HUMAN FACTORS, AUTOMATION, AND ALERTING MECHANISMS IN NURSING HOME ELECTRONIC HEALTH RECORDS

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Doctor of Philosophy

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by

GREGORY LYNN ALEXANDER

Dr. Marilyn Rantz, Dissertation Supervisor

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The undersigned, appointed by the Dean of the Graduate School, have examined the dissertation entitled.

HUMAN FACTORS, AUTOMATION, AND ALERTING MECHANISMS IN NURSING HOME ELECTRONIC HEALTH RECORDS

Presented by Gregory L. Alexander

A candidate for the degree of Doctor of Philosophy

And hereby certify that in their opinion it is worthy of acceptance.

Jill Scott- Cawiezell

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ABSTRACT

OBJECTIVES: Evaluate a clinical decision support system in an electronic medical record (EMR) to determine activation frequencies, patterns of activity, and how automated alerting mechanisms affect clinical responses.

DESIGN: Descriptive

SETTING: Three nursing homes

PARTICIPANTS: Midwestern nursing homes where administrative staff had committed to implementing an EMR and clinical decision support system called OneTouch Technologies.

MEASUREMENTS: Automated alerts in the OneTouch EMR including constipation, decline in condition, dehydration, improvement in condition, skin integrity, weight gain, and weight loss were evaluated. Using alert calculations, frequencies of alerts and triggers were counted. Spearman's rank correlations were determined between the frequency of active alerts and the number of secondary diagnoses for residents. Finally, a comparison was made of clinical responses to active and non-active alerts.

RESULTS: Alert data from two facilities totaling 155 days were included in the study. The most frequent alerts were dehydration and improvement in condition. One moderately significant positive correlation was found between the number of secondary diagnoses and weight gain alert frequencies in residents who had a CVA. There were more clinical responses than no clinical responses overall. However, there were as many clinical responses to conditions with no active alerts as active.

CONCLUSIONS: Frequencies of alerts is an indicator of how much information has to be managed in order to meet complex issues in nursing home residents. Automated alerts play a role in reminding nursing home staff of potential trouble spots in resident care.

PART I

RESEARCH PROPOSAL

INTRODUCTION

The U.S. population is aging with the oldest old proportion of the elderly growing the fastest. The fastest growing age group is aged 85 years and older (Institute of Medicine, 2001b). The Institute of Medicine (IOM) (2001b) indicated that the rapid growth of the oldest old population will have a major effect on the demand for and supply of long term care services with projected ranges between 10.8 million and 14 million older Americans needing long term care, and 4.3 million to 5.3 million needing nursing home care by the time the baby boomers enter elderly ages in 2030. Continuing concerns about quality, cost, accessibility, adequacy of oversight, and enforcement issues in nursing homes are driving the need to implement better information systems in nursing homes where a proportion of the oldest old population resides. Information systems that provide valid, reliable, and timely data about the care provided, the recipients of care, the facilities, and the caregivers providing care is fundamental to all strategies for monitoring and improving the quality of nursing home care (Institute of Medicine, 2001b).

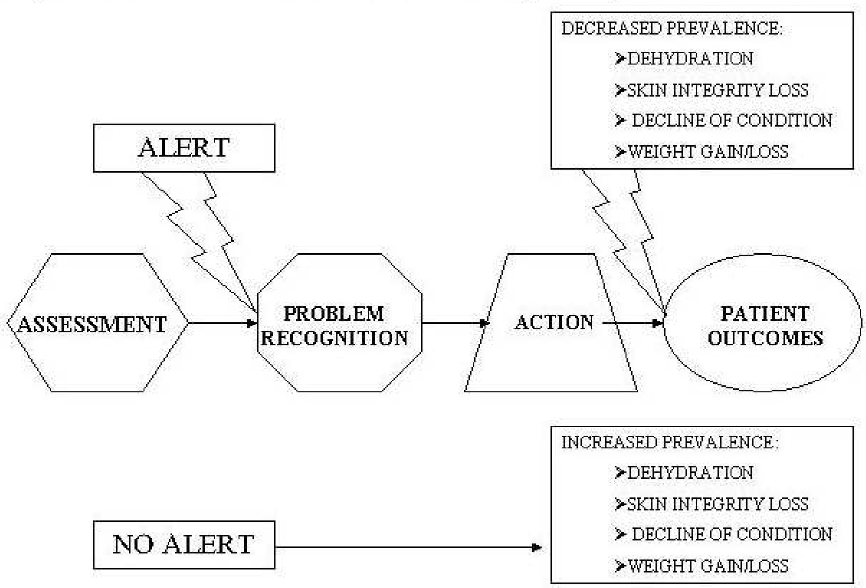
Functional Models in Health Information Systems

Over the last decade, leading healthcare leaders have stressed the importance of integrating information systems (IS) and healthcare systems to enhance clinical practices, improve the quality of patient care, and reduce medical error (Institute of Medicine, 2001a; Ozbolt, Bulechek, & Graves, 1993). One missing link that continues to plague the deployment of IS and technology is how to instill complex health information structures into practical, usable models to improve the work of healthcare providers, the health care environment, and patient safety (Sensmeier & Delaney, 2004). Recognizing the core functions of electronic health record (EHR) systems can assist IS developers to design models for EHR that are more practical and usable. Primary functions of the EHR are to support the delivery of personal health care services, including patient care delivery, care management, care support processes, administrative processes, and patient self-management (Committee on Data Standards for Patient Safety, 2003). The IOM committee (2003) recognized other secondary functions of electronic health records as being education, regulation, research, public health and policy, and policy support.

Electronic health records should be designed to meet core functionalities and should address the following criteria: 1) improve patient safety, 2) support the delivery of effective patient care, 3) facilitate the management of chronic conditions, 4) improve efficiency, and 5) must consider the feasibility of implementation, including software development (Committee on Data Standards for Patient Safety, 2003). This study will utilize these criteria to evaluate the functionality of an integrated, clinical decision support system in a nursing home EHR called One Touch Technologies (OTT). Specifically, this study will utilize the model for clinical decision support systems illustrated in Fig. 1.

The model for clinical decision support systems in Figure 1 illustrates how alerts, used in clinical decision support systems, should aide in problem recognition and should lead to clinical actions that improve resident outcomes. Resident assessment data used to document resident conditions is entered into the EHR. Predetermined criteria or triggers within the resident assessment are then used to build decision support tools including alert mechanisms. Once the predetermined criterion associated with each alert is met an alert becomes active and the information system automatically indicates a problem has been identified within the assessment data entered into the record. Upon activation staff using the EHR receive an automated message notifying them of the active alert. Staff can then choose to take clinical action or not. When the condition associated with each of the predetermined criterion is resolved the alert automatically becomes inactive. In the absence of the alerts, staff is responsible for assimilating resident assessment data and making decisions about resident care based upon their own recall and synthesis of vital information. In this study, active alerts associated with the EHR are being evaluated to determine how they affect clinical responses when compared to time periods when alerts are not active.

Fig. 1: A Model for Clinical Decision Support Systems in EHR



Information systems used to direct nursing home care staff or to evaluate effects of improvement interventions are absent in most nursing homes (Schnelle, Bates-Jensen, Chu, & Simmons, 2004). Schnelle and colleagues (2004) go on to report that, "improvements in NH care quality cannot be expected until information systems that provide accurate measures of the actual care provided to residents are implemented (p.

1382)." In a recent report, *Making Health Care Safer: A Critical Analysis of Patient Safety Practices*, critical practices identified in the literature to improve patient safety in clinical environments included the use of alerts and computer detection to search for adverse events, incorporation of human factors into design and development of IS to improve medical device safety, and the utilization of clinical decision support systems that identify patient specific clinical variables to aid in clinical decision making (Gandhi & Bates, 2001; Murff, Gosbee, & Bates, 2001; Trowbridge R. & Weingarten, 2001). Health systems researchers should take advantage of these recommended practices and begin to research ways to improve on existing information systems in nursing homes and other types of healthcare organizations.

Human Factors Approaches Health Systems Research

Human factors is the development and application of knowledge about human behavior and physiologic responses in an operational environment (Nemeth, 2004). In health care, human factors researchers attempt to understand the interrelationships between humans, the tools they use, the environments in which they live and work, and the tasks they perform (Staggers, 1991; Staggers, 2003; Weinger, Pantiskas, Wiklund, & Carstensen, 1998). The goal of a human factors approach in health care is to optimize the interactions between technology and the human, minimize human error, and maximize human-system efficiency, human well-being, and quality of life (Staggers, 1991). Human factors models have been depicted as containing subsystems including the operator, the machine (e.g. technology), and the environment (Czaja, 1997; Helander, 1997; McCormick & Sanders, 1982; Nemeth, 2004). Critical research issues associated with each of these subsystems have been identified.

Operators

Humans, as operators of machine systems, are at the core of human factors models. A challenge for designers, concerned with human factors, is that each human operator has distinct, individual, and identifiable attributes that characterize who they are, their interactions with the system, and their performance within the system. This design challenge represents the first critical issue, related to operators, in human factors research. Depending on functions that are to be performed, options for designers of human-machine environments exist to allocate certain functions to humans or to some physical components within the machine system (McCormick, 1970). Human factors that contribute or hinder the success of these functionalities in technology innovation include the usability of the technology, human physiologic and psychological readiness to act, standardization, and intuitiveness of design (Alexander, Hauser, Steely, Ford, & Demner-Fushman, 2004; Hasler, 1996; Wears & Perry, 2002; Weinger & Englund, 1990). The second critical research issue, related to operators within human machine systems, centers around attempts to understand and exploit human capabilities and human strengths within the area of human perception and cognitive abilities (Leveson, 1986; Sawyer, 1996). Systems analysis of medical mishaps and process breakdowns in health care settings have been identified and associated with perceptual and cognitive deficiencies as evidenced by delayed or omitted procedures, insufficient monitoring, delayed or omitted laboratory workups, inappropriate medication administration, inappropriate treatments, and documentation errors (Alexander & Stone, 2000). System breakdowns resulting from fragmented, decentralized health care systems have been recognized to contribute to unsafe conditions for patients and have been recognized as an essential research area by the Institute of Medicine (Institute of Medicine, 2000; Institute of Medicine, 2001a; Institute of Medicine, 2001b)

Machines

Since the initial onset of the Machine Age in the 18th Century up to the current Machines for Minds age efforts have been made to extend human capabilities with machines (Christensen, 1976). Critical research issues in the current technological systems age are derived from design features such as automation, use of controls, visual displays, and workstation structure which all play a role in the ability of the operator to perform work during human-machine interactions (Bennett, Nagy, & Flach, 1997; Bullinger, Kern, & Braun, 1997; Sarter, Woods, & Billings, 1997; Smith & Cohen, 1997). Efforts in health care technologies are focused on designing out hazards and designing in engineering controls that separate hazards from workers (Foley, Keepnews, & Worthington, 2001). Critical research areas should focus on developing systems that avoid the four types of human failure when coupling humans and machines including human loss of vigilance, human complacency, shifts in trust and confidence levels, and loss of adaptability or feedback(Hoc, 2000). Research in safety critical systems, such as health care technologies, should focus on creating machine systems that improve hazard awareness, alerting mechanisms, identification of conflicts, and reduce unnecessary communication (Baldwin & Struckman-Johnson, 2002; Bisantz, 2003; Fields, Paterno, Santoro, & Tahmassebi, 1999; Fuchs, Heller, Topilsky, & Inbar, 1999; Grabowski & Sanborn, 2003; Patterson, Nguyen, Halloran, & Asch S.M., 2004; Rind et al., 1994).

Environment

The final subsystem in human factors models is the environmental subsystem. The environmental subsystem is critical to the discussion of human factors and may be the most complex of all the subsystems. No matter what environment we are studying whether it is everyday situations or complex systems, we encounter technology that is beyond our capacity to control (Vicente, 2004). Vicente (2004) indicated that when we turn to safety critical systems, including health care systems, the consequences of technological mishaps can be much more worrisome for the environment than the day to day technological experiences encountered; errors in safety critical systems can cause catastrophic circumstances leading to expensive litigation, ecological disasters, endangered nations, and may result in huge burdens to society or significant threats to the future of humankind.

Critical environmental issues, in human factors research, must address the following attributes of organizations: culture, organizational relationships and interactions, work patterns, and organization performance. Organization culture defined as a set of enduring, organization wide beliefs and values are established norms which determine employee behavior and perception (Gillies DA, 1994). Recent research, on nursing home culture found critical differences in cultural views between nursing home staff and leadership that could affect sustained improvements. Scott-Cawiezell and colleagues (in press) found in a study of 31 nursing homes that staff reported a dominant group culture with a family and team orientation while, organizational leaders reported an hierarchical value orientation that emphasized efficiency and compliance with rules and procedures. The ability of an organization to continually improve is driven by the nature of these relationships and interactions of stakeholders within the organization (Scott J, Vojir C, Jones K, & Moore L, 2004). The major responsibility of an organizations leadership is to help alleviate cultural dysfunction by focusing on internal issues to the organization, creating opportunities for change, creating open communication channels, developing new knowledge structures, and continuously improve nursing home operations (Main, Kutner, Pennington, Nutting, & Scott-Cawiezell, 2005; Scott-Cawiezell J et al., 2004).

One critical research area in the environmental domain, related to cultural change, regards the impact of the adoption of technological innovations; leading to reduced, proceduralized, rote tasks workers must perform and subsequent increases in cognitive workloads and demands (Militello, 1998). Task and role changes, resulting from the adoption of new technologies, result in task uncertainty and require greater coordination and feedback within the organization to prevent failures from occurring (Aydin & Rice, 1992). A second critical research area, related to nursing home culture, includes the utilization of methods to create a culture focused on quality improvement and data accuracy (Schnelle et al., 2004). To improve nursing home processes, Schnelle and colleagues (2004) recommended methodologies that will assure data quality such as incorporation of point of service documentation and automated information analyses, increased auditing and quality control mechanisms, and reduced incentives for inaccurate documentation, such as appropriate staffing levels.

Use of Technology in Health Care to Improve Quality of Care

The Presidents Information Technology Advisory Committee (PITAC), a federally appointed group to help accelerate the adoption of information technology (IT) in health care, provided guidance to overcome technological barriers. The groups members identified root causes of information barriers in health care including: 1) limitations in the ability of individual caregivers to maintain full background information on every patient and their inability to maintain current scientific knowledge and best practices in their heads in order to make the best clinical decisions, 2) absence of patient information and medical knowledge necessary to make decisions at the point of care delivery, 3) information recording systems that rely on human interpretation, and 4) the rapid pace of medical advancements that are overwhelming to caregivers (Presidents Information Technology Advisory Committee, 2004).

To overcome these barriers, PITAC (2004) recommended federal support for health IT that further promotes the development of the electronic medical record (EMR), clinical decision support systems, and technology that facilitates computerized provider order entry. The committee's recommendations encouraged federal support for: 1) economic incentives for health IT investments including demonstration-based studies that will measure costs and benefits of EMR investment and practice, 2) research and development of community and regional demonstration projects that emphasize clinical integration of disparate data from multiple sources, 3) creation of task forces to identify actual and perceived legal restraints to sharing EMR information, 4) development of standards for EMR systems such as data format, labels, terminology, codes, limits, units, components, and criteria for which data elements are to be recorded, 5) inclusion of standardized clinical vocabularies in the EMR, 6) development of a single set of data standards for the most common forms of clinical information, 7) research promoting innovation, efficiency, and optimal use of human-machine interfaces that support medical-domain voice recognition and data conversion processes and improved automated entry of instrument data and recall technology, and 8) creation of a broad senior level coordinated leadership body to oversee EMR system development that is critical for patient safety and biosurveillance of public health and homeland security.

Health care researchers, over the last decade, indicated that technology helps caregivers provide improved patient care. Axford and Carter (1996) suggested, in a research study titled *Impact of Clinical Information Systems on Nursing Practice: Nurses' Perspectives,* that computer technology has significant impacts on work practices, patient encounters, and professional outcomes. The researchers found that nurses feel increased security regarding information use when using technology; computer charting and access to information improved as a result of computer-based systems; increased professional status was acquired with use of modern technology; there was improved record keeping and accountability for nursing documentation; patient outcomes were improved because faster information access resulted in improved decision making; and finally care plans, developed from standards, had improved follow-up as a result of technology (Axford & Carter, 1996).

Other research studies have evaluated the quality of nursing documentation, compliance, and patient satisfaction in healthcare settings using point of care technology (Dennis, Sweeney, Macdonald, & Morse, 1993; Nahm & Poston, 2000). Nahm and Poston (2000) showed how computerized clinical documentation systems make a difference in the quality of nursing documentation after implementation of an integrated point of care documentation system on hospital nursing units. The researchers emphasized that there was a 13% increase in compliance with Joint Commission Accreditation Requirements during the study. In similar research, Dennis, Sweeney, MacDonald, and Morse (1993) found an increase in 11 (34%) of Joint Commission accreditation requirements for nursing documentation. Patient satisfaction was not affected by the implementation of the documentation system.

In other research, exploring human-machine interfaces, a cognitive based observational approach was used to determine if failed attempts to enter coded data using a standardized controlled terminology were due to terminology content, terminology representation, or user interface problems (Cimino, Patel, & Kushniruk, 2001). Cimino et colleagues (2001) described that 22% of 238 data entry points failed with 13% of observations failing as a result of content issues, 10% associated with representation, and 6% related to usability. Other noted research in display design included the effects of trend graphs on clinical decision-making in a neonatal intensive care unit, use of different interface designs and their impact on the ability of novice nurses to learn to use computer simulation and performance in critical care environments, and finally, comparisons of response time, errors, and satisfaction between text based vs. graphical user interfaces in the process of completing nursing care (Alberdi et al., 2003; Effken & Doyle, 2001; Staggers & Kobus, 2000). Creating research opportunities that promote technology as an infrastructure to enable safe clinical practices will enable researchers to explain how complex health information structures can be more effectively used in clinical environments (Newbold SK et al., 2004).

<u>One Touch Technologies</u>

The OneTouch Technology System

The One Touch Technologies Corporation has developed and implemented its technology system, OTT, which represents a shift from a manual paper and pen to a digital environment where nursing home staff has access to real time, automated information. The OTT system incorporates technologies that have not previously been available to the nursing home industry. This new level of data collection incorporated into an EHR should have a positive effect on the quality of individual resident care. The OTT system integrates iButtons, radio frequency, infrared, palm digital assistants (PDA), and wireless technology, through the corporation's proprietary software.

Clinical data used in the OTT is collected at either at the bedside (point of care) or entered on personal computers. The data automatically populates all the appropriate sections in the EHR and the MDS. One of the strengths and defining features of OTT is the ability to collect data at the patient's bedside using handheld PDA equipment. Combining the use of the iButton technology located on the resident's identification (ID) bracelet and the caregivers ID badge, caregivers become more accountable for resident care and documentation at the point of care. Furthermore, the PDA modules are designed to provide a template for complete, verifiable documentation, as well as, interactivity of specific items in the clinical record. Within each touch of the PDA to the iButton there is a bidirectional exchange of information between the iButton and the PDA. Information currently provided at the point of care includes vital signs, clinical alerts, nurse to nurse messaging, certified nurse assistant (CNA) task lists for care plan items, active physician orders, and medications and treatments (OneTouch Technologies Corporation,).

Clinical Alerts in OneTouch Technology

Automated clinical alerts in OneTouch assist to identify when a resident may be experiencing constipation, dehydration, skin integrity, a change in condition, weight loss, and weight gain. Each alert mechanism has a specific alert calculation (see Appendix 1). Within specific alert calculations exist identifiable triggers that automatically initiate an active alert when certain triggers are identified in the patient record. Triggers are identified and alerts become active when nursing home staff collects data at the point of care and it is combined with detailed data elements including physician orders, care plans, nurse notes, detailed clinical assessments, and other clinical documentation into a relational database (OneTouch Technologies Corporation,). Immediate access to this database through electronic information displays and system reports can be used to manage resident care activities.

Problem Statement

There is limited research that considers the use of EHR in the nursing home setting. Computer use in nursing homes have generally been limited to business applications and management of the federally required minimum data set (MDS) (Brooks, 1998; Ossip-Klein et al., 2002; Wassenaar, 1996). Little development beyond the MDS data collection, transmission, and care planning has occurred. Utilizing the infrastructure of the OTT EHR, the goal of this study is to evaluate the affects of automated clinical decision support technology, or alerts, being used in nursing home care by determining: a) the frequency of active alerts per residents with specified diagnoses, b) the frequency of alerts in residents with increasing secondary diagnoses, c) the frequency and types of triggers in active alerts per resident with specified diagnoses, and d) the plan of care changes including problem identification, interventions, and task assignments, recorded in the EHR by healthcare workers, during periods when alerts are active compared to periods when alerts are not active. All analyses will be completed on data taken from the OTT system during a 6 month period of time.

Purpose

The purpose of this study is to provide an evaluation of current alerting mechanisms within an EHR system found in some nursing home settings. This study will include an analysis of alert and trigger frequencies. We will determine the proportion of active alerts and triggers for each alert category in residents with specified diagnoses during the 6 month data period. Furthermore, the average length of time alerts remain active will be reported. As part of the study, the frequency of active alerts will be analyzed as the frequency of secondary diagnoses also increases in residents. Our goal is to examine if the number of secondary resident diagnoses has an impact on the frequency of active alerts. Finally, an analysis of care plans including problems, interventions, and certified nurse assistant task list items recorded during periods when alerts are active and inactive will be completed. The goal of this final analysis is to determine if there are differences in the clinical responses when alerts are active versus when they are not active. Understanding these elements will provide insights into how functional models in electronic health records, associated with clinical alerting mechanisms, support safer, more effective patient care delivery and how clinical decision support systems facilitate the management of certain resident conditions. Specifically, this analysis will provide a better understanding of how alerting mechanisms are currently being used in an existing information system in multiple nursing home settings.

Specific Aims, Research Questions, and Hypotheses

Specific Aim (1)

Determine the relative frequency of active alerts and the average time alerts are active in residents with specified diagnoses during a period of 6 months of data collection.

Research Questions:

1) What is the proportion of active alerts for each alert category in residents with specified diagnoses in the EHR including: dehydration, constipation, skin integrity, decline in condition, weight loss, and weight gain?
2) What is the average time each alert is active per resident with specified diagnoses in the EHR?

Specific Aim (2)

Discover if the relative frequency of active alerts increases in residents as the number of secondary diagnoses increase.

Research Question:

What is the relative frequency of active alerts associated with residents who have secondary diagnoses?

Hypothesis:

There will be a significant positive correlation between the number of secondary diagnoses assigned to nursing home residents and the number of active alerts.

Specific Aim (3)

Determine the frequency and types of triggers in active alerts in residents with specified diagnoses during a period of 6 months of data collection.

Research Question:

What is the proportion of triggers for each active alert in each alert category: dehydration, constipation, skin integrity, decline in condition, weight loss, and weight gain within and across resident diagnoses?

Specific Aim (4)

Describe the plan of care changes including care plan problem identification, interventions, and tasks assigned on CNA task lists recorded in the EHR by healthcare workers during periods when alerts are active compared to periods when alerts are inactive in the EHR.

Research Question:

What is the frequency of care plan problems changed, interventions performed, and tasks assigned on CNA task lists on residents with specified diagnoses in each alert category during periods when alerts are active and inactive?

Hypothesis:

There will be a significant difference between the numbers of clinical actions taken with active alerts as compared to when alerts are inactive.

Definition of Terms

Alerting system: System that monitors a continuous signal or stream of data and generates a message (alert) in response to patterns or items (triggers) that may require action of the part of the care provider.

Alert: A decision support mechanism, in an information system, which automatically detects changes in critical assessment data and notifies the healthcare provider with an automated message indicating an active alert.

Trigger: A decision support mechanism, which serves as a subcomponent of the alerting system, which are established criteria or definitions for when an alert shall become active.

One Touch Technologies (OTT): An integrated clinical software system for long-term care that is a wireless, point of care, handheld electronic documentation system that automatically populates all sections in the Electronic Medical Record and the Minimum Data Set.

Task List: A list, created during the care planning process that is transferred by the PDA to the resident's iButton and provides the CNA with a resident specific duty list for that particular shift.

iButton: Microchip technology located on the resident's ID bracelet and caregiver's ID badge.

Personalized Digital Assistant (PDA): Handheld technology that allows the caregiver to collect data at the patients bedside.

Functional Models in Electronic Health Records: These are defined as models that information systems developers utilize to design the functional components of an EHR. The designers of functional models should be focused on developing components that are practical and usable. Furthermore, these components should address identified functions of the EHR including patient safety, delivery of effective patient care, management of chronic conditions, improved efficiency, and feasibility of implementation.

Assumptions

Electronic alerting mechanisms in electronic medical records in the nursing home will promote faster reaction times to patient problems.

Electronic medical documentation systems provide data that is more accurate and timely.

Nursing home personnel have the resources and competence to effectively utilize electronic medical records.

Significance of the Study

Research that increases development and understanding of existing information systems is important to overcome technological barriers that constrain adoption of information tools that can improve nursing home care. In particular, the mechanisms within an information system, such as alerts and triggers, play an important role in earlier identification, notification, and response of caregivers regarding potential patient problems. These devices may have an impact on the overall outcome of a nursing home patient's health.

The implications of this study are that it will provide a better understanding of how alerting mechanisms are currently being used in an existing information system in nursing home settings. Furthermore, this research will provide insights into how newly implemented decision support mechanisms facilitate the care of residents within the nursing home setting. Future research should examine the validity of the alerts and triggers used to make clinical decisions, evaluate the associations between the use of valid alerting mechanisms in automated systems and the prevalence of illnesses associated with nursing home quality measures, and finally, explain how the use of alerting mechanisms affect cognitive workload of nursing home staff.

REVIEW OF LITERATURE IN HUMAN FACTORS

Healthcare is a complex technological industry that is prone to accidents. One of the greatest contributors to accidents in complex organizations is human error (Reason, 1990). Implying that accidents are caused by human error does not mean that humans should be assigned blame for the accident because most accidents are the result of problems resulting from system failures (Berwick, 1991). System failures pose the greatest threat to safety because they have been built into system processes and may have been present long before any active errors occurred (Reason, 1995). Applying human factors to system problems is an approach used to understand where and why systems or processes breakdown (Rasmussen, 1990).

Human factors has been defined as the study of how humans accomplish work-related tasks in the context of the human-machine system operation and how behavioral and non-behavioral variables affect that accomplishment (Meister, 1989). In healthcare, human factors researchers attempt to understand the interrelationships between humans, the tools they use, the environments in which they live and work, and the tasks they perform (Staggers, 1991; Staggers, 2003; Weinger et al., 1998). Approaches to human factors research includes the systematic application of information about human characteristics and behavior to the design of tools people use and the methods for their use, and to the design of the environment in which people live and work (McCormick, 1970). The goal of a human factors approach is to optimize the interactions between technology and the human, minimize human error, and maximize human-system efficiency, human well-being, and quality of life (Staggers, 1991).

Within the domain of human factors the central focus of study is the human-machine system (Czaja, 1997). The human-machine system combines one or more humans and one or more physical components that interact to transform inputs into outputs. This interaction occurs within specific task environments and can be affected by social and organizational environments where tasks are performed.

Human factors that affect performance within these systems include the human-machine system and subsystem properties, human capabilities, human-machine interfaces, and the environment (Kantowitz & Sorkin, 1983). The remaining sections of this review will be organized around a discussion of systems approaches to human factors, identified subsystems and properties of human-machine systems, performance evaluation in human factors, and outcome measures in human factors research.

Over the last decade, leading nursing and healthcare organizations have stressed the importance of integrating nursing information systems into healthcare systems to enhance the clinical practice of nursing, improve the quality of patient care, and to reduce medical error (Institute of Medicine, 2001a; Ozbolt et al., 1993). During this period, the deployment of technology have been plagued by how to instill complex health information structures into practical, usable models to improve the work of healthcare providers, the healthcare environment, and patient safety (Sensmeier et al., 2004). The purpose of this discussion is to elevate our level of understanding about systems approaches using a human factors model, to facilitate the infusion of human factors concepts into healthcare research by identifying properties of human-machine systems, and to describe how human factors evaluation can lead to recommendations to improve performance and outcomes in healthcare systems.

Systems Approaches to Human Factors

The development of systems thinking

Adam Smith in 1776, who has been called the first systems thinker, explained the behavior of market economies by explaining the relationships between buyers and sellers as opposed to other economists of the time who focused only on buyers (Vicente, 2004). At the beginning of the 20th Century, Frederick Taylor, in his classic texts *Principles of Scientific Management* (1911) and *Shop Management* (1919), focused on the design of work, management of workers, and effects on human productivity in industrial systems (Salvemini, 1998; Sluchak, 1992a). Most recently, human factors principles and study of human machine systems have been divided into three time periods (Czaja, 1997).

First the knobs and dials period, between 1945-1960, focused on aircraft and weapon systems primarily in the military sector with limited applications in automotive and communications industries (Czaja, 1997; Sanders & McCormick, 1993). During the second period, 1960-1970, systems theory became a dominant way of thinking to predict human machine performance, human factors groups were established beyond the military, and human factors incorporated the design of highly costly, complex systems regulated by the Federal government such as the Three Mile Island nuclear power plant (Sawyer, 1996). Finally the third period, post 1970, saw rapid developments in computer technology and automation (Bakken-Henry, 1995; Dowell & Long, 1989; Staggers, Thompson, & Snyder-Halpern, 2001).

There was increased complexity in human machine systems and interaction. Primary emphasis for the human machine system shifted to one of exchange, storage, and processing of information (Atkinson & Peel, 1998; Czaja, 1997). The development of effective design support tools in human machine systems emerged within the domain of systems design based on design problems, designer characteristics, and human information processing abilities (Hasler, 1996; Rouse, 1987).

Systems components

A system is defined as any organized collection of elements that interacts to achieve desired goals and objectives (Nemeth, 2004). The systems concept implies a unified way of thinking where components or elements are only meaningful if one considers the whole, how its parts interrelate, and how it relates to the environment (Effken, Kim, & Shaw, 1997; Meister, 1989; Rasmussen, 1997; Sluchak, 1992b; Zielstorff, 1977). This way of thinking represents the opposite of the mechanistic, reductionist worldview. The reductionist worldview emphasized, “that more molar entities are composed of less molar entities and that the former can be decomposed into the latter without (and this point is critical) changing the characteristics of the larger whole” (Meister, 1989). Meister indicated that no matter how justifiable systems theory might seem, to break a system down into its component parts, the independent actions of the parts will not explain how system components function when they are integrated into the whole system.

All systems have characteristic components. System components that have been identified include: *Elements* such as personnel and equipment, *processes* which can result in system change, *inputs* or technical data, *outputs* representing the total number of units produced, *environment*, *purpose and functions, attributes* like reliability, *management and decision makers,* and *structure* (Czaja, 1997). Figure 2 provides a systems model for human factors research illustrating the components of a system. During systems design and evaluation each component must be considered.

Figure 2. A Systems Approach to Human Factors (Helander, 1997)
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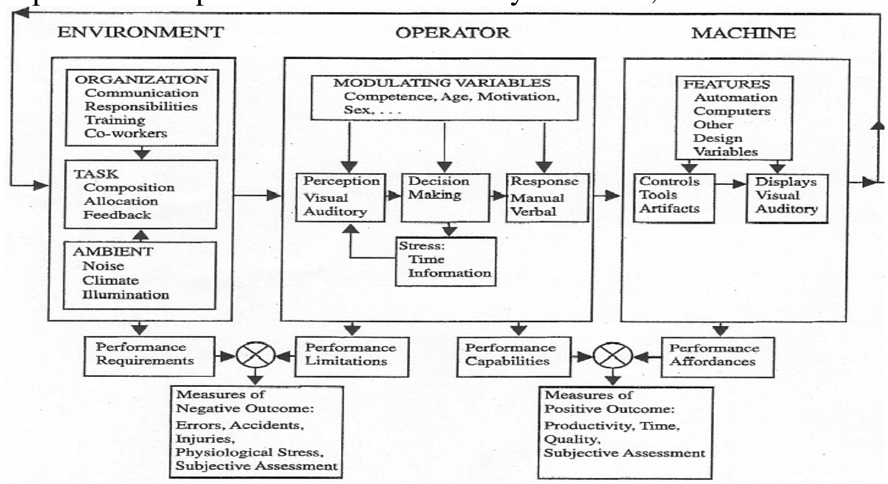

<u>*Subsystems and Properties of Human-Machine Systems*</u>

In human factors models, human-machine systems have been depicted as containing subsystems associated with the operator, the machine, and the environment (Czaja, 1997; Helander, 1997; McCormick et al., 1982). Each of these subsystems has properties that effect outcomes. The following sections describe each of these subsystems.

The operator subsystem

Humans assume the roles of operators and end users of machine systems and are situated at the core of the human machine system (Helander, 1997). Human operators have distinct, individual, and identifiable personal attributes that characterize who they are, how they will interact with the system, and how they may perform. Human-tech, a concept used to describe a systems approach to the design of human technology interfaces, reminds us that people and technology are recognized components of the system with important relationships. Human-tech approaches should identify human and societal needs before addressing technology, should have an affinity for human nature, and should address human needs and capabilities (Vicente, 2004).

One goal of human factors is to optimize the total system by adopting indirect ways of accommodating personnel within the system (Meister, 1989). This goal can be met by designing technology that fits two dimensions of human capabilities, which are basic to human factors, including physical and sensory characteristics and perceptual and cognitive abilities (Hasler, 1996; Sawyer, 1996).

Physical and sensory characteristics. Human performance in work and other venues is a consequence of information processing, including some or all of the following human functions: attention, sensation, perception, coding and decoding, learning, memory, recall, reasoning, making judgments, making decisions, transmitting information, and executing physical responses (McCormick et al., 1982). Depending on the functions that have to be performed, options exist in human-machine environments to allocate certain functions to humans or to some physical (machine) components (McCormick, 1970). Decisions to allocate certain functions to humans or machines are based on some preconceived notions of human machine abilities and can affect performance within the system. A discussion of some of human machine abilities and how they are integrated into human factors design follows.

Table 1 lists some classic human factors generalizations comparing human and machine abilities in human machine interactions.

Table 1: A Comparison of Human-Machine Ability (Federal Aviation Administration, 2004; McCormick, 1970)

Humans surpass machines in:	Machines surpass humans in:
1. Ability to detect small amount of visual and acoustic energy.	1. Ability to quickly respond to control signals, and to apply great force smoothly and precisely.
2. Ability to perceive light and sound.	2. Ability to perform repetitive, routine tasks reliably.
3. Ability to improvise and use flexible procedures.	3. Ability to store information briefly and then to erase it completely.
4. Ability to store large amounts of info. for long periods and recall relevant facts at the appropriate time, reliability of recall is low.	4. Ability to reason deductively, including computational ability.
5. Ability to reason inductively and generalize from observations.	5. Ability to handle highly complex operations—to do many different things once.
6. Ability to exercise judgment, make subjective estimates, and evaluations.	6. Sense stimuli outside of man's normal range of sensitivity vibrations).
7. Prioritize most important activities when overload conditions require.	7. Maintain efficient operations under distractions.

The most basic physical and sensory capacities for humans include vision, hearing, manual dexterity, strength, and reach (Sawyer, 1996). Ergonomics, a term used interchangeably with human factors, is derived from the Greek word "ergo" meaning work, and "nomos" meaning law (Nemeth, 2004). Ergonomics attempts to define working conditions that enhance individual safety, comfort, and productivity by applying physiological, psychological, and engineering principles to the interaction between people and machines (Hannah, Ball, & Edwards, 1999). Ergonomics applications are concerned with designing the workplace and the organization of the job to human physical, physiological, and behavioral limitations (Hawkins, 1987).

Research in healthcare that has incorporated ergonomic considerations for an operator's human characteristics and physical sense into the design of technology is abundant in the literature. For example, as alarms have increased with the use of technology, to substitute for an operator's attention, ergonomic variables that have been considered include alarm outputs, design of alarm displays and control settings, alarm test procedures, and preparation of labeling and instructional materials (Hyman & Drinker, 1983). Ergonomic approaches aimed at assisting professionals to keep up with professional developments were recommended by incorporating new forms of technology into the workplace to lower stress and improve coping (Hawkins, 1987)

Most recently, research on anesthetic errors and mishaps has found that complex jobs such as anesthesiology require maximum vigilance, a state of maximal physiologic and psychological readiness to react (Weinger et al., 1990). Weinger et colleague (1990) suggested that applying human factors to complex jobs such as anesthesiology would increase human reliability, reduce the probability of error, and improve performance. In other research, Hasler (1996) indicated that by knowing the dimensional ranges of 90% of all female hands including, length, breadth, and circumference human factors experts could recommend new designs to improve grip strength, which might prevent injury or improve performance. Knowledge of this type of information could be used to improve designs that could affect a female's ability to apply force while moving heavy equipment (Hasler, 1996).

A case study of ergonomic factors in an emergency room setting described the medical workplace as an "ergonomic nightmare" (Wears et al., 2002). Wears et al. (2002) identified ergonomic issues such as design flaws that prohibited passage of equipment through doors, an organizational culture that supported development of ways to work around things that did not work and the ability of humans to devise novel methods for a work around problems based on experience, and finally, that infusion pumps are the most common example of bad design in healthcare settings due to a lack of interface standardization and intuitiveness.

Perceptual and cognitive abilities. Perception provides humans with the capability to detect, identify, and recognize sensory input, while cognition refers to higher level mental phenomena such as memory, information processing, use of rules or strategies, formulating hypotheses, problem solving, learning, and judgment (Hasler, 1996; Sawyer, 1996). The perceptual system has been classified into five areas including: 1) The basic orienting system responsible for general orientation and body equilibrium, 2) the auditory system for listening which is useful for obtaining external information from nature and locating vibrations, 3) the haptic system, or touching, which aids in human exploration, 4) the taste-smell system for savoring nutritive and biochemical substances, and 5) the visual system which provides information about objects, animals, motions, events, and places (Gibson, 1966).

Cognition, derived from the Latin word cognoscere, to learn and to know, is used to describe psychological processes associated with the acquisition, organization, and use of knowledge (Hollnagel, 2003). Hollnagel (2003) indicated that cognitive tasks are driven by purposes and intentions, cognitive tasks include cause based (feedforward) controls and error-based (feedback) control mechanisms, cognitive tasks require thinking and planning vs. instant reactions, and cognitive tasks are not limited to humans but can also be found in organizational functions. The importance of cognitive task design, which is concerned with how organizational functions can be used to achieve organizational goals and to maintain control in human machine systems, stems from the influence of new technologies, increased functionality, and organizational change on the working conditions of people in the system and the cognitive tasks they perform (Hollnagel, 2003).

Perceptual and cognitive processes in human machine interaction are complex and involve continuous exchanges of information between operator and machine. Perceptual and cognitive processes in human machine systems involve the operator providing input to the machine, the machine acting on the input and displaying information back to the operator; the operator processes information through sensing mechanisms such as visual, auditory, somatosensory, and vestibular systems; and finally, the operator determines if the information from the machine is accurate and correct communication, decides what actions to take, and provides new input to the machine (Proctor & Proctor, 1997). Attempts to understand and exploit human capabilities and human strengths within the area of human perception and cognitive ability are critical to the safe design of technology (Leveson, 1986; Sawyer, 1996).

A recent report, by the US Department of Transportation and the FAA, analyzed and classified human errors, based upon Reason's (1990) concepts of error, into four levels of failure addressing perceptual and cognitive issues including: 1) Unsafe acts, 2) Preconditions for unsafe acts, 3) Unsafe supervision, and 4) Organizational influences (Shappell & Wiegmann, 2000). Table 2 lists types of errors and sources of errors, based on the HFACS report, associated with each of these levels. The FAA established this framework to investigate human causal factors in aviation incidents and to improve aviation accident investigations (Shappell et al., 2000).

Table 2: Framework for Human Factors Analysis and Classification System (Shappell et al., 2000)

Unsafe Acts	Preconditions for Unsafe Acts
Skill based errors • Failure to prioritize attention • Procedural steps omitted	**Adverse mental states** • Complacency • Mental fatigue
Decision errors • Misdiagnosed emergency • Wrong response	**Adverse physiological states** • Physical fatigue • Impaired physiological state
Perceptual errors • Spatial disorientation • Misjudged distance	**Physical/Mental limitation** • Insufficient reaction time • Visual limitation
Unsafe Supervision	**Organizational Influences**
Inadequate supervision • Failure to provide guidance • Failure to provide training	**Resource management** • Human resources • Monetary/budgetary • Equipment/facility resources
Planned inappropriate operations • Failed to provide correct data • Mission not in accordance with rules/regulations	**Organizational climate and process** • Structure • Policies • Culture • Operations • Procedures • Oversight

Similar areas of accident investigation have been recommended and applied in the health care sector. Systems analysis of medical errors and process breakdowns have been identified and associated with perceptual and cognitive deficiencies as evidenced by delayed or omitted procedures, insufficient monitoring, delayed or omitted laboratory workups, inappropriate medication administration, inappropriate treatments, and a lack of documentation (Alexander et al., 2000). In other research, human factors engineering has been used in an attempt to map the cognitive processes of nursing work (Potter et al., 2004). Potter et al (2004) found that cognitive pathways in nursing processes were nonlinear, requiring frequent shifts in the process of delivering care due to interruptions and delays; illustrations of cognitive pathways, through link analysis methods, provided a conceptual map of the organization of nursing care activities and interventions; inconsistencies in nurses evaluation of patients were found during nursing processes; and finally, cognitive pathways demonstrated how well nurses were able to prioritize care and conditions that supported or interfered with patient care in the clinical setting. Understanding perceptual and cognitive abilities of operators in the health care sector will provide better understanding of physical and operational structures that affect clinical decision making and clinical reasoning that may lead to potential failures (Simmons, Lanuza, Fonteyn, Hicks, & Holm, 2003).

The machine subsystem

The origin of human factors was in the development of simple tools, utensils, and shelters (McCormick et al., 1982). The machine age, a period of human factors development, has been characterized in terms of three phases: Phase I (1750-1890) known as the Age of Machines or the Eons of Tools was characterized by stunning inventions in the textile and steam power industries; Phase II (1870-1945) known as The Power Revolution resulted in expansion of the use of power in manufacturing, transportation, agriculture, and electric power for communications. During this period there was increased recognition of the human factors discipline and a shift in paradigms from “fitting the man to the job” to “fitting the job to the man”; Phase III (1945-?) known as the Machines for Minds age emphasized efforts to aid, relieve, and extend human capabilities with a distinct focus on the use of machines, primarily computers, for performing functions (Christensen, 1976; McCormick et al., 1982).

The machine subsystem, illustrated in Figure 2, is broadly conceptualized and may be represented by any artifact controlled by a human such as a knife, a pocket calculator, a toilet seat, or a computer (Helander, 1997; Kantowitz et al., 1983). Features that make a machine unique, more user friendly and safer, such as an appropriately designed curvature of a toilet seat to avoid cutting off circulation and numbness in lower extremities, can be aesthetically pleasing as well as functionally attractive (Kantowitz et al., 1983). In machine systems, such as computers, design features such as automation, controls, visual displays, and workstations have effects on the human operators ability to perform work when interacting with the machine (Bennett et al., 1997; Bullinger et al., 1997; Sarter et al., 1997; Smith et al., 1997). These characteristics must be considered when evaluating human factors in machine subsystems and will be discussed in the remainder of this section.

Automation. Increasing attention to error in medicine and concern for patient safety have prompted general recommendations for development of automated technologies to support clinical decision making to ensure that errors are caught, to promote data standards, and to develop systems that communicate with each other (Bates et al., 2001). Systems approaches to prevention and improved patient safety, a standard practice in occupational health and safety arenas, is called “designing out” hazards and is used to eliminate hazard in a process by using engineering controls to separate hazards from workers (Foley, Keepnews, & Worthington, 2001). Current trends in automation to design out hazards has resulted in increasing levels of system autonomy, authority, complexity, and coupling which increases the need for coordination and communication between human and machine systems (Sarter et al., 1997).

Automation has been defined as the execution by a machine of functions previously carried out by humans (Parasuraman, 2000). Automation has been characterized as a continuum ranging from full manual control to full automation; under conditions of full manual control particular functions are controlled by the human and at the other extreme of full automation machines control all aspects of functioning, including monitoring (Parasuraman & Riley, 1997; Thurman, 1984). Parasuraman (2000) indicated, "that automation can fundamentally change the nature of the cognitive demands and responsibilities of the human operators of systems, often in ways that were unintended or unanticipated by designers."

In cases of human error, four main kinds of failure have been recognized in coupling humans and automation: 1) Human loss of expertise or loss of vigilance results when machine design facilitates increased autonomy by performing low level (decision implementation) or high level functions (diagnosis); 2) human complacency or over-reliance on automation as a result of smart machines performing high level functions; 3) shifts in human trust or self-confidence in machines based on past experiences; and finally, 4) the loss of adaptability in human-machine systems due to the lack of feedback when a machine performs certain operations (Hoc, 2000).

As technology evolves, research continues to be produced to better understand and improve how humans interact with automated systems. In safety critical systems, such as air traffic control operations, nuclear power, and shipping technology, human factors research in automated systems has improved hazard awareness, alerting mechanisms, identified conflicts, and reduced unnecessary communication in congested situations (Baldwin et al., 2002; Bisantz, 2003; Fields et al., 1999; Grabowski et al., 2003; Meyer, 2001). Similar research is being conducted in health care, another safety critical system. For example clinical reminders and automated decision support systems used to take advantage of existing electronic patient information to alert providers of recommended actions have been used to improve compliance with established treatment guidelines and improve diagnosis (Fuchs et al., 1999; Patterson, Nguyen, Halloran, & Asch, 2004b; Rind et al., 1994). Furthermore, research regarding the design of automated medical equipment has led to safer systems and improved patient outcomes (Alberdi et al., 2003; Lin et al., 1998; Vicente, Kada-Bekhaled, Hillel, Cassano, & Orser, 2003b).

Controls. Controls, used to facilitate human machine interaction, are interface elements that allow humans to transfer mechanical energy into a technical system in order to perform automated control functions (Bullinger et al., 1997). Bullinger et al. (1997) indicated that the dimensions of control design such as shape, size, material, surface, and control task must be compatible with anatomical, anthropometric, and physiological conditions of the human or performance levels may suffer. Performance factors that are particularly influenced by task control design include resistance, accuracy, and speed and can be influenced by human stature, structure, and physical function (Bullinger et al., 1997; Nemeth, 2004). Controls that are not designed well may increase stress during human machine interaction and create unsatisfying, frustrating, and threatening interactions that affect human performance levels (Creedon, Malone, Dutra, & Perse, 1998; Pabst, Scherubel, & Minnick, 1996).

Research on control and display design in human machine systems is evident in the literature. Rogers et colleagues described four warning process components that could affect a human's ability to detect a warning including: 1) Ability to notice a warning, 2) internally translating the warning, 3) comprehending the meaning of the warning, and 4) complying with the warning (Rogers, Lamson, & Rousseau, 2000). Person variables and warning variables have been identified for each component, for example, ability to notice a warning was affected by a persons age, familiarity with the label, and information seeking behavior, as well as, a warnings color, placement, size, and interactivity, respectively (Rogers et al., 2000). In other control and display design research, variables associated with color, attentional demands, and validity of warnings have been shown to affect operator performance (Maltz & Meyer, 2001). Furthermore, controls designed to facilitate navigation, functionality, and usability has been shown to support complex learning activities in smaller virtual environments, such as handheld computers (Alexander et al., 2004; Luchini, Quintana, & Soloway, 2003).

In health care, the Association for the Advancement of Medical Instrumentation (AAMI) issued a set of guidelines and preferred practices for the design of medical device controls (Association for the Advancement of Medical Instrumentation, 1988). In the guidelines, AAMI described design elements or features for medical devices to be considered "human factored" (Cook, Potter, Woods, & McDonald, 1991). Cook et al (1991) demonstrated, using these guidelines, how human engineering deficiencies related to the arrangement and integration of controls and displays, markings and symbols associated with hazard warnings, and how separation of control features adversely affected the usability of a heated humidification system used to control humidified gas temperatures in an operating room. In research with elderly subjects using electronic medication compliance devices tactile, auditory, visual design of buttons, switches, pill compartments, labels, and alarms were factors in this populations ability to access there medications (Creedon et al., 1998). Research on the interface controls of patient controlled analgesia (PCA) pumps verified redesign of PCA interfaces, using human factors engineering processes, improved patient safety, decreased drug concentration errors, and reduced task completion times for experienced users of the device (Lin, Vicente, & Doyle, 2001; Vicente, Kada-Bekhaled, Hillel, Cassano, & Orser, 2003a).

*Visual displays.*One of the current barriers to creating an effective healthcare information infrastructure is a lack of standard design for clinical systems that affects the ability of end users to extract data from the information system (Sensmeier et al., 2004). One of the problems associated with designing technology, using cognitive approaches, is that physical aspects of the human-computer domain can be touched and inspected; while, the abstract functional aspects, including the concepts and relationships defining the practitioners domain, must be understood (Elm, Potter, Gualtieri, Easte, & Roth, 2003). Research using principles of cognitive ergonomics attempts to overcome these barriers by understanding and explaining how humans think and use knowledge, describing how to represent relationships between knowledge and human performance, and finally, designing tasks and visual displays that enhance reliable, safe, and effective user performance (Wilson, Jackson, & Nichols, 2003). One method for designing effective, safe retrieval systems is to take advantage of established, semantic and symbolic approaches to visual display and menu design by considering human expectancies and mental models (Sawyer, 1996).

Humans are habitual. Sawyer (1996) recommends that designers take advantage of these stereotypical behaviors in the general population, as well as established protocols and standards in the medical community to develop visual displays that are consistent with these behaviors. Building conceptual models and designs that match human expectancies allows users to predict the effects of their interactions with technology; without a good conceptual model, users operate blindly, unable to function independently, and have little knowledge of what to expect from the system (Norman, 1990). Conceptual models that clash with human expectancies can lead to error and system failure (Benner et al., 2002; Sawyer, 1996).

Conceptual models are part of an important concept in design called mental models which are described as "the models people have of themselves, others, the environment, and the things with which they interact" (Norman, 1990). Mental models allow the user to build expectations of system behavior and to allocate attention span across numerous information rich displays (Sarter et al., 1997). Furthermore, mental models allow users to predict, explain, and understand interactions that are occurring (Staggers, 1991; Staggers & Norcio, 1993). Staggers (1991) explained that difficulties in representing accurate mental models in a computer system arise from the inequalities between what users think images mean and what they accomplish.

In recent research considering the functionality of online design conventions Alexander et al. (2004) found that over one third of the participant observations, during a usability study of an interface for an information retrieval system for healthcare providers, were associated with perceived functionality of conventions used in the design of the interface. Conceptual design problems identified in the research included a lack of understanding of what conventions were supposed to do and a lack of familiarity with conventions used. This resulted in users making incorrect choices, increased search time, and decreased satisfaction (Alexander et al., 2004). In other research, exploring the human computer interface, a cognitive based observational approach was used to determine if failed attempts to enter coded data using a standardized controlled terminology were due to terminology content, terminology representation, or user interface problems (Cimino et al., 2001). Cimino et al. found that 22% of 238 data entry points failed with 13% of observations failing as a result of content issues, 10% associated with representation, and 6% related to usability. Other noted research in display design includes the effects of off-ward trend graphs on clinical decision-making in a neonatal intensive care unit, use of different interface designs and their impact on the ability of novice nurses to learn to use computer simulation and performance in critical care environments, and finally, comparisons of response time, errors, and satisfaction between text based vs. graphical user interfaces in the process of completing nursing care (Alberdi et al., 2003; Effken et al., 2001; Staggers et al., 2000).

*Workstations.*Traditional workplace designs, depending on an employees job responsibility, might consider such issues as posture, visual acuity, office structure including height of office furniture, or exposure to environmental factors like lighting and noise (Smith et al., 1997). These and other ergonomic factors continue to be important considerations in the healthcare workforce today (Hannah et al., 1999; Walker, 1986). The physical design of the workspace should include ergonomic dimensions associated with user height, weight, and strength; furthermore, in analyzing the workspace designers should consider what users have to be able to see, what they have to be able to hear, what do users have to manipulate or reach, how much space is needed to perform the work, what potential exist for disturbance or inactivation of controls, is the work environment adequate for emergency situations, and what other systems or devices are in use (Salvemini, 1998).

With the "new frontiers" in remote healthcare delivery methods, such as telemedicine and wireless computing, the nature of the workstation is changing in healthcare environments (Lathan, Kinsella, Rosen, Winters, & Trepagnier, 1999; Lindberg, 1997; Wakefield, Flanagan, & Specht, 2001). Healthcare providers who are implementing and using these tools should consider opportunities for and challenges of remote computerization in healthcare. Table 3 contrasts some of the opportunities and challenges that have been discussed (Fischer, Stewart, Mehta, Wax, & Lapinsky, 2003; Powsner, Wyatt, & Wright, 1998).

Table 3: Opportunities and challenges for computerization

Opportunities	Challenges
Simultaneous Remote access Flexible layout Continuous data processing Confidentiality and security Greater range of output methods • Computer generated voice, pager, email • Automated interactions Tailored output • Still and moving imagery	Lack of intuitiveness of computer layout Need for structured coded data Loss of design control and flexibility Costs Reliance on hardware and software Impact on patient-clinician relationship

The environmental subsystem

The final subsystem component in the human factors model, shown in Figure 2, concerns the environment. The environmental subsystem is critical to the discussion of human factors and may be the most complex of all the subsystems. No matter what environment we are studying whether it is everyday situations or complex systems, we encounter technology that is beyond our capacity to control (Vicente, 2004). Vicente (2004) indicated that when we turn to safety critical systems, including health care systems, the consequences of technological mishaps can be much more worrisome for the environment than the day to day technological experiences encountered; errors in safety critical systems can cause catastrophic circumstances leading to expensive litigation, ecological disasters, endangered nations, and may result in huge burdens to society.

Contemporary theorists indicate that the environment encompasses human beings and their responses to energy fields, social systems, family, society, and culture (Meleis AI, 1997). Critical environmental issues, important in human factors research, include: organizational structures and processes that address communication, responsibilities, training and relationships among co-workers; tasks, task composition, allocation of tasks, and feedback mechanisms in the system; and ambient variables in the environment (Helander, 1997). Each of these attributes will be discussed.

Organizational structures and processes. Our society is just beginning to understand the impact the substantial growth of technology such as Internet interactions, lasers, satellite-based universities, genomics, and hosts of other technological improvements has had on organizational structures and processes (Porter-O'Grady & Malloch, 2003). The growth of technology has begun to create shifts in healthcare structures from a compartmentalized, rigid, Newtonian organizational structures to a quantum structures characterized by integration, wholism, relatedness, and connectivity (Krueger-Wilson & Porter-O'Grady, 1999; Porter-O'Grady et al., 2003). The survivability of a health care organization during this period of technological growth will depend on its reaction to change, its clarity of purpose, and access to organizational intelligence (Wheatley, 1999).

Survivability will be affected by the ability of leaders to communicate to stakeholders within the system how technology will affect organizational culture. Culture has been defined as the set of established norms, beliefs, and values that determine employee behavior and perception (Gillies DA, 1994). One major responsibility of organizational leadership is to help alleviate cultural dysfunction by assisting members in the organization to adopt new values in order to serve the organization more effectively (del Bueno DJ & Vincent PM, 1986). One critical research area in the environmental domain, related to cultural change, regards the impact of the adoption of technological innovations that may lead to reduced, proceduralized, rote tasks workers must perform and the subsequent increases in cognitive workloads and demands brought about by the innovation (Militello, 1998). Task and role changes, resulting from the adoption of new technologies, result in task uncertainty and require greater coordination, feedback, and training within the organization to prevent failures from occurring (Aydin et al., 1992).

Tasks. Tasks involve interplay between physical and cognitive activities and may be considered to follow a continuum between nearly pure physical tasks, such as running, to nearly pure cognitive tasks, such as studying a book (Alty, 2003). The term task and function are often used interchangeably. Functions tend to describe continuous, macro level behaviors, such as analyzing or detecting, and tasks tend to describe discrete, detailed behaviors needed to carry out functions (Sharit, 1997). Task composition, allocation of tasks, and feedback mechanisms for task evaluation are important to human factors design and will be discussed in this section.

Task composition. A task or action sequence, described in Norman's (1990) Action Cycle, starts with a goal, then steps are initiated based upon user intentions, the sequence of actions to be performed or intended to be performed, and the steps in the execution of the task. After tasks are executed they are evaluated based on user perception, interpretation, and evaluation of the interpretations of the actions. Norman (1990) described task structures as being shallow, narrow, wide, and deep. Most every day tasks, which occupy most of a human's time, are considered shallow, narrow structures that are opportunistic in nature, requiring little complexity in analysis and minimal conscious activity, in these types of structures humans need only examine alternative actions and act; alternatively, wide and deep structures require a considerable amount of conscious planning and thought, and usually require deliberate trial and error functions (Norman, 1990). .

Formal task load models have been used in research to determine appropriate levels and form of interaction in human-machine interactions. Quantitative models of the degree of automation based on the number and complexity of tasks have been used to determine the appropriate level of automation for optimizing system performance while maintaining the appropriate role for the human in the system (Wei, Macwan, & Wieringa, 1998). Cognitive task analysis (CTA) has been used in healthcare settings to document the goals to be achieved, to understand functional means necessary for achieving goals, and to describe job demands and bottlenecks faced by users during human computer interactions in work processes (Elm et al., 2003; Lin et al., 2001). Examples of CTA, in health care research, include the identification of potential errors performed with computer-based infusion devices used for terbutaline administration in preterm labor; to evaluate cognitive and physical burdens during period of high workload and stress while using computer-based physiologic monitoring systems in cardiac anesthesia; and to gain new perspectives in the work of nursing processes to understand how disruptions can contribute to nursing error in acute care environments (Cook & Woods, 1996; Obradovich & Woods, 1996; Potter et al., 2004).

Allocation of tasks. Function allocation is used to assign the performance of each function or task to the elements, including humans, hardware, or software that is best suited to perform it (Nemeth, 2004). Allocation decisions have been based on six allocation strategies including: 1) Comparisons of human-machine capabilities, as shown in Table 1; 2) Leftover allocation where as many functions are assigned to the computer as possible and remaining functions are allocated to the human; 3) Economic allocation considers which element incurs the least cost to accomplish functions; 4) Humanized task allocation, the converse of leftover allocation, allocates a significant functions to an operator and then the remainder is assigned to the computer; 5) Flexible allocation allows users to assign functions according to values, needs, and interests; 6) Allocation by users is a process where alternative ways are created to accomplish the same set of tasks and operators choose the type and amount of allocation used (Bailey, 1989).

Several function allocation models using systems design methodologies have been proposed in the literature (Sharit, 1997). These models use decision matrices to determine performance demands between human and automated functions in computers. Function allocation models can be used to ensure that design considerations: 1) promote the development and updating of adequate mental models, 2) ensure that appropriate levels of human involvement in tasks are maintained, 3) human capabilities are maximized, and 4) the negative consequences of human limitations are reduced (Sharit, 1997).

Feedback mechanisms. Conditions that have been found to hinder feedback in healthcare environments include incomplete awareness that system failures have occurred, time and work pressures, delays in action or outcome sequences, case infrequence, deficient follow-up, failed communication, deficient reporting systems, case review biases, shift work and handoffs (Croskerry, 2000). In the model in Figure 1, feedback is an important element derived from display information in human computer interactions and is fed back to the environment subsystem where it becomes important in the perception, implementation, and evaluation of tasks (Helander, 1997). Emotional risks associated with the failure to provide feedback including loss of confidence, uncertainty about performance, and increased stress (Porter-O'Grady et al., 2003).

Communication has been called the conduit of the feedback process (Croskerry, 2000). Historically, authors of the first book written on human factors in health care (Pickett & Triggs, 1975) addressed feedback mechanisms as major human factors concerns in several papers. For example, communication processes and equipment available in comprehensive emergency medical services serving rural areas were insufficient to provide adequate feedback regarding patient conditions (Olsen, 1975); automated feedback circuits available in automatic defibrillators, that automatically adjusted duration of the pulse to provide preset values of energy when defibrillating, was unable to consider other necessary parameters including voltage and peak current which resulted in voltage delivery errors (Stanfield, 1975); lack of feedback on quality of performance in dental training institutions was recognized as a barrier to effective learning by academicians (Salvendy, 1975); and finally, inadequate feedback mechanisms and process control issues resulted in alterations in prosthetic stumps by individuals who had not assessed the patient resulting in increased discomfort, pressure, and skin problems for patients (Isherwood, 1975).

Recently, feedback mechanisms have been recognized as important components in nurse computer interactions. Improvements have been recognized in the visibility and standardization of the coordination of care during implementation of computerized case management systems (Williams, 1998). Improved feedback mechanisms and changing communication patterns in automated clinical pathways improved quality and efficiency of patient care (Brugh, 1998). Finally, an evaluation of response times to critical laboratory results using automated feedback mechanisms had shorter response times following an appropriate treatment order in 38% of the cases. Researchers concluded that information technologies that facilitate transmission of important patient data can improve the quality of care (Kuperman et al., 1999).

Ambient variables. Adaptation is a set of changes in an individual response that make it possible to deal with adverse conditions which may result in reduced stress levels and improved performance (Nemeth, 2004). Numerous ambient variables in the environment may create adverse conditions by creating acute, prolonged, or chronic stressors for human operators. External acute stressors, or those that affect learning, performance, and decision making, may include heat, cold, darkness, noise, vibration, or sleep loss and can result in eye strain, hearing loss, heatstroke, frostbite and performance errors. External prolonged stressors include repeated motion and tropical or arctic climates which can result in chronic degenerative conditions such as repetitive motion injury or arthritis (Nemeth, 2004). Internal and prolonged acute stressors may be recognized as fear or anxiety and may include phobias; these conditions may result in inhibition, avoidance, withdrawal, depression, ulcers, somatic symptoms, and accidents (Nemeth, 2004).

Performance Evaluation in Human Factors

It has been stated that the goal of human factors design and ergonomics approaches is to design safe and healthy work systems, especially the human machine interactions between individual operators and variable factors associated with the work system, that improves the overall functioning and performance of the organization (Salvendy & Carayon, 1997). Salvendy (1997) described two concepts that are critical to overall system performance including effectiveness and efficiency. Performance measures include system output, input, and reliability measures. These measures are affected by performance capabilities and limitations, performance affordances, and performance requirements. These measures will be discussed in further detail in the following sections.

Performance capabilities and limitations

In large-scale systems humans and technology may jointly be responsible for executing tasks, performing certain operations, and monitoring system safety. These interactions can enhance or reduce system efficiency, safety, or augment human or technological benefits (Grabowski et al., 2003). Two types of performance measures are of interest to human factors researchers including task performance, as measured by performance deterioration, performance on secondary tasks (i.e. task load), and performance variability; and overall system performance measured by annual personal evaluations (Salvendy et al., 1997). These performance measures are affected by the capability of a human to know what is going on around them, a condition called situational awareness (SA) (Endsley, 2000).

Endsley (2000) identified three fundamental levels of SA important in performance including: Level 1) perception of important information or cues in order to form a correct perception of the situation; Level 2) comprehension as measured by the ability to combine, interpret, store, and retain information and to determine the relevance of the information to goals; Level 3) projection, the highest level of SA or understanding, is the ability to project the future state of the events and dynamics within the system. Endsley (2000) also identified a temporal aspects of SA important for operators, such as the ability to estimate how much time is available until an event occurs, when action needs to be taken, and the rate at which information changes. This can be critical in dynamic environments where situations are always changing.

Performance based measurement in SA measurements is any measurement that infers an operators awareness of the situation from observable actions or the effects of the actions on the system (Pritchett & Hansman, 2000). Pritchett et al. (2000) identified knowledge based measures, verbalization measures, and performance based measures of situational awareness. Table 4 outlines some of the measures with potential strengths and limitations of each measure.

Table 4: Situational Awareness Measures adapted from (Pritchett et al., 2000)

	Knowledge based measures	Verbalization measures	Performance based measures
Measurement points	Information perceived Assessment of current state Assessment of future state	Information processing Monitoring and alerting Decision making	Information available Observations of actions
Strengths	Isolates components of current SA	Insight into perceived importance of information	Assess final performance of system and record actions
Limitations	Cannot necessary be used to predict final performance	Cannot necessary be used to predict final performance	Not a direct measure of operators SA

Performance affordances

Norman (1990) defined affordances as the perceived and actual properties of an object that determines just how it is to be used; affordances provide strong clues to the operations of things. At any point of the existence of an object it is said to exist in a certain state. States change, therefore objects exhibit an affordance for transformation that may lead to other changes in system states (Dowell et al., 1989). Affordances have also been described as a relationship between properties of the environment and the properties of an operator's capability to act (Kirlik, Miller, & Jagacinski, 1993). According to Kirlik and colleagues (1993) the importance of recognizing affordances is in the skilled operators ability to differentiate environmental attributes for efficient selection of actions. Implications for systems are that operators with different abilities may perceive the environment differently resulting in different action selections, and thus, possibly resulting in different outcomes.

<u>*Outcome Measures in Human Factors Research*</u>

Data on outcomes in human factors is important to determine if goals have been achieved. Potential contributors to outcomes in human factors have been discussed and include: 1) the individual, 2) tasks, 3) tools and technology, 4) and environment, (Smith

& Carayon-Sainfort, 1989). A study of the relationships between outcome measures and work related risk factors aids human factors researchers in the design process by identifying elements that need ergonomic attention (Salvendy et al., 1997).

In early research, human factors principles were used, mostly by engineers, to evaluate the difficulty of nursing assignments using observational measures of work such as time to complete nursing tasks and energy expenditure which resulted in a computerized interactive nursing assignment model being developed and tested to achieve more optimal nursing assignments in hospitals (Freund, 1975) In other early research in human factors mathematical models were developed to analyze the impact of facility design on nursing practice, circular nursing units vs. rectangular units, on nursing efficiency and costs of building such facilities (Lippert, 1975).

In more recent research, nursing services are beginning to utilize human computer interactions to capture nursing relevant data about nursing services in the field. For example, in research using a nationally recognized, standardized nursing classification system researchers were able to analyze perinatal advanced practice registered nurses practice patterns, diagnoses/client problems, and interventions across multiple sites (Marek, Jenkins, Stringer, Brooten, & Alexander, 2004). The information system used allowed researchers to communicate the contributions of APRNs to positive patient outcomes. In other health care research, human factors barriers in the use of clinical reminders in an information system were identified including: 1) workload during patient visits, 2) time to document when a clinical reminder was not clinically relevant, 3) inapplicability of the clinical reminder for context specific reasons, 4) limited training on use of clinical reminder software, 5) perceived reduction of quality of provider patient interactions, and 6) the decision to use paper forms prior to order entry of physician orders (Patterson, Nguyen, Halloran, & Asch, 2004a). Patterson concluded the reducing the human factors barriers would potentially increase the use of the clinical reminders and improve the quality of care.

Conclusion

This review has discussed a systems approach for the evaluation of human factors. Specific components identified as being important in human factors research include the operator of the system, the machine (i.e. computer), the interactions the operator has with the machine, environment variables that impact the human machine interaction and feedback mechanisms affecting the work of individuals in the system, performance, and outcome measures. Understanding human factors research will enable researchers to understand how work is performed, to develop human machine systems that support the work of the organization, and will facilitate organizational and individual goal achievement. Furthermore, these types of evaluations will allow manufacturers and designers of human machine systems to instill complex health information structures into practical, usable models to improve the work of health care organizations, the environment, and patient safety.

METHODOLOGY

Research Design

This cross-sectional descriptive study will use data, obtained during a 6 month period, from an information system called One Touch Technologies (OTT). This technology was recently implemented in three Missouri nursing homes. Data was obtained from the 6-12 month post implementation periods. The purpose of this study is to utilize the infrastructure of the OTT EHR to provide an evaluation of current alerting mechanisms within an EHR system found in some nursing home settings. OTT staff and the 3 nursing homes, working under a cooperative agreement in a research project currently being conducted at the University of Missouri-Columbia (*RFP-CMS-03-001, Evaluation of the Use of Bedside Technology to Improve Quality of Care in Nursing Facilities,*PI: Marilyn Rantz PhD, RN, FAAN), will provide a large dataset from the information system where OTT has been deployed and that is currently being used in the 3 Missouri nursing homes. The dataset will include all dataset elements from the OTT system listed here:

- Fictitious unique nursing home identifier assigned by the OTT Corporation
- Fictitious unique patient identifier assigned by the OTT Corporation
- Patient diagnosis
- Alerts initiated
- Triggers initiating the alerts
- Date alert initiated
- Time alert initiated
- Care plan problems identified when alert initiated
- Date alert removed from record

- Time alert removed from record
- Care plan problems identified when alert removed
- Task list items identified when alerts initiated
- Task list items identified when alerts removed

Data obtained for this study will include all patient care data continuously recorded by nursing home staff in each of the three facilities for 6 months, ranging between 6-12 month post implementation. The following date ranges, in Table 5, correspond to the implementation times for each facility included in this study.

Table 5: Date ranges for data captured in OTT system in participating nursing homes

Nursing Home	6 month post implementation date	12 month post implementation date
A	January 2004	July 2004
B	March 2004	September 2004
C	August 2004	February 2005

<u>*Sample*</u>

The sample will include all data obtained from three Missouri nursing homes during the specified time range. The active alerts per resident will be used as a unit of analysis while controlling for a specific type of alert and primary patient diagnosis. The nursing home facilities have a total of 518 skilled nursing beds. Nursing homes were selected from a group of homes participating in a concurrent study, titled, "*Evaluation of the Use of Bedside Technology to Improve Quality of Care in Nursing Facilities,*" PI:

Marilyn Rantz. The evaluation study used a stratified purposive approach to recruit facilities from Missouri. Facility size was taken into account during the recruitment phase. Additionally, nursing home facilities representing profit, not-for-profit, and governmental ownership structures were represented. Characteristics of each nursing home in this proposed study are outlined in Table 6.

Table 6: Facility characteristics

Facility	Certified Beds	Ownership
A	180	Government
B	240	Non-Profit
C	98	For Profit

Within each of these facilities, the percent of occupied beds ranged from a low of 68% in facility A to a high of 96% in facility C in February 2004. In February 2005, the lowest percentage of occupied beds was in facility A with the highest occupancy rate in facility B, ranging between 72% and 95% respectively. In February 2004, the highest percentage of residents in facility A, 40%, experienced more depression or anxiety, while the highest percentage from 51% to 75% of the residents in facilities C and B respectively, were identified as low risk residents who lose control of their bowel or bladder. In February 2005, 40% of the residents in facility A, 80% of the residents in facility B, and 75% of the residents in facility C represented the highest percentage of residents identified as low risk residents who lose control of their bowel or bladder. Total number of nursing staff hours per resident per day noted in the February 2005 for each of the facilities was 4.26, 3.09, and 3.52 for facility A, B, and C accordingly. Average for the state of Missouri is reported as being 3.7 nursing staff hours per resident per day.

Data Collection Procedures

A dataset captured from OTT, during the 6-12 month post implementation period, will be used in this evaluation of the database. The dataset from each of the nursing homes will be received from OTT on a preformatted hard disk that will be reposited for analysis in a relational database on a secure computer in the Department of Health Management and Informatics, Clark Hall, 4th floor, 426J. SPSS 11.5 for Windows and Microsoft Access 2000 are the primary databases that will be used to analyze the dataset. These data will include assessment, intervention, care planning, treatment, and other services elements as indicated in the previous description of the research design. Before data are provided to the MU evaluation team, OneTouch technology staff will remove all resident and nursing home facility identifying information, resulting in a de-identified dataset. Original identifiers will be kept confidential by OTT staff and will not be available for researchers in this study. OTT will assign fictitious unique resident identifiers and fictitious unique nursing home identifiers in the dataset that will replace corresponding residents or nursing home names or numeric identifiers. There are no foreseeable risks to residents or employees of the nursing home facilities as all information will be de-identified. Data will be stored in a secure computer kept in a restricted area on the MU campus that is accessed only by authorized MU staff.

<u>Statistical Analyses</u>

Specific Aim (1)

Determine the relative frequency of active alerts and the average time alerts are active in residents with specified diagnoses during a period of 6 months of data collection.

Research Questions:

1) What is the proportion of active alerts for each alert category in residents with specified diagnoses in the EHR including: dehydration, constipation, skin integrity, decline in condition, weight loss, and weight gain?
2) What is the average time each alert is active per resident with specified diagnoses in the EHR?

Analysis:

Controlling for specific types of alerts including dehydration, constipation, skin integrity, decline in condition, weight loss, and weight gain and the primary patient diagnoses, descriptive statistics will be used to trend and graph the periods of time alerts were active, types of alerts that were active, and average time alerts were active within each alert category during the 6-month period. Controls used in the analysis include the alert category and patient diagnoses. Each alert category and patient diagnosis will be given a unique dummy-coded variable to allow them to be manipulated in the database. Total diagnoses and type of diagnosis per resident will be calculated. The total amount of active alerts for the most common diagnosis types will be trended and graphed. We are looking for trends in the specific types of alerts identified with the most frequent primary diagnoses identified. Furthermore, we will be assessing the average length of time alerts are active for different diagnoses.

Specific Aim (2)

Discover if the relative frequency of active alerts increases in residents as the number of secondary diagnoses increase.

Research Question:

What is the relative frequency of active alerts associated with residents who have secondary diagnoses?

Hypothesis:

There will be a significant positive correlation between the number of secondary diagnoses assigned to nursing home residents and the number of active alerts.

Analysis:

While controlling for specific categories of alerts as mentioned in *Specific Aim (1)* and the primary patient diagnoses, Spearman's Rank Correlations will be performed on the number of secondary diagnoses assigned to residents and the number of active alerts in the EHR since these are both counts and will not be normally distributed.

Specific Aim (3)

Determine the frequency and types of triggers in active alerts, in residents with specified diagnoses during a period of 6 months of data collection.

Research Question:

What is the proportion of triggers for each active alert in each alert category: dehydration, constipation, skin integrity, decline in condition, weight loss, and weight gain within and across resident diagnoses?

Analysis:

While controlling for specific categories of alerts and the primary patient diagnoses, descriptive statistics will be used to trend and graph the trigger frequencies in active alerts in each alert category during the 6 month period. Each alert category and patient diagnosis will be given a unique dummy-coded variable to allow them to be manipulated in the database. The frequencies and types of triggers associated with active alerts for each diagnosis type will be determined.

Specific Aim (4)

Describe the plan of care changes including care plan problem identification, interventions, and tasks assigned on CNA task lists recorded in the EHR by healthcare workers during periods when alerts are active compared to periods when alerts are inactive in the EHR.

Research Question

Are care plan problems changed, interventions performed, and tasks assigned on CNA task lists on residents with specified diagnoses in each alert category during periods when alerts are active and inactive?

Hypothesis:

There will be a significant difference between clinical actions taken when alerts are active as compared to when alerts are inactive.

Analysis:

While controlling for periods when alerts are active, type of alert, time of day the alert occurred, and resident, a quantitative assessment will be performed of clinical actions recorded in the EHR including interventions, problems identified, and task assignments made during periods when alerts are active. Further, a similar quantitative assessment will be performed of clinical responses recorded in the EHR during periods when alerts are not active. Comparisons of the number of clinical actions taken by staff when an active alert occurs will be made with the number of clinical actions taken by staff during periods when alerts are inactive on the same resident. As an example, if an alert is active on Monday, a similar time period when an alert is inactive will be selected during the following week on the same day of the week (Monday) as close to the same time period as when the alert was active the week before. The day of the week and time of day is controlled for while alerts are active and inactive to offset any confounding effects related to changing staff schedules. Residents will serve as their own controls for comparisons of when alerts are active and inactive. While controlling for patient diagnoses and alert category, a descriptive analysis and comparison of both of these groups will include the frequencies of clinical responses to selected alerts by clinicians when alerts are active and inactive. A comparison of the groups will be presented in tabular format as shown in Table 3. To test the hypothesis that there would be differences in the proportion of clinical actions during a period when an alert is active versus a period when an alert is not active, a McNemar's test will be calculated using SPSS.

Table 7: Comparisons of clinical actions taken when alerts are active and inactive

Alert Active — Clinical Response	Alert Not Active — Clinical Response: NO	Alert Not Active — Clinical Response: YES
NO	NO / NO	YES / NO
YES	NO / YES	YES / YES

Limitations

1. The data has multiple nurses and CNAs involved in the history recording of the subjects in the sample . Individuals may have varied in their symptom taking history and recording of patient complaints or findings.
2. The retrospective nature of the data. Symptom reporting is dependent on patient/nurse recall and reporting of the experience (Friedman, 1997) . To minimize recall bias, the patient history examined in these data will be done in proximity to the when alerts were active in the patient record.

Protection of Human Subjects

The study proposal will be submitted to the Health Sciences Institutional Review Board for approval of research involving human subjects. Researchers will obtain an expedited review with exempt status because the study involves a secondary analysis of an existing data source. Data captured from the OneTouch Technology System from each of the participating facilities will be used in this evaluation. These data will include assessment, intervention, care planning, treatment, MDS, and other service elements.

Before data are provided to the researchers associated with this study, OneTouch staff will remove all resident identifying information and a fictitious unique identifier will replace each resident's name or numeric identifier. Data will be stored in a secure computer kept in a restricted area on the MU campus that is accessed only by authorized staff.

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Appendix 1:

OneTouch Alerts Calculations

A dehydration alert is triggered by the reporting of any of the following parameters by a staff member:

-Diarrhea reported within the last 24

-Weight loss of 3 or more pounds reported – looks back 7 days.

-Dehydrated was reported within the last 24.

-Insufficient fluids reported within the last 24.

-Fever was reported within the last 24.

-Vomiting was reported within the last 24.

-Leaves 25% or more of food uneaten at most meals was reported twice within the last 48.

A constipation alert is triggered by the recording of any of the following parameters by a staff member:

-Regular bowel movement was not reported within the last 48 hours.

-Constipation was reported within last 24 hours.

-Fecal impaction was reported within last 24 hours.

The following trigger the skin integrity alert:

-The resident was reported as comatose.

-Decisions of Daily Life reported as Severely impaired.

-Bowel movements reported as incontinent twice in last 48 hours.

-Bladder voiding reported as incontinent twice in last 48 hours.

-Resident has a diagnosis of Diabetes Mellitus.

-Resident has a diagnosis of Peripheral vascular disease.

-Resident has a diagnosis of Dementia - other than Alzhiemer's.

-Resident has an Antibiotic resistant infection (e.g. Methicillin resstaff).

-Resident has Edema.

-Resident has an Infection of the foot.

-Turning or repositioning program is ordered but has not occurred within last 6 hours.

Decline in Condition will be triggered by the presence of any 2 of the following items:

-Decision Making on the last MDS was answered as a 0 or 1 and has increased to a 2 or 3 based on today’s data.

-Sad or Anxious on the last MDS was answered as a 0 or 1 and has increased to a 2 based on today’s data.

-The sum of the answers for Behavior Symptoms, E4Ab – E4Eb on the last MDS has increased based on today’s data.

-ADL’s, G1Aa - G1Ja, on the last MDS have increased based on today’s data.

-Bowel or Bladder Continence on the last MDS, H1a or H1b was answered as a 0, 1 or 2 and either has increased to a 3 or 4 based on today’s data, or an indwelling catheter was inserted.

-Stability of conditions J5a, was unchecked on the last MDS but based on today’s data would be checked.

-Weight Loss, K3a on the last MDS was answered as no but would be answered with yes based on today’s data.

-The highest stage pf Pressure Ulcers M2a on the last MDS was answered with stage None or stage 1 and based on today's data would be answered with stage 2 or higher.

-Trunk Restraints indicated as not used on the last MDS would be answered with used less than daily or used daily based on today's data.

-Overall Condition was answered with no change or improved on the last MDS would be answered with deteriorated based on today's data.

Decline in Condition will be triggered by the presence of any 2 of the following items:

-Decision Making on the last MDS was answered as a 2 or 3 and has decreased to a 0 or 1 based on today's data.

-The sum of the answers for Behavior Symptoms, E4Ab – E4Eb on the last MDS has decreased based on today's data.

-ADL's, G1Aa - G1Ja, on the last MDS have decreased based on today's data.

-Bowel or Bladder Continence on the last MDS, H1a or H1b was answered as a 3 or 4 and either has decreased to a 0, 1 or 2 based on today's data, or an indwelling catheter was removed.

-Overall Condition was answered with deteriorated on the last MDS and would be answered with no change or improved based on today's data.

The following would trigger a weight loss alert:

- Weight loss of equal to greater than 3.5% of the resident’s total body weight over period 30 days or 7% over 180 days based on today’s data.

The following would trigger a weight gain alert:

- Weight gain of equal to greater than 3.5% of the resident’s total body weight over period 30 days or 7% over 180 days based on today’s data.

PART II

RESEARCH REPORT

An Analysis of an Integrated Clinical Decision Support System Used in Nursing Home Electronic Medical Records

Gregory L. Alexander RN, PhD(c)

University of Missouri, Columbia

Sinclair School of Nursing

Department of Health Management and Informatics

OBJECTIVES: Evaluate a clinical decision support system in an electronic medical record (EMR) to determine activation frequencies, patterns of activity, and how automated alerting mechanisms affect clinical responses.

DESIGN: Descriptive

SETTING: Three nursing homes

PARTICIPANTS: Midwestern nursing homes where administrative staff had committed to implementing an EMR and clinical decision support system called OneTouch Technologies.

MEASUREMENTS: Automated alerts in the OneTouch EMR including constipation, decline in condition, dehydration, improvement in condition, skin integrity, weight gain, and weight loss were evaluated. Utilizing alert calculations, frequencies of alerts and triggers were counted. Spearman's rank correlations were determined between the frequency of active alerts and the number of secondary diagnoses. Finally, a comparison was made of clinical responses to active and non active alerts.

RESULTS: Alert data from two facilities totaling 155 days were included in the study. The most frequent alerts were dehydration and improvement in condition. One moderately significant positive correlation was found between the number of secondary diagnoses and weight gain alert frequencies in residents who had a CVA. There were more clinical responses than no clinical responses overall. However, there were as many clinical responses to conditions with no active alerts as active.

CONCLUSIONS: Frequencies of alerts is an indicator of how much information has to be managed in order to meet complex issues in nursing home residents. Automated alerts play a role in reminding nursing home staff of potential trouble spots in resident care.

INTRODUCTION

The United States population is aging with the oldest old, 85 years and over, growing the fastest[1]. The Institute of Medicine (IOM) indicated the rapid growth will have a major effect on the demand and supply of long term care services. Projected ranges for Americans needing long term care are 10.8 million to 14 million by 2030. An estimated 4.3 million to 5.3 million will need nursing home care. Continuing concerns about quality, cost, accessibility, adequacy of oversight, and enforcement issues are driving the need to implement better information systems in nursing homes, where a significant portion of the population resides. Information systems that provide valid, reliable, and timely data about the care provided to the recipients of care, the facilities, and the caregivers providing care is fundamental to monitoring and improving quality of nursing home care[1].

Functional Models in Health Information Systems

Over the last decade, healthcare leaders have stressed the importance of integrating information systems (IS) and health care systems to enhance clinical practices, improve quality of care, and reduce medical error[2-4]. During this period, the deployment of information systems and technology into healthcare systems have been plagued by how to instill complex health information structures into practical, usable models to improve the work of healthcare providers, the healthcare environment, and patient safety[5]. Recognizing core functions of electronic medical record (EMR) systems can assist IS developers to design models for health information structures that are more practical and usable. Primary functions of the EMR are to support the delivery of personal healthcare services, including care delivery, care management, care support processes, administrative processes, and patient self-management [6]. The IOM committee (2003) recognized other secondary functions of EMRs as being education, regulation, research, public health, and policy support.

Electronic medical records should be designed to enhance core functions by: 1) improving patient safety, 2) supporting patient care delivery, 3) facilitating the management of chronic conditions, 4) increasing efficiency, and 5) considering ease of implementation, including software development[6]. This study used these criteria to evaluate the functionality of an integrated EMR, called OneTouch Technologies (OTT), being implemented in three nursing homes located in Missouri. The model for clinical decision support systems in EMR, see Figure 1, developed by the author and based on theoretical ideas from human factors experts was used as a framework to guide this investigation[7-11].

[Insert Figure 1 about here]

The model for clinical decision support illustrates how alerting mechanisms, used in clinical decision support systems, aide in problem recognition and lead to clinical actions that improve resident outcomes. Resident assessment data used to document resident conditions are entered into the EMR; predetermined criteria or triggers within the resident assessment are then used to build decision support tools, including alert mechanisms. Once the predetermined criterion related to each alert is met an alert becomes active and the information system automatically indicates a potential problem has been identified within the assessment data entered into the record. Upon activation, staff using the EMR receives an automated message notifying them of the active alert. Staff can choose to take clinical actions or not. When the condition is resolved the alert automatically becomes inactive. In the absence of alerts, staff are responsible for assimilating resident assessment data and making decisions about resident care based upon their own recall and synthesis of vital information. In this study, active alerts associated with an EMR implemented in three Missouri nursing homes were evaluated to determine the frequency of activation, to describe patterns of alerts across different resident diagnoses, and if clinical responses were different when alerts were active versus not active.

METHODS

Subjects and Setting

Three participating nursing homes, facility A, B, and C ranged in size from 180, 240, and 98 beds; type of ownership varied from government, non-profit, and for profit. Within each of these facilities, the percent of occupied beds ranged from a low of 68% in facility A to a high of 96% in facility C in February 2004[12]. In February 2005, the lowest percentage of occupied beds was in facility A with the highest occupancy rate in facility B, ranging between 72% and 95%, respectively. During this same period, the highest percentages of residents in all three facilities were reported to be low risk residents who lose control of their bowels or bladder ranging from 40-80%. Total number of nursing staff hours per resident per day noted in February 2005 was 4.26, 3.09, and 3.52 for facilities A, B, and C, accordingly[13]. Average for the state of Missouri was reported as being 3.7 nursing hours per resident per day[13].

All of the nursing homes were participating in a larger research project designed to evaluate the use of bedside technology to improve the quality of care. All homes had implemented the OneTouch electronic medical record system. Patient data used in this study were collected from the EMR during the 6 to 12 month post implementation periods at each facility. Six months of data from each facility were provided by OneTouch after fictitious, unique nursing home and patient identifiers were assigned in the data sets for patient confidentiality. Approval for the research process was obtained from the University of Missouri's Institutional Review Board. The dataset elements included were patient diagnosis, alert status including when they were active and not active during the 6 months, triggers initiating the alerts, care plan problems identified when alerts were active and not active, and certified nurse assistant (CNA) task lists items identified when alerts were active and not active.

Nursing Home Technology

The OneTouch system represents a shift from a manual paper and pen to a digital environment where nursing home staff has access to real time, automated information. OneTouch incorporates technologies that have not previously been available to the nursing home industry. This new level of data collection incorporated into an EMR should have positive effects on the quality of individual resident care by improving detection of potential resident problems through automated alerts. Evidence of the positive effects of automated alerts are found in a recent report that identified critical practices in the literature to improve quality using clinical decision support systems to evaluate patient specific clinical variables and to aid in clinical decision making[14-15]. OneTouch integrates IButtons, radio frequency, infrared, palm digital assistants (PDAs), and wireless technology, through the corporation's proprietary software to support the clinical decision support system.

Clinical data used in OneTouch is collected at either the bedside (point of care) or entered into personal computers. The data automatically populates all the appropriate sections in the EMR and the Minimum Data Set. One of the strengths and defining features of OneTouch is the ability to collect data at the patient's bedside using handheld PDAs. Combining the use of the IButton technology located on the resident's identification bracelet and the caregivers identification badge, caregivers become more accountable for resident care and documentation while being alerted to individual care and medical needs. The PDA modules are designed to provide a template for complete, verifiable documentation, as well as, interactivity of specific items in the clinical record. Within each touch of the PDAs to the IButton there is a bidirectional exchange of information between the IButton and the PDA. Information currently provided at the point of care includes vital signs clinical alerts, nurse to nurse messaging, CNA task lists, care plan items, active physician orders, and treatments.

Automated alerts in the OneTouch EMR assist to identify when a resident may be experiencing constipation, a decline in condition, dehydration issues, an improvement in condition, a loss of skin integrity, weight gain, or weight loss. Each alert mechanism has a specific alert calculation as shown in Table 1. Within specific alert calculations identifiable triggers when selected can automatically initiate an active alert as nursing home staff collects data at the point of care in the EMR. Alerts and triggers are incorporated into a relational database that uses detailed data elements which contribute to the clinical decision support system that is integrated into the EMR. Using the infrastructure of OneTouch, the goal of this study was to evaluate the automated clinical decision support, or alerts, being used in nursing home care by determining: 1) the frequency of active alerts overall in each nursing home and in residents with specified diagnoses, 2) if positive correlations exist in residents with the same primary diagnoses that have increasing numbers of secondary diagnoses, 3) the frequency and types of triggers in active alerts in residents with specified diagnoses, and 4) clinical responses including problem identification, interventions, and task assignments recorded in the EMR by nursing home staff during periods when alerts are active versus not active. The following section describes the statistical analyses used to evaluate the automated clinical decision support system.

[Insert Table 1 about here]

Statistical Analysis

Phase 1 of the analysis involved querying each day of the 6 months of data collection for active alerts and other data elements used in this study. Every facility EMR was queried at 0700 AM, the start of the day shift, beginning on the sixth month post implementation date and ending at 0700 AM on the twelfth month post implementation date. The overall frequency of active alerts in each nursing home and in residents with specified diagnoses were determined for each alert type including constipation, decline in condition, dehydration, improvement in condition, skin integrity, weight gain, and weight loss. Descriptive statistics were used to trend types of alerts that were active and average time alerts were active within each alert type. Each alert type and patient diagnosis was given a unique dummy coded variable to allow them to be manipulated in the database. Type of primary diagnoses and number of secondary diagnoses per resident were determined. The total amounts of active alerts for the most common primary diagnosis types were tabulated. The goal was to describe trends in the specific types of alerts identified for the most frequent primary diagnoses.

Average length of time was assessed per month that alerts were active overall and for residents with the same primary diagnoses. Average length of time was assessed by calculating the length of time that alerts were active on consecutive days each month. Categories of length of time alerts were active were created where natural breaks appeared in the data. Categories included no alerts during the month, alerts that were active for 1-3 days, 4-9 days, 10-19 days, and 20 or greater days. The category no alerts was an indicator of the frequency that no alerts occurred on individual residents for the month.

Phase 2 used the Admission, Discharge, and Transfer report located in OneTouch. Data was organized by alert types and the primary diagnosis of each resident. Spearman's Rank Correlations were performed on the number of secondary diagnoses assigned to residents and the number of active alerts in OneTouch, since they are both counts and are not normally distributed. The hypothesis was that a significant positive correlation would be found between the number of secondary diagnoses assigned to nursing home residents and the number of active alerts.

Phase 3 of the analysis determined the frequency and types of triggers found in active alerts in residents with specified diagnoses during the 6 months. Data was organized by alert type and the resident primary patient diagnosis, descriptive statistics were used to trend trigger frequencies for each alert type during the 6 months.

The final analysis determined if significant differences existed between clinical actions taken when alerts were active versus when alerts were not active. Data was organized by alert type, alert status (active or not active), time of day alerts occurred, and by resident. A quantitative assessment of clinical actions was performed including interventions, problems identified, and task assignments made when alerts were active. Another quantitative assessment was performed of clinical responses recorded in the EMR during times when alerts were not active, approximately 1-week from when the active alert occurred. Comparisons of the number of clinical actions taken by staff when an active alert occurred were made with the number of clinical actions taken by staff when an alert was not active on the same resident.

As an example, if an alert was active on Monday, a similar time period when an alert was not active was selected during the following week on the same day of the week, in this case Monday, at the same time period as when the alert was active the week before. The day of the week and the time of day were used to offset any confounding effects related to changing staff schedules. Residents served as their own controls for comparisons of when alerts were active and not active. A descriptive analysis of the frequency of clinical responses to selected alerts by clinicians when alerts were active and not active was performed. To test the hypothesis that there would be differences in the number of clinical actions taken during a period when an alert was active versus a period when an alert was not active, a McNemar's test was calculated. All statistical analyses were performed using SPSS and EXCEL software packages.

RESULTS

Initial queries for each day of the 6 months were examined to determine if any patterns in the active alert data could be found at the facility level. It was assumed by the research team that there would be a lot of variation between the frequencies of alerts on a day to day basis within each facility and between facilities. This assumption was based upon the diversity of care delivered to residents, changes in resident conditions, and complexity of resident care in nursing homes[16-17].

Contrary to this expectation, little variation in alert frequencies was noted in facility A during the first 10 days. Alert frequencies for dehydration, decline in condition, weight loss, and weight gain had zero active alerts; constipation, skin integrity, and improvement in condition were consistently 136, 3, and 40, respectively. Similarly, in facility A, alert frequencies had virtually no variation from day 21 of the fourth month to the last day of the sixth month. During the period from Day 11 of the first month through day 20 of the fourth month frequent variation was found in all categories of alerts.

Comparisons of the daily alert frequencies in data for facility B and C were completed. Alert frequencies were variable from day one until day 25 of the second month in facility B, when abruptly, the alert frequencies in each alert category became consistently the same from day to day. Alert frequencies in facility C remained consistently the same throughout the entire 6 months of data collection. There was no variation between the day to day frequencies. There were no active alerts for dehydration, skin integrity, and decline in condition noted during any of the 6 months in facility C. Further, active alerts for constipation and improvement in condition were 83 and 18, respectively, for each day of the analysis period; alerts for weight loss and weight gain also showed little to no variation.

As a result of these initial findings, the research team decided to include only alerts in facility A from day 11 of the first month to day 20 of the fourth month, a total of 101 days of valid data. For facility B, data from the first day of the first month to day 24 of the second month for a total of 54 days of valid data were included. Each of these time periods for facility A and B represented when alerts had day to day variability in status and therefore were considered to be periods when valid data was collected. Due to the complete lack of variation in data in facility C no valid data were assumed and were not included in this analysis.

Alert Frequencies

Average alert frequencies for valid data periods per resident by alert type for facilities A and B overall and for the most frequent primary diagnosis in each facility are shown in Table 2. The two most frequent alerts occurring in both facilities were dehydration and improvement in condition, 32.5% and 23.2% in facility A and 29.8% and 24.8% in facility B, accordingly. Constipation was the third most frequently occurring alert in facility A, 21.2%; skin integrity was the third most frequently occurring alert in facility B, 16.1%.

[Insert Table 2 about here]

The most frequent alerts in residents with Ventilation Pneumonitis were dehydration and improvement in condition, 32.0% and 23.3%, respectively. The highest percentage alert, 31.9%, in facility B was dehydration and occurred in residents with osteoarthritis. Residents with osteoarthritis also had the least frequently occurring alert type; the weight loss alert only occurred in one of seven residents.

In facility A, a wide range of alert frequencies were found in residents with the same primary diagnosis. Of 89 residents with a primary diagnosis of ventilation pneumonitis in facility A, 42.7% (38/89) had at least one alert type occurring for 101 days, the maximum number of days an alert could be active. Of these residents, 65.7% (25/38) were of the alert type improvement in condition. In facility B, the most frequent primary diagnoses included 83 residents. The maximum number of days an alert could be active was 54; 28.9% of residents, (24/83) had at least one alert type occurring for the maximum number of days. Seventy five percent (18/24) of these were of the alert type improvement in condition.

Average length of time alerts were active, measured by the number of day's individual alerts were consecutively active for residents in each facility, are shown in Table 3. Specifically, these tables depict the frequency of time alerts were not active for a resident during the months with valid data, or the number of times that alerts were consecutively active during the months with valid data. Facility A had the most periods of active alert times. In facility A, 5339 active alert periods were found during the 4 months; facility B had 5276 periods of consecutive days of activity. The most frequent alert where no active alerts occurred were found in weight gain and weight loss alerts; 82.1% and 84.4% for facility A and 64.0% and 66.4% for facility B, respectively.

The most frequently occurring alert for both facilities, according to consecutive days of active status, was skin integrity. Skin integrity alerts also had the shortest time interval of active status for both facilities. Facility A had 21.5% (1148/5339) of the active alert periods occurring in the skin integrity category and 76.1% of these alerts occurred for 1-3 consecutive days. In facility B, 32.7% (1726/5276) of the total periods of activity were skin integrity alerts. Most of these alerts, 77.9%, were only active for 1-3 days. The longest periods of activity, 20 or greater consecutive days an alert was active, occurred 28.2% and 30.9% in the alert for improvement in condition in facility A and B, accordingly. The dehydration alert in facility B was also active for a period of 20 or greater consecutive days 30.9% of the time.

[Insert Table 3 about here]

Correlations

Facility A had a total of 136 residents. The most frequent primary diagnosis in this group was ventilation pneumonitis, which occurred in 66.9% of this population. The next most frequent diagnoses were hypertension and heart disease with 2 patients in each category. Twenty eight of the residents appeared to be miscoded under an identifier called "17". These residents did not have a primary diagnosis identified. Out of 228 residents, the most frequent primary diagnoses in facility B were dementia, CVA, Alzheimer's, hypertension, pneumonia, osteoarthritis, and depressive disorder; representing 36.4% of this population.

Nonparametric Spearman's rank correlations were completed on all alert types. Only one moderately, significantly positive, correlation (N=18, r=.531, p=.023) was found in the Weight Gain alert type in residents who had been primarily diagnosed with a CVA. The mean number of secondary diagnoses was 6.06 with a standard deviation of $\pm$2.817. The minimum numbers of secondary diagnoses were 3 maximum was 13. According to Table 3, residents with a primary diagnosis of CVA experienced an average of 8.22 active weight gain alerts.

Trigger Frequencies

Trigger frequencies and active trigger types for each alert were calculated, see Table 4. The most frequent trigger was in the dehydration alert and was activated when staff documented 25% or more of food left uneaten twice within 48 hours. Out of all triggers this one was used the most often; 39.7% in facility A and 30.8% in facility B.

When a constipation alert was active in facility A, the most frequent trigger activating the alert indicated a resident had not had a regular bowel movement, 6.6% of the time. Residents with Dementia, in facility B had the same trigger only activated 0.5% of the time. In facility B, residents with Dementia had bladder incontinence, associated with the skin integrity alert, activated 29% of the time. In facility A, bladder incontinence triggers were only activated 6.0% of the time. Other frequent triggers were associated with the alert improvement in condition and included documentation regarding improvements in decision making, bladder incontinence, and ambulation. In contrast, the trigger for decline in condition, sad or anxious increased from 1 to 2, had no active triggers in residents with CVA, depressive disorder, or pneumonia.

[Insert Table 4 about here]

Clinical Responsiveness to Alerts

As discussed previously, 32.7% of skin integrity alerts in Facility B had an active frequency ranging from 1-3 days. This alert had the most frequent status change from active to not active. Alerts for the final analysis were selected from this group to determine if clinical responses could be a factor in the frequently changing status of the alerts. Only alerts from facility B were included in this analysis to minimize effects of differences in documentation and clinical practices between facilities.

A total of 118 alerts were analyzed from 59 residents. Six administrative and clinical reports in OneTouch were used to determine clinical actions taken, including: 1) care plan changes, 2) CNA task lists, 3) skin and wound report, 4) turning and repositioning report, 5) toileting report, and 6) progress notes.

The analysis indicates there is no significant difference in clinical responses during periods when alerts were active vs when alerts were not active, (N=59 residents, p=1.00), as shown in Table 5. There were just as many clinical responses to conditions when alerts were active than when they were not active.

Utilizing the turning and repositioning reports, it was determined that 39 out of 58 residents (67.2%) who had no documentation on the date the skin integrity alert became active actually, had documentation on turning and repositioning when the alert was not active a week later. Conversely, CNA task lists, utilized to communicate important resident tasks between nurses and nurse assistants, were utilized very little to delegate skin integrity care planning. Of the 46 residents that had no documentation on the CNA task list related to skin integrity, when the alert became active, 100% had no documentation a week later when the alert was not active.

[Insert table 5 about here]

DISCUSSION

This study evaluated a clinical decision support system which is part of an automated, EMR being implemented in nursing homes across the United States. This evaluation included an analysis of 7 clinical alerts including constipation, decline in condition, dehydration, improvement in condition, skin integrity, weight gain, and weight loss. A critical finding was that data integrity in facilities is dramatically affected by documentation, system changes in clinical practice, choices made during implementation, or by the design of the EMR. This is evident in the lack of variability of alert frequencies in resident data found across facilities in the initial steps of the evaluation. This lack of variability may be due to no documentation resulting from workarounds, inability of staff to find appropriate fields to document, not enough training, or difficulties encountered during implementation[18].

Conditions that involved dehydration, improvement in residents, constipation, and skin integrity have the most frequent active alerts. Skin integrity alerts changed status from active to not active most frequently; most lasting approximately 1-3 days. This rapid frequency of change could be due to changes in skin condition being documented, alerts being activated, and effective clinical responses to the skin conditions being performed. However, in the analysis of clinical responses to skin integrity alerts, clinical responses did not change when an alert was active versus when alerts were not active. This does not mean the alerts were not effective. Perhaps the alerts were a reminder to staff and they responded even in times alerts were not active because of their increased awareness of the problem.

Weight gain and weight loss alerts had the most frequencies of no active alerts.

The internal decision tree of the EMR could affect this level of inactivity. Specifically, the weight gain alert will become active if a resident gains over 3.5% of total body weight over 30 days or 7% over 180 days. These parameters may be too broad and may not capture subtle changes in weight. The alert with the longest consecutive active time was improvement in condition. This was a positive finding because it indicated that staff focused on documenting positive aspects of resident care, such as, improved decision making and improved participation in ADL activities.

Another surprising finding is that frequencies of active alerts do not appear to be affected by the number of secondary diagnoses residents have. This was not expected; the researchers assumed that as the complexity of care increased along with number of potential problems associated with secondary diagnoses so would the number of active alerts. Perhaps this finding might be different if primary diagnoses were combined into larger, broader groups to increase sample size.

Evaluations of information systems in the actual settings where they are being used provides knowledge of how these tools might improve patient safety, support effective care delivery, facilitate management of chronic conditions, improve efficiency, and how feasible they are for nursing home administrators and staff to implement and use. What this study did not consider was the human factors, or human computer interaction principles, including how staff interacts with the computer, the physical nature of the information system and its effect on staff, and the environment in which the information system is implemented. Applications of these principles in future research studies would provide better information about the effectiveness of clinical decision support systems in nursing homes.

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APPENDIX TO RESEARCH REPORT

Figure 1: A Model for Clinical Decision Support Systems in EHR

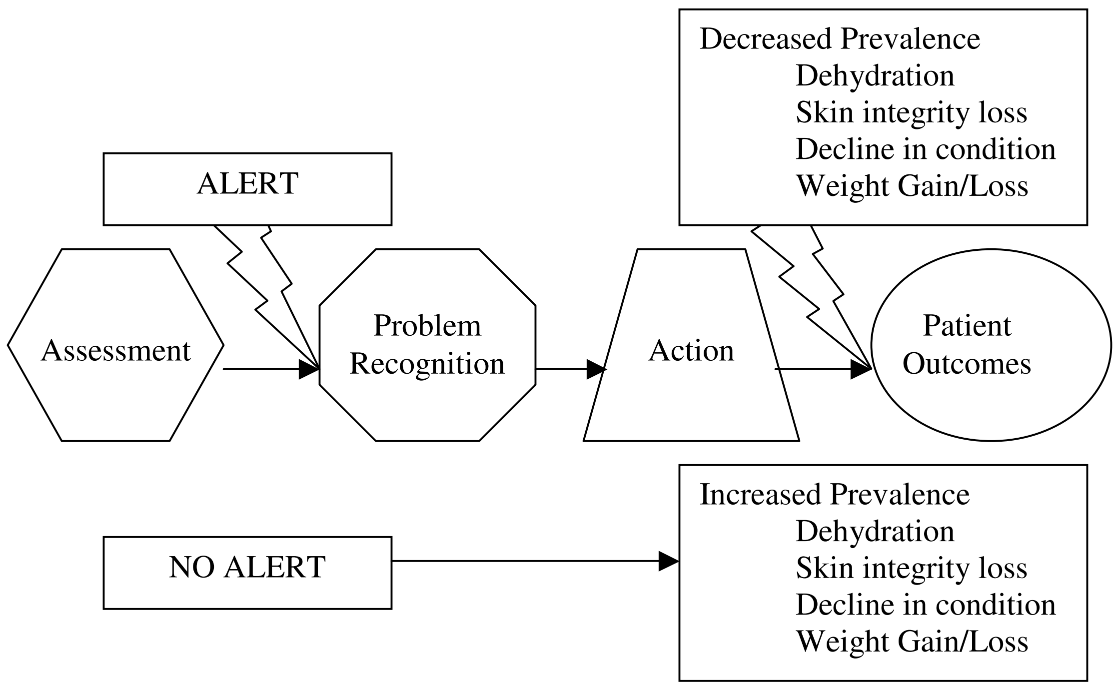

Table 2. Average Alert Frequencies by Alert Type per Valid Data Periods

Facility, Diagnosis, and Descriptive Data	Alert Type						
	Constipation	Decline	Dehydration	Improve	Skin	Weight Gain	Weight Loss
A: Overall (N=136 residents)	Frequencies of Active Alerts						
Mean (alerts/resident)	50.49	8.19	77.42	55.29	20.23	13.50	12.97
††SD	9.12	3.94	8.26	3.58	6.80	7.64	2.76
Sum (alerts)	5099	827	7819	5584	2043	1364	1310
Total Alert Types (%)	21.2	3.4	32.5	23.2	8.5	5.7	5.4
Minimum (alerts/resident)	33	1	22	48	9	5	8
Maximum (alerts/resident)	86	17	93	62	49	27	18
B: Overall (N=228 residents)							

Mean (alerts/resident)	50.74	47.39	172.76	144.07	93.20	39.50	32.48
SD	51.91	11.40	26.49	6.84	24.10	4.21	6.87
Sum (alerts)	2740	2559	9329	7780	5033	2133	1754
Total Alert Types (%)	8.7	8.2	29.8	24.8	16.1	6.8	5.6
Minimum (alerts/resident)	20	5	61	120	22	33	22
Maximum (alerts/resident)	226	62	195	156	170	51	45
Selected Primary Diagnosis by Facility							
Facility A: Ventilation Pneumonitis (N=89)							
Mean (alerts/resident)	41.33	6.67	63.20	46.06	16.76	13.45	10.01
SD	27.07	10.53	34.89	45.01	17.20	24.58	22.73
Sum (alerts)	3678	594	5625	4099	1492	1197	891
Total Alert Types (%)	20.9	3.4	32.0	23.3	8.5	6.8	5.1

Minimum (alerts/resident)	0	0	0	0	0	0	0
Maximum (alerts/resident)	101	49	101	101	101	101	101
Facility B: Dementia (N=20)							
Mean (alerts/resident)	9.15	9.60	44.60	43.55	28.80	7.15	8.40
SD	4.89	13.98	10.35	12.98	15.40	16.20	15.27
Sum (alerts)	183	192	892	871	576	143	168
Total Alert Types (%)	6.0	6.3	29.5	28.8	19.0	4.7	5.6
Minimum (alerts/resident)	4	0	19	14	8	0	0
Maximum (alerts/resident)	23	36	54	54	49	54	53
Facility B: CVA (N=18)							
Mean	15.22	10.11	33.67	17.67	18.33	8.22	9.11

(alerts/resident)							
SD	15.47	13.68	18.15	19.55	12.13	18.34	18.45
Sum (alerts)	274	182	606	318	330	148	164
Total Alert Types (%)	13.6	9.0	30.0	15.7	16.3	7.3	8.1
Minimum (alerts/resident)	4	0	6	0	3	0	0
Maximum (alerts/resident)	48	44	54	54	44	53	53
Facility B: Alzheimer’s (N=13)							
Mean (alerts/resident)	12.69	17.77	43.46	40.38	25.31	14.69	7.62
SD	10.55	16.40	12.98	16.39	13.33	23.31	16.40
Sum (alerts)	165	231	565	525	329	191	99
Total Alert Types (%)	7.8	11.0	26.8	24.9	15.6	9.1	4.7
Minimum (alerts/resident)	4	0	9	0	0	0	0

Maximum (alerts/resident)	32	43	53	54	52	53	53
Facility B: Hypertension (N=11)							
Mean (alerts/resident)	13.91	16.82	44.73	43.45	19.36	11.64	5.27
SD	13.12	19.73	9.80	17.51	15.60	21.29	11.06
Sum (alerts)	153	185	492	478	213	128	58
Total Alert Types (%)	9.0	10.8	28.8	28.0	12.5	7.5	3.4
Minimum (alerts/resident)	4	0	16	0	3	0	0
Maximum (alerts/resident)	46	52	52	54	47	53	30
Facility B: Pneumonia (N=7)							
Mean (alerts/resident)	18.14	16.71	33.00	23.86	15.29	8.71	13.29

SD	17.96	13.24	22.51	27.43	9.78	10.80	17.86
Sum (alerts)	127	117	231	167	107	61	93
Total Alert Types (%)	14.1	13.0	25.6	18.5	11.8	6.8	10.3
Minimum (alerts/resident)	4	0	0	0	0	0	0
Maximum (alerts/resident)	54	34	54	54	30	24	43
Facility B: Osteoarthritis (N=7)							
Mean (alerts/resident)	9.57	13.57	44.00	41.57	26.71	2.29	.14
SD	9.14	20.90	10.76	20.07	14.03	6.05	.378
Sum (alerts)	67	95	308	291	187	16	1
Total Alert Types (%)	6.9	9.8	31.9	30.2	19.4	1.7	0.1
Minimum (alerts/resident)	4	0	31	0	9	0	0
Maximum	30	49	53	54	49	16	1

(alerts/resident)							
Facility B: Depressive Disorder (N=7)							
Mean (alerts/resident)	12.43	8.57	40.43	33.86	20.29	16.86	8.00
SD	9.68	9.69	13.92	14.86	13.47	17.63	19.84
Sum (alerts)	87	60	283	237	142	118	56
Total Alert Types (%)	8.9	6.1	28.8	24.1	14.4	12.0	5.7
Minimum (alerts/resident)	4	0	12	12	2	0	0
Maximum (alerts/resident)	32	25	52	49	36	42	53

††SD = Standard Deviation

Table 3: Frequency of Active Alerts in Consecutive Days

Facility A			Frequency Alerts are Consecutively Active During the Month Total (%)				
Month	Days/Mo of valid data	Number of residents with No Active Alerts	1-3 Days	4-9 Days	10-19 Days	20 or > Days	Total active alerts
Alert Type							
Constipation							
1	21	26(49.1)	83 (15.5)	57(21.3)	9(15.0)	19(22.4)	
2	29	9(17.0)	160(30.0)	51(19.1)	13(21.7)	22(25.9)	
3	31	9(17.0)	166(31.1)	101(37.8)	13(21.7)	20(23.5)	
4	20	9(17.0)	125(23.4)	58(21.7)	25(41.7)	24(28.2)	
Total	101	53(5.3)	534(53.5)	267(26.7)	60(6.0)	85(8.5)	999
Decline in condition							
1	21	95(24.1)	24(32.0)	20(32.8)	2(14.3)	3(50.0)	
2	29	97(24.6)	25(33.3)	14(23.0)	5(35.7)	2(33.3)	
3	31	106(26.8)	11(14.7)	8(13.1)	42(28.6)	0(0.0)	

4	20	97(24.6)	15(20.0)	19(31.1)	32(21.4)	1(16.7)	
Total	101	395(71.7)	75(13.6)	61(11.1)	14(2.5)	6(1.1)	551
Dehydration							
1	21	16(30.2)	95(22.9)	43(16.8)	23(18.3)	40(27.4)	
2	29	13(24.5)	139(33.6)	57(22.3)	30(23.8)	45(30.8)	
3	31	9(17.0)	106(25.6)	91(35.5)	30(23.8)	46(31.5)	
4	20	15(28.3)	74(17.9)	65(25.4)	43(34.1)	15(10.3)	
Total	101	53(5.3)	414(41.6)	256(25.7)	126(12.7)	146(14.7)	995
Improvement in condition							
1	21	56(24.2)	21(18.9)	18(22.8)	5(14.7)	49(27.4)	
2	29	55(23.8)	38(34.2)	24(30.4)	11(32.4)	45(25.1)	
3	31	57(24.7)	38(34.2)	17(21.5)	7(20.6)	45(25.1)	
4	20	63(27.3)	14(12.6)	20(25.3)	11(32.4)	40(22.3)	
Total	101	231(36.4)	111(17.5)	79(12.5)	34(5.4)	179(28.2)	634
Skin Integrity							
1	21	44(23.4)	220(25.2)	11(14.7)	1(14.3)	1(25.0)	
2	29	47(25.0)	297(34.0)	19(25.3)	1(14.3)	1(25.0)	
3	31	44(23.4)	293(33.5)	18(24.0)	3(42.9)	1(25.0)	
4	20	53(28.2)	64(7.3)	27(36.0)	2(28.6)	1(25.0)	
Total	101	188(16.4)	874(76.1)	75(6.5)	7(0.6)	4(0.3)	1148

Weight Gain							
1	21	97(23.3)	2(12.5)	3(14.3)	2(50.0)	23(46.0)	
2	29	94(22.6)	4(25.0)	15(71.4)	0(0.0)	14(28.0)	
3	31	111(26.7)	5(31.3)	2(9.5)	0(0.0)	9(18.0)	
4	20	114(27.4)	5(31.3)	1(4.8)	2(50.0)	4(8.0)	
Total	101	416(82.1)	16(3.2)	21(4.1)	4(0.8)	50(9.9)	507
Weight Loss							
1	21	106(24.9)	3(37.5)	1(5.9)	4(28.6)	11(27.5)	
2	29	100(23.5)	2(25.0)	12(70.6)	2(14.3)	13(32.5)	
3	31	106(24.9)	3(37.5)	2(11.8)	6(42.9)	10(25.0)	
4	20	114(26.8)	0(0.0)	2(11.8)	2(14.3)	6(15.0)	
Total	101	426(84.4)	8(1.6)	17(3.4)	14(2.8)	40(7.9)	505
Facility B							
Constipation							
3	31	90(100.0)	171(73.4)	49(17.0)	11(44.0)	15(75.0)	
4	24	0(0.0)	62(26.6)	239(83.0)	14(56.0)	5(25.0)	
Total	55	90(13.7)	233(35.5)	288(43.9)	25(3.8)	20(3.0)	656
Decline in condition							
3	31	111(45.5)	70(63.1)	58(50.0)	32(61.5)	24(70.6)	

4	24	133(54.5)	41(36.9)	58(50.0)	20(38.5)	10(29.4)	
Total	55	244(43.8)	111(19.9)	116(20.8)	52(9.3)	34(6.1)	557
Dehydration							
3	31	11(64.7)	111(62.0)	85(59.4)	56(38.6)	138(63.9)	
4	24	6(35.3)	68(38.0)	58(40.6)	89(61.4)	78(36.1)	
Total	55	17(2.4)	179(25.6)	143(20.4)	145(20.7)	216(30.9)	700
Improvement in condition							
3	31	45(52.9)	74(50.7)	75(56.4)	39(41.5)	111(54.1)	
4	24	40(47.1)	72(49.3)	58(43.6)	55(58.5)	94(45.9)	
Total	55	85(12.8)	146(22.0)	133(20.1)	94(14.2)	205(30.9)	663
Skin Integrity							
3	31	17(63.0)	834(62.1)	137(50.9)	31(42.5)	13(100.0)	
4	24	10(37.0)	510(37.9)	132(49.1)	42(57.5)	0(0.0)	
Total	55	27(1.6)	1344(77.9)	269(15.6)	73(4.2)	13(0.8)	1726
Weight Gain							
3	31	133(42.8)	37(80.4)	46(100.0)	10(62.5)	35(52.2)	
4	24	178(57.2)	9(19.6)	0(0.0)	6(37.5)	32(47.8)	
Total	55	311(64.0)	46(9.5)	46(9.5)	16(3.3)	67(13.8)	486

Weight Loss							
3	31	138(42.6)	41(74.5)	13(92.9)	67(94.4)	3(12.5)	
4	24	186(57.4)	14(25.5)	1(7.1)	4(5.6)	21(87.5)	
Total	55	324(66.4)	55(11.3)	14(2.9)	71(14.5)	24(4.9)	488

Table 4. Trigger Frequencies by Most Frequent Primary Diagnosis

Primary Diagnosis with Total Active Triggers (N)		Ventilation Pneumonitis N = 16,961	Alzheimer's N = 5578	CVA N = 4380	Dementia N = 9263	Depressive Disorder N = 2379	Hypertension N = 4644	Osteoarthritis N = 3399	Pneumonia N = 2471
Alert Type	Trigger	Fac. A	Fac. B						Fac. B
		Frequency of Trigger (% of Total Triggers)							
Dehydration	Left 25% or more of food uneaten	6738 (39.7)	1571 (28.2)	1261 (28.8)	2233 (24.1)	733 (30.8)	1298 (28.0)	745 (21.9)	743 (30.1)
Constipation	Regular bowel movement has not occurred	1123 (6.6)	57 (1.0)	158 (3.6)	49 (0.5)	50 (2.1)	66 (1.4)	21 (0.6)	57 (2.3)
Skin Integrity	Bladder Incontinent	1018 (6.0)	1181 (21.2)	945 (21.6)	2686 (29.0)	620 (26.1)	834 (18.0)	914 (26.9)	385 (15.6)
Skin Integrity	Turning and repositioning	855 (5.0)	206 (3.7)	165 (3.8)	344 (3.7)	86 (3.6)	132 (2.8)	110 (3.2)	63 (2.5)

	program has not occurred								
Improvement	Decision making decreased from 2 to 0	591 (3.5)	55 (1.0)	44 (1.0)	98 (1.1)	53 (2.2)	103 (2.2)	14 (0.4)	27 (1.1)
Improvement	Bladder continence decreased from 4 to 2	484 (2.9)	55 (1.0)	41 (0.9)	117 (1.3)	29 (1.2)	56 (1.2)	55 (1.6)	28 (1.1)
Improvement	Bladder continence decreased from 3 to 2	439 (2.6)	145 (2.6)	121 (2.8)	254 (2.7)	45 (1.9)	132 (2.8)	104 (3.1)	55 (2.2)
Skin Integrity	Bowel incontinent	204 (1.2)	215 (3.9)	148 (3.4)	351 (3.8)	69 (2.9)	68 (1.5)	56 (1.6)	73 (3.0)
Dehydration	Dehydrated Output exceeds input	180 (1.1)	174 (3.1)	257 (5.9)	299 (3.2)	99 (4.2)	183 (3.9)	126 (3.7)	96 (3.9)
Improvement	Walk in room decreased	331 (2.0)	35 (0.6)	48 (1.1)	42 (0.5)	21 (0.9)	56 (1.2)	63 (1.9)	77 (3.1)

	from 8 to 3								
Decline in Condition	Sad or anxious increased from 1 to 2	9 (0.1)	83 (1.5)	0 (0.0)	45 (0.5)	0 (0.0)	8 (0.2)	47 (1.4)	0 (0.0)

Table 5: Analysis of Clinical Responsiveness to the Skin Integrity Alert

		Alert Active		Number of residents	††Exact sig. *P*
		Clinical Response Absent	Clinical Response Present		
Alert Not Active	Clinical Response Absent	1	6	7	*1.00*
	Clinical Response Present	6	46	52	
Number of residents		7	52	59	

††McNemar's Test

VITA

Gregory L. Alexander was born January 2, 2005 in Webster County, Missouri. After attending public schools in Missouri, Greg became a registered nurse after receiving his diploma from Burge School of Nursing in Springfield, Missouri in 1988. Following his graduation from nursing school, Greg continued his undergraduate education at Southwest Missouri State University where he received his Bachelor of Science in Biology and Nursing. Greg continued his postgraduate education at the University of Missouri-Columbia and received his Master in Health Administration in 1999 from the department of Health Management and Informatics. Finally, Greg served as a National Library of Medicine predoctoral fellow in informatics while completing his PhD in nursing from 2001 to 2005 at the University of Missouri—Columbia.

Greg is married to Mary Margaret Alexander of Warrenton, Missouri and is the father of two sons and 3 daughters, Daniel, Samuel, CaraBeth, Rachel, and Margaret. He is the son of Leroy and Thelma Alexander of Springfield, Missouri; he is also the son in law of Albert and Jean Briggs of Innsbrook, Missouri. Dr. Alexander is currently an Assistant Professor in the Sinclair School of Nursing at the University of Missouri—Columbia.