goes wrong, we think about it carefully.
9. On this unit, after a mistake has happened, we think long and hard about how to correct it.
10. On this unit, when a mistake occurs, we analyze it thoroughly.
11. On this unit, if nurses cannot rectify an error by themselves, they turn to other nurses on the unit for help.
12. On this unit, if nurses cannot figure out how to correct a mistake, they can rely on other nurses on the unit for help.
13. On this unit, when nurses make mistakes, they ask others about how they could have prevented it.
References


medication errors. *American Journal of Health-System Pharmacy, 59*(23), 2314-2316.


consequences of shared beliefs about failure in organizational work groups. *Journal of Organizational Behavior, 22*(2), 161-177.


errors. *JAMA, 293*(10), 1197-1203.


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Rothschild, J. M., Landrigan, C. P., Cronin, J. W., Kaushal, R., Lockley, S. W., Burdick, E.,
et al. (2005). The critical care safety study: The incidence and nature of adverse events and serious medical errors in intensive care. *Critical Care Medicine, 33*(8), 1694-1700.


hospitalization. *Archives of Internal Medicine, 166*(5), 565-571.


