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Evaluation of the Application of Lean and Just-in-Time Information for Dynamic Decision-making to Reduce the Occurrence of Nurse Medication Administration Errors: A Clinical Trial and Agent Based Modeling Approach

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To the Graduate Council:

I am submitting herewith a dissertation written by Thomas A. Berg entitled "Evaluation of the Application of Lean and Just-in-Time Information for Dynamic Decision-making to Reduce the Occurrence of Nurse Medication Administration Errors: A Clinical Trial and Agent Based Modeling Approach." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Industrial Engineering.

Rapinder Sawhney, Major Professor

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Evaluation of the Application of Lean and Just-in-Time Information for Dynamic Decision-making to Reduce the Occurrence of Nurse Medication Administration Errors: A Clinical Trial and Agent Based Modeling Approach

A Dissertation Presented for the

Doctor of Philosophy

Degree

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Thomas A. Berg

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DEDICATION

To my wife

Karen Dierman Berg

and, my daughter

Alice Jordan Berg

Thank you for your unending patience, and unwavering support as I very slowly and methodically trudged through the efforts of my life, my studies and my research. It is only because of your tolerance, sacrifice, support and love, that I have been able to reach this lifelong goal.

To my friend

David John Smallwood

Thank you for saving my life and for being the truest of friends

To my sister

Jean Marie Berg

Thank you for your love, spiritual insight and being a channel to sanity as I move through the phases of life.

To my brother

Douglas Robert Berg

I stand in awe of how you were able to raise your family as a single father; you will always be an inspiration to me, and I continue to learn from you

To my parents

Robert Lincoln Berg Jr. and Doris Jean Berg

You have provided me with the foundation to be able accomplish those things that are most important to me.

And finally, to my study buddies

Izzy, Gracie and Shadow

Thank you for being ever-present companions and on providing the diversions to help break up those countless, tedious hours at my desk

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ABSTRACT

The primary objective of this study is to measure the effects of providing just-in-time (JIT) information to nurses during the medication administration process. While the expectation is that having access to JIT information is beneficial for healthcare providers, other factors such as the information being distracting, misinterpreted, difficult to use, or even have a detrimental effect, could be of no value, or lead to adverse consequences.

A clinical study was performed to evaluate the effect of JIT information on error occurrence during the administration of medication. A smartphone app was designed to convey information to the nurses on an "on-demand" basis. The clinical study used a control group which had access to conventional information resources including a laptop based electronic medical records system and Medication Administration Record, and an experimental group which had access to the smartphone app. The University of Tennessee Health Innovation Technology Laboratory was used as the test environment. The results indicated that the availability of JIT information made a significant difference in reducing the occurrence of the error, as well as improving the understanding of patient chart information and decreasing the time for administering medication.

An agent-based computer simulation model (ABM) was developed using the information generated from the clinical trial to validate that a model of the medication administration process could be developed. This model was used to estimate the likelihood of the occurrence of the error at various levels of information input.

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ABM	Agent Based Model
ABMS	Agent Based Modeling Systems
ACA	Acetaminophen
ADE	Adverse Drug Event
ADM	Absolute Deviance from the Mean
ADR	Averse Drug Reaction
AHP	Analytic Hierarchy Process
AHRQ	U.S. Agency for Healthcare Research and Quality
AKA	also known as
ANN	Artificial Neural Network
ANOM	Analysis of Means
ANOVA	Analysis of Variance
AOCCA	Association of Chartered Certified Accountants
BBN	Bayesian Belief Network
BCMAR	Bar Code Medication Administration
BIT	Built-in-test
BN	Bayesian Network
CA	Causal Analysis
CALNOC	Collaborative Alliance for Nursing Outcomes
CAS	Complex Adaptive System(s)
CCA	Cause-Consequence Analysis
CDF	Cumulative Distribution Function
CDS	Clinical Decision Support
CDSS	Clinical Decision Support System
CDST	Clinical Decision Support Tool
CE	Cognitive Engineering
CMS	Centers for Medicare and Medicaid Studies
CON	College of Nursing
CPOE	Computerized Physician Order Entry
CREAM	Cognitive Reliability and Error Analysis Method
DAG	Directed Acyclic Graph
DES	Discrete Event Simulation
DM	Decision Making
DMAIC	Design, Measure, Analyze, Measure, Improve and Control
DST	Decision Support Tool
ED	Emergency Department
EHR	Electronic Health Record
eMAR	Electronic Medication Administration Record
EMR	Electronic Medical Record (System)
ERP	Enterprise Resource Planning
FDA	US Federal Drug Administration
FMEA	Failure Modes and Effects Analysis
FMECA	Failure Modes and Effects and Criticality Analysis
GEMS	Generic Error Modeling System
GIS	Geographic Information System
GUI	Graphical User Interface
HC	Healthcare
HCI	Human Computer Interaction

HCP	Health Care Providers
HE	Human Error
HEART	Human Error Assessment and Reduction Technique
HeD	Health eDecisions
HERSA	Human Error and Safety Risk Analysis
HFACS	Human Factors Analysis and Classification System
HFE	Human Factors Engineering
HFMEA	Healthcare Failure Modes and Effects Analysis
HIMSS	Healthcare Information and Management Systems Society.
HITS	Health Innovation Technology and Simulation Laboratory
HRO	High Reliability Organization
HSD	Honest Significance Difference
I&SE	Industrial & Systems Engineering
II	Information Injection Value
IOM	Institute of Medicine
IoT	Internet of Things
ISE	Industrial and Systems Engineering
ISMP	Institute for Safe Medication Practice
IT	Information Technology
IV	Intravenous
JIT	Just in Time
KBS	Knowledge Based System
LDL	Lower Decision Limit
LEI	Lean Enterprise Institute
LI	Likelihood Index
MA	Medication Administration
MAE	Medication Administration Error
MAP	Medication Administration Process
MAR	Medication Administration Record
MC	Markov Chains
MCDM	Multi-criteria Decision Making
MCT	Mobile Computing Technology
MES	Manufacturing Execution System
MICT	Mobile Information Computing Technology
MRP	Materials Requirement Planning
NCCMERP	National Coordinating Council for Medication Error Reporting and Prevention
NHE	Non-Human Error
NKBS	Non-knowledge Based System
PC	Pareto Charts
PDF	Probability Distribution Function
PECS	Physical. Emotion, Cognition, Social Status
PFD	Process Flow Diagram
PM	Process Maps
POC	Point of Care
POCCDSS	Point of Care Decision Support System
POCCDST	Point of Care Decision Support Tool
RBS	Rule Based System
RCA	Root Cause Analysis
RFID	Radio Frequency Identification

RTLS	Real Time Location System
SA	Situation(al) Awareness
SD	System Dynamics
SE	Systems Engineering
SME	Subject Matter Expert
SOS	System of Systems
Std Dev	Standard Deviation
THERP	Technique for Human Error Rate Prediction
TQM	Total Quality Management
UDL	Upper Decision Limit
UI	User interface
USP	United States Pharmacopeia
V&V	Verification & Validation
WIA	What if Analysis

Chapter 1
Background and Overview

Background

It is estimated that between 210,000 and 420,000 hospital patients suffer harm as a result of medical errors that contribute to their death each year [1]: a separate study has corroborated this estimate [2]. To provide some perspective regarding the scope of this problem, medical errors are the third leading cause of death following heart disease and cancer, accounting for about 10% of all deaths in the United States (Figure 1. 1). Medication errors, defined as "any preventable event that may cause or lead to inappropriate medication use or patient harm…" are a major contributor to this statistic [3]. Providing medication to a hospital patient is a complex, adaptive process that includes writing the medication prescription (i.e., ordering), preparation, dispensing of the medication by the pharmacy, and administering the medication to the patient typically by a nurse (Figure 1. 2). The focus of this study is on the potential of applying lean concepts to information and using just-in-time (JIT) information to influence dynamic decision-making as it affects the occurrence of hospital inpatient Medication Administration Errors (MAEs). A MAE is defined as, "a deviation from the prescriber's medication order as written on the patient's chart, manufacturers' instructions, or relevant institutional policies" [4].

This study follows the Industrial & Systems Engineering (ISE) approach that humans are an integral part of the overall system and that the design of the system needs to consider and accommodate the error performance of the human element in order to improve overall system performance, including any effort to decrease the occurrence of medication errors.

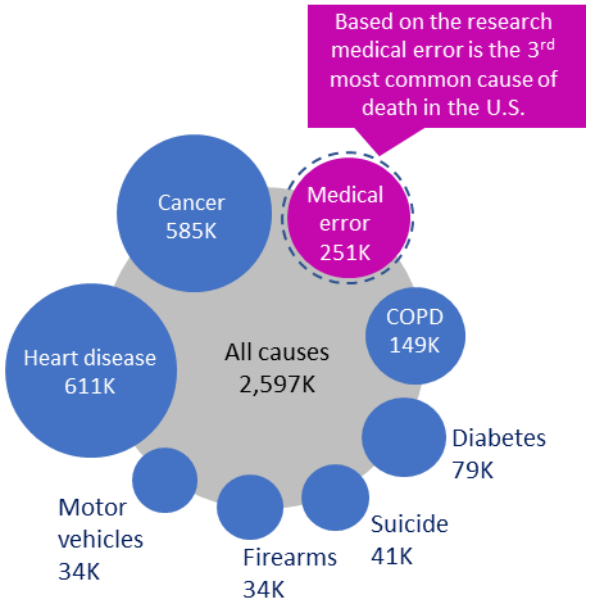

Figure 1. 1: Proportion of annual deaths due to medical errors in hospitals [2][1]

[1] Images included under title 17 section 107 U.S. Copyright Law Fair Use Doctrine as educational material distributed for use without profit. Adapted from: *BMJ* 2016; 353 doi: https://doi.org/10.1136/bmj.i2139 (Published 03 May 2016) https://www.bmj.com/content/353/bmj.i2139

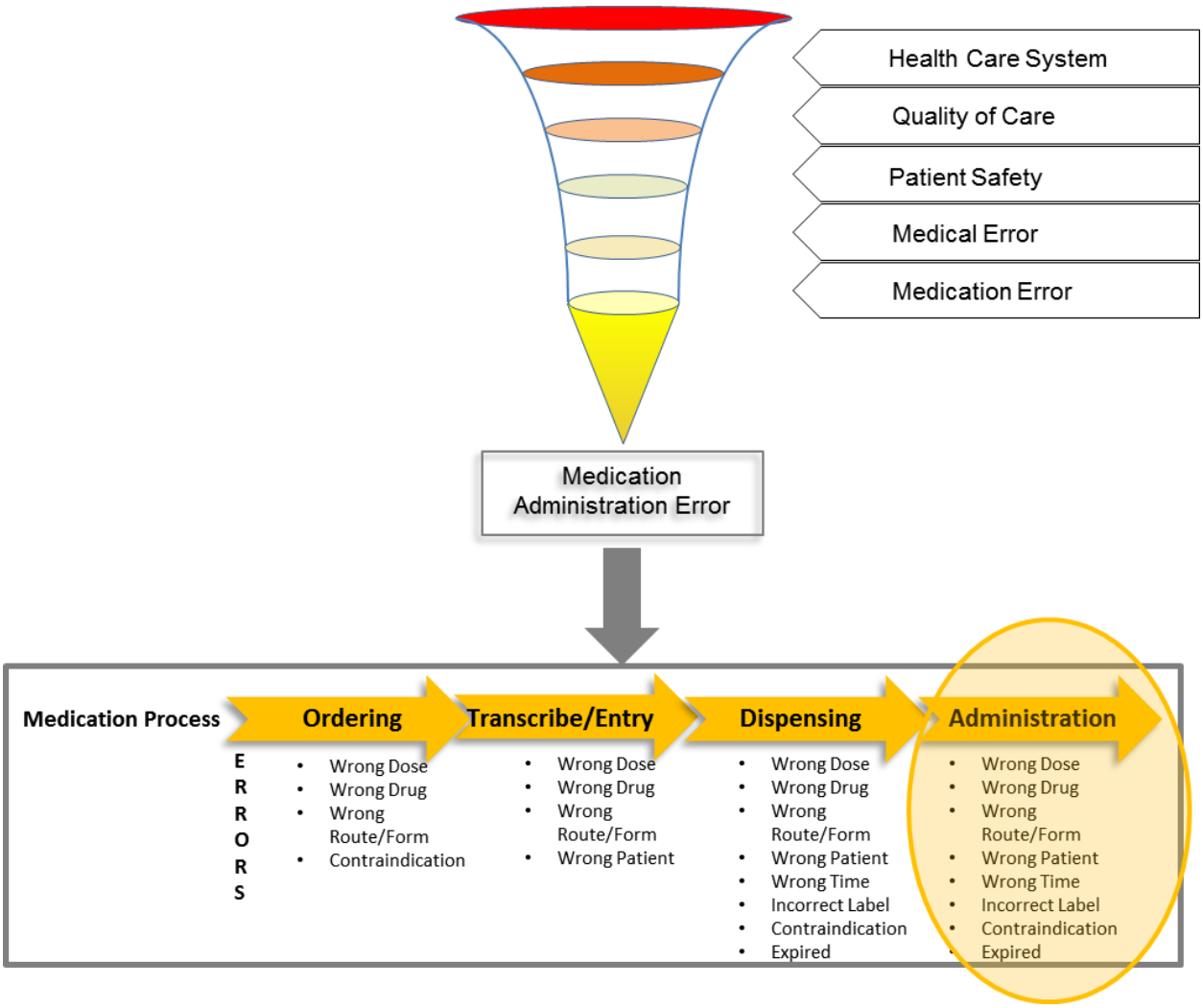

Figure 1. 2: The medication administration process and how it relates to medical errors

Rationale/Purpose of Study

A 1999 report by the Institute of Medicine concluded that as many as 98,000 annual deaths, among Americans, are associated with medical mistakes [5]. A more recent study in the Journal of Patient Safety concluded the number to be much higher, claiming that each year between 210,000 and 420,000 of those who are hospitalized suffer harm that contributes to their death. A significant number of these deaths are a result of medication errors. These reports did not consider the nonfatal implications of medical error and the short and long term personal and economic costs associated with these errors.

The primary objective of this study is to measure the effects of providing just-in-time (JIT) information to nurses on the occurrence of a medication administration error. While the expectation is that having access to JIT information is beneficial in executing the MAP, it is quite conceivable that other factors such as the information being distracting, misinterpreted, difficult to use, or another detrimental effect, could occur [6, 7].

As an example, electronic medical record (EMR) systems are enterprise-level computer systems that provide integrated patient information, including diagnostic reports, medical charting, physician orders, drug prescriptions, medical treatments, etc., were heralded as a resource that could provide significant process

Improvement for healthcare and have positive impacts on healthcare costs and the quality of patient care. However, studies indicate that EMR systems are not necessarily delivering the breadth of positive benefits originally attributed to them and, in some instances, have resulted in various unintended negative consequences [8-10].

In their report, “Building a Better Delivery System: A New Engineering / Healthcare Partnership”, published in 2005, the Institute of Medicine (IOM) notes that while other industries have embraced systems engineering tools to improve performance, the healthcare industry has been slow in adopting these methods. In particular, the IOM identifies “Human-information/communication technology system interfaces” as a fundamentally important area for improvement in healthcare operations [11].

The implementation of technology into end-user settings, such as EMRs, is typically fielded with exuberance and the promise of the technology to directly solve key problems. As referenced previously however, the challenges and unintended consequences resulting from the implementation of new technology demonstrate the reality of the actual difficulties and challenges faced when inserting technologies in a real-world setting. The proposed research intends to begin to address the challenges of insertion of this technology into healthcare.

Hospital staff nurses are faced with numerous challenges in executing their tasks. Nurses are the frontline of providing patient care, serving as the backbone of the healthcare system: their performance is a key factor in determining patient outcomes. Interestingly, the impacts of nursing care have not been given the same consideration in terms of impact on systems performance of healthcare as other areas. From an I&SE perspective, much of the research and dialogue to-date has been related to nurse staff levels, workload, scheduling, or conventional ergonomics issues, such as back injury. Significantly less research has been done on how nurses execute their job functions and the associated considerations of performance [12-15]. The proposed research considers how nurses function from a system point of view and intends to determine how providing lean JIT information can improve nurse performance and enhance the quality of patient care by reducing MAEs.

Most decisions by healthcare providers in acute settings require dynamic decision-making (DDM), a process that occurs in continuously changing environments with multiple interdependent factors that are common in acute medical situations. A decision on one factor will impact the behavior of the other factors or decisions made in real-time. Using the right method of information delivery is key to making correct decisions in a dynamic environment, as well as receiving the right information at the right time.

The advent of affordable and powerful mobile computing technology (MCT), such as smart phones, provide the means to deliver key information in a just-in-time (JIT) fashion. This type of mobile technology has the benefits of

being programmable and versatile, unobtrusive, commercially available, relatively inexpensive, and easy to use. There also might be potential drawbacks of MCT in its current form such as limited battery life, information input, and computer security.

The Research Problem

Medical errors, especially MAEs, happen surprisingly frequently, with results ranging from having no consequence to patient death. The overarching question is, what can be done to mitigate the occurrence of MAEs? In particular, we are asking if JIT information can reduce the number of errors and improve dynamic decision-making when tailored to address specific types of medication administration errors. This undertaking raises several other corollary questions: How can systems engineering methodologies be applied to the nurse medication administration process to identify and mitigate errors? Can the error types of medication administration be identified and ranked or prioritized, and if so, how can it be used to improve the content of JIT information to reduce the likelihood of error occurrence? Lastly, computer modeling and simulation has found utility in many areas in healthcare, including evaluating the impact of changes to healthcare processes [16-18], however, based on extensive literature review, despite its utility and benefits, computer simulation and modeling, has not been used as a methodology to assess nurse performance in MAEs.

Objectives of the Study

The primary objective of this research is to develop a more fundamental understanding from an Industrial and Systems Engineering (I&SE) perspective of what causes MAEs by nurses and to explore possible strategies to reduce the incidence of these errors.

At its core, the purpose of this study is to measure the effect of using just-in-time information on the occurrence of medication errors in acute care settings and, as a result, on the quality of care a patient receives, which is a key metric for healthcare performance. Specifically, we are attempting to evaluate how, or if, providing nurses with just-in-time (JIT) patient or medication information might affect the occurrence of a MAE. While the expectation is that having access to JIT information is beneficial for nurses in reducing the occurrence of errors, other factors, such as the information being distracting, misinterpreted, difficult to use, or even have a detrimental effect, could happen from the use of JIT information from a smart phone app. A key element of this effort will be to develop and demonstrate a model that simulates the nurse Medication Administration Process and the impact of process changes on MAE.

Efforts contributing to the overall objective of this research effort are to:

- explore and apply the concepts of JIT information delivery to determine their effects on MAEs and support dynamic decision making,
- apply lean information concepts to determine the best subset of information content to provide,
- assess the applicability of building a simulation model (e.g. Agent-based model, Bayesian network, or other modeling approach) to model MAEs from the context of nurse processes to a) determine if an acceptable model can be created and b) if such a model can simulate and measure the effectiveness of error prevention techniques, such as JIT information, on MAE occurrence.

Additionally, with this study, I intend to demonstrate:

- the use of MCT or a similar device in a simulated acute care setting,
- the ergonomic advantages of personal mobile technology in a healthcare setting,
- a qualitative/quantitative assessment of the effect of using JIT healthcare information delivered in a convenient and unobtrusive way, and
- using feedback from students and faculty, determine how the use of this technology could be improved in a healthcare setting.

Research Question

We make the following propositions:

- Nurses receive increasing amounts of information to process and act upon.
- Effective "just-in-time" transfer of information to and from nurses improves decision-making and enhances the quality of care, patient safety, and, if done correctly, can reduce costs.
- Information transfer and utilization can be studied through a system engineering approach (much like a manufacturing process) and, as a result, can be analyzed, modeled, and optimized.

These propositions can be distilled down to the following core research questions:

- What are the effects of just-in-time (JIT) information on improving the quality of care, patient safety, and decreasing costs via nursing care?
- Can the organizationally and functionally complex JIT information dynamics, within clinical operations of nursing, be effectively modeled to determine the performance of systems operations by using advanced I&SE techniques and methodologies?
- If so, what are the effects of employing specific mobile computing technologies (MCT) (e.g. smartphones) in an operational setting?

Null Hypothesis (H_0): JIT information will *not* make a measurable difference in the occurrence of MAEs.

Hypothesis (H_1): Providing key (e.g. lean) information to nurses in a JIT fashion *will have* a direct effect on nurse performance during the delivery of patient care as measured by QoC and PC; it will also have the benefit of reducing the cost of delivery of care.

This hypothesis will be tested by: 1) defining the process(es) to identify the actual JIT information inputs/variables that influence the ability of nurses to execute operations; 2) considering the systems drivers that effect information transfer and integration, and defining methods to enhance and improve the efficiency of information utilization; 3) developing a systems model(s) using computer simulation that provides a mechanism to evaluate the effect of JIT information utilization on overall systems operations; and 4) identifying and implementing a prototype technology approach using technology in the form of a smartphone app.

Research Design and Methodology/Proposed Approach

Data Collection Approach

The nature of this study directly lends itself to using a randomized control trial (RCT), which is the gold standard for clinical trials. To this end, three groups were defined: a control group receiving no intervention, a design group to assess the intervention protocol (aka pre-training group), and an experimental group to test the final intervention approach (aka post-training group). The intervention in this case is the delivery of JIT via Mobile Computing Technology (MCT) in the form of a smartphone app.

A specific scripted training scenario on medication administration was constructed in conjunction with the University of Tennessee (UT) College of Nursing faculty. The scenario was conducted as a simulation in the UT Health Innovation Technology and Simulation (HITS) laboratory. This protocol provides an experimental environment that allows control for most variables. University of Tennessee fourth year student nurses participated as test subjects. Student nurses were presented with a scenario using the instrumented mannequins of the HITS lab and their performance was unobtrusively observed via the HITS monitoring cameras. All of the simulations were video and audio recorded for a detailed review. The process of medication administration will be evaluated for errors and near misses for each of the key steps of the medication administration process.

The simulation scenario concerns a juvenile who is hospitalized for a tibia/fibula fracture. The patient has been prescribed too much acetaminophen and is in the early stages of hepatotoxicity. The scenario is structured to see if the nurses detect the medication error/dosing error. While seemingly simple, this is a complex scenario and requires the nurses to exercise considerable critical thinking and dynamic decision-making. The decision tree consists of over 100 nodes.

The video recordings of the student nurses will be reviewed to determine the set of variables to include in assessing errors and support building the computer model. Potential variables could include:

- Total number of errors committed
- Specific errors committed
- Near misses, i.e., behavior they self-corrected before the error was actually committed
- Use of External information resources (e.g. DocuCare—A simulated medical records system provided as part of the simulation system)
- Utilization of MCT

A key component of this research effort is to construct a computer model that simulates the medication administration process (MAP) performed by nurses in a hospital. The goal is to have the model reflect the interaction of nurse(s), medication(s), and patient(s). This simulation will consider the generation of potential errors (e.g. near misses) and actual errors, and the effects of possible interventions in the form of JIT information on the mitigation of error occurrence.

Expected attributes of the data generating process and resultant data and analysis of the process includes the following:

- Limited data set—50-70 data points
- Data will be obtained from a control group and an experimental/intervention group
- The medication administration process is essentially a discrete-time random process
- The medication administration process should follow a prescribed sequence of steps; in reality, the sequence of steps can change. It is possible the sequence of events could change the probability of error occurrence; this is particularly true for downstream events.
- The process is assumed to not be recursive
- The data includes the occurrence/non-occurrence of events, and the probability of their occurrence with the initial assumptions that all occurrences are detectable
- The decisions/actions within the MAP are assumed to be binary (e.g. *Yes/No*, *Perform/Don't perform*)
- The process is at a minimum a function of the nurse's actions, but could also be affected by the medication type, patient attributes, and environmental elements.

Based on the attributes of the data and the MAP process, three modeling techniques have been identified along with their potential advantages and limitations as they relate to this effort: agent-based model (ABM), Bayesian Network (BN), and Markov model. The final modeling approach will be defined by the system attributes and attributes of the data collected. Figure 1. 3 is a graphical representation of the research approach.

Agent Based Model Design Approach

A standard methodology will be used to construct an agent-based model for simulating nurse MA. Figure 1. 4 provides a high-level flow chart describing the elements of the design approach. The development process is iterative as noted by the red line indicating the flow of effort back to previous steps as additional insights are gathered in the development process.

Agent Based Modeling has been initially selected as the approach to simulate the processes of nurses in delivering medications and assessing the occurrence of MAEs and approaches for mitigations. A variety of modeling approaches have been considered, including discrete event simulation, Bayesian networks, and Markov chains. The ABM approach to modeling was selected because of its unique features that were described previously.

The modeling approach will be to iteratively design more complex models exploring the feature set and functions of the model in order to determine the optimum combination of function, performance and complexity.

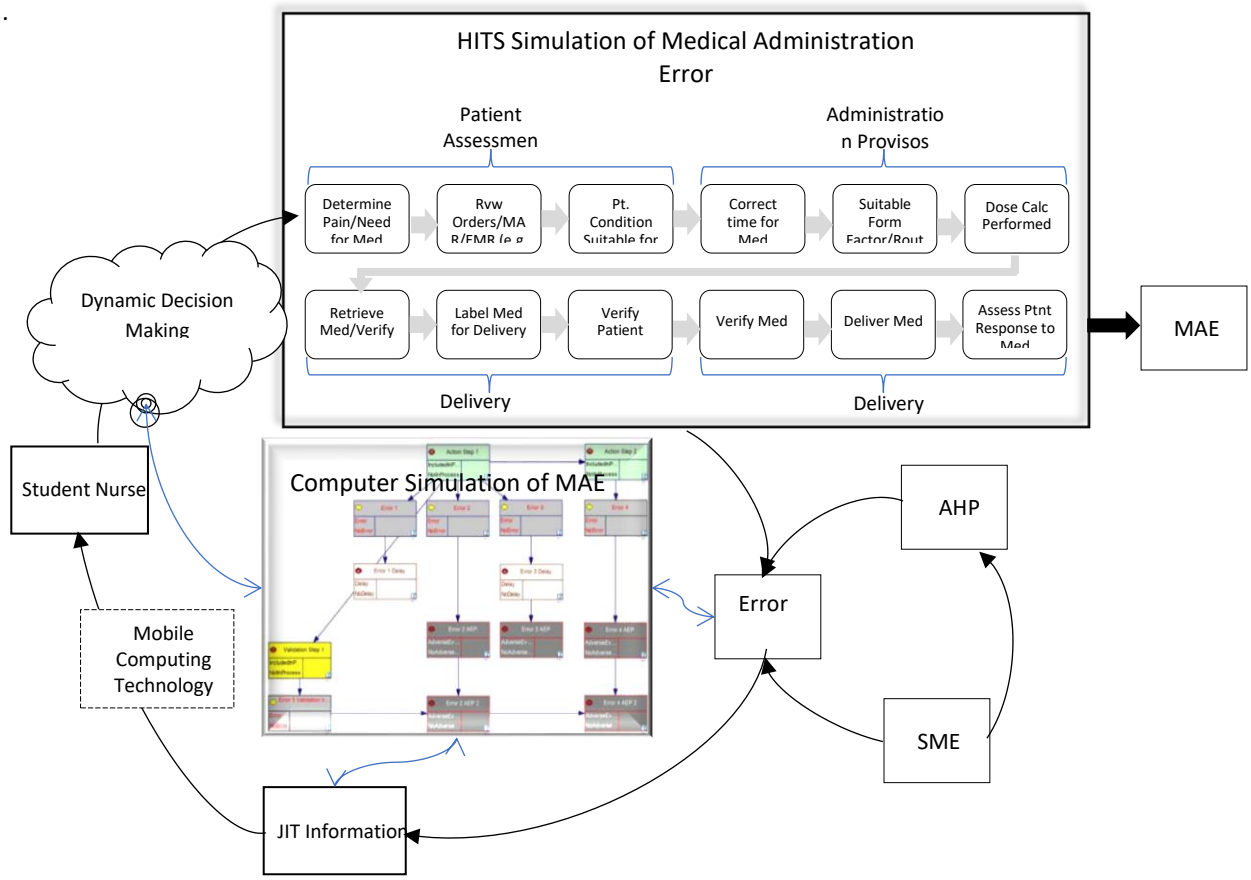

Figure 1. 3: Overview of research approach

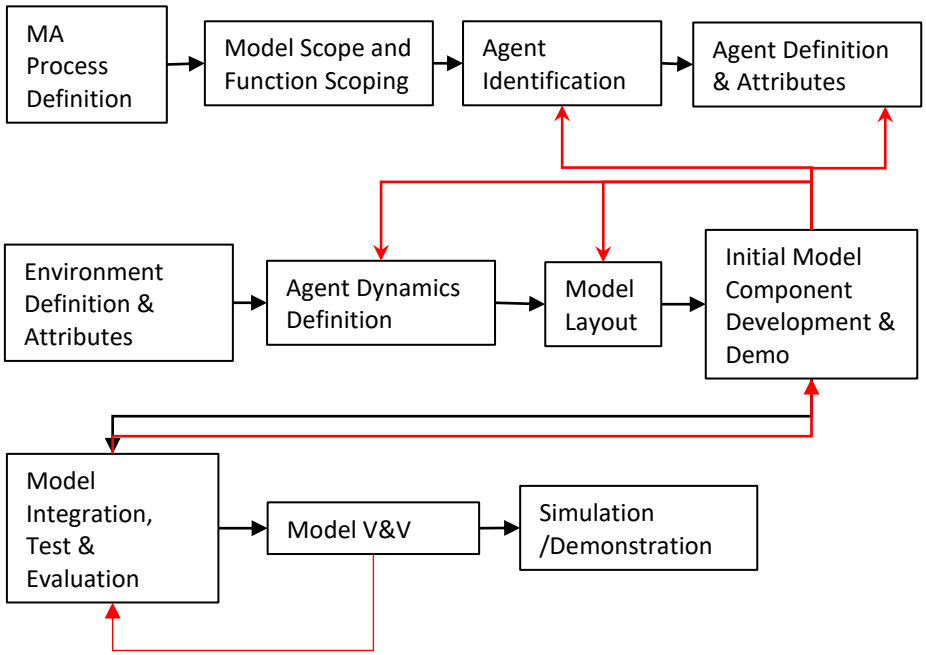

Figure 1. 4: Agent based model development process

An initial step in constructing an ABM is the definition of the agents. Potential agents could include nurses delivering medication, other nurses, medical staff (e.g. physicians, administrators, supervisors, pharmacists, etc.), equipment and/or facilities (e.g. mediation carts, work stations), patients, family members, and medications. Within each agent there can also be classes of agents. For example, the agent patient can be subdivided into pediatric and adult or by hospital ward (e.g. surgical, cardiac, obstetrics/gynecology, etc.).

Following the definition of agent types, the potential states that each agent can be in will be considered. Using the patient as an example, states to be considered include, pain level, severity of malady, location (in room or not), consciousness, emotional state, etc. States will be determined for each agent based on the factors identified in existing literature, model complexity and the model performance. State charts will be developed for each agent.

Other features of agents will be explored. Considerations for agent features will include the ability to learn, interaction with other agents, adaptability to the environment, goal direction, and heterogeneity.

Considering modeling of human behavior, specifically in HC using ABM, brings in an interesting construct. Based on my effort evaluating the research to date, very little research has been identified during this literature search that relates specifically to considering the behavior, specifically cognition emotion or mental state, of healthcare providers as part of the ABM structure. A considerable body of work exists on the modeling of patient behaviors at the macro level, such as in epidemics, or actions related to healthcare or similar venues. Contributory factors have been studied that influence the error occurrence with nurses These include, for example, stress, workload, and experience. Table 1. 1 represents how these factors would look if they were mapped into the PECS structure.

Little work has been done to understand the underlying causes of errors by nurses: it could be possible to draw analogies on underlying error causes from other areas such as aviation or nuclear facility operations.

The environment within which the agents operate will be defined. While conceptually simple, this can become quite complex. In the instance of the research, the environment will be the “hospital”, but other environment features will need to be defined ranging from floor layout (effecting travel times perhaps) to elements that affect interaction of agents or the states of agents themselves. Other environmental factors, such as policies, protocols and procedural boundaries, will be considered. Considerations for the development of the model environment will include static vs. dynamic, complexity, emergent behavior, adaptiveness and self-modulation vs. external control.

Agents can interact with their environment, as well as other agents as noted in the survey of the literature. The two key features that will be explored are determining which agents will interact and the dynamics of the interactions. Similarly, the environment-agent interaction will be defined as well. It is assumed, at this point, that a network topology will be the initial construct for agent interaction.

Table 1. 1: Notional mapping of nursing error contributors into PECS structure

Social Status	Cognition	Emotion	Physical
Seniority	Stress	Frustration	Experience
Nurse type	Fatigue	Overwhelmed	Workload
Education level	Distracted	Indifference	Work area
	Motivation		Patient type(s)
	Critical thinking		Knowledge
	Awareness		Training
	Self confidence		Communication

Model verification and validation will be based on comparing the output of the model simulations with observed performance of the nursing students. Comparison will be done on the pre and post intervention trials to determine the alignment of the simulation results with the results of the student nurse outcomes. Recall that the intervention for both the simulation and the student nurse exercise is the insertion of information at key moments of the MA process. The final result being measured is the degree to which medication errors are mitigated. Also, under consideration are near misses and alignment with the 5-rights of medication administration.

Contribution

This research provides a unique approach to understanding and potentially mitigating errors committed during the medication administration process. This study will provide a more complete understanding of how mistakes occur, the cognitive engineering drivers of the errors, how the errors might be mitigated by providing JIT information, and the development of a computer model that represents the medication administration process and the associated errors.

This research is intended to demonstrate the utility of training simulation as a mechanism to provide a controlled environment for patient-related research. Performing similar research would have proved difficult for a variety of reasons, including an inability to provide a controlled experimental environment. Integrating systems engineering with the nurse training simulation has also increased the fidelity of the training simulation environment by providing a cognitive ergonomics approach to the design and execution of the simulation resulting in a better training experience for the students.

Boundary of Research

The boundary of this research is established along two vectors: the types of errors it examines and the way in which they are studied. At its most general, this is a study on errors in system-processes and how to attempt to prevent them. Errors in complex adaptive systems are evaluated from a bottom up perspective or in a component-oriented, hierarchal modeling approach as noted by Urban [19]. Hence, within the construct of the modeling, I am considering the behavior at the agent or individual level. Specifically, this research uses the approach of looking at each process step and modeling the process based on the actions of the agent that is part of an overall system at the level of the individual carrying out the process.

This research does not necessarily make a distinction between HE and non-HE as the triggering element of the error. Rather, it is considering the cause and the cure as independent. As an example, if the pharmacy has delivered the wrong medication or the infusion pump is broken does not matter, the study hopefully reflects on if the nurse recognizes the error. However, HE is a focus of the research from the perspective of the agent executing the tasks.

As JT Reason explained, the human is an integral part of any system. I have adopted this philosophy, so in effect, the research focus is on how one element of the system, the human, functions in the overall sub system, the medication administration process (MAP).

There are many ways to minimize or prevent error. Providing appropriate information is one mechanism to do this. This research goes several steps further in narrowing considering, specifically, the role of JIT information at the stage of task execution in preventing error. Furthermore, as a conceptual boundary, I am attempting to build on the concept of poka-yoke to build a safety net of JIT information that helps to prevent errors.

The boundaries of this research are (Figure 1. 5):

1) The approach – considers an integrated or systems approach for looking at errors [Reason]
2) The topical area – for the purposes of this research, it only looks at nurse MAE, but could be more broadly applicable
3) The context – Looks at process systems components, i.e. elements of larger systems [think of systems dynamics]

4) The model - Considers the application of ABM as a way to model the performance of individuals in the error matrix
5) The tools - Engages specific IE tools to deconstruct the potential causes of errors (i.e. FMEA)
6) The intervention - Considers Just in Time information as the way of mistake proofing processes

Similarities/Differences of this Research

This research is based on a firm foundation of existing work from many sources. Mark Twain had an uncanny ability to get to the point in a very poignant way:

> "There is no such thing as a new idea. It is impossible. We simply take a lot of old ideas and put them into a sort of mental kaleidoscope. We give them a turn and they make new and curious combinations. We keep on turning and making new combinations indefinitely; but they are the same old pieces of colored glass that have been in use through all the ages."

So, while the same is undoubtedly true for this research, the following highlights what I believe to be the similarities and differences of the research I have uncovered to date (Table 1. 2).[2]

[2] Quote from Mark Twain, Mark Twain's Own Autobiography: The Chapters from the North American Review

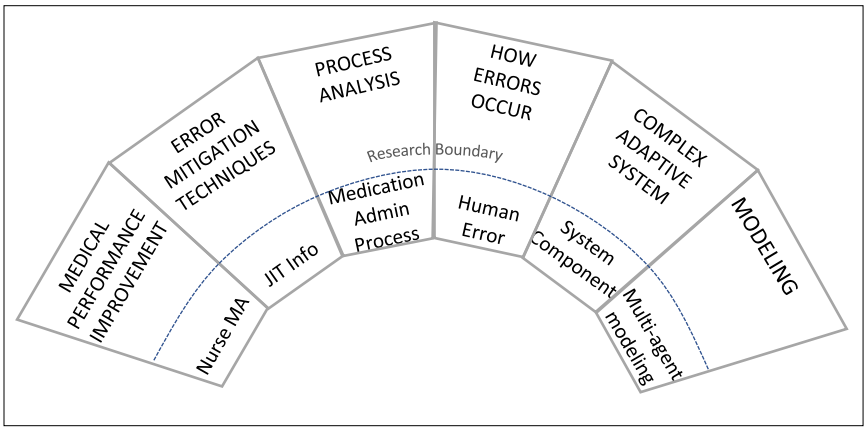

Figure 1. 5: Boundaries of research

Table 1. 2: Similarities and differences of research

Similarities	Differences
Use of process and error analysis tools to identify key areas for improvement	Combination of process, error and information to mitigate error impact
Considering systems approach for error mitigation	JIT as error mitigation "safety net"
Evaluation of Nurse MAE	Systems approach to Nurse MAE error
Application of simulation approach to model a system	Use of ABM for *error* evaluation especially for MAE
Randomized control trial for healthcare studies	Simulated environment (HITS Lab) to create controlled condition for nurse MAE
Considering Lean applications to healthcare	Using JIT information as an approach to Lean and poka yoke

Chapter 2
Literature Review

Approach

This literature review will provide an overview of what medication administration errors are, what causes them and how they might be mitigated. A comprehensive review of the literature was performed. The structure of the search for research articles focused on the mitigation of medication administration error (MAE). The databases used included Google Scholar, PubMed, Web of Science and Academic Search Complete. Search terms included a variety of approaches and combinations to ensure a comprehensive review:

- "Systems Engineering" mitigation
- "Systems Engineering" "medication administration" also with "Medication administration errors"
- "Industrial Engineering" "medication administration" also with "Medication administration errors"
- Medication administration error factors (along with various combinations)
- Medication administration error reduction (along with various combinations)
- Other terms in addition to factors included tools, techniques, approaches and efforts
- Focused searches on medication bar-coding, nurse MAE, medication delivery, medication delivery, medication error, adverse drug reactions
- Other search terms and approaches were also used when specific references identified other research target areas

As part of framing the research problem and defining a research approach, considerable effort has gone in to identifying and evaluating previous research and industry efforts related to this study. One of the interesting and challenging aspects of this endeavor is the multidisciplinary nature of the proposed research. The topic of interest is at the interface of a number of disciplines, which greatly expands the body of literature that is relevant. Research areas that have been identified, that are pertinent in some form to this study, are noted in Table 2. 1. Column one depicts the area of research reviewed, the indented research areas are subcategories of a broader area and each of these has been explored to some degree in the course of preparing for this research. Those annotated with check marks have been deemed of direct relevance. The research literature has been explored in depth for these areas: more than 400 citations have been referenced, considerably more were reviewed. The following literature review will provide a much-truncated version focusing on:

- Overview of the application of industrial and System Engineering (ISE) concepts to Healthcare
- The current state of point of care clinical decision support tools (POCCDST)
- Human error and its mitigation as related to the administration of medication and medication administration errors (MAE)
- Just in time (JIT) information and the contribution to system performance
- Application of agent-based modeling (ABM) to the modelling behavioral systems
- Existing methods and technologies for mitigation of MAEs
- Consideration of Lean concepts for improving the delivery of information
- Industrial and Systems Engineering tool application to defining and preventing systems errors as related to MAEs

Table 2. 1: List of relevant literature area topics that were evaluated

Research Area	**Applicability**
Lean Concepts	✔
Human Performance	✔
JIT Information (Knowledge Management)	✔
Process Map	
Human Factors	✔
Systems Engineering	✔
Systems Modeling	✔
Systems Monitoring	✔
I&SE Tools and Methods	✔
Systems Dynamics	✔
Soft Systems	✔
Complex Adaptive Systems	✔
Nurse Functions/Tasks	✔
Nursing Errors	✔
Factors Influencing Nurse Performance	✔
Physical Factors	✔
Environmental Factors	✔
Cognitive Factors	✔
Organizational Factors	✔
Patient Centered Care	✔
Quality of Care	✔
Simulation/Training	✔
Failure to Rescue	
	✔
Dynamic Decision Making	✔
Decision Engineering	✔
Risk Management	
Group Decision Making	
Behavioral Decision Theory	
Decision Analysis	✔
Classical Decision Theory	
Decision Making Models	✔
Cognitive limitations	
Heuristic Limitations	
Information integration theory	
Cognitive Engineering	✔

Table 2.1: List of relevant literature area topics that were evaluated (continued)

Research Area	**Applicability**
Statistical Analytics	
Bayesian	✔
Predictive	✔
Frequentist	✔
Decision Models	
Multi-criteria Decision Making	
AHP	✔
ANP	✔
Fuzzy VIKOR	
PROMETHEE	
ELECTRE	
Simulation Models	
Agent Based Model	✔
Bayesian Network	✔
ABM/Bayesian	✔
System Dynamic Model	✔
Monte Carlo	
Markov Chain	
Failure Modes	
FMEA	✔
FMECA	✔
HFMEA	✔
Process Tree	✔
Fault Tree	
Event Tree Modeling	
Decision Tree	✔
Root Cause	
Cognitive Reliability and Root Cause Analysis	
Causal Analysis	✔
Cause-consequence	
What if	
Relative Ranking	
Preliminary Hazard	
Probability Risk Assessment	
Error Definition	✔
Mental Workload Modeling	

Table 2.1: List of relevant literature area topics that were evaluated (continued)

Research Area	**Applicability**
Design of Experiments	✔
Random Clinical Trial	✔
Human Factors/Ergonomics	✔
Cognitive Ergonomics/Engineering	✔
Risk Assessment	
Human Error Analysis	✔
Human Error Models	✔
Latent Risk (Swiss Cheese Model)	✔
Human-Computer Interface	✔
Human Reliability Assessment	
Absolute Probability Judgment	
Human Error Assessment and Reduction Technique	
Human Reliability Analysis	✔
Cognitive Reliability and Error Analysis Method (CREAM)	✔
Human Factors Analysis and Classification System	✔
Technique for Human Error Rate Prediction (THERP)	✔
Operator Action Tree Analysis	✔
Justified Human Error Data Information	
Success Likelihood Index	
Technique for Human Error Prediction	✔
Standardized Plant Analysis Risk	
Accident Sequence Precursor	
Dynamic HRA	
Situation Awareness	
Mental Models	
Natural Language	
Distribution Cognition	
High Reliability Organizations	
Patient Safety	✔
Medication Error	✔
Medication Administration Error	✔
Medical Error	✔
Adverse Drug Events	✔

Medication Administration and Medication Administration Error Overview

The administration of medication is an essential function for the care and treatment of hospital inpatients. The process flow of delivering a medication is, at face value, not particularly complex. However, it does have any number of process steps that are subject to the vagaries of human and system errors. The process can be described by a simple process flow diagram (Figure 2.1). A healthcare provider orders a medication which gets sent electronically or is faxed to the pharmacy for preparation. The medication, once prepared, gets delivered to the patient floor where it is typically administered by a nurse. Somewhat surprisingly, while the process flow for nurse medication administration is well defined, it apparently has not undergone tremendous study or review from an I&SE perspective. Each healthcare facility will have their own unique approach depending on medications and equipment available. Ghenadenik et al describes a general process for administering medications in Figure 2.1 and Figure 2.2.

Figure 2.2 breaks the administration process into additional detail. The four general categories of Medication Administration (MA), patient assessment, administration provisos, delivery prep and delivery highlight the major considerations for the major elements in the reliable administration of medication. Each of these elements, in turn, can be expanded into their respective constituent elements (Table 2. 2).

Medication administration comprises 25%-30% of typical nursing shift; this varies across various clinical settings and patient types. The tasks associated with administering medications are: information retrieval, obtaining and, verifying medications, medication delivery, documentation of medication administration, and management of physician order entry (Figure 2.3) [20].

Medications are an essential component of modern medicine's arsenal to mitigate disease and illness. Medications are defined as "a substance intended for use in the diagnosis, cure, mitigation, treatment or prevention of disease; a substance (other than food) intended to affect the structure or any function of the body; and a substance intended for use as a component of a medicine but not a device or a component, part or accessory of a device" [21]. Medications include, but are not limited to, any product considered a drug by the Food and Drug Administration (FDA). Given the number and variety of definitions for medication errors, the Institute of Medicine (IOM) has recommended that international definitions be adopted for medication error, adverse drug events, and near misses [22].

As noted previously, at its surface, MA would seem to be straightforward, but the actual process is much more complicated requiring multiple inputs and steps from the initiating step of prescribing a medication to the point of administering it to the patient. Along each step, error can be introduced potentially resulting in inappropriately administering medication. While there are varying definitions of what medication error is, the National Coordinating Council for Medication Error Reporting and Prevention (NCCMERP) definition of a medication error is:

> "…any preventable event that may cause or lead to inappropriate medication use or patient harm while the medication is in the control of the health care professional, patient, or consumer. Such events may be related to professional practice, health care products, procedures, and systems, including prescribing; order communication; product labelling, packaging, and nomenclature; compounding; dispensing; distribution; administration; education; monitoring; and use…" [23].

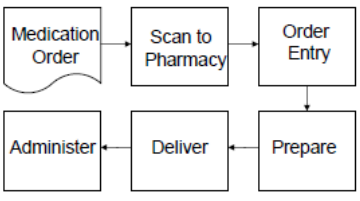

Figure 2.1: Simple flow chart of hospital medication administration process

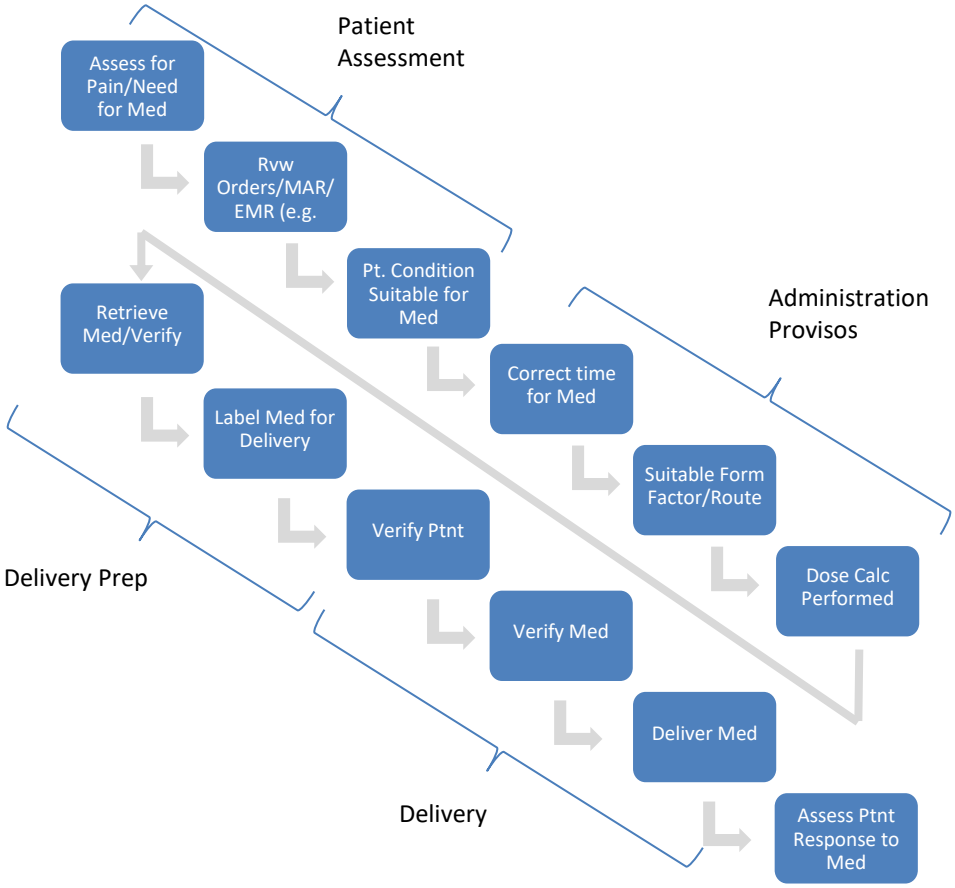

Figure 2.2: Process flow for medication administration

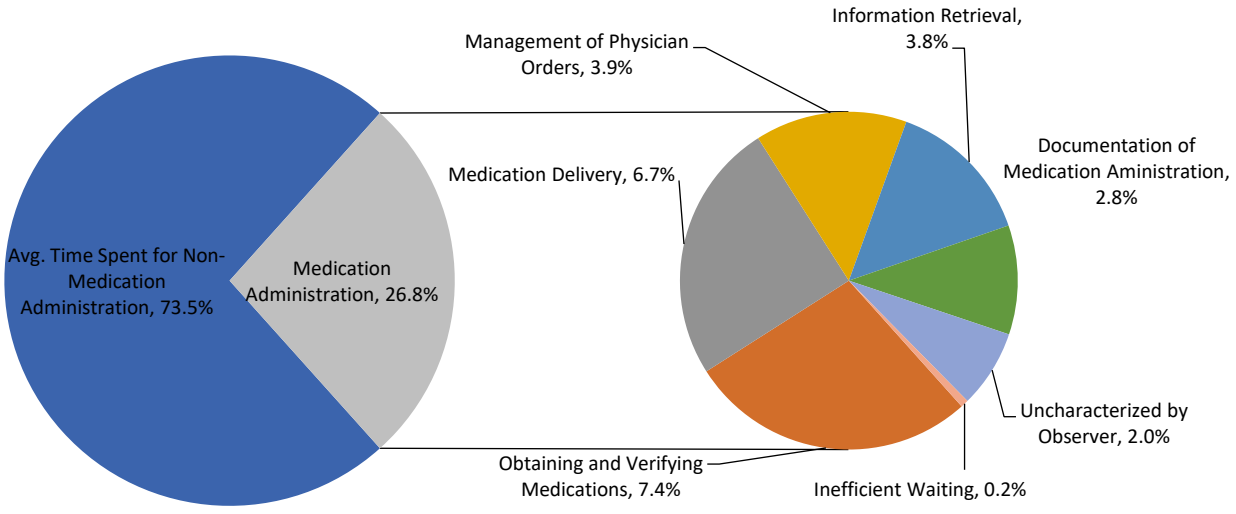

Figure 2.3: Average percentage of time spent on medication related activities by type

Table 2. 2: Description of medication administration elements

MA Elements	MA Steps	Description
Patient Assessment	Assess for Pain/Need for Med	Includes greeting the patient and initial assessment of patient's condition (e.g. vital signs, cognitive state, etc.)
	Review Orders/MAR/EMR	Check the patient's latest orders, lab results and other relevant records
	Patient Condition Suitable for Med	Determine medical appropriateness of medication administration
Administration Provisos	Correct time for Med	Based on orders and MAR determine if it is the right time to administer medication
	Suitable Form Factor/Route	Based on orders and patient condition assess the correct physical form of the medication including the route in which the medication should be delivered (IV, orally, liquid, solid, etc.)
	Dose Calculation Performed	Using the current information calculate the correct medication dosage
Delivery Prep	Retrieve Med/Verify	Retrieve the medication and verify that it is the correct medication in the right form and amount, including preparation of the dosage amount
	Label Med for Delivery	Label the medication with correct information (e.g. dose, patient name, etc.)
Delivery	Verify Patient	Bring medication to the patient and verify that it is the correct patient through the approved process (barcode, query name or DOB, etc.)
	Verify Med	Verify that the correct medication is at the correct dose and the correct form
	Deliver Med	Provide the medication to the patient
Evaluate medication effect /Follow-up	Assess Patient Response to Med	Check on the patient (via direct interaction or telemetry) to determine if the medication has had the desired response or has had a deleterious effect

Medication Administration Errors (MAEs) are a subset of medication errors. As with the definition of medication error, MAE has a variety of definitions. Most typically the definition of a MAE is "any deviation from the physician's medication order as written on the patient's chart". This definition, however, misses the perspective that physicians are no longer the only prescribing entity and does not consider the entire systems perspective of causative factors for MAEs. In a review of literature, the definition typically cited, that is authored by nurses, is that of Wolf who defined MAE as "mistakes associated with drugs and intravenous solutions that are made during the prescription, transcription, dispensing, and administration phases of drug preparation and distribution" [24]. The operational definition of MAE, for this study, will focus on the nursing process functions of medication dispensing. Errors in medication administration can include[25]:

- Prescribing the incorrect medication or dose
- Writing or typing the wrong medication or dose
- Illegible writing resulting in the wrong medication or dose being given
- The wrong medication or dose is prepared by the pharmacy
- The wrong medication or dose is delivered to the patient floor
- The medication is not checked for contraindications with other medications or patient conditions
- The medication order is misunderstood because of lookalike names or sound alike medication e.g.
- Dose miscalculation
- Medication is given at the wrong time
- Medication is given in the wrong form or by the wrong route
- Mistakes resulting from misreading of measurement units e.g. micrograms vs. milligrams
- Misinterpreted or miswritten orders

The MA process can be viewed as a system with inputs, outputs, resources, and controls. Figure 2.4 diagrams the interactions of this process [26]. Ghenadenik also provides a detailed process map for the nurse medication administration process (Figure 2.5 and Figure 2.6). While the medication administration process can vary significantly based on hospital specific procedures, available technology available resources, hospital ward and other factors, the process map is illustrative of a notional set and the interaction of medication administration process steps.

MAEs can typically be classified as either acts of omission or commission. These acts are frequently described in the context of the "rights" of medication administration. The most frequently used list of the rights are the five rights consisting of the right dose, right route, right patient, right medication, and right time.

There are multiple definitions and classifications in the literature about types of medication errors, they however fall into a number of standard causal factors as shown in Table 2. 3[27].

The Ishikawa diagram in Figure 2.7 represents proximate and latent causative factors of preventable adverse drug events (ADE). Note that ADEs are a direct result of medication errors. The literature indicates that that ADEs, in all health care settings, arise from a combination of contributing elements including patient, organizational, provider, policy, and procedure factors. While the items identified in Figure 2.7 may not play a role in all settings they certainly should be considered as possibly contributory elements [28].

In a limited study using a semi-structured survey, Tang explored the causes for MAEs from the nurse's perspective. The great majority (76.4%) believed that there was typically more than one factor contributing to the occurrence of MAEs. The 75 nurses, participating in the study, identified the following as major contributory elements in order of the percent of the nurses identifying each factor with 'Personal neglect' (86.1%), 'heavy workload' (37·5%) and 'new staff' (37·5%) which were the three main factors in the eight categories. 'Need to solve other problems while administering drugs, 'advanced drug preparation without rechecking,' and 'new graduate' were the top three of the 34 conditions. Medical wards (36·1%) and intensive care units (33·3%) were the two most error-prone places. The errors common to the two were 'wrong dose' (36·1%) and 'wrong drug' (26·4%). Antibiotics (38·9%) were the most commonly mis-administered drugs [29]. In a study using a somewhat similar methodology, the authors sought to uncover MAEs using a different set of questions. Table 2. 4 highlights the results.

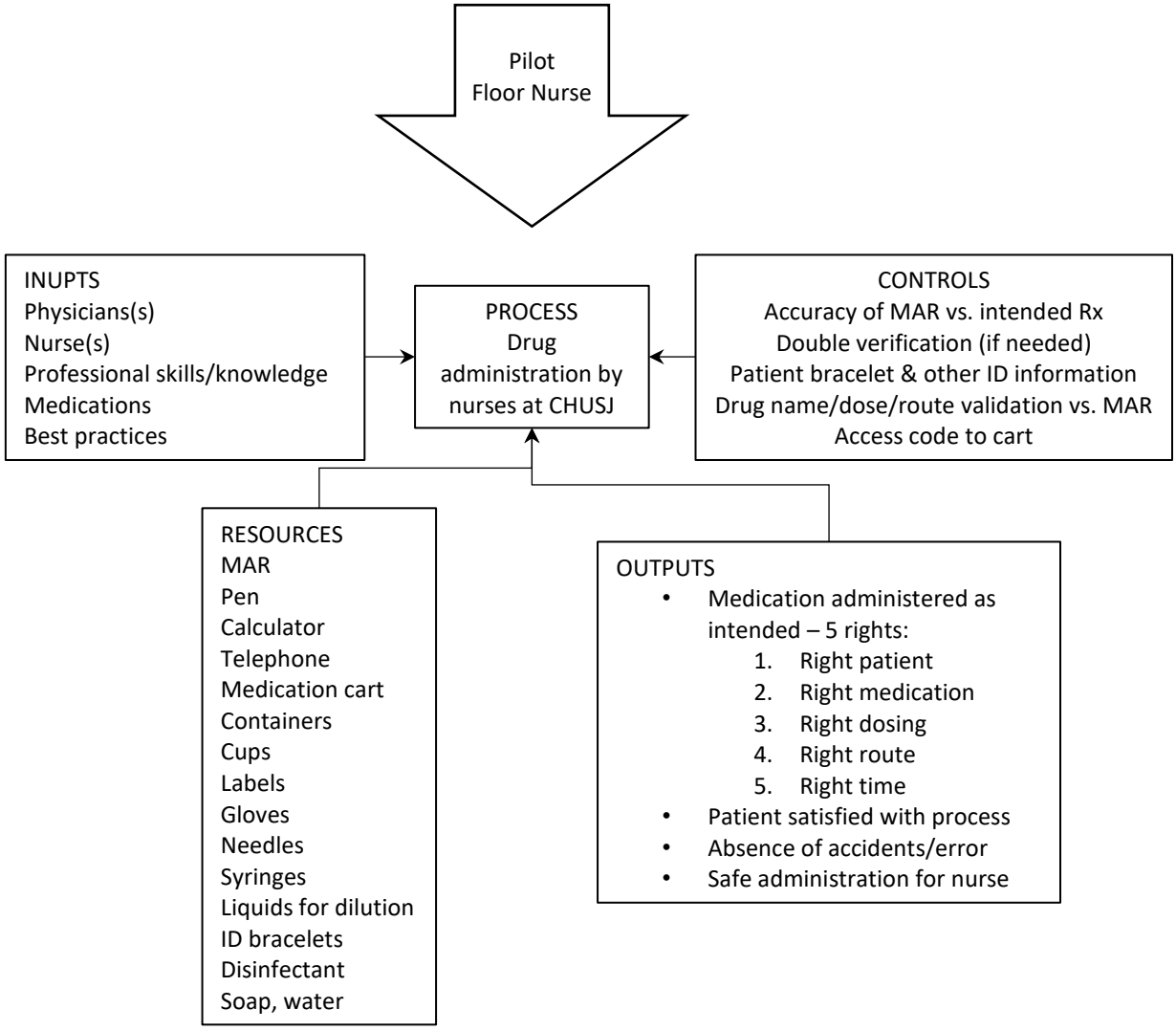

Figure 2.4: Inputs to the medication administration process[3]

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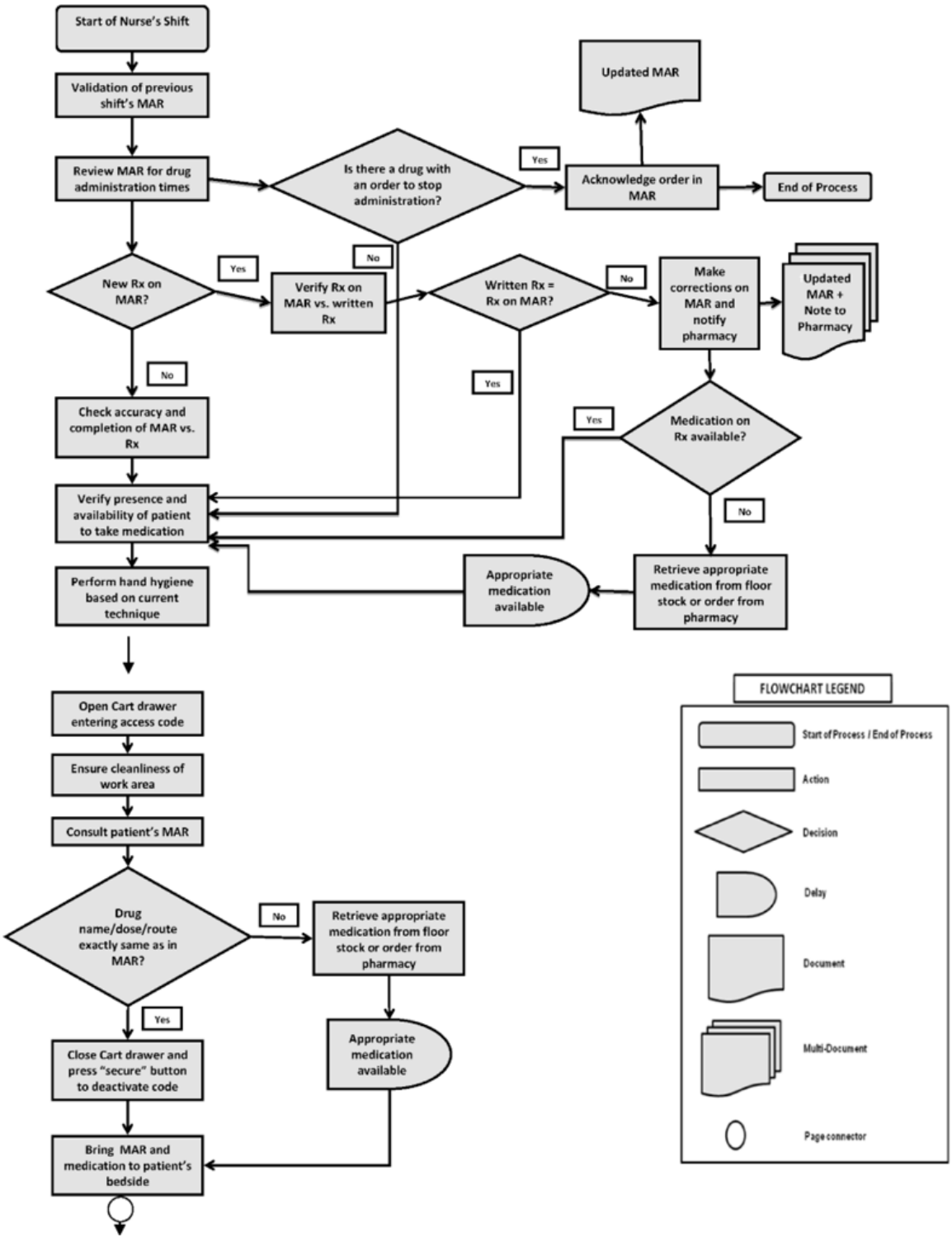

Figure 2.5: Elements of the medication administration process Part 1[4]

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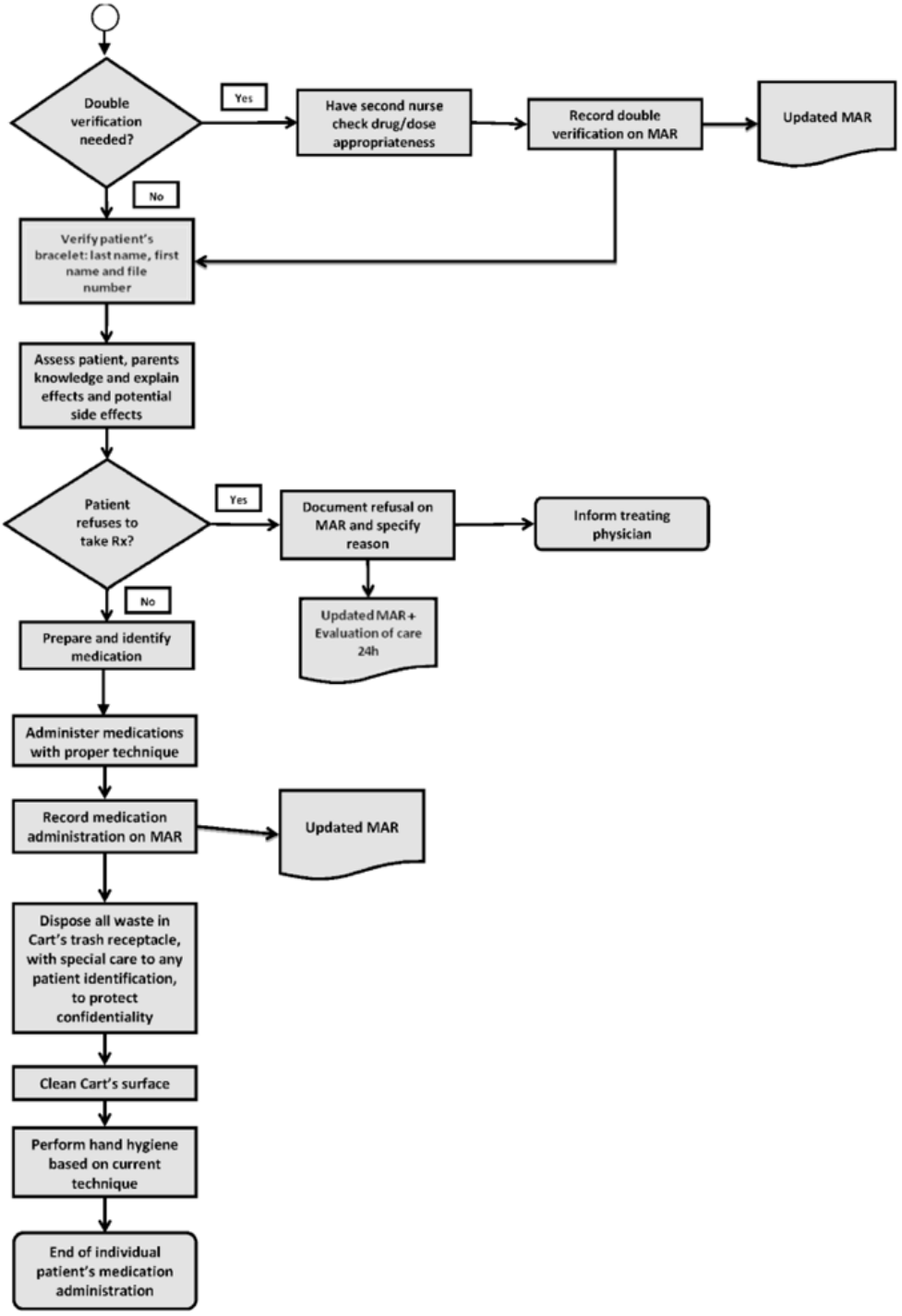

Figure 2.6: Flowchart of mediation administration process Part 2[5]

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Table 2. 3: Categorization and definition of medication errors

Types of errors	Definition	Example[6]
Dosage errors	Medications administered in doses greater or smaller than what had been prescribed	Prescription for 25mg of captopril and a 50mg dose was administered
Time errors	Medication administered to patient in a time different from that which had been prescribed or predetermined (e.g. more or less than a 1-hour difference)	Prescription for vancomycin at 6 pm and administered at 7:20 pm or prescription for enalapril at 10 am and administered at 8 am
Unauthorized	Administering medication that has not been prescribed by the physician	Administering amoxicillin instead of amoxicillin combined with clavulanate
Technique error	Medication incorrectly formulated or manipulated, before administering or using inappropriate procedures or techniques to administer a medication	Not measuring doses appropriately, or not using the infusion pump for the administration. For instance, to administer iron sulfate after meals or not verify the systemic arterial blood pressure before administering hypertensive medication
Route errors	Administering medications using a route different from what had been prescribed	Prescription for intravenous administration and administered orally
Wrong dose	Administering an extra dose to what had been prescribed or a medication that had been suspended	Administering captopril that later was suspended in the prescription
Prescription error	Incorrect selection of the medication, dosage, presentation, administration route, infusion speed, inadequate use of instructions by physician and not registering a verbal prescription	Prescribing omeprazole for 8 pm, when it should be administered at 6pm, before dinner
Omissions	Not administering the medication to the patient	The professional prepared the aerosol with saline at 0.9% and berotec and did not add the ipratropium bromide that had also been prescribed
Wrong patient	Administering the medication to the wrong patient	Phenytoin was prescribed to patient A but was administered to patient B
Wrong form	Administering medication in a way different from what had been prescribed	Furosemide tablets were administered instead of an ampoule

[6] Captopril – ACE inhibitor for high blood pressure; vancomycin – antibiotic; elapril – blood pressure medication; captopril – high blood pressure medication; omeprazole – medication for acid reflux; berotec – bronchodilator; ipratropium bromide – bronchodilator; phenytoin – antiseizure medication; furosemide – diuretic.

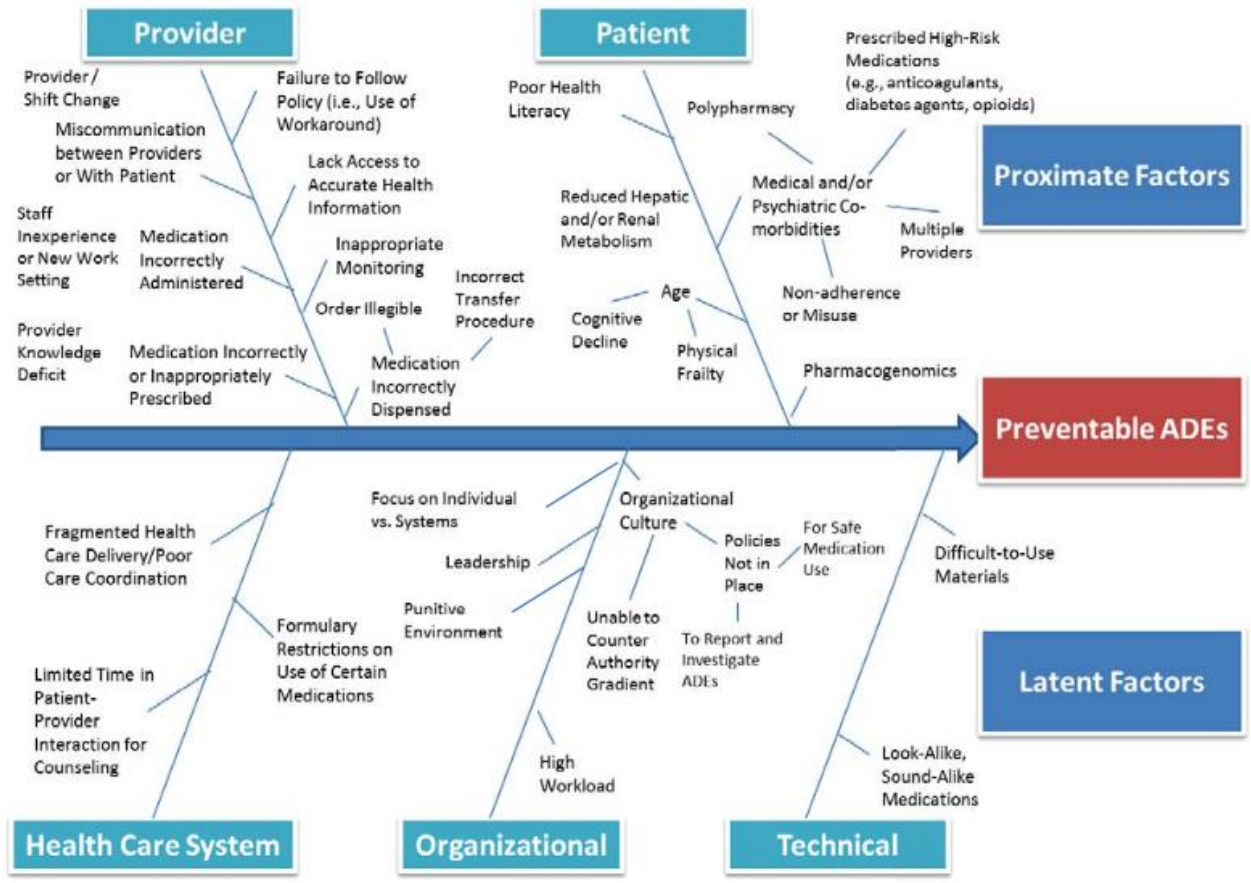

Figure 2.7: Ishikawa diagram of medication administration error[7]

Table 2. 4: Causative factor of nurse MAE

Causes	% of Nurses
Nurse fails to check name band with MAR	45.8
Nurse is tired and exhausted	33.3
Physician prescribes wrong dose	30.4
Nurse miscalculates dose	29.2
Confusion between 2 drugs with similar names	29.2
Physician's writing is illegible	28.0
Nurse distracted by patients, co-workers, and events in the unit	25.0
Nurse confused by different types and functions of infusion device	25.0
Medication labels/packaging is poor quality/damaged	25.0
Nurse sets up/adjusts infusion device incorrectly	24.0

Source: [30]

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How and why MAEs occur has been studied extensively. Research in the 1960's evaluated MAE as part of implementation of drug distribution systems [31]. Over the ensuing almost 60 years technology has changed but MAEs and the associated causes have not changed significantly. The statistics on errors vary depending on the study methodology. A review of research on MAE occurrence evaluating 66 studies concluded Medication administration errors among inpatients is frequent with the median error rate estimated at 10% of medications administered not including wrong time errors [32].

Individual areas, such as slips and lapses, are the most commonly reported unsafe acts, other factors include knowledge-based errors and deliberate violations of procedures. Conditions leading to errors in medication administration include communications (verbal orders, poor writing), medication supply, unusual medication (off-label, special order), patient factors (acuity, availability), staff factors (shortages, floating nurse), staff health status (fatigue, stress) and interruptions/distractions during drug administration.[4].

Medication errors are typically divided into four categories: prescribing, transcribing, dispensing and administration. Various studies provide slightly different rates of error in these categories; however, the rates are relatively close[33], [34, 35],[35]. MAE is consistently represented as one of the top causes of medication errors (Figure 2.8).

A systems level evaluation of systems factors identified various causative factors contributing to errors in medication administration. Drug distribution systems, including scheduling, delivery and dispensing of medications, are a key source of errors. The Medication distribution system can be described as a system of systems. Included in this would be medication delivery from the pharmacy, medication preparation, scheduling of medications, and (e.g. Monday-Friday System vs. out of hours system) [36].

Many activities in healthcare are process dependent, executing tasks in a specific manner is required to achieve the desired outcome. Deviation from procedures, both intentional and unintentional, results in errors. These deviations can result from increased workload, understaffing, stress, long hours, inexperience and lack of knowledge [36].

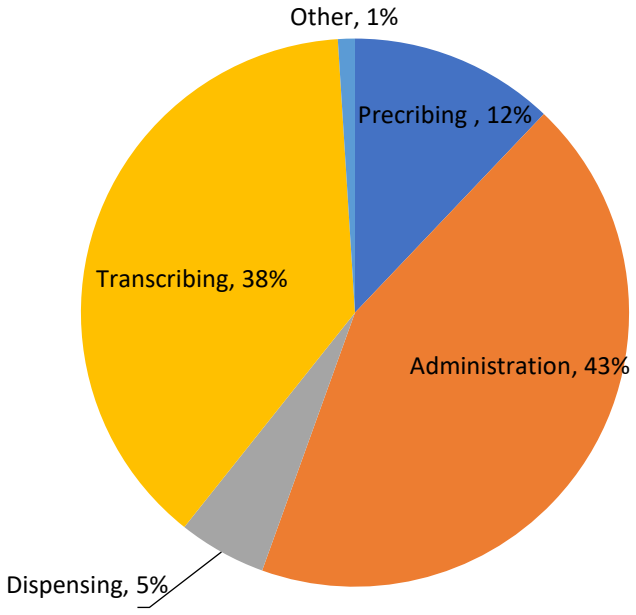

Figure 2.8: Allocation of error type for medication errors

When focusing specifically on causative factors of how nurses fall victim to MAEs, a number of factors come to the forefront. The studies are consistent in identifying underlying factors, such as personal neglect, heavy workload and new staff [29, 37].

Nursing is a dynamic and complex process. On average nurses are interrupted between seven and ten times per hour, that is once every six minutes, and these breaks in concentration and workflow are known to be significant factors influencing error occurrence[38-40]. In virtually all cases, more than 90%, these interruptions resulted in negative outcomes effecting efficiency and error rates [40].

Other factors are obviously at play for effecting MAE rates by nurses. Tang et. al. summarizes these factors in Table 2. 5. As a point of definition, Personal Neglect could perhaps be more aptly termed personal distractions and includes such elements as: must solve other problems while administering drug, advance drug preparation without rechecking, poor mood that day, interruption, physical discomfort, tired, etc. Sears observes that in addition to the "5 Rights" that work, environment plays a key factor in the occurrence of MAEs [41].

In a research literature review by Robinson of medication errors made by students during the medication administration phase, their findings provide a number of important observations (Table 2. 6). Most medication errors were those of omission; patients did not receive the ordered medication. Wrong dose errors occurred with the next most frequency followed by providing the medication to the wrong patient. Table 2. 11 summarizes their results on the type and frequency of MAE by students. [24]

Also relevant to our study is the underlying cause of MAE as it relates to student performance. Zane lists the causes and frequency of Student's medication errors. Notable in terms of relation to this dissertations' research are the top three causes of error listed in Table 2. 6. Also significant, in terms of errors, are drug dose calculation and contraindications: these factors would be ideal candidates for JIT information or knowledge management approaches to reduce MAEs.

In a study, using a somewhat similar methodology, the authors sought to uncover MAEs using a different set of questions. Table 2. 7 highlights the results:

This study focused on medical-surgical nurses and as with the study by flung, used a survey to gather the perception of nurses on the causes of medication error [30].

Westerbrook et al focused-on interruption in the clinical setting as a cause for an increase in the occurrence and severity of MAEs. In their study they noted a 12.1% increase in procedural failures and a 12.7% increase in clinical errors resulting from the influence of interruptions. As part of their study, they also baselined the general occurrence of MAEs independent of interruption.

Of course, training and education play an important role in reducing MAEs. Pauly-O'neill explored simulation in training as a means to improve patient safety in pediatric medication administration. Master's level Nursing students were cycled through a training simulation in an education simulation center. The training scenario included calculating IV dose and rate. One set of students performed the simulation prior to specific training on IV delivery while a second group of Junior BSN Nursing students were provided training on IV administration (intervention group). Results indicated that the post intervention group had consistently fewer MAEs. [43].

One of the challenges in studying MAE is the inconsistency or lack of event reporting. While certain seminal events are widely publicized and well known, MAEs are considered to be largely under-reported [44, 45]. Perhaps equally as important are the near-misses which are known to be indicators or predictors of the occurrence of actual errors [46, 47]. The issue of under-reporting errors directly impacts the fidelity of simulations that might be constructed to model the occurrence of MAEs and using these models to measure the effect of modifications to the MAE process.[48]

Table 2. 5: Nurses' report of the cause of medication error (N = 72; multiple response)

Category	Nurse (*n*)	Percentage	Rank
Personal Neglect	62	86.1	1
Heavy Workload	27	37.5	2
New Staff	27	37.5	3
Unfamiliarity with Medication	23	31.9	4
Complicated doctor-initiated order	17	23.6	5
Unfamiliarity with patient's condition	16	22.2	6
Complicated prescription	15	20.8	7
Insufficient training	11	15.3	8
Others	1	1.4	
Total	**199**		

Source: [29]

Table 2. 6 Medication administration error types by students (N=1208)

Type	n	%
Omission error	248	19.00
Improper dos/quantity	242	17.16
Wrong time	221	16.93
Extra Dose	184	14.09
Wrong patient	120	9.19
Unauthorized drug	110	8.42
Wrong route	47	3.60
Wrong administration technique	44	3.37
Wrong drug preparation	40	3.06
Wrong dose form	5	0.38
Prescribing error	1	0.07
Not classified by type	61	4.67
Total	1305	100.00
Records in which types of errors were reported	1208	92.56
Total no, of types of errors	**1244**	

Source: [42]

Table 2. 7: Causes of students' medication errors (N=1,135)

Cause	n	%
Performance (human) deficit	579	51.01
Procedure/protocol not followed	362	31.89
Knowledge deficit	301	26.52
Communication	192	16.92
System safeguard(s)	90	7.93
Documentation	88	7.75
Monitoring inadequate/lacking	46	4.05
Dose form confusion	33	2.91
Calculation error	29	2.56
Written order	24	2.11
Incorrect medication activation	21	1.85
Drug distribution system	19	1.67
Handwriting illegible/unclear	18	1.59
Dispensing device involved	16	1.41
Transcription inaccurate/omitted	16	1.41
Packaging/container design	14	1.23
Abbreviations	10	0.88
Brand names look alike	10	0.88
Brand names sound alike	10	0.88
Pump improper use	9	0.79
Brand/generic names look alike	7	0.62
Computer entry	7	0.62
Generic names look alike	7	0.62
Information management system	7	0.62
Preprinted medication order form	7	0.62
Brand/generic names sound alike	6	0.53
Diluent wrong	6	0.53
Equipment design	6	0.53
Labeling	5	0.44
Generic names sound alike	4	0.35
Label (manufacturer's) design	4	0.35
Prefix/suffix misinterpreted	4	0.35
Computer software	3	0.26
Label design	3	0.26
Measuring device	3	0.26
Reference material	3	0.26
Similar packaging/labeling	3	0.26
Verbal order	3	0.26
Contraindicated-drug allergy	2	0.18
Contraindicated- drug/drug	2	0.18

Table 2. 7: Causes of students' medication errors (N=1,135) (continued)

Cause	n	%
Decimal point	2	0.18
Pump- failure/malfunction	2	0.18
Storage proximity	2	0.18
Contraindicated in disease	1	0.09
Contraindicated<comma> drug/food	1	0.09
Fax/scanner involved	1	0.09
Leading zero missing	1	0.09
Nonmetric units used	1	0.09
No cause identified	170	
Records in which types of cases were reported	1,135	86.97
Total no. of causes reported	1,990	

Source: [42]

Mitigations of Medication Administration Errors

While much study has been conducted on approaches to the reduction of MAEs, it appears fractured and disjointed. Additionally, the approaches have been largely based on considering the elements of the process and not considering the overall medication administration process as a system. Systems factors have been identified by several authors [49-51] in considering approaches to remediating MAEs. However, at the risk of sounding critical, the inclusion of systems thinking is at a somewhat superficial level. It is perhaps interesting to note that at the time of this writing, a systems model or simulation has not been identified in the published literature.

Most of the remedies to MAEs are focusing on elements of the process, such as barcoding of medications [52], reduction of interruptions [53, 54], and automated medication delivery systems [55]. The challenge with each of these individual approaches appears to be missing the underlying systems (as defined in a Systems Engineering context) causes contributing to MAE occurrence.

Industrial and Systems Engineering Context for MAE

Many of the issues and challenges in HC are a result of how HC workers conduct their work. The same factors influencing performance in sectors such as auto manufacturing, airlines, shipping, and aerospace, have also been found in HC (Kullberg). While each sector can argue they are different, the fundamental features are the same. ISE is in a unique position to find the remedies to the ills of the HC system as we have done for these other sectors.

The consideration of using Industrial and Systems Engineering (ISE) in HC are traced back to Dr. Lillian Gilbreth. In the original foreword to the book Hospital Management Engineering, Gilbreth wrote:

> *"Many hospital people who hear of industrial engineering and the possibility of its application to their work react by claiming that their work is different. However, when such people see the similarity between their work and work in other areas, a good start has been made – a start which permits objective review and evaluation"* [56].

While the practice of ISE is said to have started in the 1940's, the efforts of Gilbreth and Smalley go back to 1952.

The challenges faced by the HC system Smalley identified in the first edition of his book in 1966, matched what he wrote in the revision in 1982, and are the same today. He talks to the consistently large increases in cost referencing $13B in 1950 to $200B in 1980. Not surprisingly, as an industrial engineer, he states:

> *"Improvements in the operation of hospitals depend, in large measure, on the capabilities of those who manage hospital affairs and, on the methods, procedures, and systems used in striving towards hospital goals. Thus, hospital improvements are realized through both management improvement and methods improvement"* [56].

Smalley's book goes over many of the key areas one would consider appropriate when considering ISE applications to HC (hospitals in this case). One will find Table 2. 8 contents edifying.

The contents of this book from the 1960's, with only changing a few dollar figures and references, could be reprinted today and be equally as relevant. The book also considers elements such as lean, total quality management (TQM), modelling and simulation, integration of information systems into day-to-day management efforts of hospitals and multidisciplinary approaches to management of HC operations.

In 2010 the U.S. Agency for Healthcare Research and Quality (AHRQ) held a workshop to "develop a research agenda at the intersection of industrial and systems engineering and health care" [57]. This background report, along with the associated documents, identified a number of key themes, items particularly relevant to this research are italicized:

1. The current health care delivery system is both unsustainable in terms of cost and suboptimal in terms of value.
2. The current health care delivery system cannot adequately respond to changes in the larger environment and within the medical sciences.
3. Solving the problems of the health care delivery system is complex and will require approaches that are multidimensional, multileveled, and inclusive of multiple stakeholders.
4. *Information technology will play a key role in the future health care delivery system*.
5. Incentives are needed to promote change, including the use of systems engineering tools, information technology, and evidence-based medicine.
6. *Opportunities are needed for cross-education and collaboration between health care professionals and scientific and technical professionals such as engineers and computer scientists*.
7. Research funding is needed to explore the intersections between health care and the use of systems engineering tools, computer science methodologies, and information technology.

Table 2. 8 Contents of Hospital Engineering: A guide to the improvement of hospital management systems

Chapter 1 Introduction (need for improvement)	Chapter 2 Hospital History
Chapter 3 The Nature of Hospitals	Chapter 4 The Methods of Improvement
Chapter 5 Modern Professional Programs	Chapter 6 Foreign Programs
Chapter 7 Management Problem areas	Chapter 8 Improving Work Methods
Chapter 9 Measuring Performance	Chapter 10 Staffing and Scheduling
Chapter 11 Sampling Hospital Activities	Chapter 12 Personnel Management
Chapter 13 Dealing with Variability	Chapter 14 Forecasting
Chapter 15 Managerial Control	Chapter 16 Waiting Lines
Chapter 17 Facility Planning	Chapter 18 Economic Evaluation
Chapter 19 Resource Allocation	Chapter 20 Information Systems
Chapter 21 Health Systems Planning	

This report provides detailed discussions of developing and implementing a research agenda for improving the operational efficiency of HC. In particular, it focuses elements that can be conducted within the next 5-7 years with implementation in less than 15 years. The output from this workshop provides a reasonable outline of research areas matching the needs of HC. The summary of these research areas is summarized below. Table 2. 9, reproduced in total from the final report, highlights areas of research for ISE in HC.

The tedious replication of this information was for the benefit of highlighting those key areas of research that considers sensor data integration. Of special interest are those areas that integrate real time data acquisition along with modelling and simulation.

The observation to be made by considering the 1950'3-1980's view and efforts of applying ISE techniques to healthcare and those of 2010 is that despite six decades of effort to improve, HC we still face many of the same challenges. In many circumstances the problems are even more complex and challenging.

With this in mind one is left to wonder why, after 60 years of effort, has there not been what appears to be satisfactory progress in improving HC operations. While a comparison of operational progress between industries has not been found yet (e.g. improvements in the automobile or airline industry vs. HC) it appears, at least anecdotally, that HC is lagging behind other industries (although I have not seen an objective quantitative comparison). Considering the work identified in Hospital Management Engineering, it appears that attempts have been ongoing in HC well before the first printing of the book in the 1966.

The Institute of Medicine produced a Report "The Path to Continuously Learning Health Care in America" which identifies that a learning system is needed where incentives are actively aligned to encourage continuous improvement and reduce waste [58]. They recognized the need for an integrated approach both at the micro but also operational level portrayed below in Figure 2.9.

Just-in-time, Real-time, Lean Information in HC

The advent of lean has slowly progressed into HC. Given the pressures for increased performance and lower cost, lean has gained a strong foothold and has generally been embraced by larger medical facilities in the early 2000s [59]. A survey of internet websites using "Lean "healthcare" or "health care" resulted in over a million hits. Phillips Health Care, Deloitte, McKinsey, Price Waterhouse, Kaiser, Boston Consulting Bain and virtually every other HC management consulting firm advertises an ability to support lean efforts in HC. A simple search of Amazon .com for books on lean healthcare resulted in more than 280 titles. There are certifications available for lean healthcare management and many organizations and universities offer short courses or for credit courses for it.

The realities of implementing lean are being experienced by HC as they have previously by other industries. It is not uncommon to have over-inflated expectations, receding results and resistance to implementation of lean processes. Although lean offers considerable potential benefits, the challenges and issues that it is facing in the complex environment of HC are resulting in the recognition that lean "might not be the easy remedy for making both efficiency and effectiveness improvements in healthcare" [60].

Lean has been applied to many aspects of HC mostly focusing on narrow albeit a broad array functions such as surgery [61, 62], emergency departments [63, 64], and laboratory operations [65]. These are just a few examples of the applications of lean in healthcare. Notable is the application in narrow fields and the lack of implementation of a system that will semi-automatically are automatically provide reporting of status on performance or a means to provide reporting across functions to determine cross functional impacts. That is, no research has been found yet in HC that identified a system that provides real-time information on the process to allow its effective monitoring.

Table 2. 9: Areas of research for ISE in HC[8]

Area of Application	Description
System Monitoring (Knowledge Innovation)	• Identification of best practices for dissemination and adoption of ISyE knowledge • Identification of best practices for spreading new ISyE knowledge between research and industry institutions and among industry institutions • Methods to characterize processes, inputs, and outcomes • *Methods to collect and present information that is valuable to diverse stakeholders such as patients, nurses, primary care and specialty physicians, pharmacists, and social workers* • *Theories and methods for the translation of numerical, analytical, and computational results into understandable and actionable information that multiple stakeholders (nurses, primary and specialty care physicians, pharmacists) and lay people can seamlessly retrieve to ensure the human monitoring of the system*
System Modeling (Knowledge Innovation)	• Models to mitigate uncertainties about the future • *Models to explore the role and consequences of automation, and provide guidance about what can be fully, partially, or not at all automated* • *Optimization models* • *Models that incorporate errors and interaction of events*
System Modification (Knowledge Innovation)	• Improving lay people's understanding of analytical results by developing enhanced data visualization techniques • Determining the benefits, limitations, and appropriate use of national, regional, and institutional forcing functions within the health care setting • Determining the role of culture as a necessary element of health care improvement, including the national political conversation and at the level of the patient and provider

[8] Source: Valdez RS, Ramly E, Brennan PF. Industrial and Systems Engineering and Health Care: Critical Areas of Research--Final Report. (Prepared by Professional and Scientific Associates under Contract No. 290-09-00027U.) AHRQ Publication No. 10-0079. Rockville, MD: Agency for Healthcare Research and Quality. May 2010. http://healthit.ahrq.gov/portal/server.pt?CommunityID=666&spaceID=399&parentname=&control=SetCommunity&parentid=&PageID=0&space=CommunityPage&in_tx_query=Industrial+and+Systems+Engineering+and+Health+Care&Submit.x=11&Submit.y=4&parentid=&PageID=0&space=CommunityPage&in_tx_query=Industrial+and+Systems+Engineering+and+Health+Care&Submit.x=11&Submit.y=4

Table 2. 9: Areas of research for ISE in HC (continued)

Area of Application	Description
Knowledge Transfer	• Identification of best practices for dissemination and adoption of ISyE knowledge • Identification of best practices for spreading new ISyE knowledge between research and industry and within industry
Meta-Knowledge Integration	• Mapping the usefulness of ISyE knowledge to different health care contexts • Characterizing research frontiers and directions at the intersection of ISyE and health care
Research Agenda Items That Support Breakthrough	
System Monitoring (Knowledge Innovation)	• Consumer-facing health IT solutions that allow patients to self-support their observations, that track and report on trends, and that interact with providers' annotations • Technologies which enable data to flow quickly and securely through the whole health care delivery system and be available in real-time when and where needed • Methods to operationalize contextual knowledge • *Methods to effectively collect and share data in real-time to foster situational awareness of all individuals involved in patient care*
System Modeling (Knowledge Innovation)	• Frameworks that explore the integration of many care sources in the production and delivery of care services, and the coordination among these sources (e.g., end of life care) • Methods to model systems as set of flows and processes not just sets of components • Models that explore the effective use and allocation of different vehicles of health care delivery (e.g., “focused factories” versus integration, such as Mayo Clinics and Kaiser Permanente) • Models to evaluate entire systems and large-scale system changes before they are implemented • Models of collaboration and competition among health care stakeholders • Models that consider how health IT can be integrated into decision making processes, how evidence-based knowledge can be integrated into practice • Models of collaboration and competition among health care stakeholders • Methods to build models from incomplete, inaccurate, and unreliable data • Methods to build models from inconsistent data coming from disparate sources • Methods to model unstable systems • Methods to model large-scale distributed systems

Table 2. 9: Areas of research for ISE in HC (continued)

Area of Application	Description
System Modification (Knowledge Innovation)	• Determining ways to modify public and private incentives to influence patients to stay healthy, providers to work in the best interest of their patients, and organizations to be efficient, without unintended negative consequences • Exploring payment structures that accommodate technologically-mediated interactions between providers and patients (e.g., text messaging, email, or visits by teleconference) • Determining appropriate approaches to stimulating system-wide change, exploring ways to coordinate between bottom-up integration and top-down decomposition
Meta-Knowledge Integration	• *Exploiting synergies within ISyE knowledge derived from different sub disciplines*
Research Agenda Items That Support Sustainability	
System Monitoring (Knowledge Innovation)	• Identification of best practices for use of ISyE knowledge • Efficient and pervasive methods of data capture • New automatic data collection technologies to capture observations from patients and their environment (e.g., sun exposure and food intake) • Theories and methods beyond natural language processing for the translation of lay person language into structured computable data • Efficient methods for integrating large amounts of data from disparate sources • Adequate integration of data collection into workflows in manners which ensure data validity while minimizing interference with clinical workflows • Efficient means of integrating information generated from different perspectives (e.g., different providers, patients, administrators) • Methods to characterize how the outcomes relate to the processes
System Modeling (Knowledge Innovation)	• Models of trust between patients, providers, and technology • Models that provide guidance about when standardization or customization is necessary • Models that appropriately consider the conflicting objectives of multiple stakeholders and make system-optimal recommendations • Methods to model the dynamics between micro-changes (at the provider level) and macro-changes (at the market and policy levels)

Table 2. 9: Areas of research for ISE in HC (continued)

Area of Application	Description
System Modification (Knowledge Innovation)	• *Iterative knowledge development and transfer between research and practice* • *Improving translation from mathematical and technical languages into lay person terminology* • *Testing of change and implementation theories, and exploration of the tension between pushing for the application of existing knowledge and trying to develop more usable new knowledge* • Exploring how social network theories can be used to trigger and facilitate culture change
Meta-Knowledge Integration	• Characterizing health care challenges • Identification of best practices for use of ISyE knowledge

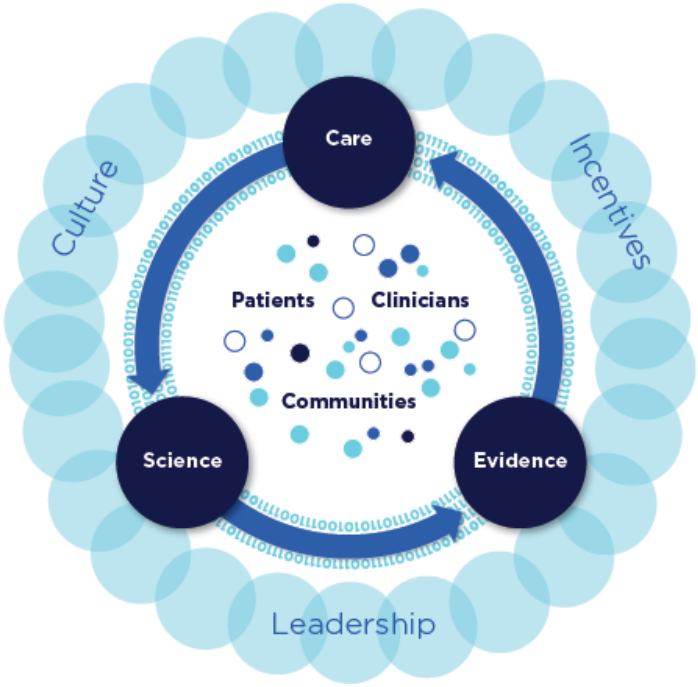

Figure 2.9: Interactions required for a learning system in Healthcare[9]

[9] IOM (Institute of Medicine). 2012. *Best care at lower cost: The path to continuously learning health care in America.* Washington, DC: The National Academies Press.

The view of the success of lean, in contributing to process improvement, is mixed. A recent review of the literature suggests, based on 177 articles on six sigma and lean, that there is weak evidence that Six sigma and lean improved HC quality [66]. Another survey article indicated that, while there is apparent significant benefit from implementing a lean process, the rigor of the evaluation was lacking and suggested performing comparative studies like that sued in evidence-based medicine (rigorous randomized studies) [67]. So, based on its limited review of reviews, it appears that while there is significant anecdotal evidence for the improvements resulting from lean in HC, the HC community is still not convinced of its benefits.

Pressures to improve the healthcare operations and the rapidly changing environment, within which healthcare operates, is driving all segments of the healthcare industry to focus on how to improve performance. Conventional approaches, such as financial analysis to reduce costs, application of lean and other similar principles, insertion of new technologies, mergers and acquisitions, and others are being used. The reduction of cost, referred to here, is defined as reduction of the systems level cost of providing the actual healthcare service. Simply put, it is reducing the cost of the bill for providing a service.

There are thousands of journal papers on the implementation of Lean/six sigma in HC. The effort here is not to provide a comprehensive evaluation of these, but rather to gain an understanding of what the lean /six sigma approaches might benefit from in order to improve its implementation and sustainability of the assumedly improved outcomes. At its fundamental level, HC is not different than other service industries; generalizing more it is the same as other complex sectors as noted previously. An article in the Wall Street Journal documents the outcome of over 100 improvement events, half of which failed over time. The causes for the failures were generally attributed to the hysteresis of the system (i.e. old habits die hard, people slipped back to their old way of doing things after the boss stopped watching) and also the response of the system to the increasing pressures induced by the change to the point of failure. Once the drive to improve is removed, the system goes back to near its original steady state [68]. One reason for this could be the lack of adequate metrics and the ability to *easily* and frequently measure the intended performance. While it might be straightforward to measure the output of manufactured items and set objective evaluation criteria for measuring quality, it is much more difficult to do the same for human performance related to how they perform in a HC setting. That said, the integration of data from multiple data sources, such as EMR and RTLS, might provide some support in this area.

Lean has been considered as a means to improve medication administration safety. The overall outcome, when implementing lean, appears to be positive with a significant reduction in the number of errors as measured by safety violations [69]. General quality improvements, including reduction of medication errors, have also been noted [70]. That being said, the longer-term benefits of lean are still uncertain with effective recidivism, flipping back to old methods, and reducing longer term benefits of lean implementation [66]. This again argues for taking a systems level perspective on efforts to reduce MAE.

Another concept of lean is its application to information management. As noted earlier, among the challenges faced by nurses, is the amount of information, including non-essential information, along with difficulty in accessing the desired information at the time it is needed. Applying the principles of lean to information management supports the concept of providing the information that is needed at the time it is needed [71]. Stainback considered the use of lean communication techniques to increase the effectiveness of communication of race teams which can be considered similar to medication administration in terms of the high consequence risks, dynamic nature and complexity of operations [72].

Delivering information, or knowledge, at the time it is needed follows the same principles as Just-in-Time (JIT) for manufacturing processes. With the goal of providing the right material to the right people at the right time we relieve the dependency on memory or requiring the practitioner to integrate information from multiple disparate data sources. The challenge is to meet the system requirements of meeting the unique needs of the user, providing an appropriate interface to convey the information, and integrating the data sources in a meaningful and efficient way.[73]. While the consensus is that healthcare suffers from a glut of information, perhaps a more appropriate view is that it lacks an appropriate mean to select and search for the right information, cull the

currently extraneous information and analyse the available information to support the care giver in decision making [74].

In the context of healthcare, JIT information affords the promise of literally putting the information in the hands of the HC provider as they need it. The truth is that many of the systems actually make it harder, not easier, to do their jobs [75]. Electronic Medical records Systems, Medication Administration Records, and virtual displays of vital signs have all been sued with limited success and adoption. They still face the challenge of providing an integrated information system that meets the needs of the floor nurse particularly as it relates specifically to mediation administration. The concept of JIT information management in HC is not new; reference to the concept and consideration of the promise it holds goes back to the 1990's [76].

Knowledge management tools are well established in a variety of other fields such as aerospace, defence, and manufacturing. Their application to HC is relatively recent. Empirical data indicates that healthcare needs a personalization approach focusing on using interactive knowledge while other disciplines use somewhat different approaches [77].

Specific MAE Mitigation Approaches

Effort to mitigate MAEs can take several forms principally administrative, process and engineered solutions. Administrative mitigations would include efforts such as checklists, increased education/training, procedures, signage, and decreasing interruptions. Engineered approaches to decrease MAEs would include medication dispensing equipment, bar coding, and Radio Frequency Identification (RFID) tagging. Process changes to reduce MAEs would include lean efforts and systems design changes. Noted below are the primary areas identified in the literature that have been addressed in the literature for the mitigation of medication administration errors.

- Engineered approach MAE mitigation:
    - Bar code medication administration (BCMAR)
    - Medication dispensing equipment
    - Smart IV/Infusion pump
    - eMAR/EMR
    - Radio Frequency Identification tagging
    - Clinical Decision Support Software tools

- Administrative approach MAE mitigation:
    - Training/education
    - Interruption mitigation
    - Improved work environment
    - Check lists

One review of the literature focused on the application of technology to reduce MAEs. Of the observations, one insight matched my perception of reviewing over 100 articles for this question: The research related to measuring the effectiveness of using technology to reduce MAEs is generally positive towards their benefits but the evidence overall is equivocal. The majority of studies were not theoretically driven, were limited in breadth of data (i.e. used one to several hospitals) and were limited to the quantitative. The review goes on to report that the majority of studies reported the development of workarounds with medication administration that could compromise patient safety. This infers that the technologies from the studies were lacking in their overall benefit and introduced conditions for the nurses that prompted them to search for approaches that would make their jobs less difficult and avoid the sue of the technology [78].

Drug Dispensing Systems

Unit dose medication dispensing was first used in hospitals in the 1960's to increase efficiency and decrease MAE. A descriptive definition of unit dose is [79]:

> "those medications which are ordered, packaged, handled, administered and charged in multiples of single dose units containing a predetermined amount of drugs or supply sufficient for one regular dose application or use… system for preparation and distribution of drug served in a single dose and made ready to be consumed once".

In one study, the potential that unit or patient dose systems can have on reducing missed doses verses administration from a ward stock (imprest system[10]) was evaluated. Four hospitals with similar wards were utilised; three used the imprest system, one the unit dose system. Of the three hospitals using the imprest (stock-based system) 5.7% of total doses were identified as missed. In the one hospital using unit dose approach 4.1% of total doses were identified as missed ($p<0.005$) [80]. The authors noted that hospitals switching from bulk medicine ward-based systems to unit dose systems reduced missed doses from 17% to 1.6%.

Similar results were observed in a study in a geriatric facility where a unit dose dispensing system was implemented. The researchers observed a 53% reduction in MAEs. While the study only considered one facility with a small number of observations and a limited patient type (geriatric patients), a considerable decrease in errors, including wrong dose and wrong drug, was observed [81].

In another application, an automated drug dispensing system was installed in four hospitals. The authors evaluated for efficiency and error reduction. The process was assessed in terms of drug inventory, drug distribution, pharmacy staff requirements, missed doses, clinical interventions and nurse satisfaction. The number of pharmaceutical line items available in in-patient care areas was increased by 324% using the controlled storage and delivery of the automated system. Over 95% of required items were available at ward level during the trial. Pharmacists' time was reduced by 46% and technicians' time was increased by 36%. The overall staff cost increased by 2.5%. Missed doses declined from 29% to 24%. The prescription turnaround time for items in Med stations was decreased by 88% compared to pharmacy-based dispensing. Dispensing interventions by pharmacists increased by 16%. Most nurses (91 %) in the wards preferred the automated system and 54% of nurses in the intensive care areas thought the system should be adopted [82].

While automated dispensing provides increased efficiency in MA, reduction in MAE has not been uniformly realized, and some studies have noted increases in errors with some forms of automation. As might be suspected, there is considerable nurse-nurse variability in the error rate between an automated system and conventional unit dose. Interesting unintended consequences have arisen with these machines including increased nurse need during busy administration times, removal of doses ahead of time to circumvent waiting and overriding the device when a dose was needed quickly. These issues demonstrate that, as in other industries, new technologies are not necessarily a remedy for inadequate or faulty processes or procedures [51, 83]. While there are issues with automated drug dispensing systems, the consensus in the literature is that they generally have a beneficial effect on MAEs and improve the MA process [55, 84-86]

Bar Code Readers

Bar code readers have been employed to help reduce MAEs. It was estimated that 24% of hospitals in the US have adopted bar code scanning technology for medication administration [87]. The bar code readers serve several functions during the MA process including patient verification, enhancing access to the EMR system, and validating the correct drug. One general study by Anderson noted that MAEs decreased 59%-70% on individual nursing units [88]. However, not all results from use of bar code Medication Admiration (BCMA) are positive. Numerous studies have identified issues resulting in MAEs, including a decrease in critical thinking, bypassing technology, and occurrence of new errors [89-91]

[10] An imprest system is a form of inventory management where a fixed amount is reserved which after a certain amount of stock is used the inventory will be replenished. It has its roots in financial accounting where an example would be a petty cash system where the cash is used until it hits a base limit and then is replenished.

A study by Bowers et al proposed that implementing barcode readers for MA would increase real-time medication administration documentation, decrease medication administration-related errors, increase Workstation on Wheels usage at the bedside for medication administration, and increase use of the electronic medication administration record for medication retrieval. After conducting a pre-post comparative design, they concluded that there was an increase in use of the computer on wheels at the bedside, as well as real-time documentation. However, they noted that the use of the electronic medication administration record to retrieve medications did not increase. Medication errors showed a slight rate increase after bar-code medication administration was introduced [92].

As with many technology implementations in Healthcare (HC), BCMA was introduced into practice without a comprehensive understanding of what the actual impacts would be. Hassink et al performed a comprehensive literature review on the impacts of BCMA on MAE. In summary, the observations were that the frequency of decrease in errors from the pre-BCMA implementation to the post-BCMA implementation ranged from 56.0% to -20.4% (an increase in MAE rate). If MAEs related to time errors were excluded, the range changes to 56.9% to -16.3%. Two-thirds of the studies in the first category showed a decrease in MAEs and nine-tenths in the second category showed a decrease in MAEs. Of the studies in this review there was a beneficial effect of BCMA on decreasing the severity of the MAE. The review did not observe any increase in nursing efficiency for medication delivery [93].

With any type of engineered approach, there is a human interface that will ultimately determine overall effectiveness of the solution. An example of this consideration is a study done by Gooder that evaluated nurses' perceptions of BCMA. The conclusion of the study was that there was a decrease in the overall satisfaction with the medication process after the BCMA system was implemented. This emphasizes the need for an understanding of the overall impact of a system such as BCMA on the actual performance of a process such as MA.[94].

Song et al evaluated the technology acceptance based on behavioural intentions toward BCMA. The study considered nurse feedback and communications which had a positive impact, not the use of the technology; increasing age of the nurse had a negative correlation. The degree of teamwork within the nursing unit and perceived usefulness of the technology also contributed to the adoption of the technology [95]. A corroborating study by Holden considered the effects pre- and post-BCMA implementation at a hospital: he used a second similar hospital that was not implementing BCMA as a control. Holden summarized the results as follows [96]:

> "Nurses' perceptions of the administration process changed at the hospital that implemented BCMA, whereas perceptions of nurses at the control hospital did not. BCMA appeared to improve the safety of the processes of matching medications to the medication administration record and checking patient identification. The accuracy, usefulness, and consistency of checking patient identification improved as well. In contrast, nurses' perceptions of the usefulness, time efficiency, and ease of the documentation process decreased post-BCMA. Discussion of survey findings is supplemented by observations and interviews at the hospital that implemented BCMA."

PubMed identified 127 possible relevant citations; Scopus identified 136 for the application of bar coding to medication administration. Not surprisingly there is significant overlap between the two data bases. The conclusions to be drawn from reviewing these studies can be summarized as [97-100]:

- BCMA has a generally positive effect on MAE
- The severity of MAE is generally decreased by BCMA
- Human factors considerations play an important role in the use and benefit of BCMA
- BCMA does not appear to have a negative effect on process efficiency
- BCMA has a mixed effect on decreasing errors among the "5 rights" of MA
- BCMA is not a comprehensive solution for the reduction of MAEs

As with any engineered solution, end-users will develop workarounds if they find the use of the technology or solution cumbersome or problematic. Koppel et al studied workarounds to the use of barcode medication administration systems. The authors identified 15 types of workarounds including affixing patient identification barcodes to the computer cars, doorjambs, scanners or delivering "pre-scanned" medications to patients. The causes driving the nurses to work around the barcoding were varied but generally included issues related to bad patient or medication barcodes or equipment issues [90]. The implication of this study is that any technology that might be used for the mitigation of MAEs must be simple, convenient and robust.

Electronic Medication Administration Record

Use of electronic medical records systems (EMR), including electronic medicine administration records (eMAR), have been in various stages of implementation for several decades. The use of these systems is being driven now by mandate of the US Government to implement these systems and be able to demonstrate meaningful use by 2014 [101]. eMARs are typically included in EMRs by hospitals in an attempt to provide comprehensive patient charting and are under the impression that this reduces MAEs. One study that considered the effectiveness of eMARs in mitigation MAEs in combination with other technologies concluded that they are in fact beneficial in reducing errors [102].

Another before and after study considered the implementation of eMAR but considering both performance and cost implications. The researchers in this study observed an overall increase in patient safety and timeliness of care noting a remarkable total elimination of prescription transcription errors, and modest to slight reduction in cost of services. The authors did not appear to control the effect of other activities that might have been occurring that could have affected costs nor was there any type of control group noted [103].

A more comprehensive study was performed, Appari et al, where they conducted a retrospective cross-sectional analysis of data from three Federal healthcare Information Technology database sources Computerized Physician Order Entry (CPOE)/eMAR usage from HIMSS Analytics, medication quality scores from CMS Hospital Compare, and hospital characteristics from CMS Acute Inpatient Prospective Payment System). They concluded that the implementation and duration of use of eMARs are associated with improved adherence to medication guidelines at US hospitals thus indicating reduction of MAEs. The benefits are evident for adoption of eMAR systems alone and in combination with CPOE [104].

A primary medication delivery mechanism is via intravenous (IV) infusion. The HC industry has developed IV pumps as an approach to provide consistent medication delivery. MAE associated with IV pumps occur frequently, have the potential to cause injury, and are diverse. Smart pumps are an important component of a hospital's medication delivery system. However, while envisioned to be a means to mitigate MAE, the incidence of error is high. In one study 66.9% of observed medication deliveries using smart pumps had errors associated with their delivery. Currently available smart pumps will fail to generate meaningful improvements in patient safety until they can be interfaced with other systems such as the electronic medical record, computerized prescriber order entry, bar coded medication administration systems, and pharmacy information systems. Future research should focus on the effectiveness of new technology in preventing latent and active errors, and on new types of error that any technology can introduce [105-107].

Radio Frequency Identification

Radio Frequency Identification (RFID) technology is ubiquitous in a wide variety of industries for the tracking and logging of items. One long-discussed application is the use of RFID in HC and in particular MA [108]. There are numerous studies that have assessed the impact of RFID on MAEs: the virtually universal conclusion is that RFID is effective in reducing the occurrence of MAEs, particularly when included as part of an overall dedication delivery control and monitoring system [109-112].

One can envision what could, in effect, be an error-proof medication delivery system based on RFID and eMAR, EMR, barcoding and wireless telemetry. RFID would be used to track the medication and the dosage, its delivery, identify the patient, identify the nurse delivering it to the patient, ensuring that the patient and nurse are in the

correct room, and verifying the time of delivery. The issue with RFID is not the potential benefit of the technology, rather it is with the prohibitive cost, infrastructure requirements, potential liability concerns, privacy concerns, user and patient reluctance and cost and effort to fully integrate and maintain the system [113-116].

Clinical Decision Support Software tools

The Just-in-Time (JIT) delivery of medical information for health professionals is being revolutionized through the use of mobile computing apps. While software programs exist as part of a hospital's enterprise level Electronic Medical Record system, including clinical decision support systems that help manage portions of the MA process, they are limited in their utility because they are typically tied directly to the computer stations and are still considered to be in their early stages of deployment despite being around for several decades. These systems are noted to be cumbersome and problematic to use with mixed reports on their benefits [117, 118].

A clinical decision support tool is an application that provides information to a clinician that assists in taking action or making judgment in support of the care of a patient. There are a large number of clinical decision support tools (CDST) with a broad range of complexity, functions and applications. While they have found some use in healthcare settings, their use is not as ubiquitous as you would find in other settings, such as finance and manufacturing. For healthcare, the range of CDSTs ranges from relatively simple smartphone applications that include checklists, reminders, calculators or information sources (e.g. epocrates®) to complex, robust systems that provide extensive knowledge processing and artificial intelligence integration into the decision making process (e.g. IBM Watson®)[11]

While there are chronic issues with implementation of EMRs, they offer direct benefits for application of decision support tools. Various CDST applications have been developed for medication administration. Research related to those CDST have concluded benefits arising from their use, notably improving workflow, improving patient safety, as well as more attention to alerts, and less impact from interruption [119-121].

The evolution of mobile computing using tablets, smartphones or similar devices is creating a dynamic environment for the creation of apps[12] for healthcare professionals. The area of interest for this study, medication administration, has a relatively limited number of applications. Apps in this area have the same challenges as apps for other areas of healthcare, specifically: uncertain regulatory framework, liability concerns, accuracy and performance validation, providing current information, standardization, and cybersecurity [122-124].

There are relatively few apps developed for medication administration. As of this writing, only a modest number of apps specifically for medication administration were identified as commercially available apps for small mobile computing devices:

Micromedex[13]
Medhost[14]
PatientTouch[15]
Medrills[16]
Allscripts[17]

[11] Extracted from a portion of the answer to Comprehensive Examination question 1 from Dr. Tami Hodges and developed by T. A. Berg. The complete answer can be provided upon request.
[12] Apps refers to software programs developed for use on mobile computing devices that are self-contained programs usually designed to address a particular need or set of needs.
[13] iTunes app aligned with larger healthcare management software
[14] iTunes app aligned with larger healthcare management software
[15] iTunes app aligned with larger healthcare management software
[16] iTunes app aligned with training software
[17] iTunes app aligned with larger pharmacy management software

Other of apps are available that provide comprehensive drug information including:

Epocrates
Merck Manual
A2ZDrugs
iPharmacy
WebMD
Davis's Drug Guide

The apps noted above could include general medication reference, dose calculation, contraindications, drug interactions, etc. They do not include decision support tools that guide practitioners through the medication administration process.

The question can be asked: do apps actually provide a benefit in the form of improved patient safety and more specifically a reduction in MAEs? The best, but unfulfilling answer is that it depends. Most of the research on the uses and benefits of mobile apps is anecdotal or the research is not based on controlled studies which weakens the described benefits [125].

Mobile apps provide benefit for health care providers (HCP) mostly by providing information at point-of care (POC). Improving access to tools at POC is recognized as improving patient outcomes [126-128]. As noted previously, there are a wide range of apps that support HCPs including [129]:

- Information and time management
- Health record access and maintenance
- Communication and consulting
- Reference and information gathering
  - Literature search
  - Drug information
  - Physiology and test values
- Calculators and support aids

- Patient management
  - Clinical decision-making support
  - Patient monitoring
- Medical education and training

The benefits associated with mobile app tools for HCP include convenience, decision making support, reduction of errors, enhanced communication between the provider and patient, and increases in efficiency and productivity [129-132].

At the time of this writing no mobile apps have been identified that are designed specifically to support the administration of medications and having the intent of improving patient safety and reducing the occurrence of medication administration errors.

Education/Training

The level of training and education has been evaluated as a potential influence on the occurrence of MAEs, particularly with regard to medication calculation and pharmacology. In an overarching review, the effectiveness of a range of training and education programs focused on medication administration were examined. The results of these programs provided mixed results: it was found that while these programs increased general knowledge, they did not translate directly into the reduction of MAEs. The study goes on to report that more hands-on training through simulation-based approaches and multifaceted approaches that involved combinations of risk management strategies and education, resulted in some decrease in MAE occurrence [133].

Using nurses trained specifically in the MA process and using them as a dedicated resource to administer medications is one approach that has been considered to lower MAEs. Greengold et al conducted a randomized trial to assess the use of medication nurses to administer medications to mitigate MAEs [134]. Her conclusion was that there was no statistically significant value in using dedicated medication nurses over the control group. It should be noted that this was a limited study using two hospitals and 16 nurses in total.

Interruptions Reduction

An area of interest to mitigate MAEs is to reduce interruptions of nurses while going through the MA process. Numerous studies have been done to associate interruptions with an increase in MAEs [29, 39, 53, 135-137]. A variety of studies have been performed to evaluate the impact of interruption mitigation methods [138-141]. While interruptions and other distractions are well recognized as sources of error within healthcare, as well as other high consequence, the literature for healthcare in the effect or benefit of interruption mitigation efforts is mixed.

In a systematic survey of ten studies, Raban et al concluded that there is weak evidence on the effectiveness of interventions to reduce the effect of interruption on the rate of MAEs. They concluded that while there is modest indication of the reduction of errors, that other interventions were also used and that no controlled studies were performed to ensure the effectiveness of interruption mitigation techniques. As with other MAE mitigation techniques, the authors commented that more research is required to better understand the complex integrated system of MA and the effect of these methods [142]. This was also supported by O'Shea in a similar review of available research [138, 140, 143].

Improve Work Environment

It is often reported that work conditions, such was shift length, stress, and overwork, can lead to increased MAEs [4, 50, 144]. Lessons learned from other industries have been explored from other industries such as airline, nuclear, chemical operations and other high consequence operations [145-147].

Nurse workload continues to be an ongoing area for debate: for the purposes of this review, workload is used as a general topic area covering areas including stress, fatigue, burnout, etc. While one could argue that this is not entirely accurate, the literature generally groups these areas. On one hand the literature clearly relates high workload and its corollary element, fatigue, as a direct cause of decreased patient safety and increased MAEs [29, 144, 148-151]. This risk is offset by the real-world issue of higher costs associated with increased nurse staffing levels: note that the correlation of increased nurse staffing levels and increased patient safety is well documented [152-157]. The most relevant comment on this topic came from an interview conducted with the Dean of the College of Nursing at the University of Tennessee-Knoxville, Dr. Niederhauser. Dr. Niederhauser stated "the primary reason someone goes to the hospital is for professional nursing care".

Included in the discussion of the work environment is the level of education of the nurses. Similar to reduced workload, increased nursing education, particularly baccalaureate and advanced practice nursing education, contributes directly to improved patient outcomes and a decrease in MAEs [158-161].

While a straightforward solution to address medication errors would be increased staff levels, better scheduling and better educated nurses, the economics of healthcare would generally not support this. Hospitals are driven to lower staffing levels, including registered nurses, in order to address financial challenges [162]. Healthcare has used various industrial engineering tools to help mitigate the balance of the need for improved scheduling and increased staffing levels by applying various scheduling and staff balancing techniques [163-165].

The disconnect between the desire to improve product quality (in the case of healthcare this means increasing patient safety and improved outcomes) and the drive to reduce costs is not unique to healthcare. What is unique to healthcare has been the resistance to drive change forward including or especially engaging technologies that can augment performance such as using just-in-time information.

Checklists

Seemingly mundane and simplistic, checklists seem to be an obvious solution to address some of the more typical oversights that cause MAEs. In his book, *The Checklist Manifesto*, Atul Gawande takes the concept of checklists, particularly in healthcare, and describes how in this increasingly complex field it is too easy to miss a step that results in some form of error. Checklists, either in the form of computer base instruction or hand-written notes, are recognized as successful in reducing MAEs [135, 166, 167]. Studies corroborating this cover various forms of checklist implementation. In one instance, simple checklists were effective in reducing pump programming errors for oncology treatments between 38%-55% [168, 169].

Human factors/Cognitive Engineering and Systems Engineering for MAE

Human factors engineering (HFE), which also includes usability engineering, cognitive engineering (CE) or user-interface engineering, integrates the areas of psychology, ergonomics, human dynamics, man-machine interface and engineering [170]. Systems engineering (SE) is a multidisciplinary approach to applying engineering principles to the operation of the integrated composite of people, products and process that provide a capability to satisfy a stated need or objective (aka a system) [171].

Human factor and systems engineering have enjoyed application to healthcare as a means to improve operations and ensure the wellbeing of patients and providers. The application of these disciplines is somewhat more limited in the study of MAEs.

While not at the core of this research, HFE studies on CPOE have demonstrated the benefits of considering HFE and SE issues as part of the protocol in designing or assessing these systems. One study assessed the project lifecycle of a CPOE in the re-engineering of the system and was reported as a case study. Various issues and potential solutions were identified, which resulted in a redesign of the system to increase patient safety and human performance [172].

Another HE study on CPOEs identified 22 types of medication errors associated with CPOE systems including double dosing, incompatible orders, generating wrong orders and missing contraindications due to a lack of integration with other systems. This study considered the cognitive engineering aspects of CPOEs and noted the causes of errors as 1) information errors generated by information fragmentation errors leading to a lack of information and 2) human-machine interface flaws reflecting rules that do not correspond with work processes [173]. A similar study by Wettemeck had similar conclusions [174]. These same factors would clearly hold true for nurses as well as physicians.

It has been noted that EMRs and CPOE systems have had unintended impacts on nurse-physician interaction [6, 175, 176]. This phenomenon is a multifactor issue including work behaviours, work polices and software design. A HE/SE evaluation that effectively evaluates an often overlooked and underestimated key factor could conceivable have identified and defined solution options for this issue.

A limited amount of research has been done on HFE and SE specifically related to the physical distribution portion of the medication administration process. Some effort has gone into the understanding of causes of MAE as noted earlier. At the risk of repetition these are [177-180]:

- Stress
- Workload
- Fatigue
- Emotional/cognitive issues
- Interruption/working conditions
- Slips
- Lapses
- Education/Training
- Rule violations

- Poor communication
- Lack of critical thinking
- Poor equipment design

Various studies have been done on attempts to find HFE/SE insight on potential solutions to these factors. While not comprehensive the following table provides a representative listing of the research I the field (Table 2.10).

At its core, healthcare is a service industry with human interface being the overriding method of work execution. This includes provider-provider, provider-patient, provider-equipment, provider-computer, provider-organization interactions along with all of the other permutations and combinations. With humans as the key element of the healthcare system, it is curious that healthcare has found relatively little use for HFE including cognitive engineering in medication administration.

Some applications of HFE/CE that have an effect on MAE have already been explored in this review including bar coding, work interruptions, medication infusion equipment, MAR software, and computerized order entry. One application of HFE/CE is on the naming, labelling and packing of medication. One study reports that up to 25% of medication errors are a result of name confusion errors, and 33% are a result of packaging or label confusion. The US Federal Drug Administration and US Pharmacopeia provide direction naming conventions, labelling and naming. However, these guidelines have not lead to an elimination of errors. In this paper, Berman provides a set of guidelines which could reduce the incidence of MAEs, however does not provide studies to back up her suppositions [211]. Other industries have considered the use of CE and HFE for these purposes and could be applied to healthcare. While changing labelling, names and using text size, font and packaging colour differences can be beneficial, it can also result in unintended consequences and errors as well [212]. Also confounding this area are the restrictions placed on changes to packing, naming and labelling by the regulatory agencies. Clearly this area is a source for future research support in HFE/CE.

Another paper provides an interesting insight on the effect of package design on accuracy recognition for medications. In this study the research evaluated the error incidence of the standard medication packaging against packaging that was designed with modified colours, text form and size, and emphasis of medication type. The redesigned packages lowered the incidence of error by a factor of five [213]. Appendix 9 provides a depiction of the similarity of drug packaging that could lead to MAE based on the similarity of packaging resulting in providing the wrong medication to a patient.

Table 2. 10: Listing of reviewed literature HFE/CE and SE

MAE Error Factor	Citation
Workload	[181-184]
Fatigue	[185, 186]
Emotional/cognitive issues	[187-189]
Interruption/working conditions	[40, 146, 190-194]
Slips/Lapses	[195-197]
Education/Training	[42, 154, 198, 199]
Rule violations	[34, 200]
Poor communication	[201-203]
Lack of critical thinking	[204-207]
Poor equipment design	[208-210]

Decision Support Tools

This question actually poses two thoughts. First is the consideration of the recent research contributing to the advance or understanding of Point of Care (POC) Clinical Decision Support Tools (CDST) and in considering this information, how it will impact consideration of my future research related to POCCDSTs. This is decoupled but relates directly to the second part of the questions which considers the temporality of the information.

Clinical decision support systems (CDSSs) provide clinicians, staff, patients or other individuals with knowledge and person-specific information, intelligently filtered and presented at appropriate times, to enhance health and health care. CDS encompasses a variety of tools to enhance decision-making in the clinical workflow. These tools include computerized alerts and reminders to care providers and patients; clinical guidelines; condition-specific order sets; focused patient data reports and summaries; documentation templates; diagnostic support, and contextually relevant reference information, among other tools.
CDSSs have a number of important benefits, including:

- Increased quality of care and enhanced health outcomes
- Avoidance of errors and adverse events
- Improved efficiency, cost-benefit, as well as provider and patient satisfaction

A CDS is a sophisticated health IT component. It requires computable biomedical knowledge, person-specific data, and a reasoning or inferencing mechanism that combines knowledge and data to generate and present helpful information to clinicians as care is being delivered. This information must be filtered, organized and presented in a way that supports the current workflow, allowing the user to make an informed decision quickly and take action. Different types of CDS may be used for different processes of care in different settings.

Health information technologies designed to improve clinical decision making are particularly attractive for their ability to address the growing information overload clinicians face, and to provide a platform for integrating evidence-based knowledge into care delivery. The majority of CDS applications operate as components of comprehensive EHR systems, although stand-alone CDS systems are also used.

While POCDST applications are unique in terms of setting and specific application, the science and theory behind them are similar to decision support tools (DST) in general (i.e. covering all aspects of their application). The research on DSTs is extensive and varied. Their development and application go back decades, preceding the advent of artificial intelligence starting with the use of operations research and statistical modeling during WWII to support logistics (now called supply chain), troop movements and submarine hunting [214]. The complexity of operational decisions requires a systematic approach to decision making, which can sift through numerous (interacting) options, trading off multiple (quantitative and qualitative) objectives, incorporating conflicting inputs, helping to minimize the impact of distractions and non-value-added information, while minimizing risks and handling huge amounts of data. Such decisions can greatly benefit from state-of-the-art decision support tools.

Decision support tools found wide adoption, primarily in the area of manufacturing, to improve operations and productivity. As computing capabilities, the applications of computer-based decision support found more varied applications, growing rapidly from the 1960s. Decision making tools of all types have found their way into finance, tourism, entertainment, transportation, sports, etc. [215].

These varied applications and the related research serve as the foundation for the application of DST in healthcare. Wu et. al. reviewed types of decisions and DSTs from a number of areas outside of healthcare and noted considerable similarities between the types of decisions that are made, the functions of the associated DSTs as well as the factors that influence the performance of DSTs. They concluded that “complex, high-level decision-making has common features across disciplines as seemingly disparate as defense, business, and healthcare. National efforts to advance the health information technology agenda through broader CDS adoption could benefit by applying the DST principles identified in this review” [216].

A serviceable definition of a decision support tool (DST) is:

> A tool or set of tools that facilitates the use of data, models, and employs a structured decision process to help answers question, solve problems and supports or refutes conclusions [217].

For this discussion no distinction will be made between a decision support system and a decision support tool. While one could make a conceptual distinction of a decision support "tool" as having specific or limited application focused on providing support in a narrow area and a decision support "system" as having broad application covering a variety of areas, the literature does not seem to make a clear distinction bin the use of "system" or "tool". For our purposes the terms will be used interchangeably.

CDSTs are a natural extension and subset of DSTs. HealthIT.gov defines a CDST as:

> …a system that provides clinicians, staff, patients or other individuals with knowledge and person-specific information, intelligently filtered or presented at appropriate times, to enhance health and health care. CDS encompasses a variety of tools to enhance decision-making in the clinical workflow [218].

POCCDSTs are a subset of CDSTs. While the application of POCCDST is narrower, the elements are the same as the overarching DSTs. These basic elements and their interaction are highlighted in Figure 2.10. When adding the concept of POC the focus is on those tools used by the clinician immediately during or proximate to an encounter with a patient. Adding the feature of POC application to CDSTs creates extra demands for the tool's functionality including enhanced ease of use, succinctness of information, integration into user workflow, and collection of information from various sources and provide in an integrated and appropriately processes fashion.

With the state of the science of DSTs being the superset including CDSTs, the domain of DSTs will be considered in reviewing the state of the elements of science to contributing to progress in POCCSTs. An important element of POCCDST is the need to have the information from the CDST provided in near real-time which emphasizes the aspects of human-computer interface, cognitive engineering, mobile computing, and mobile healthcare.
State of the Science of Just in Time (JIT) Point of Care Clinic Decision Support Tools (POCCDSTs)
At its essence this research is exploring how JIT information might influence decision making with the hopes of decreasing the rate of error in the MAE process. JIT information must be delivered through some mechanism, in this approach a simple POCCDST will be used to provide the information to the research subjects. There is a considerable corpus of research on POCCDSTs and a vast array of POCCDSTs that have been developed many of which are used in clinical practice.

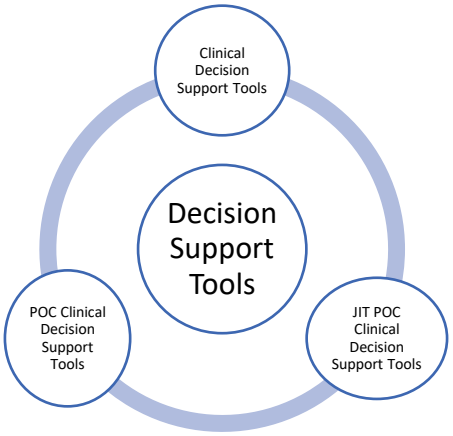

Figure 2.10: Clinical decision support tools are a subset of the family of decision support systems

A clinical decision support tool is an application that provides information to a clinician that assists in taking action or making judgment in support of the care of a patient. There are a large number of clinical decision support tools (CDST) with a broad range of complexity, functions and applications. While they have found some use in healthcare settings their use is not as ubiquitous as you would find in other settings such as finance and manufacturing. For healthcare the range of CDSTs ranges from relatively simple smartphone applications that include checklists, reminders, calculators or information sources (e.g. epocrates®) to complex, robust systems that provide extensive knowledge processing and artificial intelligence integration into the decision making process (e.g. IBM Watson®).

The dawn of CDST is reported to have started in the 1960s with commercial application occurring in the early to mid-1990's [219-221]. CDSTs take on a wide variety of forms, applications and levels of complexity ranging from disease specific applications (e.g. cancer), application specific (e.g. medication administration) to general use decision making tools. As the robustness and complexity of CDSTs increases, so do the challenges of their implementation, operation, maintenance and utility for the end-user.

The need and resulting desire for CDSTs is clear. The complexity of delivering efficient and error free care that engages evidenced based medicine is overwhelming. The belief is that using CDSTs will improve overall clinical performance by providing the clinician with tools that will help process information leading to better decisions and outcomes. Effective CDSTs have the following attributes [222]:

- speed in processing information,
- anticipation of user needs and delivery of information in real-time (aka Just-in-time information),
- ease of use,
- fit with the user workflow and other information systems,
- limit required input from the end-user to a minimum,
- simple man-machine interface (e.g. ease of switching between screens and limited information per screen),
- information is current and correct.

A fundamental part of the evaluation of testing a new drug is to validate that it is efficacious. Similarly, a first step in considering POCDSTs is to perform the same assessment and answering the question: do CDST improve clinical practice and what are the critical features that contribute to performance? A review conducted by Kawamoto demonstrated that CDSTs significantly improved clinical practice in 68% of randomized control trial performed on individual CDSTs. Four features were identified as contributing to improved clinical practice: automatic provision of decision support as part of clinician workflow, provision of recommendations rather than just assessments, provision of decision support at the time and location of decision making, and computer-based decision support. Of the systems with all four features that were evaluated, 94% significantly improved clinical practice [223].

Clinical Decision Support Tool Structure

A Clinical Decision Support Tool (CDST) can be thought of as having two basic components. One is the part that interacts with the user, referred to as the user interface (UI). The other component can be considered the Decision Engine, it is the set of algorithms, data, and behind the scenes processing that takes the queries from the UI, processes them and then provides the desired information to the user via the UI. The basic architecture of PCDST provides a structure on how to parse the functional elements relevant to PCDST. The key elements for our discussion here are the cognitive elements related to the user interface, the user interface itself, the knowledge base and the decision engine. The other elements like the use of cloud computing and interfacing to the data are certainly important, but not directly germane to the science areas of interest.

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- Limit required input from the end-user to a minimum,
- Simple Man-machine interface (e.g. ease of switching between screens and limited information per screen),
- Information is current and correct [222].

Figure 2.11 provides a simple diagram of a generic decision support system. “Data” refers to any information input into the system without regard to its origin including electronic health record, manual input, sensor input, etc. “Model” can be considered as the set of algorithms, heuristics or functions that process the inputted information. The user interface provides the user the mechanism to input information and access the processed information, a typical graphical user interface in a computer-based Decision Support Application. The Decision Support Application is the integration of the three previously mentioned elements to provide the user with the desired function(s).

Figure 2.12 provides an expanded view of the possible interfaces for a CDST[224]. The interfaces and their interactions depend on the functions and design of the CDST. Sophisticated CDSTs will be fully integrated with a number of databases, will have robust decision engines, will provide multiple functions and will require significant computing requirements. Advanced networking technology, cloud computing and more powerful mobile computing platforms allow more advanced POCCDST functionality, notwithstanding the man-machine interface and cognitive ergonomic limitations of smaller platforms, as well as the operating environment for PCDSTs.

The user interface (UI) in Figure 2.12 includes user input, type of platform (e.g. smartphone, laptop, portable workstations, etc.), and the UI. The decision engine combines the logic programming, model, rules or a statistical program of the knowledge base with the patient knowledge based data [219, 225].

A fundamental part of the evaluation of testing a new drug is to validate that it is efficacious. Similarly, a first step in considering POCDSTs is to perform the same assessment and answer the question: do CDST improve clinical practice and what are the critical features that contribute to performance? A review conducted by Kawamoto demonstrated that CDSTs significantly improved clinical practice in 68% of randomized control trial performed on individual CDSTs. Four features were identified as contributing to improved clinical practice: automatic provision of decision support as part of clinician workflow, provision of recommendations rather than just assessments, provision of decision support at the time and location of decision making, and computer-based decision support. Of the systems with all four features that were evaluated, 94% significantly improved clinical practice[223].

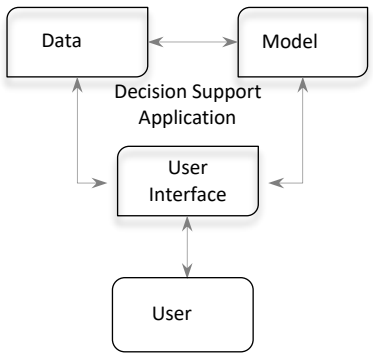

Figure 2.11: Simple diagram of generic decision support system

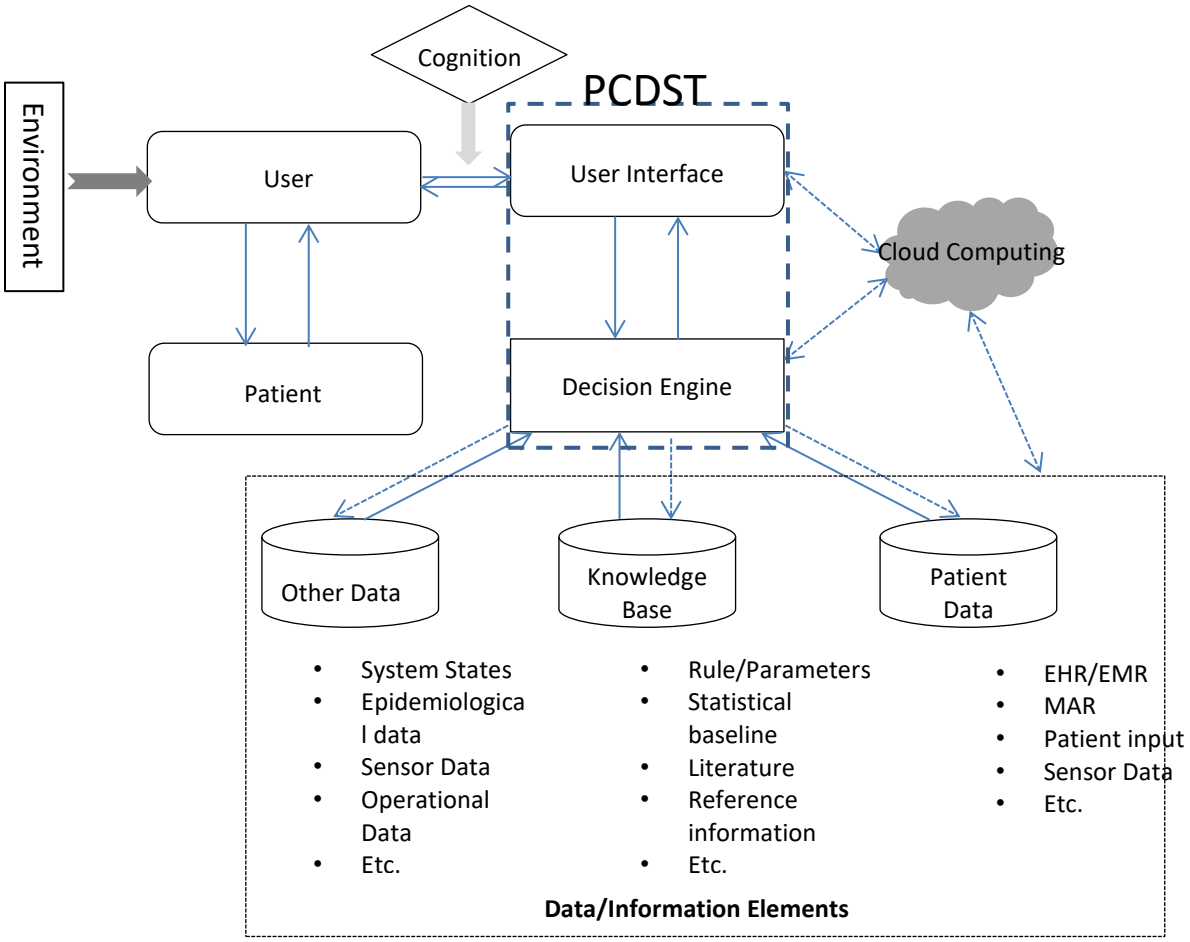

Figure 2.12: Expanded point of care clinical decision support diagram

POCCDSTs can be applied throughout the medical management cycle to optimize safety and other relevant outcomes. Not surprisingly the 5 rights of medication administration have been duplicated to create the POCCDST 5 rights noted below [226].

- The *right information*: evidence-based, suitable to guide action, pertinent to the circumstance.
- To the *right person:* considering all members of the care team, including clinicians, patients, and their caretakers.
- In the *right CDS intervention format*: such as an alert, order set, or reference information to answer a clinical question.
- Through the *right channel*: for example, a clinical information system (CIS) such as an electronic medical record (EMR), personal health record (PHR), or a more general channel such as the Internet or a mobile device.
- At the *right time in workflow*: for example, at the time of decision/action/need.

While these elements are necessary in building an effective POCCDST, they are not necessarily sufficient to ensure optimal performance of the system. Elements that are frequently missed in designing such systems include user interface and cognitive ergonomics perspectives that provide the appropriate functionality, compliance with procedures, consideration of information security protocols and usability of the tool based on the actual needs of the end user.

Summary of Decision Engine Research

CDST's are divided into two general categories, knowledge-based-systems (KBS) and non-knowledge-based systems (NKBS) (Figure 2.13). KBS based CDST's are in essence expert systems that use rules such as IF-THEN statements to process the user input and in combination with the decision engine process, use this input to develop the desired output such as suggested actions for the user.

NKBS use machine learning, a form of artificial intelligence. As opposed to constructing rules and using expert input, this architecture allows the system to find patterns in clinical algorithms or examples of information or learn from past experiences. Artificial neural networks and genetic algorithms are examples of this type of system. This duality provides flexibility in their interpretation and provides both the ability to track the decision process and incorporation of new data hence is a learning system.

Extensive research has been done on KBSs. Rule based expert systems, decision trees, and Bayesian models are examples of KBSs. These types of systems are preferred for clinical implementation because the performance can be more accurately validated in contrast to NKBSs that are considered "black-box" having logic trains and processing that cannot be as easily traced.

Bayesian networks employee conditional probability and new knowledge to produce updated output. A Bayesian network can be viewed as both a knowledge based and statistical system. A Bayesian network can be constructed to a system that uses expert input. Bayesian networks also represent a multivariate probability distribution with the assumption of independence. The integration of the domain knowledge from the expert along with the statistical framework and ability of Bayesian networks to update themselves usually results in better performing systems [227].

Rule based systems (RBS) typified by the IF-THEN rule sets were one of the schemes used in the early days of expert system development and remains one of the main approaches for design of CDSTs. The standard RBS has been modified by adding features that add fuzzy rules. Genetic algorithms have been used to identify rules in addition to using experts [228].

Conventional Rule Based Systems (RBS) have inherent limitations because of the inflexibility of the rules. In other words, a standard IF-THEN rule does not allow for vagueness or uncertainty. A rule-based inference methodology using evidential reasoning (RIMER) for knowledge representation has been developed and applied in CDSTs. In this approach, a set of rules is designed with degrees of belief in all possible consequents of a rule. This approach is capable of capturing incomplete information, vagueness and nonlinear causal relationships [229].

NKBSs are made up of a variety of tools and approaches. Artificial neural networks (ANN) have been used extensively in CDSTs. They are used frequently because the developer is not required to understand the relationship between the output and input variables. ANNs are considered a "black box" technique that models relationships by learning from historical information, whereas approaches like Bayesian networks require adequate domain knowledge including probabilities of occurrence of events. A comparison of ANN with mathematical models was performed on a traumatic brain injury decision support system. The results suggested that ANN may be better at providing decision solutions for complex non-linear CDST than conventional statistical techniques [230]. ANN are not used as extensively in direct clinical applications because of their black box nature and the logic train of the decisions they provide are not directly traceable.

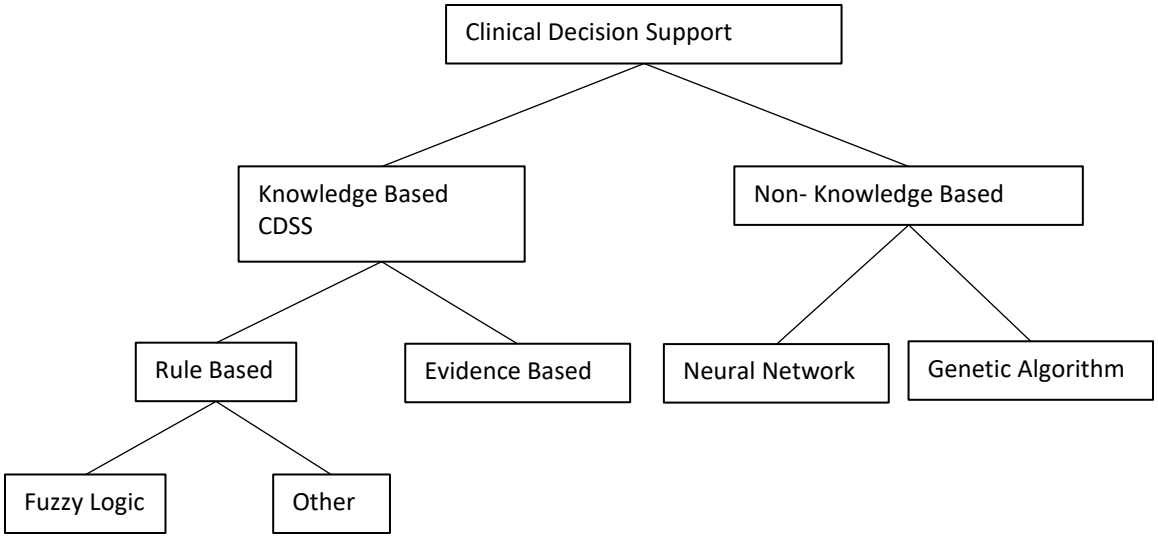

Figure 2.13: Methodologies for CDST decision engines

Genetic algorithms work by working through possible solutions reiteratively to find the optimal solution which is the most fit. Defining solution fitness is a challenge for genetic algorithms [219]. Genetic algorithms tend to be less greedy in processing, which provides global optimal solutions as opposed to locally optimal solutions. This is because genetic algorithms can identify cases using subsets of cases and consider cases which are influential en-bloc which may not be influential alone [227]. Genetic algorithm models are used in domains where the existing knowledge is difficult to encode, or traditional mathematical models are not appropriate [231, 232].

While many CDST based on ANN and genetic algorithms have been developed, their application is mainly in the realm of academic research and not continuous clinical application. ANN and genetic algorithms are computationally expensive for more complex systems and they lack the assurance of more conventional knowledge-based systems [219].

Cognitive Engineering

Cognitive engineering (CE) (also called cognitive ergonomics) seeks to understand how people make decisions in real settings and is an important element of decision support tools. Included in this domain are the ways in which people perceive and then process information under varying conditions such as time stress, high risk, group settings, organizational influences, etc. It is considered part of human factors as part of industrial and systems engineering disciplines. CE integrates aspects of cognitive and behavioral science, human factors, human-computer interaction, psychomotor response, and systems engineering.

Human factors cognitive engineering has focused on the psychomotor and perceptual aspects of how humans receive and process information or interact with their environment. More recent work begins to develop the understanding of how information is processed and understood in the context of how it is presented with respect to the overall system. This research is providing an understanding of what is needed to design DSTs. This is particularly relevant to healthcare and its dynamic decision-making environment. This research is providing answers to why cognitive behaviors occur including what causes errors/mistakes, how information is interpreted and processed, propensity to use DSTs, how DSTs can best support critical thinking, human processing of information from multiple disparate data sources, as well as optimizing decision performance in complex environments (interruptions, high cognitive work load, stressful, time critical, etc.) [233, 234].

Kushniruk has explored the analysis of complex decision-making processes in health care with regard to applying cognitive approaches to health informatics. To summarize this exploration, an improved understanding of cognition is essential for evaluating the effects of CDSTs and for improving them. Decision making, and as a result the effectiveness of decision making tools are influenced both by the individual and the environment: a novice in a high stress environment working with ill-defined information will engage a decision-making tool in a different way than an expert with well-defined information in a routine environment. Decision performance can be complicated by a dynamic environment which includes interruptions and shifting requirements. A CDST will be more effective if its design incorporates consideration on how the user will perceive, understand and act on the information provided by the system.[235].

Providing support in decision making (DM) is a primary function of POCCDST. The study of DM is integral to cognitive engineering. There are three perspectives of research in DM: psychological, normative and cognitive [236-238]. The cognitive aspects consider DM as a continuous process integrated with interaction with the environment. The psychological perspective considers decisions in the context of values, preferences and needs that the individual needs or has. Research in the realm of normative assessment analysis DM based on logic and rationality in the DM process. Each perspective has an extensive body of research supporting it and can play a role in the design of an effective POCCDST.

How someone makes decisions can change as the environment they are operating in changes. For example, logical decision making where the decision maker uses their knowledge to assess the situation, evaluate options and make rational choices based on this information would be an approach used in medical decision making when the environment is not stressful. However, as the situation changes to one with higher time pressure, more interruptions, greater ambiguity and more interruptions, the decision maker likely shifts to intuitive decision making using prior experience and simple heuristics to make decisions. Understanding this dynamic, the design of a POCCDST can accommodate this change or fill the gaps in judgment inherent to each DM approach [234, 239-242].

The question directly impacting this research is the construction of a CDST that provides the appropriate information needed by the user in a fashion that is understood. Adding POC into the construct of cognitive ergonomics for CDST increases the pressure to provide information tailored in a way that enhances understanding and supports decision making or task execution in a focused area in a timely fashion. The cognitive engineering aspects at play are:

- data visualization – how the data is presented in a form that is most meaningful, and
- knowledge representation – integration and presentation of information that is most meaningful.

Extensive literature exists on the psychomotor aspects of human-computer interface. Elements such as eye tracking, font size, color highlights, dynamic emphasis (e.g. flashing text, popups), physical user interface (e.g. touchscreen, screen size, mobile vs. portable), screen swiping, etc., have been studied extensively. While considerable research exists on how these types of factors effects usability and understanding of computer applications, much less work has been done on how this might specifically affect POCDSSTs. While many of the tools from human computer interface (HCI) are applicable, lessons learned from recent research indicates that it is also likely domain dependent.

Human-Computer Interface

If a POCCDST uses a computing device, an important consideration in the design and application of the technology is the design and functionality of the interaction between the human and the device and associated software. Human-computer interaction (HCI) is an area of research and practice that emerged in the early 1980s, initially as a specialty area in computer science embracing cognitive science and human factors engineering (Figure 2.14).

While HCI is a broad field, our interests are focused on how to improve the physical interface between the POCDST user and the backend system providing the information. Computers in a clinical setting include various form factors and physical user interfaces ranging from stationary workstations to “computers on wheels” transportable

works stations to truly mobile platforms including laptops and hand-held devices. The form factor of the computer plays a role in its usability for different purposes. A workstation with a larger screen and keyboard offers easier input for notes and charting purposes, as well as easier reading of large documents or detailed data. Whereas, a smartphone provides easy portability and quick reference to summary level information and the ability to respond quickly to alerts and just-in-time information but the smaller screen size limits the its functionality for some applications [243, 244].

The user interface (UI) defines how the user interacts with the system and is paramount in determining the effectiveness of the system's usability. This is particularly true for smaller form factor computing devices such as smartphones. Many factors influence the user interface experience. For example, smaller screen devices impose more difficulties for children and middle-aged or older adults who were sensitive to cognitive demands imposed by current smartphone GUI designs [245].

Extensive research exists on graphic user interface (GUI) including layout, font, color active graphics, data entry, etc. [246, 247]. A number of studies have investigated text-based approaches versus GUIs for computerized order entry. The general results indicated that GUIS increased accuracy and were more efficient than text based entry [248, 249].

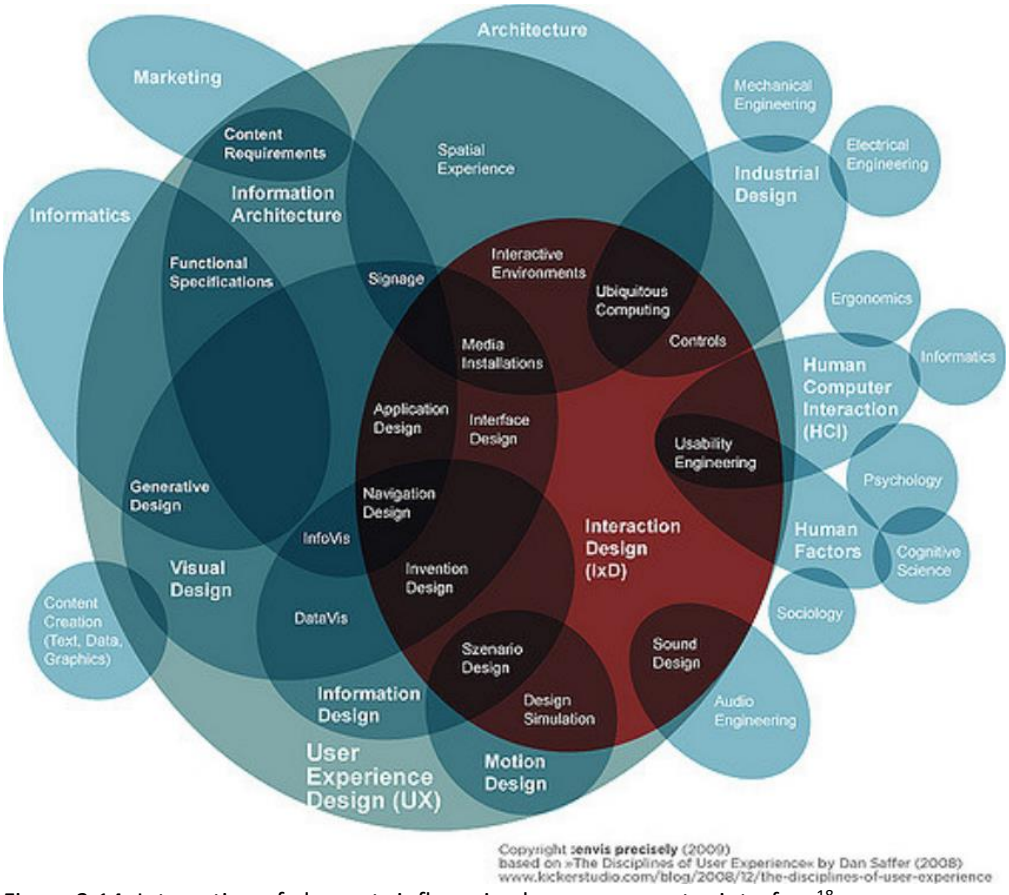

Figure 2.14: Interaction of elements influencing human-computer interface[18]

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Developing an interface that provides an appropriate user experience that accommodates both the challenges of the environment and meets the ergonomic criteria for the target population of users is challenging. The interface will ideally be intuitive, simple, match the workflow, be compliant with procedures, and provide ease of input as well as readability. Consideration could be given to haptic feedback to augment other types of notifications. End user testing and evaluation of the GUI, while it is in development, is an important step of the GUI design. Physical considerations such as infection control, physical handling of the device, patient perception, durability and other factors.

Mobile Computing

POCCDST requires a dynamic interface and the ability to provide a number of simultaneous interfaces principally between the user and the information resource but also the user and the patient. Optimally, the interface and the information exchange must be in real time. Ideally the information content will provide the correct information in the right form in the correct amount to allow easy interpretation. Mobile information communication technologies (MICTs) have considerable promise in patient care settings. That promise can only be realized if the MICT applications are used by the medical staff. This paper reports on a study examining nurses' decisions to utilize MICTs. A mixed-methods approach is used, consisting of both qualitative and quantitative elements, that reveals and empirically tests the significance of novel constellations of fit (i.e., identification, information, patient interaction, physical, time criticality, user comfort, and workflow fit) and individual characteristics, presented as basic human drives (i.e., drive to acquire, bond, defend, and learn). Findings indicate that fit is a multi-faceted construct and that archetypical human drives have an influence on these various notions, which in turn, impact technology adoption in the healthcare context.[250]

The potential for handheld devices to support healthcare providers is well recognized [251-253]. Point of care clinical support systems targeting bedside nurses have positive effects on outcomes and hold promise for improving care quality; however, this research is lagging behind studies of CDS targeting medical decision-making in both volume and level of evidence [254].

Interestingly, no research has been found related to the ideal features for mobile computing devices in healthcare and how these would influence adoption of mobile devices for use in healthcare. These considerations might include size, battery life, features and functions, haptic interface, voice recognition, video capture/playback, GPS, network features, processing, wear-ability, provider/patient interaction considerations, durability, infection control, to name a few features that might influence the ultimate design of a mobile device for HC.

Considerable study has been done in the areas of utilization of mobile devices, mobile device applications and acceptance of mobile device use. Wu has evaluated the acceptance features of MCT in HC and found that perceived usefulness and perceived ease of use contributed significantly to the use of MCT by HC providers [255]. As part of another study he found that adoption of this technology was driven by the healthcare provider's traits of innovation adoption and the perceived availability of the technology [256].

Research literature on the applications of mobile devices, particular smartphones, is becoming ubiquitous. The research covers both specific applications such as medical reference material, disease diagnosis and general areas such as smartphone use for patients or HC professional education and training [252].

Smartphone-like devices provide an array of sophisticated sensors that can provide information related to location, speed of movement, activity, and social interaction, proximity/interaction with other devices or equipment and more. This information can provide the ability for anticipatory computing where the device provides appropriate information to the user based on the context of interactions and other data without requiring action from the user [257].

Figure 2.15: An example of Mobile Computing Technology -Google Glass- with augmented reality capability[19]

Just -in-Time Information

Just-in-time information borrows from the context of Lean. For the sake of completeness, Lean is the concept of maximizing customer value while minimizing waste. JIT is a system of delivery that provides just what is needed, just when it is needed, just in the amount that is needed. JIT relies on three operating concepts: takt time, the pull system and continuous flow.

JIT information differs from real-time information in at least one important way. Real-time refers to the delivery of information as it is generated and does not necessarily have additional processing to restrict the volume of information, enhance its value to the end user or control its time of delivery based on the needs of the user. In accordance with Lean principles, JIT information is adjusted to meet the needs of the user by providing the information in a contextual form, only the information that is needed is provided, and it is provided as needed. A simple example is monitoring stock prices. Real-time information would be represented by a stock ticker as a continuous rolling display without regard to temporal need or specific information needs by the end user (Figure 2.16, image 1). A JIT information delivery system would provide information based on predefined requirements or user query. The JIT information would be preprocessed to provide only the key information the user needed at that time, e.g. significant price change, forecasted change, company news, market influences, trends, etc. (Figure 2.16, image 2).

[19] Image included under title 17 section 107 U.S. Copyright Law Fair Use Doctrine as educational material distributed for use without profit. Source: http://www.u1group.com/blog/article/working-with-google-glass

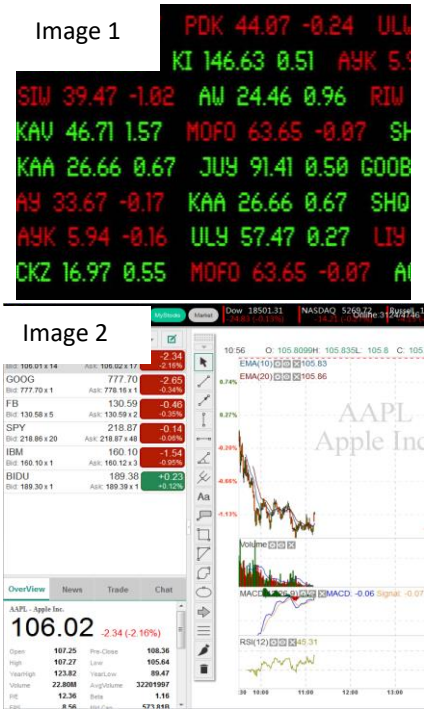

Figure 2.16: Real-time vs JIT information[3, 20]

One of the best examples of JIT information is the Google Maps application for driving. Google Maps is a Geographic Information System based mapping system that provides current updates to the user, or this example a driver. Google Maps takes input from the user in the form of destination and things like preferred route, integrates it with historical knowledge base information including traffic patterns, and input data from multiple sensor sources like data from other cell phones in the area that fit certain criteria (e.g. speed, proximity to other phones, location, etc.), accident information from other sources, etc. It integrates all this information and provides the driver with route information, indicates potential issues (e.g. road construction, disabled vehicle, debris in road), suggests reroutes if there is a traffic slowdown, provides the estimated time delay if there is a slowdown, and estimates the time of arrival. Upon additional query Google Maps will provide nearest location, and route to nearby destinations of interest like gas stations, coffee, rest stops, etc. Audio output in the form of direction information, such as turns or exits, is provided to the user to aid in driving without having to refer to the smartphone. As a turn or exit is approached, the display will change to provide an expanded more detailed view of the turn. All this information is updated in real-time and more importantly just-in-time (Figure 2.17).

Google Maps provides the driver with a large amount of information in a simple one screen format. Running behind the scenes is a massive decision support system that integrates multiple data sources. This information is processed and integrated to provide the user with just the information they need at the time, just when it is needed, and just the amount that is needed (including the contextual information to help provide insight on potential future decisions that might need to be made).

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JIT information integrates various disciplines including cognitive ergonomics, decision science, computer science, Lean, systems engineering, as well as the discipline specific areas that JIT information is being applied to as in our case, healthcare.

Davenport discusses the potential that JIT information delivery provides for healthcare and suggests caution on some of the challenges such a system will face based on an early implementation of a JIT information system at Brigham and Women's Hospital in Boston. Davenport highlights the application of JIT information to decrease the occurrence of error as part of POC activities by making information "so readily accessible that it can't be avoided". The JIT system described is a POCCDST with an extensive backend logic system that combines information from various EHR sources

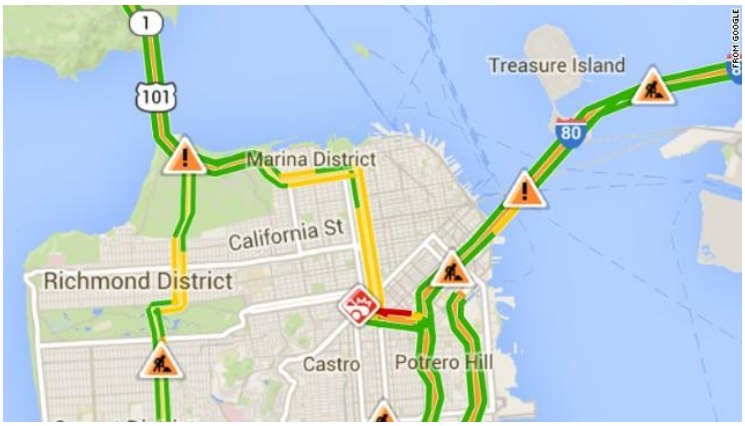


Figure 2.17: Google Maps implementation as a JIT information source[21]

Key insights provided were that: only processes and knowledge domains that are critical in the sense they have overarching importance due to drivers such as safety, cost, or risk; appropriate management and end-user support including the ability to measure utilization and performance; and, appropriate data sources and technical ability that can provide current and accurate information [75].

The concept of lean or Just-in-Time information fits squarely in the domain of patient centered point of care clinical decision support tools. JIT information aligns with delivering the right information at the right time in the right way to enable optimal use by the user. Barnesteiner argues that for nurses, JIT information contributes directly to improving patient safety when used as a POCDST, especially when integrated into organizational and operational priorities.

Information for decision making needs to be available at the point of care. This includes easy access to drug formularies, evidence-based-practice protocols, patient records, laboratory reports, and medication administration records. Many organizations now have drug formularies and practice protocols available as applications for smart phones, thus providing for just-in-time information availability [258].

There are a large number of applications of JIT POCCDST. One study considers the application of a POCDST to antibiotic use and patient outcomes in a critical care unit concluded that point of care handheld computer-based decision support contributed to a significant reduction in patient length of stay and antibiotic prescribing in a critical care unit [259]. This corresponds with the observations from Davenport mentioned previously.

[21] Image included under title 17 section 107 U.S. Copyright Law Fair Use Doctrine as educational material distributed for use without profit. Source: http://www.cnn.com/2013/08/20/tech/mobile/google-waze-mobile-maps/

One recent area of research focuses on the technology and tools underpinning JIT POCCDSTs. Linan explored the development of clinical decision support rules that are based on computer interpretable guidelines. In this application, pharmacogenomic guidelines were used to represent the semantics and decision logic [260]. This research highlights recent advances in building a common format for metadata, actions, events, and conditions as well as an expression language. This common format construct was driven by the National Coordinator for Health Information Technology. This common format, Health eDecisions (HeD) interchange format also defines a methodology or schema for validation of compliant documents containing guidelines. Together, the HeD model and its schema represent the workflow and decision logic of interventions such as CDS rules, order sets and documentation templates. The HeD editor has features that assist in modeling and testing clinical decision logic [261, 262]

Another interesting area of active research on JIT POCCDSTs is medical education. A review by Mi analyzed the use of mobile devices by health profession students. Summarizing this review, mobile devices such as smartphones, tablets and the now somewhat obsolete PDA, found significant benefit in supporting the performance of health profession students in areas such as POC decision support, accessing healthcare information (e.g. online reference material, manuals, procedures, etc.). The review indicated that students increased their use of JIT information sources as their familiarity with the system and information available increased. This was particularly true for POC use [14].

Rees et. al. considered use of JIT POCCDST specifically for nursing education. According to Rees, student nurses use mobile devices in clinical settings to look up specific and abbreviated information to support decision making primarily during direct patient care. Information areas include medication administration, best practices, and mobile apps (calculators, reference material, etc.) [263].

JIT information and POCCDST are, or should be, integrated concepts. A POCCDST will rely on a steady stream of timely, contextually relevant, appropriately structured information (AKA JIT information) as input to support the processing it does in order to provide the user with the best set of solutions to act upon. Conversely, one can also argue that it is the role of a POCCDST to provide JIT information to the user for the same purpose. So, different types of JIT information can act as both input and output for a POCCDST.

Relationship of JIT to POCCDST

Figure 2.18 shows the relationship of some of the primary elements of POCDSTs relative to JIT information delivery for healthcare. What it hopes to show is that healthcare JIT information is directly influenced by advances in each of these areas. Of particular interest, and I believe relevance, are the roles of cognitive ergonomics, data integration and adaptive/learning computing as it relates to the roles and functions of nurses in acute care settings. Research and applications in other areas such as smartphone GIS systems (e.g. Google Maps), Pandora Music, advanced avionics systems (formerly known as - Pilots Associate), and NEST home automation, have commercial applications that exhibit utilization of varying degrees of JIT information integrated into DSTs.

Similar to how behavioral economics has dramatically changed the view of micro and macroeconomics; cognitive engineering will optimize the human-computer interface for POCDST. Behavioral economics create a fundamental shift from the classical economic core belief of rational markets and objective behavior to what Dan Airely has coined predictable irrational, which views economic forces driven by the idiosyncrasies of human beliefs and behaviors. In the same way cognitive engineering will accommodate human behaviors, perceptions and abilities to optimize utility and function for the end user. I believe that applications of cognitive engineering will define how, and very likely if, any given POCCDST will find its way to implementation.

Decision theory, decision science and systems engineering, along with their respective sub disciplines, have a very well-developed research base that will influence JIT POCCDSTs. With a few exceptions, developers of JIT POCCDSTs will focus on how to apply the current science in these areas to healthcare. A key consideration is how to integrate these areas in the overall system to provide a decision support tool that is seamless for the end user and will instill confidence in performance. Worthy of note is that use of POCCDST will be tempered as much by organizational and individual behavior factors, as by technical functionality.

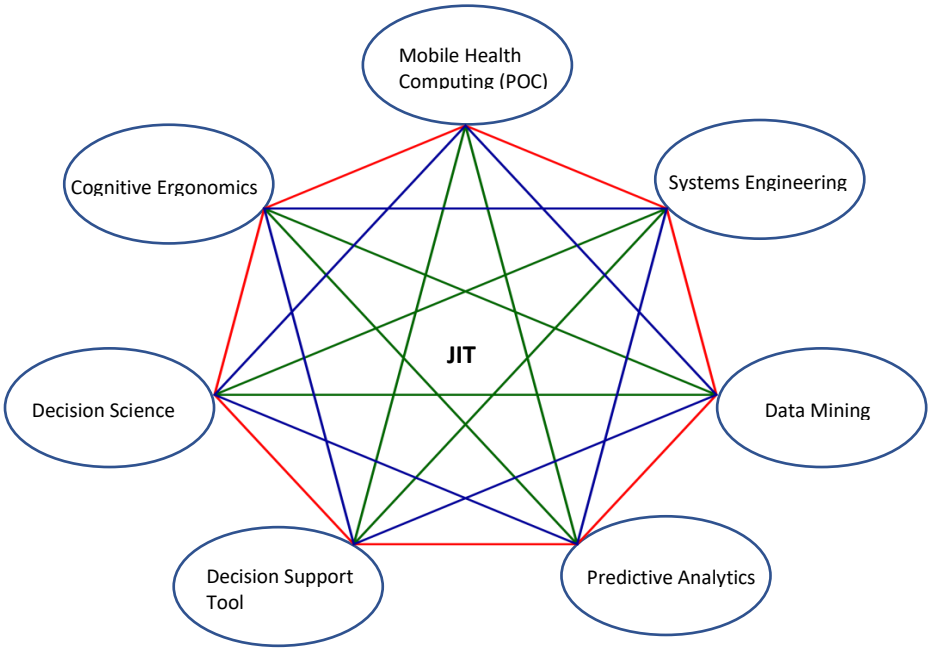


Figure 2.18: Major elements of JIT information interface

The advent of mobile computing in healthcare, especially in the form of engaging smartphones or tablets, will find diverse applications. The limit, I believe, will not be technology based either in the form of hardware or software, rather the limit will be defined by organizational, administrative and behavioral causes. Rees notes that the use of tablets and smartphones are in one sense a cultural phenomenon and the use by student nurses as an inherent part of their behavior will positively impact the use in the clinical setting [263]. Phillippi and Wyatt, renowned nurse educators and dreadnaughts of nurse education research, highlight the potential of smartphones as learning devices and clinical tools [264]. Exactly how mobile computing will be implanted in healthcare over time is difficult to predict. While the commercial sector is rapaciously expanding its adoption of the technology, structural limitations inherent (or perhaps endemic) to healthcare, will act as a brake on the infiltration of the technology into the acute healthcare setting as formal decision support tools. Interestingly, users of apps such as epocrates® do so at their own risk as indicated by the terms of the User Agreement with no warranty that the information is accurate. Other apps describe their products as Educational Use Only.

Augmented reality (AR) is the live integration of digital information with the user's environment. It is the natural extension of the kind of JIT information systems that have been discussed here. Where JIT information tends to focus on providing information in a particular area, augmented reality is envisioned to provide a suite of information as the user moves through their environment. Hollywood provides the best instantiations of augmented reality with examples from the vision system of the Terminator and Ironman. As with POCCDDSTs, AR processes, integrates and presents information to the end user, the difference is in the way the information is presented, namely, as a digital overlay of the user's environment. While there are significant concerns on incorporating AR into a clinical environment, it also holds the potential for tremendous advantage. Some of these advantages are:

- The integrated view provided by AR provides a more contextually rich environment for users, translating, hopefully, into fewer errors and a better patient experience;
- AR should improve direct interactions with patients by providing the clinician with information such as vein location, areas of pain, etc. that would not otherwise be immediately available;

- AR is predicted to have a significantly positive impact on the training and education of healthcare providers by providing a richer more realistic experience.

With the previous discussion as a backdrop for considering future work on JIT POCCDSSs, several other generalizations can be made:

- POCDSS are making inroads into application by healthcare providers but there does not appear to be any uniformity of approach notwithstanding the efforts of various organizational bodies,
- Specific features focusing on usability, timeliness of information and aligning the application with specific need is crucial for end user adoption,
- The backend or "intelligent" part of the system, while not seen by the user, will define the performance of the system including accuracy (e.g. correct diagnosis, valid laboratory result ranges, etc.), integrative functioning, and direct benefit to the end user,
- How the user interacts with the system, the UI, needs to be carefully thought out and tested to ensure the desired performance and utility for the user. Items to consider are text input, screen manipulation (e.g. swipe vs. tab vs. button), alerts/alarms, haptic responses, screen layout, colors, text style and size, customizability (for display, alerts, information layout, etc.), and ultimately (also my favorite consideration) the use of predictive and prescriptive analytics (including adaptive computing) to guide the user.

Limitations/Considerations on Use of JIT Information Based POCCDST

The rapid rate of change of software and hardware technology will create a lagging environment between implementation and development unless more flexible approaches can be used for integration of new technology. Cybersecurity is an example of where such flexible approaches have been accommodated.

As noted by Phillippi and Wyatt, use of mobile platforms can be expensive. The expense can be particularly prohibitive if the smartphone platform is pushed down to individual users (each user has their own device). With technology obsolescence occurring at an increasing rate and the cost of capital investment becoming more difficult, the insertion of new POCCDST can be problematic.

Regulatory matters remain an issue for CDSTs. An assumption would be that the more dynamic the tool in the sense of getting input from multiple data sources, such as JIT information, the more complicated the regulation of the associated tool. The Federal Drug Administration (FDA) is the regulatory authority for CDSTs. Part of the issue is that these systems fall into several categories depending on how the tool influences clinical outcome. Lower level solutions, such as Body Mass indicators or medication reminders, are not likely to create regulatory issues. Tools that support intervention or decisions that have the potential to harm patients are subject to regulation. With no clear time frame for congress to act, many commercial developers have moderated their efforts. While this will not likely directly influence research, it could dampen clinical evaluation and implementation.

Risk/liability is another factor that could have an overarching effect similar to regulatory issues. Even with regulatory clarity, research on systems that could impact patient health in a negative way carries the potential for legal concerns. One consideration is that JIT POCCDSTs that use some form of statistical, or rule-based approach by definition will create some wrong decisions. Then the question will be how administrators will deal with this uncertainty.

As we recognized the advent of other forms of JIT information, delivered mainly through smartphones, such as social media inputs, text messages or even apps designed to assist performance, can be a significant distraction to performing complex tasks such driving equipment operation. They can also degrade performance of the more mundane or rote tasks such as walking. Based on sound research, the myth of the human's ability to multitask has been shattered many times over.

Lean approaches, such as JIT, have their own inherent problems. JIT systems require either a predictable even flow or robust on demand capability. Performance of the JIT system degrades as these factors decrease. The core assumption of JIT is that whatever is provided is what is needed. For healthcare JIT information, it is easy to conceive of circumstances, that due to the complexity of the situations, the information is not entirely sufficient or

worse yet, inappropriate under the circumstance. JIT inventory relies on its supplier sources for timely and accurate delivery, the same holds true for JIT information.

No system is infallible. It is conceivable that information provided by the JIT could be wrong either for an individual patient, which could propagate errors quickly creating serious unknown potential consequences. This raises the question of what fail-safes could be built into the system to prevent or at least identify errors?
A sociotechnical issue is that users, especially those with less experience in the area off interest, could become too reliant on JIT information and do not balance the information the JIT POCCDST provides against their critical decision skills. In other words, the user could blindly follow the recommendation of the tool and they do not evaluate the information from the tool against their experience and judgment.

Human Error

Humans are engineered to make mistakes, and they make the preponderance of errors in contrast to sources of non-human errors (Figure 2.19). Perhaps more aptly put, we were not engineered to be infallible. Our neural connections, mental processing, perceptions[22] and even DNA is prone to mistakes. As we begin to understand the neuro-physiological basis for human error processing [265, 266] it becomes clear that there is an organic or physical basis for humans to be consistent in their lack of performance, that is making mistakes is inherent to being human [267].

The increasing interest in the areas of cognitive engineering and behavioral aspects of the science is shedding more light into the intricacies of how and why humans make mistakes. The concept of the rational consumer, or, the logical scientist, does not exist, at least in pure form. Dan Ariely and others have considered the effect of emotion, biases and perceptions on errors in decision making. The considerable body of work by Ariely and his colleagues contributes to the general observations [268-271]:

- Humans are inherently irrational, while we believe are behaviors and actions are logically based on good judgement and reason we are driven largely by emotion and misperception ;
- People are different with different capabilities, experience and biases [this is an important consideration in error-proofing since errors occur at the level of the individual];
- Performance is, at least in part, determined by the work environment;
- Performance is influence by peers, an individual's past and circumstances;
- Motivation for improving performance (including reducing errors) is a complex mix of rewards, incentives, peer pressure, and a notion of team;
- People have inherent mental blocks that contribute to consistent and continuous error generation;
- People have limited capacity to effectively acquire and process all relevant data; they have difficulty in determining which data is actually important or even relevant.

An extensive body of literature exists on human error (HE) with the earliest citation noted being from 1900 on the maneuvering of ships. Interestingly, this author, Balestrieri, considered the effect of emotional influences, in particular fear and anxiety, on a ship pilot's ability to maneuver a ship and recommended the use of simulators to enhance performance [272]. This is remarkable in the sense that much of the early literature focused on the mechanistic of human error. That is, they considered factors such as mental slip lapses, inattention, forgetfulness, etc. and the potential remedies for these fallibilities. Balistreri viewed HE from the systems perspective and evaluated the human as a part of the overall ship maneuvering system. The fact that he was before his time might explain, in part, why his work was cited only three (and after this four) times since 1900.

[22] As an interesting digression the following video is good for use in class or for your own entertainment to see how attention and perception affect error. www.theinvisiblegorilla.com/videos.html

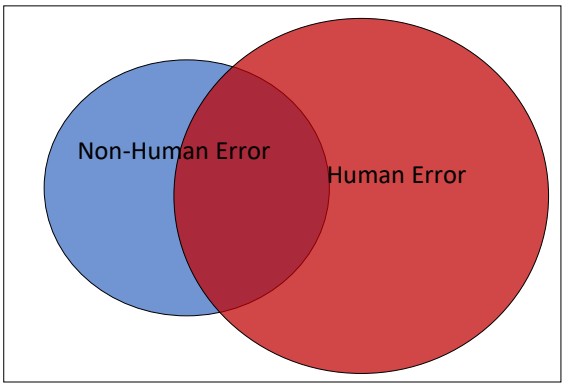


Figure 2.19: Human error greatly exceeds the occurrence rate of physical or mechanical error

As inferred from the previous paragraph, there are two general approaches to considering HE; the person approach and the system approach as coined be Reason [273]. The Person Approach focuses on the psycho-mechanistic performance of the individual. That is, it attempts to consider the cognitive and psychological capabilities of humans as they relate to performing tasks. In doing this, it evaluates elements such as memory, attention, understanding, emotional states, awareness, motivation and other factors relative to error occurrence. In simpler terms, the person approach views human error from the perspective of how people make mistakes.

Different types of errors have different types of causes. Reason parses errors or mistakes in execution failures (slips, lapses, trips and fumbles) and planning or problem-solving failures (aka mistakes). Mistakes are divided into rule-based mistakes and knowledge-based mistakes. Reason also makes a distinction that errors result from information-handling problems and violations which are purposeful deviations from rules or procedures. The state of errors/mistakes can be active and latent: active errors are those that are committed by those directly involved with the activity, latent errors are those that are organizational, procedural or in some other way not immediately coupled to the direct performance of work[274] (Figure 2.20).

The systems approach J. Reason speaks of considers the human with all its fallibilities as an element of the system. The design of a system with humans in the loop needs to consider that errors are to be expected and as a result, the design of the system needs to accommodate these errors. An interesting shift in perspective with this approach is that human errors are seen as a consequence of the system design. A system designed under this approach would build in error proofing both as part of the operation of the system but also the organizational

Human errors have been classified as:

- Errors of omission (tasks that are skipped, forgotten, missed)
- Errors of commission (tasks that are performed incorrectly)
- Sequential errors (tasks performed out of sequence)
- Compensating error (multiple errors that have an offsetting effect, they cancel each other out)
- Temporal errors (tasks performed too early too late or not within the required time)

These types of errors can obviously take on many forms across many disciplines. Each of these error classifications can be separated into their own respective taxonomy which will partially depend on the area to which is being applied.[275]

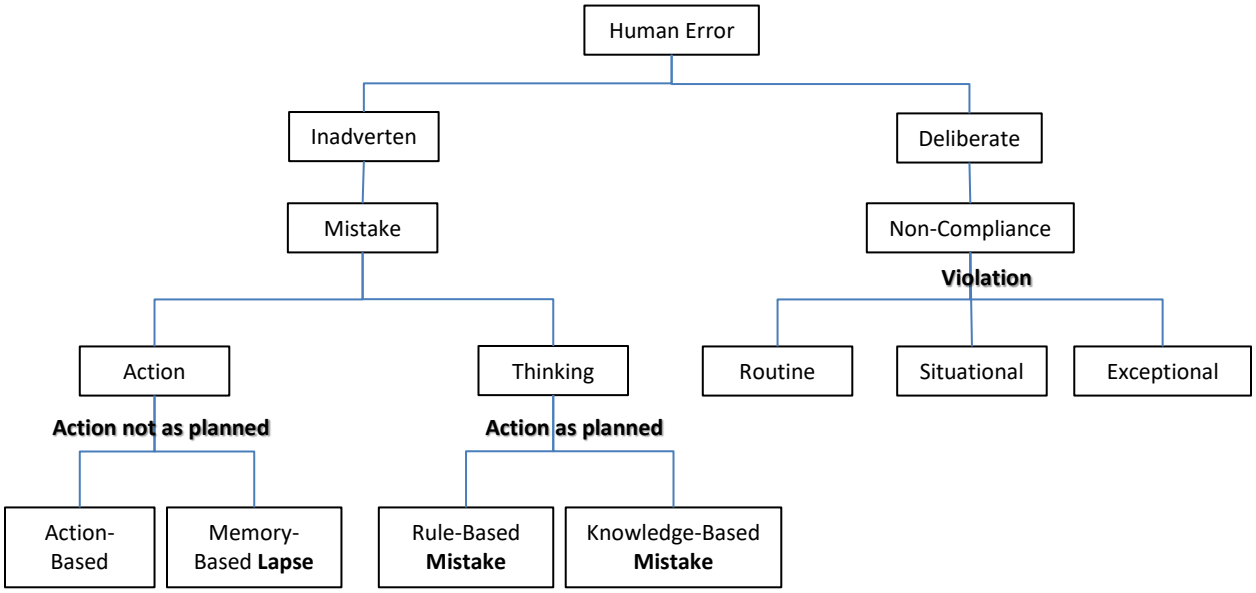


Figure 2.20: General taxonomy of human error

There are a variety of factors that influence human performance as it is related to the occurrence of errors. These include factors such as fatigue, disorientation, training, motivation, stress, lack of skill, confusion, boredom, knowledge/experience, and inadequate or impaired perceptual or cognitive ability. processes that influence the operation of the system. A basic concept of this approach is that human performance as it relates to errors cannot be changed, rather the conditions under which human's work need to be designed to accommodate human performance [276].

Extensive research has been done on the types and causes of human error and how to attempt to prevent it. This is particularly true for potentially high consequences such as aviation, nuclear facility operations, healthcare, mass transportation, and pipeline and oil rig operations [277-281]. While every error is unique, the contributing factors can be classified based on the behaviors leading to the error.

It is widely recognized that most errors do not happen in isolation. Instead, they are a result of a chain of events or conditions that lead to the occurrence of the error. From Heinrich's work first published in 1931, Industrial Accident Prevention: a Scientific Approach [282], to its further development by Bird and Germain in Practical Loss Leadership [283], as well has Bird's "Domino Theory, and Reason's "Swiss Cheese" model of human error [284] (Figure 2.21), the integrated and multiple interactions of causative factors have been embraced by most in the field of human error [285].

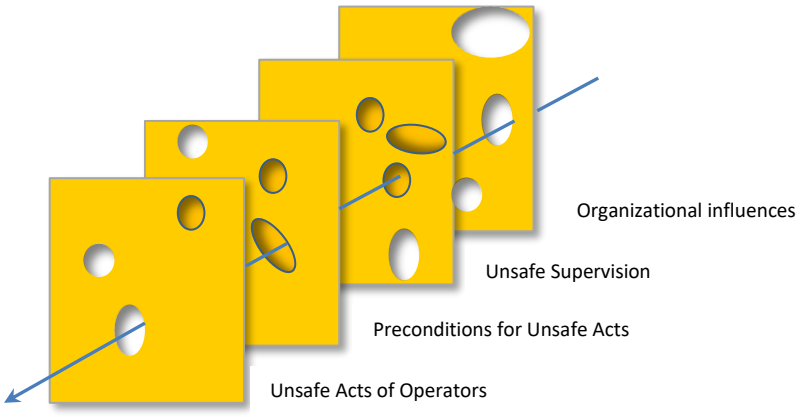


Figure 2.21: Reason's Swiss cheese model of error occurrence

Situation Awareness

An important element of HE occurrence is Situation[al] Awareness (SA). A particularly applicable definition of SA is provided by Endsley [286]: "Situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and projection of their status in the near future" Endsley goes on further to define specific levels of SA, which is provided in expanded form [287]:

> Level 1 – Perception of the elements in the environment – in this level the agent recognizes the status, attributes, and dynamics of relevant elements in the environment.
> Level 2 – Understanding the current situation – building upon the disjointed elements of Level 1, the agent comprehending the significance of these elements and how they might relate in the present situation.
> Level 3 – Projection of future statue – here the agent understanding of the potential impacts that the combined elements form Levels 1 and 2 might portend and formulates courses of actions that avoid or mitigate the error.

Cognitive Error

Cognitive error (CE) can be defined as mistakes made resulting from faulty mental models, heuristics, misinterpretation of information or other types of conscious error in decision making. Cognitive error can be classified into two general categories:

- Faulty assessment of the likelihood of something happening (e.g. overestimating disease likelihood)
- Failure to consider all relevant possibilities

The Merck manual categorizes cognitive error as follows [288]:

- Availability error – misestimating the prior probability of a condition because of recent experience or event
- Representation error – when the likelihood of a solution is based on how closely the event fits a typical pattern without considering all of the alternatives
- Premature closure – failure to consider other possible solutions and stop collecting data (jumping to conclusions)
- Anchoring error – when an initial conclusion or decision is clung to even when contradictory or conflicting new information is accumulating
- Confirmation bias – When data confirming one's decision is considered and contrary data is ignored or under-weighted
- Attribution error – negative stereotypes that lead decision makers to misjudge or minimize other factors

- Affective error – avoiding generating additional information because it will create a negative or distasteful situation

Similar in both aviation and healthcare, the procedural and diagnostic errors have been observed to be the greatest source of cognitive type error [178, 290-292].

O'Hare defined a decision-making approach that led to a multistep process for diagnosing cognitive failure. This model assumes that information is being processed from the start of the action using detection cues in the environment and ending with action execution (Table 2. 11) [289].

While HEs are recognized to be a result of broader system errors, they are exhibited by the frequency of their occurrence. There are many factors that influence the human error rate; the values listed in Table 2.13 are only representative of error rate. The value of this table is that it does provide some insight in the stochastic nature of human error rates and that, in a general sense, human error is both predictable and, in some ways, unavoidable. Review of this table indicates that humans do not perform well when tasks require precision or great care and doing complicated non-routine tasks. Adding increasing levels of stress increases the error rate [293].
Smith provides the broad guidelines in Table 2. 13. He states that in any particular situation, the human-response reliability will be shaped by any number of factors which include:

- Environmental factors
  - Physical
  - Organizational
  - Personal
- Intrinsic
  - Individual idiosyncrasies and selection
  - Training
  - Experience
- Stress Factors
  - Personal
  - Circumstantial

Without much imagination, one can think of how these errors and probabilities would relate to medication administration errors. Errors, such as failing to respond to an annunciator, reading an indicator incorrectly, attaching a connector (e.g. IV tube) incorrectly, are all directly applicable to healthcare. While the actual probabilities might be different, Smith's work has man analogs in healthcare.

Reduction/Elimination of Errors

There is a seemingly endless variety of methods and techniques to reduce or eliminate errors. In the conventional realm of industrial engineering, reliability/quality engineering and mistake/error proofing are the central areas. There are two basic approaches to reduce or eliminate errors - assessing how the errors occur in a process, and building approaches prevent them from occurring.

The Institute for Safe Medication Practice (ISMP) has provided a rank order of error-reduction strategies (Table 2. 12). The heading "Power" indicates the effectiveness of error reduction for system changes for safe medication use. The list starts at engineered controls without humans in the loop down to activities that rely solely on direct action by humans. This table is a succinct commentary on the practices industrial and systems engineer's use in implementing reliability and maintainability practices [293-295]. The ISMP list of error-reduction strategy can be generalized to most other areas.

Table 2. 11: Categorization of cognitive error types

Error Type	Error Description
Non-Human Error (structural, mechanical, electrical, S/W, other	Agent intervention could not prevent the error or is directly impacted by the error
Information Error	The agent did not detect cues arising from the change in the system states
Diagnostic Error	The agent did not accurately diagnose the state of the system based on the information available
Goal Setting Error	The agent did not choose the appropriate goal that was reasonable given the situation
Strategy Selection Error	The agent did not choose a strategy (means of attaining) that would achieve the desired outcome without error
Procedure Error	The agent did not execute procedures consistent with a correct strategy or approach
Action Error	The agent did not execute the procedures as intended

Table 2. 12: Rank order of error-reduction strategies[23]

Error-Reduction Strategy	Power (leverage)
Fail-safes and constraints	***High***
Forcing functions	
Automation and computerization	
Standardization	
Redundancies	
Reminders and checklists	
Rule and policies	
Education and information	
Suggestions to be more careful or vigilant	***Low***

[23]Source: https://www.ismp.org/newsletters/ambulatory/archives/200602_4.asp

Table 2. 13: Human error rates [293]

Task	*Read/Reason*	*Physical operation*	*Everyday yardstick*
Simple possible task			
Fail to respond to annunciator	0.0001		
Overfill bath			0.0001
Fail to isolate supply		0.0001	
Read single alpha-numeric incorrectly	0.0002		
Read 5-letter word with good resolution incorrectly	0.0003		
Select wrong switch		0.0005	
Fail to notice major cross-roads			0.0005
Routine simple tasks			
Read a checklist or digital display incorrectly	0.001		
Set multi-position switch incorrectly		0.001	
Calibrate dial by potentiometer incorrectly		0.002	
Check or wrong indicator in an array	0.003		
Incorrectly carry out visual inspection for a defined criterion (e.g. leak)	0.003		
Select wrong switch among similar switches in a set		0.005	
Read analog indictor incorrectly	0.005		
Read 10-digit number incorrectly	0.006		
Leave light on			0.003
Routine tasks with care			
Mate a connector incorrectly		0.01	
Fail to reset valve after some related task		0.01	
Record information or read graph incorrectly	0.01		
Let milk boil over			0.01
Type character incorrectly		0.01	
Do simple math incorrectly	0.01-0.03		
Wrong selection-vending machine			0.02
Incorrectly replace detailed part		0.02	
Do simple algebra incorrectly	0.02		
Read 5-letter word with poor resolution incorrectly	0.03		
Put 10 digits into calculator incorrectly	0.05		
Dial 10 digits incorrectly	0.06		
Complicated non-routine tasks			
Fail to notice adverse indicator when reach for a wrong switch or item	0.1		
Fail to recognize incorrect status in roving inspection	0.1		
New work shift - fail to check hardware unless specified	0.1		
General (high stress)	0.25		
Fail to notice wrong position of valves	0.5		
Fail to act correctly after 1 min in emergency situation	0.9		

In failure rate terms the incident rate in a plant is likely to be in the range of $20(10)^{-6}$ per hour (general human error) to $1(10)^{-6}$ per hour (safety related incident).

Error Analysis and Evaluation Methods

There is a voluminous and sweeping amount of published work on error analysis and evaluation methods. For both my sake and the sake of the reader, we will cover only a very limited amount of the material. The following outline highlights some of the better-known techniques. A comprehensive description of this material is covered in the literature review of the dissertation and the answers to the Comprehensive Questions related to this research.

Error Analysis Techniques and Evaluation Methods[24]

a. Failure Modes Assessment
    i. FMEA
    ii. FMECA
    iii. HFMEA
b. Sequence Diagrams
    i. Ishikawa (fish bone)
    ii. Fault Tree
    iii. Event Tree Modeling
    iv. Decision Tree
    v. Influence Diagram
c. Root Cause
    i. Cognitive Reliability and Root Cause Analysis
    ii. Causal Analysis
    iii. Cause-Consequence
    iv. Process Maps
d. What-if Analysis
e. Pareto Charts
f. Humans Reliability
    i. Human Error and Safety Risk Analysis (HERSA)
    ii. Human Error Assessment and Reduction Technique (HEART)
    iii. Cognitive Reliability and Error Analysis Method (CREAM)
    iv. Generic Error Modeling System (GEMS)
    v. Probabilistic Risk Assessment
        1. Technique for Human Error Rate Prediction (THERP)

Human Factors Analysis and Classification System (HFAC

Failure Modes and Effects Analysis

Failure Modes and Effects Analysis (FMEA) is perhaps among the most well-known techniques for risk evaluation and assessment. Developed by the military in the 1940s, it gained wide application in the 1990's and has been used extensively in a wide range of fields include aerospace, automotive, construction, and HC. [296, 297] FMEA has undergone many modifications and has been modified for unique application in certain disciplines: The Healthcare (HC) industry has created its own version of FMEA known as Healthcare FMEA or HFMEA developed originally by the Veterans Administration National Center for Patient Safety [297]. HFMEA combines the detectability and criticality steps of the traditional FEMA into an algorithm presented as a decision tree. It also replaces the calculation of the risk priority number with a hazard score. Failure Modes and Effects and Criticality Analysis adds a criticality function that determines the relative severity of the potential effects of the failure through either qualitative or quantitative methods.

[24] For the sake of brevity only an outline of error analysis will be provided

FMEA is a process to assess risks of failure or errors within a system by breaking it down into its constituent elements and assigning risk priority numbers (RPN). The Institute for Healthcare Improvement IHI) defines FMEA as:
"…a systematic, proactive method for evaluating a process to identify where and how it might fail and to assess the relative impact of different failures, in order to identify the parts of the process that are most in need of change."[298]

While not surprisingly, the IHI defines FMEA in the context of analyzing errors from healthcare processes, FMEA is applied to a varied set of activities. The following diagram from Ambekar highlights the types of FMEAs. It has been modified to reflect additional process FMEAs (Figure 2.22).[299]. FMEA provides a number of benefits in terms of understanding the source and potential mitigations of errors and their associated impacts (or risks), the FMEA process:[300-303]

- Captures the collective knowledge of the team
- Provides a methodical and structured process for identifying process areas of concern
- Provides a model for evaluating the impact of changing the assumptions related to the elements of the FMEA
- Provides documentation of the risk reduction activities
- Helps identify critical-to-quality characteristics
- Provides a risk-based prioritization of safety items/risks
- Can be used with qualitative or quantitative data

The Risk Priority Number (RPN) is a product of three separate values, namely the occurrence of the failure mode (O), the severity of the occurrence (S) and the chance that the occurrence is detected (D). The elements of the RPN are multiplied together to provide a composite score which provides an overall risk ranking. So,

RPN = O x S x D

Various approaches have been taken to rate the risk for O, S and D. Most typically, the scale is similar to a Likert scale such as applying values based on a 5, 7 or 10 point scale[304]. Subject Matter Experts (SMEs) are engaged to assign risk scores for each failure mode or if the system has defined probabilities for the failure modes, such as historical quality or reliability data< those can be used to assign risk values[305]. "D" can be based on variety of measures, most typically it relates to the odds or likelihood of detection defect items, such as percent or odds ratios. "S" can be a subjective assessment where a subject matter expert assigns a qualitative score to the degree of impact of the error or a quantitative approach may be devised such as actual mortality ranges or number of homes without power. "O" as with the other factors has quantitative measures based on historical data such as the frequency of defects of a particular component, or the number of time a medication dose calculation is not performed.[306-310]

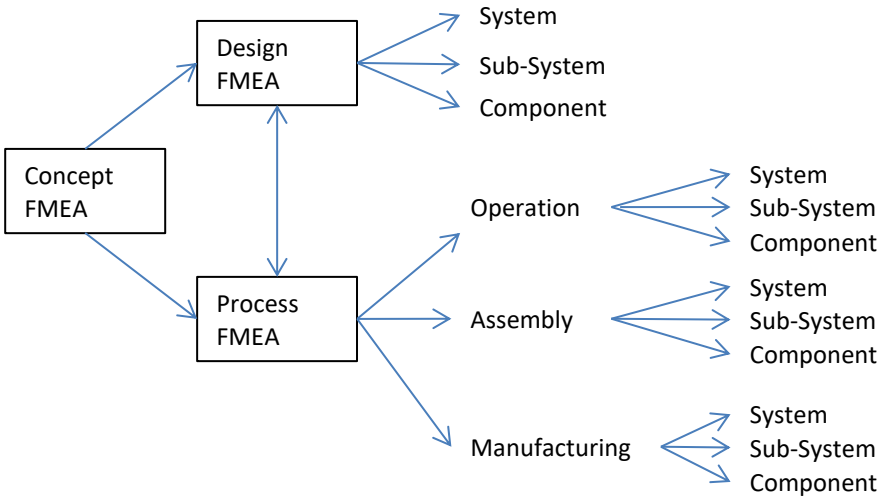


Figure 2.22: Types of FMEAs

With the long history and wide use of FMEA, there have been many permutations to the implementations of the process, particularly related to developing the RPN, which is at the heart of the risk ranking. While developing the RPN can be relatively straightforward, the RPN can also create challenges. Significant and diverse efforts are reported in FMEA literature to address shortcomings of the traditional RPN [311-313]. One of the challenges is for the SMEs to assign discrete values to the RPN factors making it difficult to evaluate the risk factors precisely. Some of these criticisms include, but are not limited to, the following:

- Different values of O, S. and D might produce the same value of RPN, but their actual risk implication might be different
- The relative importance of O, S and D is not taken into consideration in a conventional FMEA, whereas the three risk factors are assumed to be equally important, that might not be the case in a practical application of FMEA.
- In practice, the actual values of O, S and D can be difficult to be precisely estimated: the value of the risk factors can be expressed "linguistically" such as *Infrequent*, *Occasionally Likely*, *Somewhat Important*, *Very Important*, and so on.
- Certain of the risk factors, typically S, cannot be reduced in practice, for example death is terminal and difficult to reverse therefore its consequences are difficult to mitigate. This makes the FMEA a theoretical exercise as opposed to a practical one.
- The RPN presupposes that the scale used is an interval scale where each interval is equal and consistent. This might not be the case in practice, for example the value 10 might have 7 times the implication of 5 as opposed to twice the value.

One approach used to help remedy this is a fuzzy approach to define the RPN factors. Ambiguous or vague information and/or subjectivity in the ranking scales add inconsistency in FMEA. This deficiency has been addressed by introducing fuzzy logic as part of the RPN decision process. Another approach to providing more perspective for the RPN value is to use Multi-Criteria Decision Making (MCDM) which also includes the Analytic Hierarchy Process (AHP) as well as other methods (Table 2. 14). "Fuzziness" in this context refers to establishing risk factors that reflect a range of likely values as opposed to a single discrete value. This approach considers the most likely values for a risk value and represents the values as a composite score. This part of the method is referred to as "defuzzifying" the data.

Table 2. 14: References for incorporating fuzzy logic into FMEA

Authors and Year	Title	Computational Technique	Application Area	Description
Meng, Peng 2006 [319]	Fuzzy FMEA with a guided rules reduction system for prioritization of failures	fuzzy rule based (if/then) guided rules reduction system	NA	Overview of fuzzy RPN approach
Kahraman, Kaya, Senvar 2012 [316]	Healthcare Failure Mode and Effects Analysis Under Fuzziness	linguistic variables if-then rules	Healthcare	Application of fuzzy RPN to HC
Chin, Chan, Yang 2006 [320]	Development of a Fuzzy FMEA based Product Design System	fuzzy knowledge-based system	Product design	Design of FMEA prototype system using fuzzy methods
Xu, et. al. 2002 [321]	Fuzzy assessment of FMEA for engine systems	Fuzzy rule-based system	Automotive, diesel engine	Application of fuzzy logic-based method with diesel engine example
Kumru, Kumru 2013 [322]	Fuzzy FMEA application to improve purchasing process in a public hospital	Fuzzy rule-based system	Purchasing	Application of fuzzy FMEA to Hospital Purchasing Department
Garcia, Schirru, E'Melo 2005 [323]	A fuzzy data envelopment analysis approach for FMEA	Data envelopment analysis	NA	Determine ranking indices among failure modes using fuzzy sets
Guimareas, Lap 2004 [324]	Fuzzy FMEA applied to PWR chemical and volume control system	Fuzzy inference system	Nuclear Engineering	Nuclear reliability modeling using fuzzy IF-Then rules

Table 2.14: References for incorporating fuzzy logic into FMEA (continued)

Zaili, Bonsall, Wang 2008 [325]	Fuzzy Rule-Based Bayesian Reasoning Approach for Prioritization of Failures in FMEA	Bayesian Fuzzy System	Aerospace	Fuzzy rule-based Bayesian approach for prioritizing failures in FMEA
Abdelgaward, Fayek 2010 [326]	Risk Management in the Construction Industry using Combined Fuzzy FMEA and Fuzzy AHP	Fuzzy AHP and Fuzzy FMEA	Construction	Use of fuzzy approaches for AHP and FMEA to improve selection of RPN

This has been done with both ordinal and interval data. The use of ordinal data typically employs a fuzzy linguistic approach and a fuzzy rule-based approach to determine the criticality/riskiness level of the error. Interval data requires a somewhat different approach where the values are weighted and a means to find the central tendency is used. There are a wide variety of approaches and much has been written for each. With this increase in perspective comes a significant increase in complexity and difficulty in implementation [314-316]. Another approach to providing more perspective for the RPN value is to use Multi-Criteria Decision Making (MCDM) which also includes the Analytic Hierarchy Process (AHP) as well as other methods.

Sequence Diagrams

Sequence diagrams come in a variety of types and flavors. Ishikawa or fishbone, or cause and effect diagrams were originally used as part of quality control methods but are also used in root cause analysis and process analysis [317]. Normally the diagram starts with a problem statement on the right side of the diagram. Flowing from left to right the developer identifies influencing factors, for example: site, task, people equipment, and control. Along each of the factors, the possible causes are identified per the noted example [318].

The fishbone diagram has a number of benefits:

- It can take a complex problem and provide a relatively simple visitation of it
- It can permit an in-depth analysis and evaluation considering the entire mix of cause and effects
- Demonstrates weaknesses in understanding of the problem
- Allows integration of all the factors that influence the problem

Disadvantages of fishbone diagrams are:

- Can lead to divergent problem solving (chasing rabbits down the wrong path)
- There is a tendency to base the causes on opinion rather than fact
- Can “blow-up” from a list of too many causes

Decision Trees

Decision trees, for the purposes of this discussion, include the set of acyclic graphs that function as decision support tools. They include, but are not limited to, fault trees, event tress and influence diagrams. Decision trees fault trees, and event trees are all very similar in structure and function. They use trees, directed acyclic tree-like graphs to model decisions or error events and their possible outcomes including probabilities, event outcomes, and costs or utility as represented in Figure 2.24[327-329]. Decision tress and their siblings have multiple uses including classification, data mining, decision making, and hazards analysis [330]. Decision or event trees can be combined with other tools such as Monte Carlo to add uncertainty for the occurrence of the node (i.e. fuzziness) [331].

Among decision support tools, decision trees (and influence diagrams) have several advantages. Advantages of a decision tree:

- Are straightforward to understand and interpret.
- Have value even without much data.
- Allow the addition of new possible scenarios
- Help determine worst, best and expected values for different scenarios
- Use a “white box” model: the decision path and methodology is readily apparent
- Can be used for different data types including categorical data

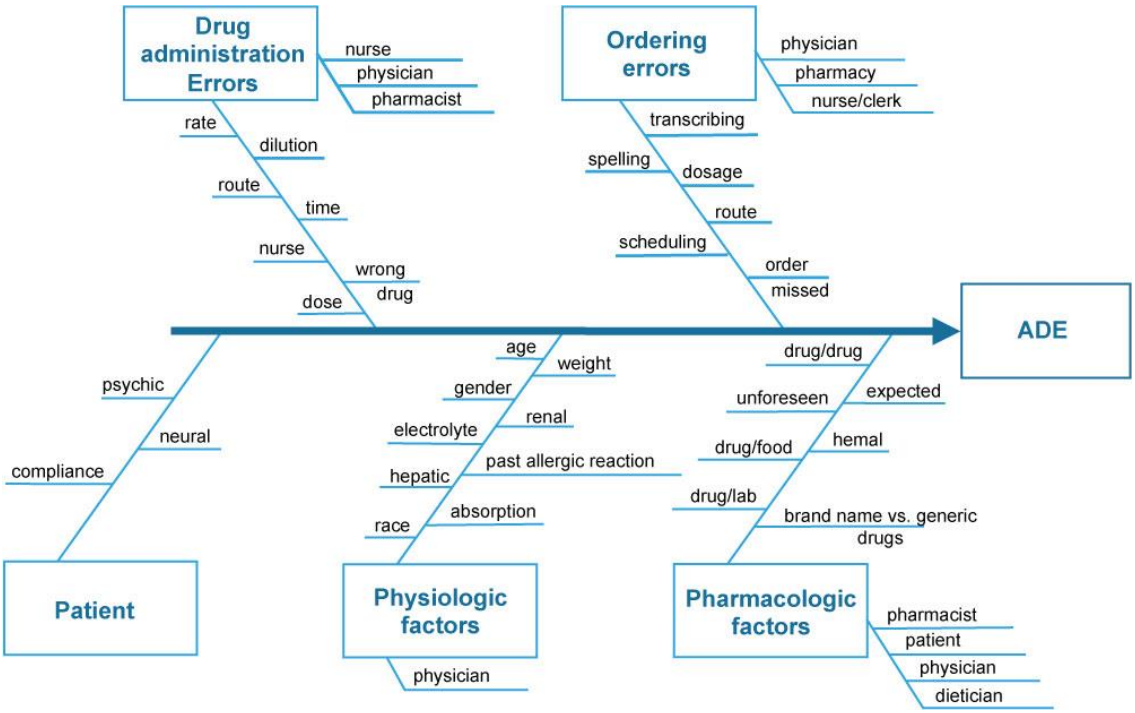


Figure 2.23: Fishbone or Ishikawa diagram[25]

[25] http://www.ck12.org/section/Elements-of-Agent-based-Models/

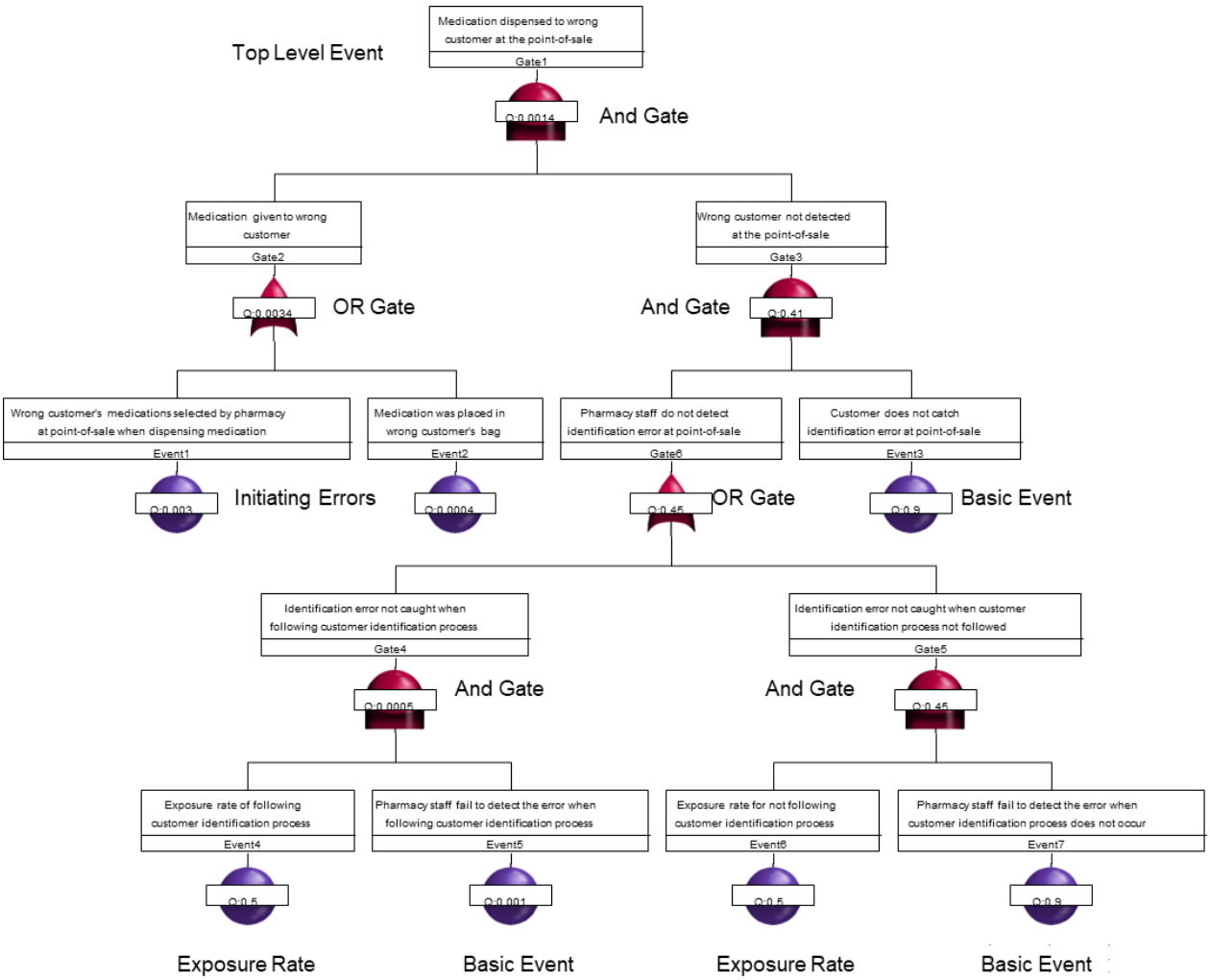


Figure 2.24: Representation of Binary Fault Tree [329]

Disadvantages of decision trees:

- Trees can get very complex particularly if many values are uncertain, and there are multiple links (i.e. more than binary) between nodes
- The size of decision trees can grow large very quickly and become computationally intensive.

Root Cause Analysis

Root Cause Analysis (RCA) enlists various tools and techniques to trace problems to their origins. It attempts to identify the origin of an error or problem using a specific set of steps. RCA assumes that systems and events are interrelated. This is a key consideration since a systems perspective is crucial for a systems level assessment of the actual underlying cause(s) of the error. Typical areas for evaluation include physical causes, human causes and organizational causes. Root cause analysis is a technique on its own, but also has a variety of techniques that contribute to the approach.

The Cognitive Reliability and Error Analysis (CREAM) technique is a Human Reliability Analysis (HRA) technique that allows examination of agents' actions through the context of performance-shaping factors. The CREAM also employs a cognitive model to explain cognitive failures. In this way it considers the context in which the agent operates and also considers the cognitive nature of the agent [332, 333]. CREAM will be described in more detail later.

Causal analysis (CA), is the subset of techniques that contribute to performing RCA [334]. Techniques included in CA include the, Five Whys, and Cause-effect diagram (a tree diagram used to break down cause into a tree-structure to define possible causes).

Cause-Consequence Analysis (CCA) is a methodology for assessing the chain of consequences leading to an error. CCA combines two different tree structures together, a consequence tree and the associated fault tree. In this way it is similar to event trees or fault trees. Similar to other trees or sequence structures, it can grow quickly and become unwieldy especially since it combines several tree approaches [335].

Process maps (PM) are a ubiquitous approach for laying out the sequence of steps of an activity: it is a workflow diagram to help in understanding a process or series of parallel processes. PMs are used in six sigma applications for improvement (value stream mapping) and can also be sued to define areas of potential error. It is typically used in conjunction with other techniques such as FMEA. The lean process maps underpin the DMAIC (Design, measure, analyze, measure, improve and control) process and provide the structure for further analysis.

What if Analysis

What if analysis (WIF) is a form of sensitivity analysis used to evaluate the impact of various alternatives. In the context of error analysis, it assesses the effect of potential errors or factors that could influence errors. WIF is a useful tool not only for evaluating the quantitative aspects of decision options; it also has application in computer simulation models. For computer simulations, WOF can be used to establish confidence with respect to changes in parameters of inputs [336].

Pareto Charts

Pareto Charts (PC) are a form of impact analysis providing a graphical representation of the relative differences among groups. They are based on the Pareto principle that states, in a general sense, 20% of the input or cause creates 80% of the result (the 80:20 rule). While this rule is not universally applicable, its application has great utility [337]. PCs are combination diagrams with both line and bar depictions of the relevant data. The bars represent the frequency or amount of the event or item of interest such as occurrence, value, time, etc. The bars are arranged in descending order. The line is a cumulative total of the representative function (Figure 2.25). PCs can be used as part of RCA, value stream development, and decision making.

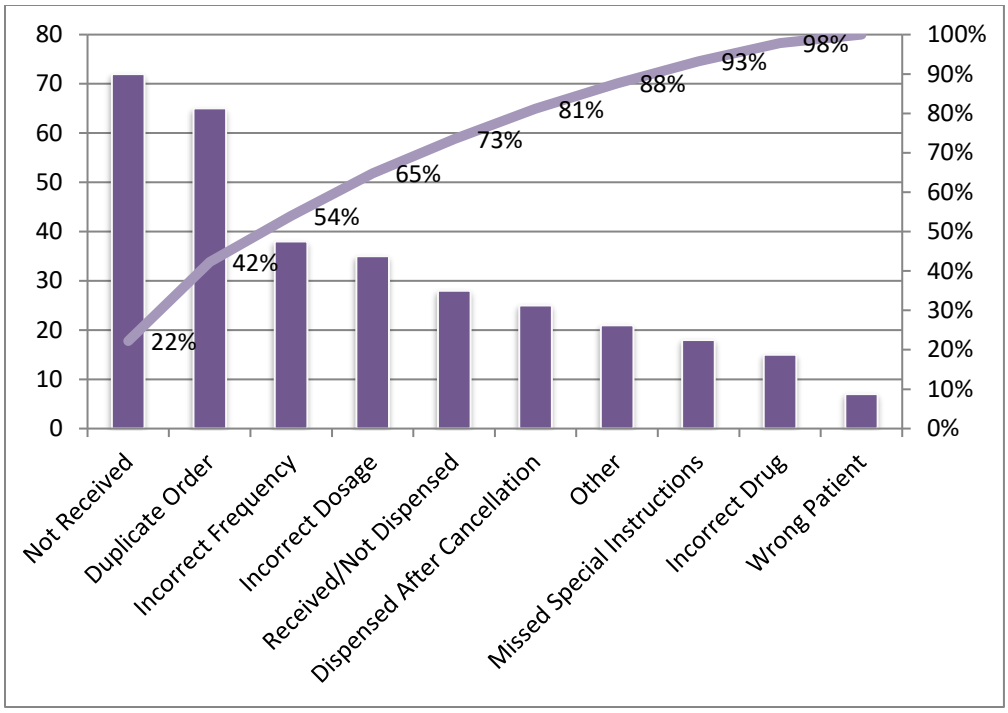


Figure 2.25: Medication administration record error Pareto chart[26]

Human Reliability/Error

Human reliability, or the lack thereof, as a source of error, has been studied extensively and a wide variety of tools have been identified to analyze and reduce these errors. A high-level summary will be provided for the techniques identified. The United States Department of Transportation, Federal Aviation Administration has done extensive review and research in the areas of human error and reliability. They have evaluated many of the techniques noted above; their assessment will be provided here largely intact as suitable summaries of these techniques.

HERSA

HERSA is a proactive tool for assessing the risk of human error. HERSA is based on FMEA but specifically considers human errors and is based on tasks. It has the same scales that FMEA does, namely Likelihood of occurrence; severity of outcome and Likelihood of detection. The goal of using HERSA is to produce an ordered list of errors/outcomes. As with FMEA, HERSA as the following attributes:

- Identifies the relative likelihood of particular errors
- Does not depend on past history, but can use this information
- Relies on relative, ordinal scaling
- Rank orders error modes
- Identifies critical single component failures
- Can utilize detection/mitigation (or not: similar to FMEA)
- Produces a task breakdown as a byproduct

[26] Source: http://www.infoworks-tn.com/lean-six-sigma-healthcare/

The methodology for HERSA is the same as FMEA.: error modes are identified by experts or data; ratings are assigned for each of the scale areas using a 1-5 scale, and ratings are calculated by –
Hazard Index (HI) = Likelihood X Severity;

Risk Priority Number (RPN) = Likelihood X Severity X Detection.

HEART

HEART is a technique to assess and define human error probabilities by matching the task being assessed to one of the nine generic task descriptions from a given database and then to modify the human error probabilities (HEPs) according to the presence and strength of the identified error producing conditions (EPCs) The nine generic task types used in HEART:

1) Totally familiar, performed at speed with no idea of likely consequences
2) Shift or restore system to new or original state on a single attempt without supervision or procedures
3) Complex task requiring high level of comprehension and skill
4) Fairly routine task performed rapidly or given scant attention
5) Routine highly-practiced, rapid task involving relatively low level of skill
6) Restore or shift a system to original or new state following procedures with some checking
7) Completely familiar, well designed, highly practiced routine task occurring several times per hour
8) Respond correctly to system command even when there is an augmented or automated supervisory system
9) None of the above

HEART has the advantages of being recognized as a proven tool for predicting human reliability and identifying methods of reducing human error. It can be applied to many different types of processes across different industries since its methodology is based on the human rather than a technical process. As with other similar processes, HEART suffers from relying on significant judgment from the user [338].

THERP

THERP was originally developed to aid military strategists to determine expected failure rates for nuclear weapons. It has also been applied to the analysis and design of human-machine interactions. THERP provides human reliability data for probabilistic risk assessment studies; namely, to predict human error probabilities and to evaluate the degradation of human-computer systems likely to be caused by human errors alone or in connection with equipment malfunctioning, operational procedures, or other system and human characteristics that influence complex system (i.e., joint human-machine) behavior. The basic assumption of THERP is that the operator's actions can be regarded in the same way as the success or failure of a piece of equipment. The theory is that the reliability of the operator can be assessed in essentially the same way as an equipment item. The operator's activities are broken down into task elements and an estimate of the probability of an error for each task element is made, based on data or expert judgment [338] .

CREAM

CREAM is a Human Reliability Assessment tool, as described by the Federal Aviation Administration (FAA) that allows:

1) Identification of those parts of the work, as tasks or actions, that require or depend on human cognition, and which therefore may be affected by variations in cognitive reliability,

2) Determination of the conditions under which the reliability of cognition may be reduced, and whether these tasks or actions may constitute a source of risk,

3) Provision of an appraisal of the consequences of human performance on system safety which can be used in a PRA/PSA, and

4) Development and specification of modifications that improve these conditions hence serve to increase the reliability of cognition and reduce the risk[333].

This approach serves the purpose of ensuring that the proper conclusions are drawn from the analysis, and that the necessary changes to the system are correctly specified. CREAM provides the core functionality of these services, i.e., the concepts, the classification system, the cognitive models, and the methods. In order to be properly used it is necessary to supplement with application specific information, e.g. in the form of values for specific performance parameters, detailed operational and process knowledge that defines the context, etc. It is based on the principles of context dependent cognitive models (COCOM)[338].

GEMS

GEMS is an error classification scheme developed by Reason that focuses on cognitive factors in human error as opposed to environmental or other context-related factors. It is based heavily on Rasmussen's three major categories of errors: skill-based slips and lapses, rule-based mistakes, and knowledge-based mistakes (SRK). GEMS is a more general description of the cognitive "black box", which can be used to address the mechanisms of both slips and mistakes. GEMS taxonomy of error types is a useful method to assess cognitive determinants in complex technological environments [338, 339].

PRA

PRA is actually an integration of FMEA, fault tree analysis, and other techniques to assess the potential for failure and to help find ways to reduce risk. It involves the development of models that defines the response of systems and their associated participants to error initiating events. Additional models are generated to identify the contributing failure modes required to cause the error mitigating systems to fail. Each component failure mode is represented as an individual "basic event" in the systems models. Estimates of risk are obtained by propagating the uncertainty distributions for each of the parameters through the PRA models [338]. PRA is used extensively in aviation, nuclear, healthcare and other industries [340-342].

HFACS

HFACS is a system to categorize both the latent and immediate factors that have been identified in errors, originally aviation accidents. Its purpose is to provide a framework for use in error analysis and as a tool for error accident trends. HFACS use four levels of failure including (1) unsafe acts, (2) preconditions for unsafe acts, (3) unsafe supervision, and (4) organizational or cultural influences. HFACS permits the analyst to identify specific types of human error at various levels in the organizational hierarchy [343].

Advantage of HFACS includes consideration that although designed originally for use within military aviation, HFACS has been shown to be effective for the identification and analysis of in other areas as well. 2) Permits the analyst to identify specific types of human error at various levels in the organizational hierarchy. 3) May be used after an event has occurred.

HFACS has several disadvantages. It is similar to other HRA tools in that it can be labor intensive and dependent on the availability of detailed quality data. Its' use can be restricted because it requires knowledgeable human factors safety analysts to use. Finally, it relies on the overt actions and sequence of actions of the operator, supervisor, or manager rather than the deliberations (the intentions and expectations) that underlay them [344].

<u>Agent Based Modeling Systems</u>

An Agent Based Modeling System (ABMS), also known as agent-based systems (ABS), or multi agent modeling systems, is a relative newcomer to modeling and simulation. ABMS is an approach to modeling systems comprised of interacting autonomous agents. Computational advances make possible a growing number of agent-based applications across many fields. Applications include modeling agent behavior in the stock market and supply chains, to predicting the spread of epidemics and the threat of bio-warfare, from modeling the growth and decline of ancient civilizations to modeling the complexities of the human immune system, and many more [345, 346].

In the case of application of ABM to this research, the interest is to assess if a complex system like MA can effectively be modeled. Macal et al considers how ABM can model a system that incorporates difficult to simulate attributes like human behavior, the collective effects of agents (agent interaction), and emergent behavior [346].

While research and application of ABMS in healthcare is becoming more widespread, its application to medical error and specifically errors related to the administration of medication is modest at best. Of the research that exists, it appears to be focused in narrow areas of application. Santos has developed an architecture for an ABM that supports doctors' decisions by "guaranteeing that all required clinical data is available and capable of predicting the patients' condition" over the course of the next hour. Santos, in this referenced paper, provides a high-level description of how an ABM might be sued for this application but falls short of describing the implementation of a system [347].

Similar in concept is the application of ABM to risk assessment. While most risk assessment approaches use a linear approach, considering each risk at a time, an agent-based approach allows the simultaneous and dynamic consideration of risk. The use of ABM for risk assessment of routine clinical processes was explored by Wobcke et al [348]. In a more general example, Bonabeau describes the application of ABM for simulating humans systems [349]. More specifically he considers real-world application including organizational simulation along with several other uses.

Somewhat further afield from medical application is the use of ABM to model supply-chain risk. That said, the ABM of supply chain appears to have some similarities to the application of MAE simulation. Notably there are various interactions that are non-linear and interactive (networked) and the errors in many instances are a function of external influences and information flows [350].

ABMs specifically considering Medication Errors are quite limited. Clancy explored the concept of complex systems in the context of nursing including consideration of medication errors. While modeling approaches such as ABM and Systems Dynamics are discussed, specific applications are not developed [351].

A preliminary study by Vasquez-Velez used NetLogo to construct an ABM attempting to model the influence of nurse behavior on medication administration. A simple model was developed that demonstrated nurse interaction, nurse multi-tasking and interruption. The study of MAE was not noted in this study [352].

Considerations for which ABMS might be appropriate are[27]:

- When there are decisions and behaviors that can be defined discretely (with boundaries)
- When it is important that agents adapt and change their behaviors
- When it is important that agents learn and engage in dynamic strategic behaviors
- When it is important that agents have a dynamic relationship with other agents, and agent relationships form and dissolve
- When it is important that agents form organizations, and adaptation and learning are important at the organization level
- When it is important that agents have a spatial component to their behaviors and interactions
- When the past is no predictor of the future
- When scaling-up to arbitrary levels is important
- When process structural change needs to be a result of the model, rather than a model input

The list above overlays directly with the operations of hospitals and clinics. Whereas many of the other simulation and modeling techniques have difficulty in modeling hospitals or clinics at the systems levels, ABMS offer the advantage of being directly applicable to them.

Sibbel et. al. describes how ABMS might be applied in the hospital setting. They outline the various factors in consideration of application of simulation in this environment and state that ABMS is an ideal approach for dealing with the unique issues facing hospital operations simulation. The authors discuss how the model could be applied,

[27] (Macal, L., North, M., Tutorial on Agent-Based Modeling and Simulations Part 2: How to Model with Agents, Proceedings of the 2006 Winter Simulation Conference)

however, but do not apply such a model. Herrler et. al. discusses the application of ABMS to scheduling and provides an example.

As a summary, Mustafee et. al. prepared a profile of literature in HC simulation. They discussed the methodology of their article selection and review techniques. The simulation types they considered were Markov Chains (MCS), Discrete Event Simulation (DES), ABS and System Dynamics (SD). Their assessment, fortunately for me, is in lockstep with this response. A brief summary follows:

- MCS: A main approach used in HC overall with the applications mainly in the areas of clinical science (e.g. treatments, drug results, prognosis, etc.). About 25% of the papers they reviewed had something to do with non-clinical operations such as the cost-effectiveness of competing technologies or HC strategies
- DES: They found this approach well suited to problems to areas of interest to this author (increasing efficiency of operations). They state that DES provides more insight in the area of health economics than MCS.
- SD: This is more frequently used to model at a more top-level or policy level
- ABS/ABM: This approach is not as widespread as the others.

ABM Building Blocks

There are a variety of perspectives on the building blocks that make up ABMs. Wall views ABMs as having a core of three building blocks (1) the agents, (2) the environment in which the agents reside, and (3) interactions among the agents [353]. This can be expanded to include time, rules, properties, actions, goals, beliefs, policies, messages, mental models, and states. Figure 2. 26 represents a more comprehensive view of the building blocks contributing to the structure of ABMs [354].

The following provides a brief description of many of the characteristics of ABMS[28]:

- *Self-explaining:* an intelligent system can explain how it came to a certain conclusion that led to the observed reaction of the system.
- *Emergent behavior:* behavior of a system that does not depend on its individual parts, but on their relationships to one another.
- *Non-linear:* The interactions that occur in AB models are inherently non-linear meaning that they are not inherently or consistently predictable. Additionally, non-linear feedback loops exist between micro and macro levels.
- *Robust:* Slight changes in the environment do not lead to a failure.
- *Fault tolerant:* Even when some parts are broken, the system can still function. This characteristic may include the concepts of self-evaluation and repair.
- *Adaptive:* A system can adapt to a new environment that may be significantly different from the original environment.
- *Self-organizing:* Intelligent systems are able to find a way to organize themselves to optimize their tasks without an internal or external authority. The structure is discovered by the systems, not programmed by their developers.
- *Deductive:* Based on a set of axioms or general knowledge, intelligent systems can derive new knowledge for a particular case.
- *Learning:* Intelligence-based systems are able to learn. They not only learn from their mistakes, they also learn from success and the communication thereof with others.

[28] Source: http://www.ck12.org/section/Introduction-%3A%3Aof%3A%3A-Agent-based-Modeling-%3A%3Aof%3A%3A-CK-12-Modeling-and-Simulation-for-High-School-Teachers%3A-Principles-Problems-and-Lesson-Plans/

- *Cooperative:* Intelligent systems work together with others to solve a problem.
- *Autonomous:* A system is able to continue to pursue its objectives without human guidance, even in unfriendly environments.
- *Agile:* Intelligent systems can rapidly and efficiently adapt to changes in the environment.

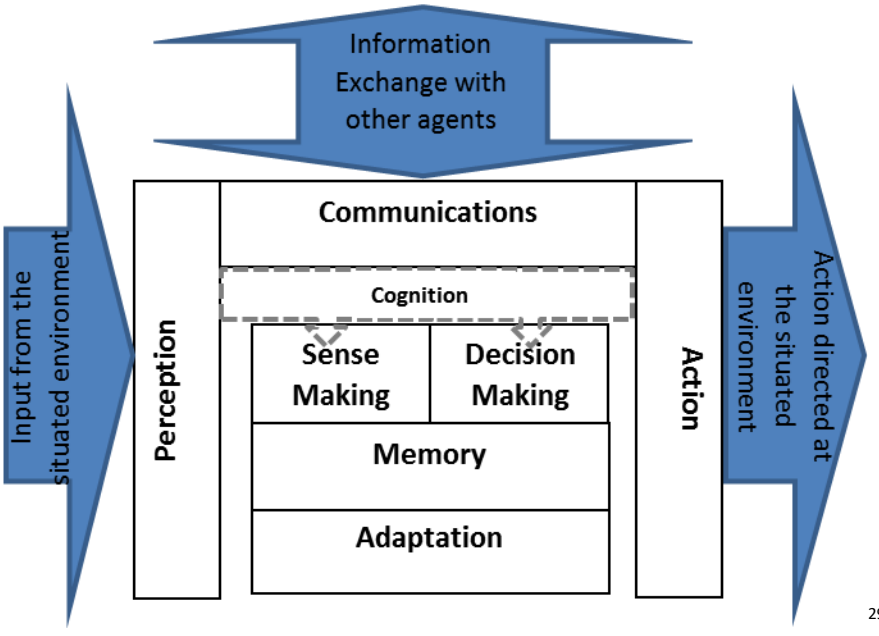
Agents will to one degree or another have the following functionality:

- Perception-The agent receives signals from his environment based on the links or sensor it has. It processes this information using the rules to interpret the input signal. The agent can be designed to learn, so, with more and more observation its behavior or interaction with the environment can adapt – and exchange of results with other agents that do the same – the closer the perception gets to the real situation.
- Sense Making-As noted in Perception, in order for observations to make sense, they need to be mapped to an internal representation. The internal representation is the picture the agent has about itself within the environment it is in (the situated environment). The internal representation does not have to be complete or can be "wrong". It is possible that the agent only uses a limited set of attributes to capture observations, such as "calculates dose" or "does not calculate dose," as a Boolean parameter that cannot capture values and accuracy. Sense making can also be fuzzy in the sense of interpreting different values under different conditions.
- Memory-the rules and algorithms that define how sense making and later decision-making are done are stored in the memory. Short-term and long-term memories and even forgetfulness (which is especially relevant if an agent were designed to be Tom Berg), can be modelled. The memory domain is the repository for all information needed for the agent to perform the tasks and includes all forms of memory ranging from data to behavior.
- Communications-Agents can interact and share information: they share results with agents or agent types. Agents can communicate directly or influence another agent through behavior (including proximity, actions, or physical interaction).
- Decision Making: -Agents can support reactive as well as proactive methods. If-then rules or complex decision algorithms based on plans, goals, and value systems can be used. Decision making can result in actions including more information seeking.
- Action- The agent can take action based on its decision-making function and these actions can influence the situated environment. This includes the agent moving itself, as well as acting on active and passive objects including other agents. The action can have a feedback effect on the agent taking the action.
- Adaptation-Agents can learn and adapt; this includes both behavioral change as well as a change in physical attributes.
- Cognition: Agents can interpret a specific environment and process the information it provides through various "filters" or with different perceptions. This filters or perceptions can be different depending on the conditions in the specific environment.

ABM Building Elements

Agent - Agents are the heart of ABMs. They, among other things, are autonomous, decision-making entities with goals and the ability to interact with their environment and other agents. Agents are considered to be autonomous because their actions are not determined directly by a central function, although, they can interact with a central function that they have some independence from. As noted, the agent receives information from their environments and other agents and they react to, and, interact with this information. Agents have the ability to pro-actively initiate actions in order to achieve their goals/objectives. Figure 2.27 stylizes the functions of an agent including its functions, inputs, outputs and interactions.

Figure 2.26: Diagram of building blocks (or features) of ABMs



[29]

Figure 2.27: Architecture framework for agents[30]

[29] Images included under title 17 section 107 U.S. Copyright Law Fair Use Doctrine as educational material distributed for use without profit. Modified from source: http://www.ck12.org/section/Elements-of-Agent-based-Models/

As noted previously, an agent is defined as an object that can take action. They can represent individuals, groups of individuals, inanimate objects such as machines or elements such as investments or projects. Agents differ in their characteristics, that is, they are heterogeneous. They can show differences with respect to most any type of dimension such as knowledge, objectives, rules, or abilities.

Environment - The environment of an ABM characterizes the tasks or problems the agents operate within: the environment represents the global constraints and, "rules of engagement" the agents have when attempting to fulfill their tasks. At the risk of being somewhat metaphysical, the environment can be a physical or geographic space, or, a conceptual space which is somewhat harder to comprehend (at least for me).

Hammond states the Environment in an ABM can [355]:

- Range from simple to relatively abstract
- Contain "agent types" itself with their own properties, actions and rules
- Can change over time for example as a result of agent action or from exogenous drivers such as policy change.

The Environment is the virtual world in which the agents act as simply stated by Gilbert. As noted previously, the Environment may be geographic or spatially explicit or using some other feature such as knowledge. The location of agents can be defined by various means such as coordinates or relative positions based on proximity to other agents in a network [356].

Time - Time is a core element in dynamic simulation. Simulation approaches like ABM have a fundamental unit of time that represents one cycle of the simulation. This is often referred to as iteration. Consideration for the time component includes [355]:

- Calibration to some unit of measures e.g. real-world time or something more abstract (e.g. dog years, which would be easy to adjust for vs. model of chronic disease incidence driven by smoking or a model of opinion-change dynamics may require more work to calibrate[357]);
- Potential involvement of multiple distinct speeds e.g. the time change of a patient's health vs the spread of a virus through the population, vs. the mutation of the virus;
- Defining the units (and rate of change) for the rules, actions and changes in agent properties or environment.

Rules – The behavior of agents is conditioned on their rules. Rules are the central drivers of the dynamics of the model and define how agents choose actions, modify properties and interact with other agents and their environment. In the simplest sense, rules can be thought of as "if-then" statements, e.g. "if age > 18, then able to vote". Note that properties affect the rules, serving as their input. Rules can also be dependent on time and may involve learning, change or adaptation – e.g. probability of mediation administration error changes for a nurse/agent after 100 times of administering a certain medication.

Rules can vary significantly in complexity ranging from simple statements to subprograms or optimization processes or other calculations. Part of the rule structure can include stochastic and deterministic probabilities. Rules can also define the creation, removal or modification of agents.

Properties - Properties are another core building block of ABMs. Whereas rules represent the behavior of agents, properties reflect the characteristics of individual agents (e.g. age, sex, breed, disease state, wealth, income, membership status, functional status (e.g. broken, fixed)). As noted under Rules, Properties can change over time or remain the same (e.g. height as a result of growth over time). The construct of the model can allow properties to either be entirely visible, not visible or only partially visible to other agents.

States - States are similar in some ways to properties, in that they refer to conditions or status that the agent is allowed to be in. States can be formally represented in the form of a state chart. A state chart is a "graphical state-transition construct based on exchanging messages or events between the system and its environment"

[358, 359]. Three key elements of a state chart are the State, the transition and the resulting relationships between States. Figure 2.28 and Figure 2.29 provide a representation of state charts [360, 361].

Urban and his colleagues used the PECS reference model (physical. emotion, cognition, social status) for construction of human-like agents. PECS follows to basic principles: 1) it uses component-oriented hierarchical modeling which is in essence building the model up from smaller constituent sub elements; 2) using a system-theoretic approach the model takes on a temporal basis where each internal state of the agent has a set of conditions at any point in time and can change as the simulation progresses. Figure 2.31 [19] illustrates the architecture of a PECS agent[30]. In our case the nurse will be an operative agent with these features.

As examples, the nurse agent might be represented as follows:

- Physical – Experience, knowledge, information state, workload;
- Emotional – Stress, fear, anxiety, confidence;
- Cognition – Situational awareness, error recognition, decision making, learning;
- Social status – Seniority, organizational position, respect.

Marsella and colleagues used an ABM system, PsychSim, designed specifically as a social simulation tool. As such, it is used to explore individuals and groups and how those interactions can be influenced.

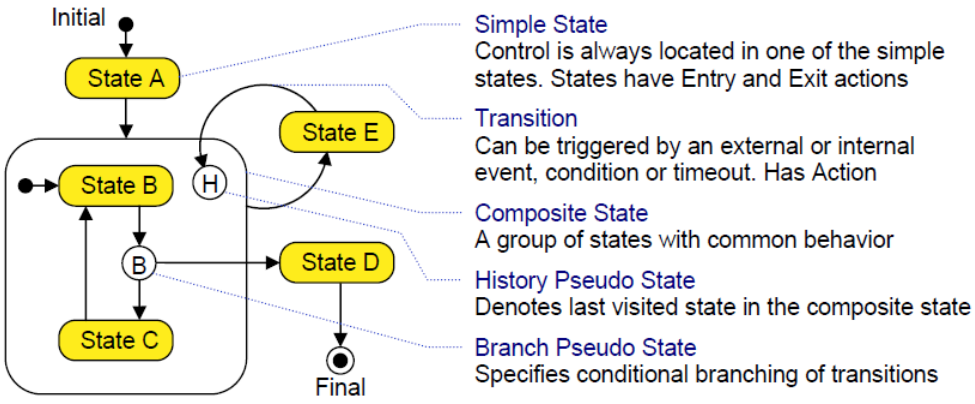


Figure 2.28: Description of statechart elements[31]

[30] The red arrow indicates a line added by the author: it seems like this would be a logical interaction. Images included under title 17 section 107 U.S. Copyright Law Fair Use Doctrine as educational material distributed for use without profit.

[31] Images included under title 17 section 107 U.S. Copyright Law Fair Use Doctrine as educational material distributed for use without profit. Ref: https://help.anylogic.com/index.jsp?topic=%2Fcom.anylogic.help%2Fhtml%2Fstatecharts%2FStatecharts.html

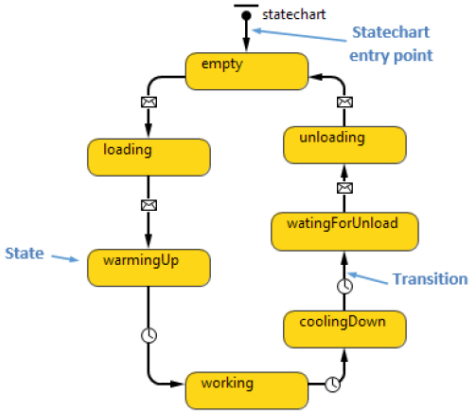


Figure 2.29: State chart for simple manufacturing process[32]

The attached video provides a reasonably good overview of the elements mentioned above (via link on photo Figure 2.30).

Figure 2.30: Agent based model for the zombie apocalypse. [33]

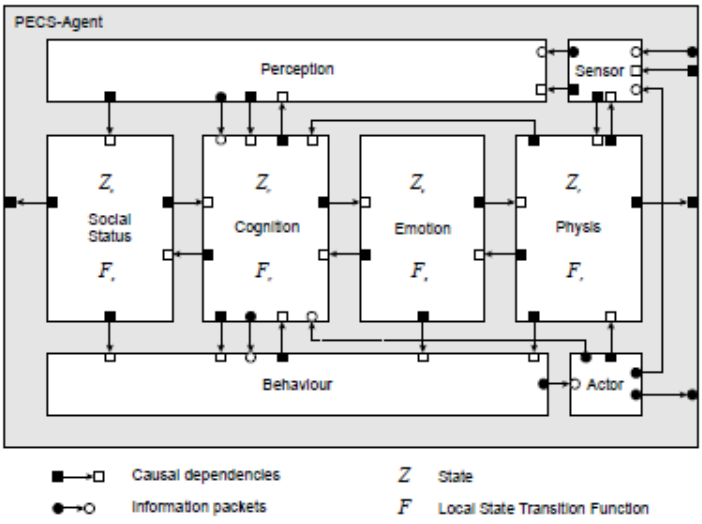


Figure 2.31: PECS agent architecture[34]

[32] Images included under title 17 section 107 U.S. Copyright Law Fair Use Doctrine as educational material distributed for use without profit.
[33] Images included under title 17 section 107 U.S. Copyright Law Fair Use Doctrine as educational material distributed for use without profit. https://www.youtube.com/watch?v=M7PeYyUczh8
[34] The redline was added to indicate an additional interaction not included in the original reference

A PsychSim starts with a generic agent from which the modeler constructs unique agents that represent groups with specific attributes. Each agent maintains independent beliefs, goals and rules (policies) for achieving those goals. The PsychSim agent has the following elements: State, Actions, Goals, Beliefs, Polices, Messages and Mental Models. The following list maps elements into this research model [362]:

- State – Patient status, medication, information available, experience, knowledge, capability
- Actions – Similar to other ABM actions
- Goals – Safety, rushing/urgency, relieving pain, avoiding criticism/errors, accuracy
- Beliefs – Assumptions of patient condition, medication assumptions
- Policies – Similar to rules
- Messages – information passed from one agent to another (e.g. pain level, corrections, influence from family, doctors' orders
- Mental Models – This is best described as preconceived notions: a child can't accurately describe pain, Tylenol is not toxic, lab results (information type as an agent) are of little value.

Both PECS and PsychSim provide interesting and potentially valuable architectures for building "humanness" into the final ABM simulation. PsychSim will have the added challenge of being a custom ABM software system that does not appear to be currently available. That said it provides unique insight into constructing emotion and cognition into agents.

Healthcare ABM Behavior Approach

Considering modeling of human behavior specifically in HC, using ABM, brings in an interesting construct. Based on my effort to date, very little research has been identified during this literature search that relates specifically to considering the behavior, specifically cognition, and emotion or mental state of healthcare providers, as part of the ABM structure. A considerable body of work exists on the modeling of patient behaviors at the macro level, such as in epidemics, or actions related to healthcare or similar venues [363-365].

While there are a number of approaches to building human behavior traits into agents [362, 366], the PECS approach provides an initial useful structure to design a structure for modeling behavior of healthcare providers – including nurses.

Contributory factors have been studied that influence the error occurrence with nurses. These include: stress, workload, experience, work conditions, familiarity with work area, patient type, slips and lapses, equipment, and communication [4, 29, 367].

Little work has been done to understand the underlying causes of errors by nurses: it could be possible to draw analogies on underlying error causes from other areas such as aviation or nuclear facility operations [368-371].

Extending the PECS model, with only superficial consideration at this point, the general formula is:

F ≡ transfer function

$Z(t_n)$ ≡ current state

$t_n \equiv$ time

$z(t_{n+1})$ ≡ Future/subsequent state

$x(t_n)$ ≡ input

$$Z(t_{n+1}) = F(t_n , z(t_n), x(t_n))$$

Urban and Schmidt state that the state variable z is not typically directly related to observable behavior function as an independent variable. Dependent variables are constructed that depend on the sate variables that ultimately

drive an agent's behavior. The relationship between the state variable, z, and the dependent variable, w, can be described by a function H [372].

W(tn+1) ≡ dependent variable influencing behavior derived from the stat variable

H ≡ function relating state variables and the dependent variable(s)

$$W(t_{n+1}) = H(z(t_{n+1})$$

The output function G determines how the new internal state of the agent, defined by the state variables $z(t_{n+1})$ and the dependent variables $w(t_{n+1})$, is transformed into an externally observable output y(tn+1).

G ≡ output function that determines expression of the new internal state

$$y\ (t_{n+1}) = G(t_{n+1}, z(t_{n+1}), w(t_{n+1}), x(t_{n+1}))$$

The fundamental assumption of PECS is that an agent's personality is conditioned on the form of F and H, the state variable and its function that transitions the state variable to expression respectively.

The transfer function F modifies the internal state variables of the agent. This happens either as the result of an input from the outside world, or it can be self-generated. The state variable could be Fatigue, for instance. This state variable could be changed by the external input x, where the agent experiences a longer than normal shift.

$$Fatigue(t_{n+1}) = F(Fatigue(t_n), Shift\text{-}length(t_n))$$

A different example of a state variable change would be Stress level. This state variable could change based on outside influences or on its own depending on the actions the agent takes

$$Stress(t_{n+1}) = F(Stress(t_n), Action\ performed(tn))$$

Stress could be constructed not to directly influence the agent's behavior. The function H, which relates Stress to the drive Workload, acts as a motive. This means that the state variable Stress is modified by the dependent variable Workload.

$$Workload(t_{n+1}) = H(Stress(t_{n+1}))$$

Two additional points will be mentioned, but they will not be explored here. One is to include "fuzziness" in certain state variables that can be "de-fuzzified" by JIT information. The other point is to use exiting statistical occurrence of states to inform the behavior of the agents: in other words, use the likelihood of a state to define its occurrence in the agent.

Lean for MAP

Considering MA and the associated errors (medication administration error) from the Industrial and Systems engineering perspective of Lean and Reliability is surprisingly unique and rare. A number of studies were identified that evaluated the use of lean methodology for medication administration. One study analyzed intravenous (IV) medication orders for 30 days to identify the specific times when medications were changed or discontinued. The researchers performed a value-stream mapping to define the current state and identify efficiency states. After evaluating the value-stream map they performed and optimization, they provided modest improvement as measured by wasted doses and cost reductions [373].

Lean principles have been applied to MAP with some success, although, the application of Lean seems rather lean (sorry I couldn't help myself). As part of a cooperative effort from the Virginia Mason Medical Center (Seattle), the Collaborative Alliance for Nursing Outcomes (CALNOC) Medication Administration Accuracy Quality Study was used in combination with Lean quality improvement efforts to address medication administration safety. The effort targeted improving several functions including the medication room layout, applying visual control (Kanban) and standardizing nursing work related to MA. Their efforts concentrated in six safe practice areas:

- comparing medication with medication administration record,
- labeling medication,
- checking two forms of patient identification,
- explaining medication to patient,
- charting medication immediately, and
- protecting the process from distractions/interruptions.

The result of this effort was a fivefold reduction in MAEs down to 2.8% of all Mas and "safe practice" violations decreased from 83/100 doses down to 42/100 doses. This study covered 18 months; no long-term longitudinal data was provided. This study indicates that Lean process improvements can contribute to decreases in nursing medication administration [69].

Another approach studied the application of Lean to hospital pharmacy operations and included the perspective of nurses. The study discussed overall error performance and mutual perceptions of the pharmacy and nursing staffs and the implementation of various error reducing strategies mostly concentrated around improving information flow and communications [70].

In a modest sized application of lean for IV medications, the authors noted increased performance in terms of the delivery of doses dispensed and a decrease in returned items. There was no discussion of error rates [373].

While this is not intended to be a comprehensive literature review of the application of Lean principles for the administration of medication by nurses, a fairly extensive search was conducted. As noted previously, the research is scarce for this application. The reasons for this could be varied including: efforts are going on in this area but they are not finding their way into the research literature, or, little research has been conducted in this area.

One of the challenges in this area is the difficulty in getting accurate reporting or recording of medication administration errors [24, 374, 375]. Not surprisingly the consensus is that MAEs are under-reported and that nurses avoid reporting errors due to the perceived repercussions.

One methodology researchers have used is having observers monitor nurse MA activities to detect if errors occur. This appears to provide a reasonably good approach to objectively gather data. As with other direct observation approaches, there can be an effect of the observer on the behavior of the subject being observed. Another challenge is the limit of the breadth of the data being collected, that is, the amount of data being collected is a function of the number of observers. As a result, these types of studies are limited to a relatively few organizations in any given study [142, 375-378].

Information System of MAP

If one critically assesses what a nurse processes during the MAP, the conclusion would be information. Consider the administration of medication as a production process with the finished product being the successful delivery of the correct medication in the right dose to the right patient.

One can envision an assembly line, where at each station along the assembly line another component of information is added. This information work in process continues until, if all goes well, a complete information product is assembled to ensure correct medication administration (Figure 2.32).

It would be naïve to assume that by simply addressing the issues around information that it would solve the issues with MAE and the efficiency challenges with the MAP. However, by addressing the issues with information, it provides the foundation for addressing the surround challenges such as timeliness of medications being available, changing medication orders, impact of procedures, work interruptions, etc. To be clear, there are many factors that affect the MAP beyond information, however, by treating MAP as a dynamic information system, the MAP should be able to adapt to change from other systems based on the input of Just-in-time information (i.e. Kanban). The key to providing benefit to the nurse and developing a truly functional system is to decrease the nurses' workload, make it easy to use and to have most of the operations transparent.

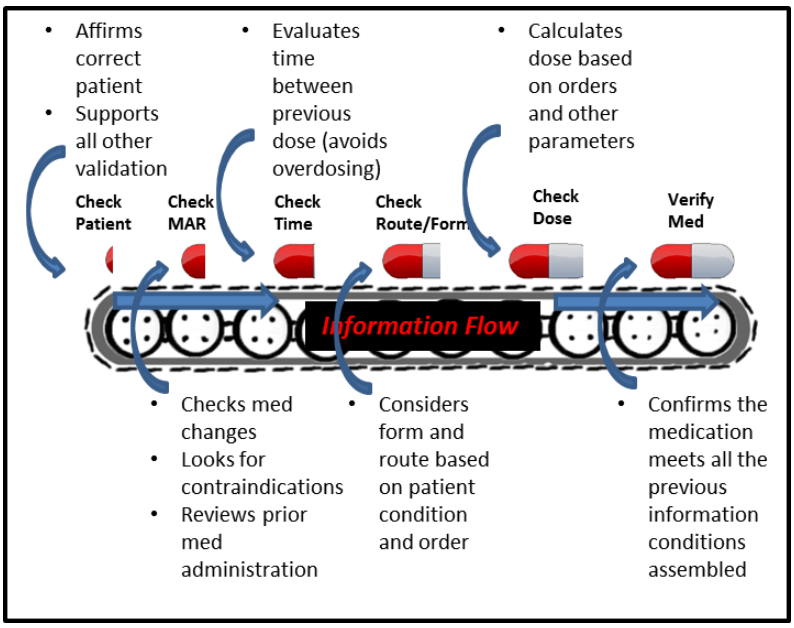


Figure 2.32: Infographic of the MAP and related information flow

Complex Adaptive Systems

Complex Adaptive Systems (CAS) have direct applicability to the study of processes and systems in healthcare and are a core concept in ABMs. CAS are part of the broader field of study of complexity theory also known as complexity science. Complexity science is an approach to studying systems representing a collection of concepts, tools and methods that takes advantage of combining a spectrum of disciplines including social sciences, mathematics, computer science, and systems engineering[379].

While the underpinnings of the study of complex systems go back many years, the coalescing of the concept of complex systems occurred in the 1980s-1990s. The Santa Fe Institute, an organization that focuses on the study of complex systems defines complex systems and complex adaptive systems as follows[35].

> *Complex system*
>
> A system composed of a large number of interacting components, without central control, whose emergent ``global'' behavior---described in terms of dynamics, information processing, and/or adaptation---is more complex than can be explained or predicted from understanding the sum of the behavior of the individual components.
>
> *Complex adaptive system*
>
> A complex, nonlinear, interactive system which has the ability to adapt to a changing environment. Such systems are characterized by the potential for the emergence of new structure with new properties. Complex adaptive systems (CASs) can evolve by random mutation, self-organization, the transformation of their internal models of the environment, and natural selection. Examples include living organisms, the

[35] https://www.santafe.edu/engage/learn/resources/complexity-glossary (Date Accessed: June 23, 2018)

nervous system, the immune system, the economy, corporations, and societies. In a CAS, semi-autonomous agents interact according to certain rules, evolving to maximize some measure like fitness to their environment.

Characteristics of CAS, not surprisingly, align with ABMs: ABMs are a software embodiment of CAS. The characteristics of CAS are noted below.

- Emergence – The enacting of lo-level rules among agents to create entirely new properties and behaviors with no single entity directing and no way to completely foresee the new properties from what is known of the constituents alone[380, 381].
- Co-evolution – The phenomena of the interplay of mutual changes of entities within the system. The environment and entities interact and influence behavior and change with the intent for achieving best fit.
- Connectivity – Entities within a CAS have the ability to share messaging, information, interactions through connections that can be permanent or temporary.
- Nested Systems – Systems can be embedded within other systems either on a hierarchical basis or on a non-hierarchical basis. This is often referred to as a system of systems
- Simple rules – Elements within a CAS often follow simple rules for behavior such as birds maintaining a certain distance during flocking behavior.
- Sub-optimal – CAS can work towards a common purpose, but, dynamics and competing needs thwart ideally optimized performance.
- Requisite variety – By its nature a CAS is made of individual entities with unique variation at the subsystem or system level.
- Self-Organizing – Entities may coordinate as a group or subgroups for example flocking behavior.
- Edge of chaos – System exists in a range of conditions ranging from chaos to equilibrium as defined by the level of order in the system, and is a "region of bounded instability that engenders a constant dynamic interplay between order and disorder"[382].

Many have considered healthcare as a CAS. Begun generally explores the application of CAS to healthcare and highlights the similarities of the properties of CAS, particularly the consideration of emergence and the structure of healthcare as represented by networks [383]. Rouse takes another approach by considering incentives and information as the two core elements of healthcare as a CAS. He makes the points that hierarchical decomposition does not work for CAS and that complex adaptive systems self-organize, and as a result an organizational design cannot be imposed. This supports the property of co-evolution of CAS [384]. Sturmberg et.al. provides a visualization of CAS in healthcare as a vortex to understand the CAS nature of healthcare systems and to illustrate the interaction of the system-of systems that characterizes healthcare [385].

CAS have been considered with respect to nursing. Chaffee and McNeill consider CAS at a broad level and constructs a metaparadigm view of nursing as a CAS. They start at the highest level of nursing and parse the system down to the down to basic subsystem level of nursing [386]. Clancy, Effkin and Pesut considers the applications of complex systems theory in nursing education, research and practice and explores areas of application of CAS n the environment of nursing care [387].

CAS has been used at various levels of application to understand operations and performance by nurses. The prevention of surgical site infection by using a CAS approach was studied by Sitterding [388]. A study of ED operations found that a CAS approach was beneficial in understanding the delivery of integrated care because "the processes of categorization, diagnosis and discharge are primarily about the linkages between services, and the communication and negotiation required to enact those linkages, however imperfectly they occur in practice" [389]. CAS was applied to the challenge of nurses in daily documentation tasks. This study reports 13% to 28% of total nurse shift time is spent documenting. The authors studied the documentation of nursing care a CAS approach and then analyzed the benefit of using a standardized nursing language. A case study of a nursing improves nurse and system performance in care planning by adopting a standardized nursing language was performed [390].

A brief overview of CAS in nursing and an associated case study cautions that CAS should be used cautiously and not overextended beyond reasonable limits and encourages considering CAS at local levels (e.g. wards and teams) as opposed to large systems such as a National Health System [391]. While there are some merits to the author's point, they seem to be missing the ability of systems engineering to accommodate broader and more generalized systems via formal systems engineering tools and approaches such as systems dynamics.

While references are made to medication administration being complex and that it is a complex system few specific references were identified that explores the medication administration process as a complex adaptive system. The under reporting or lack of reporting of medication administration errors was identified as a highly complex responsibility in separate studies by Lane and Wakefield [392, 393]. Patterson and Cook describe medication in the acute care setting as a complex system [33], and references the complex interconnected nature of the medication administration process [394]. The behavior of nurses during the MAP and their use of barcoding was briefly considered by Matlow [395]. Ebright used medication administration and nurse decision making as an example of a CAS [396].

Much has been written on CAS in healthcare. The literature appears to remain largely at the conceptual level of considering CAS and systems engineering methodologies to the study of healthcare. As noted earlier there has been some research done on using approaches like systems dynamics and ABM to model the healthcare.

Chapter 3
Methods and Approach

Overview

There are two fundamental parts to this research, a clinical trial, or case study measuring the effect of JIT information on the occurrence of medication administration error in a simulated environment and developing an agent-based computer simulation to determine if such a simulation can effectively model the effect of injecting information into the medication administration process in an attempt to mitigate Medication Administration error.

There are four components to the clinical trial. The first was the use of the Health Innovation Technology Simulation (HITS) Laboratory at the University of Tennessee- Knoxville. The second was the development of a teaching simulation scenario using the HITS laboratory equipment and facilities. The third was engaging student nurses as research subjects. The forth was the development of a smartphone app that would provide information to the student nurses while they were student nurses.

Student nurses were selected as an element of this study for a number of reasons:

- Use of student nurses provided a readily available pool of interested research subjects.
- They were a relatively uniform group in terms of education and nursing experience at approximately the same point in their academic progression.
- As part of their normal curriculum, student nurses participate in training simulations at the HITS lab. Treating this as a training simulation fit easily into their coursework and did not require extra time or work for the students.
- They have significant familiarity with the use of a smartphone as source for information and were amenable to using the technology.
- The role of the student was as a mechanism to assess the performance of JIT information on medication error occurrence.

The HITS lab provided a controlled environment for running the training simulations, as a result, extraneous events that would have occurred in an actual clinical environment were not a concern. The patient (mannequin) was consistent in that the behavior, condition and other features were the same among each simulation run. The room and environment (equipment, supplies, EMR/MAR interface, etc.) were the same for each simulation run.

Subjects

Subjects were comprised of University of Tennessee senior year nursing students participating in standard simulation training as part of their required curriculum. Nursing students go through a number of training simulations using instrumented mannequins. There were 93 nursing students used in the study over the course of two semesters. These students comprise the entire class for each semester; as such there are no other selection criteria for the participant other than being enrolled in the class. In other words, participation in the study was open to all students within the class participating in the simulation. The study was designed to use the entire complement of students from the class, approximately 45 students to be part of the study in the fall semester of 2015 and a similar number in the spring semester of 2016. The students in the fall semester served as the control group. These students will participate in the normal training simulation without using the smartphone app. Their performance was observed during their simulation class and the key performance indicators noted. The student nurses participating in the spring semester trial used their personal smart phones, to provide real-time information based on the student's query via the app that was developed for this study. The total time for each student to participate in the simulation was nominally between 6 and 15 minutes. The students using the device had an additional 20-30-minute tutorial and familiarization prior to the simulation in order to learn how to use the JIT.

The University of Tennessee Institutional Review Board was engaged and a human research proposal was submitted and approved to use nursing students as research subjects for this part of research. All protocols and guidance suggested by the IRB were followed and informed consent was obtained by each student that participated in the study. No personal information, regarding the research subjects, was required as part of this

study nor was any of the performance information linked to individual students as it relates to this study. The option on whether they do or do not want to participate in this study prior to the start of the simulation was provided to the students and a briefing on the study was also be provided. Compensation will not be provided to the students as part of the study nor will it have an impact on their grade.

The selection of participants was equitable because:

- All students within the class were invited to participate
- The control and experimental participants are separated by semesters thus making both groups uniform
- The experience and education level of the student nurses is approximately the same limiting concern for biased performance

Clinical Trial/Case Study Methods and Procedures

Student nurses perform a number of training simulations using instrumented mannequins as part of their normal curriculum. As noted previously, we used senior of Tennessee University nursing students who were in a class (N404) where simulated training was part of the course curriculum. The instructors prepared and observed the students in this study in the same way that they normally would. They briefed the students on the scenario for the simulation and provided them relevant background information that prepared them with background facts and information. A simulation scenario that provides the student the various options in decision making and care execution while using JIT information was developed by the CON in conjunction with the researcher to support this study. This scenario is typical of other scenarios used by the simulation facility. No personal information of students was collected and all performance information was de-identified.

Two groups were decided upon: the control group, and the intervention group. The control group (fall semester 2015 nursing students) went through the simulation but did not use the JIT app. The intervention group (spring semester 2016) went through the simulation using the app via their smartphones, with each member of the group participating in the simulation. The experimental group was broken into two separate groups; the Pre-training intervention group and the Post-training intervention group. The purpose of the Pre and Post-training subgroups was for the ability to control the familiarity, or lack thereof, of using the information app.

Both the pre-training and Post-training intervention groups were provided a tutorial for the app which included a 10-15-minute demo done by the researcher, followed by the students using the devices to familiarize themselves with the functions for another 10-15 minutes. In addition, the Post-training group was asked to complete a worksheet that had questions requiring use of the app. Both the demo and worksheet used a training app that looked identical to the simulation app but had a different patient with different information such as medications, lab values, contraindications, history, and so on.

The app was designed to provide similar information as the other resources that are available to the students in the simulation. The difference between the app and the EMR/MAR DocuCare based resource available via the desktop system in the patient room, is that the app provides the information in a concise and simplified manner while the EMR/MAR is more involved[36]. It also highlights key information that is temporally germane to the nurses' decision-making process consistent with the concept of JIT information.

Two to three students participated in each scenario (i.e. each simulation is done as a small group). All student performances were observed at the individual level and their performance cataloged. All data was de-identified at the end of the scenario by removing any identifiable characteristics. Data was then collected via researcher notes and transferred to a computer. The Key Performance Indicators are based on the decision tree for the scenario and are as follows:

[36] The EMR/MAR DocuCare system is a robust and complex medical records system with a comprehensive compilation of patient information and reference material similar to full EMR/MAR system found in hospital settings

- Total Errors committed
- Medication administered correctly
- Specific errors committed
- Time for simulation completion
- Use of External information resources (e.g. DocuCare –A simulated medical records system provided as part of the simulation system, available drug reference manuals, medication labels)
- Utilization of the JIT smartphone app

For the purposes of evaluation errors defined as not executing the key elements of the MAP process including:

- Failure in checking the MAR correctly
- Failure in checking the medication type correctly
- Failure in checking the patient ID
- Failure to validate the correct route
- Failure in checking the dosage correctly
- Incorrect checking the time for medication administration
- In appropriate administration of medication

Scenario Development Methodology

The College of Nursing faculty and HITS staff developed a specific simulation scenario for this research (see appendix 2 for staff background and experience). The faculty, staff and researcher developed the key objectives that met the needs of the training and research aspects for both the students and the researcher. These objectives included a scenario with key aspects of the MAP; ability to inject information as the intervention into the scenario; ability to conduct the simulation with the students in 15 minutes or less; ensured repeatability and a controlled environment; met the skills and capabilities of the students; provided a realistic experience for the students; provided a means to measure subject performance objectively relative to the MAP; errors could be scripted in to the scenario to assess the subject's performance and critical thinking.

Based on the experience and judgement of the faculty and HITS staff, a pediatric simulation that met all of the study and class objectives was developed. A pediatric medication administration scenario was developed because it required the need for accurate dose calculation; limited the need for nurse-patient information; allowed a surrogate information source (the child's mother) to help guide the execution of the simulation; and realistic potential medication administration errors could be crafted into the scenario with limited medications listed in the MAR, and; the scenario created conditions that could lead to typical medication administration errors including dose calculation errors, wrong medication, not checking the patient records or MAR, wrong medication route and not checking the patient identification.

The HITS staff has had specific training and extensive experience in developing training simulation using the mannequins. They use a standardized approach to develop the scenarios that includes the needs of the faculty teaching the course, the objectives of the course curricula and other factors such as the research objectives of this portion of the research. Appendix 2 provides the developmental outline of the training scenario.

The key aspect of this training simulation revolves around the dosing of acetaminophen, which is susceptible to overdosing and particularly toxic in chronic overdosing.

Scenario Description

The training simulation scenario consisted of a six-year-old 22kg pediatric patient named Frank that arrived at the emergency department (ED) of a local hospital. The following excerpt from the final scenario documentation highlights the key points. This briefing is between a nurse going off-shift and the nurse coming on shift that will be caring for the patient, Frank.

> Frank is 6 y/o male who was brought in yesterday to the ED by Mom and Dad after falling off the trampoline at home three days ago. His parents did not realize the severity of the injury and thought he just had a bad bruise. They treated his injury with elevation, ice and Tylenol for pain. X-ray revealed a

right tibia/fibula fracture. Pt had surgery yesterday to repair the fracture. Frank has a 22G angiocath in his right AC with D5 1/2NS with 20KCL infusing at 55 ml/hr. He has been getting scheduled morphine q2 hours and Tylenol q4hr PRN for breakthrough pain. Frank is complaining of pain. His mom just called right before report and I have not had a chance to assess his pain yet. I gave him his morphine an hour ago but he hasn't had Tylenol in 6 hours. Labs were drawn last night and they are in the computer but I haven't look at them yet.

The key points of this scenario background are that:

- Frank is a six-year old pediatric patient
- He has been given Tylenol (acetaminophen or ACA) by his parents for pain prior to arriving at the ED
- He has just had surgery to repair the broken bones in his lower right leg
- He is on medications to manage pain including Lortab every two hours and Tylenol every four hours
- Frank received his Lortab (morphine and acetaminophen (ACA) combination) dose an hour ago but has not received his Tylenol
- Frank's pain level is unknown at the time of this briefing, this will determine if pain medication will be needed
- Recent laboratory results are available but have not yet been reviewed

The students read the brief history above at the start of the simulation. There is a standard "Mom" present played by one of the HITS staff or CON faculty. The mom's interactions with the students are scripted for consistency. The mom will inform the students that she had been giving the patient Tylenol in a largely unconstrained fashion while at home just prior to entry into the hospital. That is, she had been significantly overdosing the child.
If the student(s) query the MAR (DocuCare), they will find that the patient has been prescribed Lortab, along with acetaminophen for breakthrough pain. An anti-emetic was also ordered but the order was discontinued. If the student does a correct dosing calculation, they will find that the physician has prescribed an over-dose of acetaminophen based on use of an incorrect weight. Additionally, if the student checks the laboratory results for the patient, they will find laboratory test values that indicate overdosing from acetaminophen.

The simulation scenario is complex and has a variety of challenging facets:

- An overdose amount of acetaminophen was prescribed by the physician based on a wrong weight at the time the medication was prescribed.
- Two medications have the same active substance (Lortab and acetaminophen) creating an instance for exceeding the total allowable daily dose of acetaminophen.
- The patient's laboratory values indicate an adverse drug event – elevated hepatic laboratory results indicate liver damage possibly due to acetaminophen toxicity.
- The "mom" infers she has been giving the child overdose amounts of acetaminophen after the injury and before coming to the hospital.
- The patient is complaining of symptoms that indicates a drug reaction (nausea), a possible confounding situation exists because the child could also be experiencing nausea due to anesthesia from a recent surgery, however the nausea related to this should have abated.
- The nurse should do a weight-based medication dose calculation because this is a pediatric patient.
- The situation can proceed down a large number of different pathways, having a decision tree of several hundreds of nodes.

As the student progresses with the scenario, they will find that the patient has moderate to significant pain from the surgery. The mom will agitate to have the patient get medication quickly since the child is crying and in pain. As noted in the scenario detail in appendix 2, the students have an up to date EMR/MAR with all of the patient's vital signs, correct body weight, medication orders, and medication information. A bound version of a drug reference is also available. There is a bedside computer with a hand-held scanner for validating patient ID, along with scanning in medications that are being administered.
The patient room set up matches that of a typical hospital medical/surgical ward. One exception is that there is a screen at one end of the room that serves as a divider to simulate a medication prep area. This area has the

material needed to prepare medication doses and includes cups, syringes, and med cups or a bottle of Tylenol syrup, Tylenol caplets and ibuprofen syrup. The medication preparation area has a computer for accessing the patient records and MAR, a calculator, and medication reference manuals. The patient room shown in Figure 3. 1 has multiple video cameras positioned throughout the room. These cameras provide the ability to visually monitor the execution of the scenario from multiple positions within the room. The rooms also have microphones to allow observers to listen to the simulation.
The patient is an adolescent mannequin capable of representing a six-year-old male (Figure 3. 2). The mannequin is described by the manufacturer as being "designed for skill and scenario-based training and a complete range of pediatric scenarios" [37]. While the focus of this scenario is not to use the many functions of this device, the students may take vital signs. The environment is set up so that the patient can vocalize pain and speak. The instructor in the HITS lab control center provides the vocalization of the patient.

The researcher and HITS staff monitor the execution from the control room (Figure 3. 3). As depicted in the associated image (Figure 3.3), the control center provides control of the mannequin, video cameras in the patient room, the patient monitors, access and updating of the EMR system. Observers can watch the execution of the simulation unobtrusively, as well as listen via in-room microphones.

The researcher viewed each of the simulations from the control room. The simulations were video recorded to allow follow-up review.

Figure 3. 1: Photos of patient room

[37] Laerdal mannequin description: https://www.laerdal.com/us/products/simulation-training/nursing/nursing-kid/

Figure 3. 2: Photo of Frank, instrumented pediatric mannequin

Figure 3. 3: Photo of HITS control room used during performance of training simulations

Figure 3. 4: Student nurses using app during training scenario

Execution of Training Scenario

At the beginning of the semester, each group of students/test subjects was briefed on the research project approximately one month before the simulation at the end of the scheduled class time. The briefing covered a general description of the scope and purpose of the research, they were offered an opportunity to participate in the research and provided a copy of the IRB consent form to sign should they be willing to participate in the study.

Prior to the simulation training event, the researcher met with the instructor and simulation staff to review the final simulation scenario and coordinate the pre-simulation instructions, and to plan for the simulation event and post-simulation follow-up. The pre-simulation included instruction by the simulation staff to the students which included advising the students not to discuss the simulation event with their classmates in order to ensure the education value of the simulation was not comprised and did not affect the integrity of the data generated from the research. It included a high-level overview of the simulation avoiding discussion of the clinical and procedural skills required. A discussion of the research would be reiterated by the researcher, and students that had not signed the consent form were provided an opportunity to participate in the research and sign the consent form. The students were divided into groups by the instructor based in part on the student's interest in participating in the research. That is, students who desired not to participate would be placed into the same group or multiple groups depending on the number of students not participating in order to avoid potential conflict. Participating students would also be broken up into groups ranging in size from two to three as selected by the HITS faculty.

On the day of the simulation training, just prior to the start of the simulations, the instructor provided a high level over view of the simulation event without providing detail on the actual scenario. Specific details of the scenario were not discussed.

Immediately upon the completion of the scenario, as determined by the faculty, the students are debriefed as a group: this is considered an integral part of the training environment. The room used for the debriefing was a small exam room close to the patient's room. The researcher observed the debriefing and was able to ask follow-up questions specific to the research at the end of the simulation debrief.

The course of the scenario can follow a number of different paths and associated outcomes similar to the decision tree in appendix 8. These paths can range from the nurses simply dispensing the medication per the physician order, to not dispensing the medication and calling the physician because of the high hepatic laboratory values. As in a real-world situation, there are multiple approaches that lead to correct or incorrect outcomes. From a training scenario perspective, the nurse would have observed the errors built into the scenario, specifically the incorrect dose, the multiple medications with acetaminophen and the high laboratory values, and would then contact the physician, and would have provided correct dosing information to the mom.

The use of the JIT app is intended to determine if providing information in a fashion that could be considered easier to assimilate and in a specific timeframe that it was optimum for its purpose and would reduce the occurrence of errors. To this end, we are not measuring optimal outcomes, rather, measuring whether or not we decrease the occurrence of errors as measured by app usage and the five rights of medication administration.

Facilities and Equipment

As part of their education and training at the University of Tennessee College of Nursing (CON), student nurses participate in a number of training simulations to evaluate and improve their skills. These simulations use instrumented, life-like patient care mannequins coupled with control computers that can modify a wide variety of parameters including physiologic variables, sound, physical response and manipulation. The simulations are conducted at the Health Innovation and Technology Simulation (HITS) facility on campus at the University of Tennessee (http://tntoday.utk.edu/2014/03/27/nursing-enngineering-health-simulation-lab/).

The simulations take place in a variety of rooms configured as hospital rooms within the HITS lab. These rooms are outfitted with a complete array of hospital furniture and equipment. The faculty selects the room based upon the requirements of the selected scenario. The rooms also have video cameras that provide the faculty a means for unobtrusive observation of the students during the simulation along with two-way audio for listening to the students as well as for faculty to provide direction. The medical equipment, mannequin and video feeds are linked

to a separate central observation room apart from the hospital rooms, where the faculty controls the parameters of the scenario. The researcher observed the simulations from this control room.

App description

The app was specifically designed to exhibit the features of JIT information. The design of the app went through multiple iterations to ensure ease of use and the optimal visualization of the information. The design criteria for the app is found in Table 3. 1.

The University of Tennessee College of Communications and Information was used to help with the final design of the app format. Their support was instrumental in meeting the design objectives and ensuring optimal usability of the app.

Table 3. 1: Criteria for smartphone Just-in-Time information app

Design Criteria	**Design Approach**
Easy to read	Font size and screen layout optimized, colors used to indicate crucial information
Easy ergonomics for screen manipulation	Pages accessible via swipe or buttons at the bottom
Minimal number of screens	Limited to three screens that scroll up or down and limited to two pages
Succinct presentation of information	Highlighted banners or colors to indicate important information. Only the most recent information or changes are presented
Simplified calculation of medication doses	Dose calculators specific to the medication ordered, with patient information (e.g. weight) already entered
Easy access	Use of a QR code to access the app
Rapid access to medication information and MAR	Specific screens for each of the primary areas: patient encounter, MAR and EMR/Lab
Provides some function as a decision support tool	Highlighted lab information and suggestions if results are out of normal range

While the JIT app plays an important role in assessing what role, if any, JIT information plays in reducing medication administration error, the goal of this research is not the development of the app as a tool. This app serves simply as a mechanism to deliver the information in a way that is intended to approximate JIT information. The app was evaluated by the CON HITS faculty and staff to assess its functionality, ensure the information in the MAR and EMR and that it had appropriate utility for the intended purpose. The JIT app is a web-based application. The screens were constructed as web pages. Since the functionality of the app is an information source and not a tool to be used in an actual clinical setting, it does not have direct links into the DocuCare system. That is to say, the JIT app is a virtual shell that provides static displays of information, as well as, a means to do medication dose calculations; it is not tied to any information system to allow live updates (see appendix 4-5).

Those student nurses participating in the intervention group were asked to download a QR reader app to allow quick access to the JIT app. The QR reader interprets the QR code, which is the JIT app webpage link hosted on an ISE server.

The QR code was on the patient's wrist band hospital ID, as well as on the medication preparation table in the patient's room. The nurse simply had to scan the QR code and the JIT app with all of the JIT information for that patient would load automatically.

Data Collection and Assimilation

The data to be collected during the trials was determined by the evaluation of the available research on the study of MAE, the training scenario design and guidance by the CON faculty. Allowance was also made to identify emergent data that arose during execution of the trial. Data includes a control group and experimental/intervention/response group. The experimental group used the JIT app (Figure 3. 4) to access key information while performing the scenario.

The data to be collected prior to beginning the trials included, the occurrence/non-occurrence of events principally each of the five rights, use of the MAR, observed near misses, use of the MAE app.

Population and Sample Size

There was a total of 38 groups for both semesters. Eighteen groups were from the first semester and 20 from the second semester. The first semester served as the control group and the second semester as the treatment group. The treatment group was divided further into the training group and the experimental group with 11 groups in the training cohort and 9 groups in the experimental cohort. A retrospective power analysis was done to confirm appropriate sample sizes using Minitab 18. A conservative estimated standard deviation of 1 (calculated sample standard deviation was 0.4) was used along with a difference of 1; a sample size for the cohorts of 8 was calculated with a power of 0.81. For comparison a cohort size of 11 is required to reach a 0.90 power level.

Computer Simulation of MAP

The other component of the research effort was the development of a computer simulation that approximated the performance or likelihood of error by nurses during the MAP as measured by error occurrence and its potential moderation by the injection of information.

This research effort has constructed a computer model that simulates the medication administration process (MAP) performed by nurses in a hospital. The goal is to have the model reflect the interaction of nurse(s), medication(s) and patient(s). This simulation will consider the generation of potential errors and the effects of a possible intervention in the form of JIT information on mitigation of error occurrence.

Computer simulation and modeling has been performed on a broad array of healthcare topics ranging from disease diagnosis and management to nurse staffing models. Discrete event simulation, Markov models, Bayesian networks, agent-based models, decision trees, Monte Carlo simulations, artificial neural nets, and systems dynamics models are a representation of the various approaches used in healthcare computer simulation. Of course, there are hybrids and variations of these modeling approaches e.g. hidden Markov models, Monte Carlo/Markov models, agent based/Bayesian models, and others.

For the purposes of our efforts, computer simulation and modeling will be used interchangeably to refer to emulating the activities and behaviors of the administration of medication with nurses, mediations and patients along with their consequent interactions and resultant outcomes based on use of different states or changing operating conditions.

Each simulation approach has its respective application niche based on several factors

- The type of data available
- The desired end-result or objective of the model
- The attributes of the system being modeled
- The computer modeling approach that best fits the aspects of medication administration

As a result, the features of the data, and what is trying to be accomplished, drove the final type of modeling approach selected.

Computer Model Functional Requirements

The functional requirements for this computer simulation model are a direct function of the aspects and considerations of the MAP process. The available literature on the structure and function of the MAP process, as well as, the clinical study performed as part of this research, help to shape the following functional requirements of the model.

- Results and insights from the earlier clinical trial influenced the type of model based on the outcome of the trial, the general process flow and outcomes. A key conclusion of the clinical aspect of the research was that the order of the sequence of the events was relatively constant and process steps appeared to be generally independent of one another.
- The model should resemble the major aspects of the MAP process and the interaction of the entities being modeled with their environment.
- The various possible entities and their interactions could lead to a particularly complex model. The goal will be to limit the complexity of the model to the greatest extent possible in order to focus on the major aspects of the MAP process.
- While the sequence of events in the MAP can in practice occur in any sequence, a sequence that is most representative of the standard approach, as described in the literature and clinical guidelines, will be used in order to reduce model complexity.
- It is possible that the outcomes in any given process step could influence the activity in another MAP step; this phenomenon has not been found to be addressed in the literature and will not be considered in this model. The outcome of a process step is assumed to be independent of other process steps.
- The medication administration process is treated as essentially a discrete time random process in the model.
- It is assumed that the process is not recursive, i.e. the nurse would not backtrack in the process of delivering a medication.
- The decisions/actions within the MAP are assumed to be binary (e.g. yes/no, perform/don't perform).
- The process is at a minimum a function of the nurse's behavior, but could also include the medication, patient and environmental elements.
- Each nurse is an individual entity with their own set of unique attributes.
- Similar to nurses, medications and patients are also unique entities with individual attributes.
- Emergent behavior, while not expressly designed into the system, is an acceptable outcome.
- Variability in the number of entities (nurses, patients, medications) and/or their interactions is important.
- The interaction between agents representing nurses and patients is dynamic and random, the interaction between patients and their medications is static.
- The model is dynamic in the sense that states can change and influence outcomes in other areas.
- The focus of the modeling effort is on the MAP process, specifically the actions of the nurse. The medication and patient entities relevance are a function of how they affect nurse performance.
- Measures of interest will have an overall likelihood of error occurrence calculated; the influence of JIT information on error occurrence, and the effect of nurse attributes (e.g. experience) on error occurrence.
- Steps in the MAP process can vary independently, simulating the effects of other independent influences on each part of the MAP process.
- The MAP process combined with its actual method implementation has attributes of process flow, network, stochastic, and deterministic activities.
- The number of patients per nurse and the number of medications per patient can vary between simulations.
- Medications attributes vary in type, difficulty in administering medications and the relative hazard of the medication and may have an impact on the possible MAE rate.

Based on the attributes of the data and the MAP process, three modeling techniques have been considered along with their potential advantages and limitations as they relate to this effort.

Discrete Event Simulation

- Based on a series or sequence of events
- Assumes no change in the system between the events
- Entities (e.g. patients) may be given individual attributes
- Performs well for process flow models
- Accounts for use of resources
- May be discrete or stochastic
- More difficult to deal with changes within or among individual entities such as nurses

Bayesian Network

- Stochastic
- Explicit management of uncertainty/tradeoffs
- A variable is conditionally independent of its non-descendants given its parents (no memory)
- Singly connected directed acyclic graph (DAG) (no feedback)
- Incorporates prior knowledge
- Only as good as the prior knowledge
- Computationally expensive
- Requires prior knowledge for each event
- Can cope with incomplete data sources
- Belief updates based on receipt of new information
- Provides a theoretical framework to incorporate expert knowledge (as prior information)
- Directly applicable to decision theory
- Not dynamic
- Potential ubiquity of model structures
- Difficult to describe individual behavior

Agent Based Model (ABM)

- Stochastic/deterministic
- Can be combined readily with other modeling approaches (e.g. equation-based, Bayesian, Markov, Systems Dynamics, etc.)
- Models at the elemental or individual level
- Provides insight into causes of emergent phenomena
- Generally based on the changes of an entity's state
- Provides more natural description of the process
- Possible to model agents making decisions with incomplete knowledge and information
- Easily accommodates complex interaction among model elements (agents)
- Accommodates nonlinear behavior, rule-based, "coupling" and discontinuity
- Allows for direct interaction of model elements
- Individual behaviors can exhibit, memory, path-dependence, non-Markovian behavior, learning and adaptation
- Well suited for activity -based modeling
- Incorporates expert judgment for validation and calibration
- Supports heterogeneity of elements as opposed to aggregate models

At the highest level, the model will emulate the performance of the nurse during the MAP. As part of this consideration it is contemplated that the model will include factors that influence nurse performance during the medication process including: interruptions, experience, adherence to procedures, dose calculation skills, medication type, fatigue, work load, shift change, clinical or procedural errors in medication administration steps. Review of the data, observation of the MAP scenarios (student nurse simulation), and likelihood of occurrence based on observation and the literature and model complexity will provide the criteria for down selecting the error factors to a more tractable subset of factors to be used in the model.

Based on the attributes of the data and MAP, ABM was ultimately selected to be the most suitable modeling approach. Several modeling approaches were considered in the early stages of model development in order to evaluate the best fit of the simulation approach with the data and desired functions of the model. ABM was selected because of the fit of the operational characteristics of ABM with the actual MAP process and the goals of the research. The notional comparative assessment, provided in Table 3. 2, contrasts the characteristics of modeling approaches potentially suitable for the nurse MAP process modelling effort.

The considerations for which ABM are appropriate include[38]:

- When there are decisions and behaviors that can be defined discretely (with boundaries)
- When it is important that agents adapt and change their behaviors
- When it is important that agents learn and engage in dynamic strategic behaviors
- When it is important that agents have a dynamic relationship with other agents, and agent relationships form and dissolve
- When it is important that agents form organizations, adaptation and learning at the organization level
- When it is important that agents have a spatial component to their behaviors and interactions
- When the past is no predictor of the future
- When scaling-up to arbitrary levels is important
- When process structural change needs to be a result of the model, rather than a model input

Table 3. 2: Comparison of computer modeling simulation approaches

H: High, M: Medium, L: Low	**Agent Based**	**Bayesian Network**	**Systems Dynamics**	**Discrete Event**
Dynamic	H	H	H	M
Low level of abstraction	H	M	L	H
Flexibility	H	M	M	M
Multiple environments	H	M	H	M
Process based	H	M	L	H
Scalability	H	L	H	M
Multiple autonomous entity types	H	L	L	L
Ease of application	H	L	M	H
Effective for moderately complex models	H	M	M	H

[38] (Macal, L., North, M., Tutorial on Agent-Based Modeling and Simulations Part 2: How to Model with Agents, Proceedings of the 2006 Winter Simulation Conference)

ABM Model Design and Construction

The key elements of an ABM include:

- Agents
- Time
- Environment
- Rules
- Properties
- States

Agents

Three agents were defined for the model: nurses, patients and medications. Other agent types were considered as well, such as information, other health providers, and policies. While adding these certainly would have contributed to the overall complexity and might have added to the fidelity of the model, the decision was made to limit the number of agent types in order to have a better understanding of the functioning of the primary agent types.

These agents interact either directly or indirectly among other agent types based on their respective functions (rules) and properties (attributes). That is nurses do not interact with nor are they influenced by other nurse agents but do interact with patients and/or medications. This is the same for patient-patient interactions and medication-medication agent interactions.

Agents are assigned attributes to help determine how they function (Table 3. 3). For this model, the types of attributes are set as part of the structure of the model. However, the value or degree of the impact that the attribute can change as the model runs depending on the function of the attribute. For example, the nurse starts a shift without any level of fatigue; as the shift progresses, fatigue sets in and diminishes performance for the rest of the MAP processes.

Agents are connected during run-time via a network-type of arrangement to the other agent-types. This is detailed later and is portrayed graphically in Figure 3.5.

Nurse Agents

The agent type, nurses, are the most complex agents and play the central role in the model. The attributes determine the unique characteristics of an agent and can influence how they function. Table 3. 4 highlights a nurse's attributes.

The function of the nurse, quite simply, is to administer medications. The nurse agent is connected to a set of patient agents in what resembles a network as represented in Figure 3. 5. A nurse connects randomly to a set of 2-12 patients. The literature indicates the typical nurse to patient ratio is 5-7 patients to nurse in a medical-surgical hospital ward. This number can get as high as 12-14 or as low as 1-2 patients per nurse depending on a wide variety of factors.

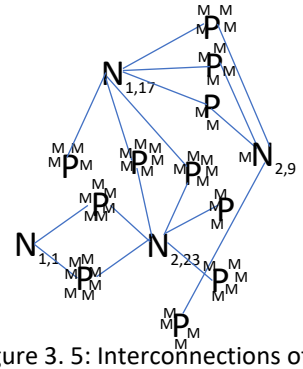
Nurses are randomly divided into two roughly equal groups to resemble the way hospitals structure their staffing. Hospitals have devised various approaches for nurse shift staffing, an approach simulating two, 12-hour shifts were used to simplify programming. A more conceptually accurate description of how the model handles the period of time that the nurses administer medication would be termed the MAP time period instead of shift. The approach of how shift time is handled in the modeled is discussed in more detail in the Time section.

The nurse-patient connections are reassigned randomly at the end of each MAP time period. At the end of the MAP time period, the connections between any given nurse agent and the currently connected patients are terminated. New connections between this nurse and the population of patients are reformed at the beginning of the next MAP time period. This approach approximates how a hospital would assign nurses during a shift. This approach also has the effect of removing potential statistical biases from having the same nurse attached to the same patient for the entirety of a simulation run.

Table 3. 3: Attributes used for ABM agents

Agent Attributes			
Nurse	Data type	Type	Description
Interruption	boolean	p	if the nurse has experienced an interruption while administering medication
Experience	experience	o	the level of nurse experience/education/capability
Shift	shift	o	the shift the nurse is assigned to
Fatigue	double	v	the impact of fatigue on a nurse
Patient Load	double	v	the impact of the number of patients assigned to a nurse
Medication Load	double	v	the impact of the number of patient's medications administered by a nurse
Patient	Data type	Type	Description
Medications per Patient	integer	p	the number of medications ordered for each patient
ADR (adverse drug reaction)	boolean	p	value for the reaction a patient has to a delivered medication
Patient medical state	patientmedicalstate	o	patient severity of illness/condition
Medication delivered	integer	p	the number of medications administered
Medications missed	integer	p	the number of medications missed
Medication	Data type	Type	Description
Medication difficulty	double	p	value that is associated with how hard it is to administer the medication, e.g. an IV vs a capsule
Medication severity	double	p	value associated with the hazard of the medication to the patient e.g. warfarin vs a vitamin
Medication delivered	boolean	p	indicates if the medication has been administered
Medication not delivered	boolean	p	indicates if the medication has not been delivered

Agent attributes p=parameter, v=variable, o=option list



The interaction between nurse, patient and medications resembles a network. Each nurse agent is connected to a range of patient (~2-10). Each patient is connected to an average of 4 medications. Agents can "communicate" and connections are reformed randomly at set times through model execution.

Figure 3. 5: Interconnections of nurse, patient and medication agents

Table 3. 4: Nurse agent characteristics

Nurse Attributes	Factor	Condition	Effect
Interruption	true/false	random, probability 53%	multiplier 0.95
Experience	novice, moderate, senior	25%, 50%, 25% to 10%, 70%, 30%	multiplier 0.95, 1.0, 1.05
Shift (MAP Time Period)	first/second	random assignment 50%	no effect
Fatigue	yes/no	med admin time > 50% of shift	multiplier 0.95
Patient Load	low/medium/high	<5, >=5 & <8, >=8	multiplier 1.1, 1.0, 0.95
Medication Load	low/medium/high	<=10, >10 & <=25, >25	multiplier 1.1, 1.0, 0.95

Nurse Agent Attributes

The nurse agent has six different attributes that define its behavior and propensity for causing a medication error as noted in Tables 3.4 and 3.5. The following provides background on the attributes for the selected computer modeling approach.

Interruption: A key factor in causing errors by nurses while administering medications. This attribute is either true (occurs) or false for each pass a nurse goes through the MAP process. An interruption has a likelihood of occurrence of 53% based on the literature. The effect of an interruption is to decrease the chance of successful medication administration by 5%. An interruption has the same effect for all nurse agents.

Experience: Is operationally defined as an amalgam of education, talent, work experience and training. It is intended to reflect the overall capability of a nurse to execute the intended task. There are three levels of nurse experience: novice, moderate and senior. The typical mix of this skill set is 25%, 50% and 25% for novice, moderate and senior experience levels respectively. While the literature has some conflicting information on the association of years of experience, education and training on the occurrence of medications errors, the general conclusion is that more of each of these factors tends to reduce overall MAE's. The error multipliers for each of these experience levels is 0.95, 1.0 and 1.05 for novice, moderate and senior respectively.

Shift (MAP time period): Nurse Agents are assigned to a shift at the beginning of the simulation and will stay in that shift for the duration of the simulation run. For this current version of the model, the shift does not have an influence on nurse behavior or performance. A shift, in the context of this model, is a programming construct to allow for the effect of some influence within a conceptual construct of a day. The term first or second does not necessarily imply a sequence, rather just a differentiator between sequential runs. The model period is from the perspective of the medication delivery period, for example 300 minutes. At the end of this medication delivery period the simulation will terminate the existing medication administration process and start a new one even if the nurse agents have not completed the delivery of medications. Process delays are built into the steps of the MAP process to influence the amount of time it takes the nurse agent to complete each pass through the process.

Fatigue: Is a physio-emotional state with a well-documented effect on decreasing human performance. The occurrence of fatigue in the model is a function of each nurse agent's time-state in the model. The onset of fatigue occurs at 50% of the MAP time period. While the literature discusses the effects of fatigue, information has not been found when fatigue occurs. The onset of fatigue was notionally set at half way through the MAP process in order to ensure an indication of its effect. In reviewing the associated literature, the negative impact of fatigue is copious, a quantitative specific measure of fatigue

on the nurse administration of medications is vacant. Error rates on overall rates were found and ranged from several percent to over 20% [397]. An impact of 0.95 (that is, a 5% decrease in performance) was selected to serve as an indicator for a decrease of performance.

Patient Load: The number of patients a nurse has in their care is defined as patient load and can be measured by the nurse-patient ratio. There is a clear correlation between nurse-patient ratio, nurse performance and medical error rates. That is as the number of nurse-patient ratio increases, nurse effectiveness deceases and error increases [398]. Many studies indicate this negative relationship, in reviewing them, a quantitative measure was not found. An impact of 0.95 was selected to serve as an indicator for a decrease of performance. The number of patients per nurse ranges from 2-12 with the typical range of 5-7 as established by law in a number of states. The number of patents per nurse is randomly assigned during each shift change in the model. This attribute also infers that having more patients creates additional workload for the nurse besides medication administration (e.g. charting, treatments, etc.).

Medication Load: This is another measure of a nurses' workload. As part of the design of the model it is possible that a nurse might have more than an average number of patients but less than the average number of medications. Similarly, they might have a smaller collection of patients with only several medications each. No specific literature has been identified on medication load and its effects on medication administration errors. However, some research exists on the effects of patient complexity and nurse workload on medication error [399, 400].

While the number of medications per patient generally reflects the average of what has been found in the literature, the actual number of medications should be viewed from a more conceptual perspective. That is, the consideration that there are low, medium and high amounts of medications per patient, which increases the workload of the nurse, is the important aspect, not what the actual amounts of the medications are. For the purposes of this model, the number of medications is used to set up the three groupings of medication load (low, medium, high).

Patient Agents

Patient agents or, simply, patients, serve the purpose of being the recipient of the nurse's actions during the MAP. When the nurse is in the process of administering medications, it is the patient that will ultimately be the agent that changes the state from the pre-administration to post-administration status; administration references the step of administering medication. The step of administration in the MAP process indicates that the patient has gone through the step of being able to receive a medication. The determination of whether they receive the medication is a uniform random distribution that is set as part of the model. In changing these states, the patient will either have or not have received a medication that was assigned to them not receiving the medication results in a missed dose. Once the patient is assigned this post-MAP state, it will revert back to the pre-MAP status waiting for their next medication

While not a central part of the model, a patient also demonstrates that ability to react to medications. These adverse drug reactions (ADR) are a function of the patient receiving a medication. The ADR state is built into this model for future applications.

Patient Agent Attributes

Medications per Patient: Each patient is randomly assigned a number of medications ranging from 1-9. The range is based on the typical range a patient might have ordered on a medical/surgical ward. The actual range is somewhat incidental to the purpose of the range which is to provide several categories that indicate the relative workload a nurse has based on the number of medications the nurse agent has to distribute. Recall that both patient load and number of medications will influence the overall likelihood of error based on the number of times a nurse traverses the MAP flow, including the increased impact of

fatigue by having a longer work period. The medication load was broken into three categories: low, 2-4 medications per patient; medium 5-7 medications, and; high 7-9 medications per patient. Each of the medication load categories is associated with a likelihood of error – or more accurately a likelihood of correctness of 1.1, 1.0 and 0.95 for medication loads low, medium and high respectively.

Adverse Drug Reaction (ADR): An ADR likelihood is calculated for each MAP revolution. This was added to the model as a conceptual demonstration of potential impact of a MAE. Some research has been done to estimate the likelihood of the occurrence of an ADR based on a MAE. This correlation is not straightforward and dependent on a large number of variables. Given this, the literature was reviewed and a simple algorithm was developed to estimate the occurrence of an ADR based on the probability of a MAE [401-403]. This relationship was developed by curve fitting the relationship of MAE to ADR's and deriving the associated line. This equation was then used in a function to compute the estimated likelihood of an ADR. The prediction is based on the following calculation:

$$ADR = -0.233* \text{ Likelihood Index}^2+0.7942*\text{Likelihood Index}+0.403$$

Likelihood Index[39] is the product of the error likelihoods of each of the elements of the MAP state chart. The ADR is a calculated probability based on the information that was derived from literature values. While this is worthy as a thought experiment and could have value as part of a simulation tool, this preliminary algorithm requires more development to ensure accuracy and applicability.
Patient Medical State: This attribute was included for future model development.
Medication Delivered: Medications are unique to each patient. The status of each medication having been delivered is tracked to build a medication administration profile for each individual patient. The model can run in various configurations to include a discrete probability of medication delivery set at 0.974 or a stochastic approach using a truncated beta distribution as detailed in Table 3. 5. The beta distribution is configured to emulate an extreme value event truncated at the upper end at 99% and a lower end of 50%. The shaping functions p (aka alpha), q (aka beta), shift and stretch of 0.999, 0.009, 0.0005 and .99 respectively provide a curve resembling Figure 3. 6.

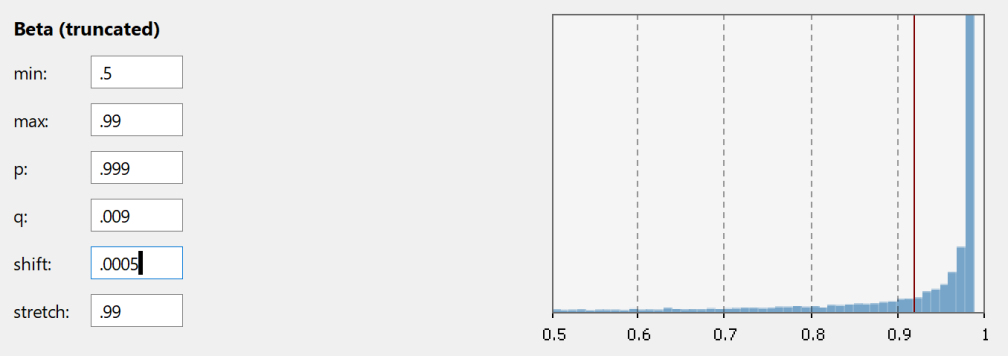


Figure 3. 6: CDF of beta distribution used for establishing variable values

[39] The Likelihood Index, also referred to as statsCalcP is a composite probability that is the product of the individual probabilities of each of the MAP process steps and the probability modifiers from the agent attributes

Table 3. 5: Patient agent description

Patient	Factor	Type	Effect
Medications per Patient	integer	random assignment between 2 through 3 categories: low, medium, high with 1.1, 1.0, 0.95 multiplier respectively	influences nurse agent medication load
ADR (adverse drug reaction)	True/False	probability of 0.01	provides notional indication of MAE occurrence
Patient medical state	good, fair, serious, critical	random assignment based on normal distribution	no effect - future application

Medications Missed: It is possible for medications to go through the MAP cycle and not be administered to the patient. These missed doses have a likelihood of 1.0 - Medication Delivered. The beta distribution was selected because it is particular suitable for modeling the random behavior of proportions and percentages. It has found application in modeling the probability of success or failure of an event. It has been described as a distribution that is suitable for modeling the probability of probabilities. It is a very flexible distribution allowing great degree of flexibility in establishing the shape of the probability density function (PDF), as was done for this study. In this application the PDF was given the shape of a curve similar to and extreme value function given the nature of the likelihood of error at each step of the MAP. In particular, the probability of an error at each step is relatively low (or the likelihood of performing the step correctly is quite high).

The AnyLogic program provides this beta distribution as part of its collection of probability functions. The estimated mean for this set of parameters is estimated at 0.94; AnyLogic does not provide a calculated mean, rather it must be determined empirically. The 0.5 and 0.99 for lower and upper bounds were established to represent a lower end 50:50 chance of performing the MAP step correctly and the upper bound of 0.99 was set to represent that there is not a 100% of successful occurrence of performing a MAP step.

Medication Agents

Medication agents, often simplified to medications, represent the set of drugs assigned to each patient at the start of the simulation. Each patient is randomly assigned a number of medications from two to nine. The patient-medication assignment does not change during the simulation. The number of medications determines what the nurse agent goes through each cycle of the MAP for every patient. The nurse will iterate through the MAP cycle for a particular patient until that particular collection of medications is exhausted. For example, if a patient agent has four medicines, the nurse will cycle through the MAP four times before moving to the next patient. Each shift will deliver the medications to each patient. The available research reviewed indicates the average number of medications per patient per day to be five to seven different medications per day. The actual number of prescribed medications vary widely depending on patient age, condition, as well as other factors [404]. It was assumed that there were two doses per day (coinciding with each shift).

Medication Agent Attributes

Medication Difficulty: Each medication has an attribute that quantifies how hard it is to administer the medication. Consider the difficulty of delivering a vitamin capsule versus an intravenous medication that is both time and rate dependent. The literature discusses differences in error rates of administering different via different routes (e.g. intravenously) and that certain type of medications have a higher incidence of error. A comparative assessment of delivery route and type of medication was not found in

the literature. A simple ratio was used (Table 3.6) to establish a relative difficulty index for administering medications. The impact to MAE was set at 0.95, 1 and 1.1 ranging from most difficult to least difficult respectively.

Medication Severity: This attribute is constructed in a very similar fashion to Medication Difficulty. Its function is to assign a value to the likelihood of error occurrence based on the potential risk associated with a medication type and the magnitude of a negative overall impact. The severity relates not just to toxicity of the medication, but the ease of errors such as overdosing, contraindications, masking of effects, and others. As with the Medication Difficulty attribute, in the real-world setting, this attribute is complex and is influenced by a variety of factors [405-407]. Finding a severity index and probabilities of MAE associated with it proved problematic. A 30%, 40%, 30% ratio for three levels of medication severity was used. The impact to MAE was set at 0.95, 1 and 1.1 ranging from most severe to least severe.

Medication Delivered/Not Delivered: As with the patient agent, medication tracks the state or measure of a medication having been delivered to the patient or not. As the medication moves from its original state in pre-Medication Administration to post-Medication administration, the attribute is changed from false to true depending on if it is a delivered dose or a missed dose. This change also sends a message back to the nurse agent that is attached to the patient with this unique medication that the attribute for this medication has been changed. The medications' delivery state is reset at the end of each shift.

The modeling approach is intended to simulate the medication administration process. The duration for administering medications varies based on a variety of factors. An average time period for administering medications, based on research that performed time studies, is approximately eight minutes [20, 408].

This duration was used in the estimate for the administration of each medication. The maximum number of medications per patient was set at nine. The total duration, without consideration of delays in the model, is 72 minutes. Various points in the model have built in delays to ensure coordination of the exaction of the model. The total shift time set for the administration of medications was initially set at 120 minutes to ensure all medications would be administered prior to the change in shift. The model is structured for the nurse to complete the execution of their portfolio of medications prior to the 120 minutes (in model time). On the final pass, as the nurse completes the administration of its medication portfolio prior to the shift reaches its 120-minute limit, the nurse diverts to the nonMAPActivity state. From there it will move to the off-Shift state. At the beginning of the appropriate shift the collection of nurses in the current shift are transitioned to nonMapActivity and then back to the MAP process.

Table 3. 6: Medication agent description

Medication	Factor	Type	Effect
Medication difficulty	minimal, intermediate, difficult	assigned randomly according to a 40%, 45%, 15% ratio	value that is associated with how hard it is to administer the medication, e.g. an IV versus a capsule
Medication severity	low, medium, high	assigned randomly according to a 30%, 40%, 30% ratio	value associated with the hazard of the medication to the patient e.g. warfarin versus a vitamin
Medication delivered	True/False	probability based on beta distribution	beta (0.5, 0.99, 0.999, 0.009, 5.0E-4, 0.99)
Medication not delivered	True/False	probability based on beta distribution	beta (0.5, 0.99, 0.999, 0.009, 5.0E-4, 0.99)

The model is designed to run in an asynchronous fashion within each agent environment. The various agents coordinate activities via messages (a feature in AnyLogic®[40] to transmit unique signals to other parts of the program). So, while the model runs asynchronously its execution is coordinated.

Environment

A unique aspect of an agent-based model is the construct of an environment that agents exist within. The environment is simply a physical or virtual space that agents exist within as they execute their operations.

AnyLogic has global environment frequently called Main. Figure 3. 7 graphically represents the relationship of the environments for this model. Main was used when constructing the function and defining the variables and parameters that would be used within the other environments. Computer code that is needed at the start of the simulation, such as creation of global arrays, and nurse-patient-medication networks, are housed in Main as well.

In AnyLogic, generally speaking, functions are executed for each agent. So, if the model requires the function to execute only once during a given time increment it resides in Main. For this reason, event transitions related to overall execution of the model, were placed in Main. There are functions that exist in Main that reach into other agent environments (i.e. Nurse, Patient Medication) to obtain information.

The interconnected set of states for nurse agents resides in the Nurse environment. The functions and parameter specific to the nurses reside in the environment. The programming elements (e.g. functions, events, parameters, controls, etc.) will operate or be executed for each individual agent. The effect of this is for each agent to be a unique entity within the model. Elements within Nurse can reach into other environments and acquire information. Nurse uses Patient information numberOfMedications, medications, medicationAdminDifficulty, medicationSeverity, and Medication information to include medication counter information.

The Medication and Patient environments are less complex as well. The Patient environment has two simple state charts and Medication has one simple state chart. Contrasted to Main or Nurse, there are relatively few programming elements. As noted in the Time section, the two state charts in Patient, in essence, run asynchronously.

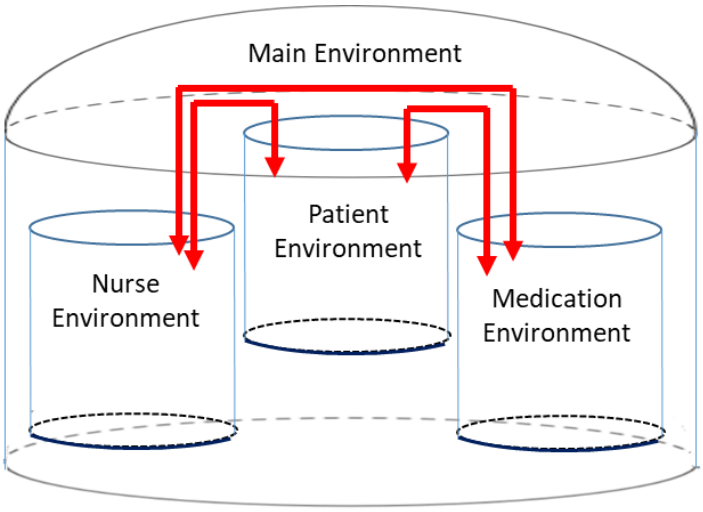


Figure 3. 7: MAP ABM environment

[40] Future references to AnyLogic® are inferred to include the registered trademark symbol

Model Construction and Execution

General Operating Parameters and Conditions

A number of foundational requirements needed to be established early in the development of the model.

> Number of patients: The number of patients was set at 100 and is an inputted parameter. This approximates the number of patients in a large medical/surgical ward[41]. The model is designed to allow changes to this value.
>
> Number of nurses: The number of nurses is also an inputted parameter but is calculated based on the desired average number of nurse-patient ratio. For the purposes of this model the average nurse-patient staffing level was set at 5[42]. This value is used to calculate the range of nurse-patient ratios.
>
> Number of shifts: A variety of shift durations and approaches was considered. As noted previously, a two-shift approach was used for simplicity. The way this model is designed, this actually means that a shift is a counting or labeling function. A shift is normally thought of as existing within a day. However, there is no "day" within this model. In the case of this model, shift 1 starts at the start of the execution of this model, after a specific period the first shift ceases and the start of the second shift. This process is repeated for the duration of the execution of the model.
>
> Random Seed: The model was developed using a fixed seed to allow reproducibility during model design, validation and verification. The seed was changed to a random seed for running experiments.

The model can be broken into four main elements as noted in the Environment section; these are Main, Nurse, Patient and Medication. While each of these elements are separate, there is, significant interplay between them. The execution of functions in one environment rely on information or operations from another environment.

Main Environment

Model execution In AnyLogic begins with a number of functions in an environment it defines as Main (Table 3.7). While other environments have this capability, it was not used. At startup, the two-primary group of functions are executed which relate to the random allocation of agents within their respective networks and the creation of V&V mechanisms to evaluate the execution of the simulation. Data sets in the form of arrays (AnyLogic calls the type of arrays used collections) are also created to support execution tracking and medication administration processes in the model.

These startup functions set the stage for execution of the next key step in the program. An AnyLogic function called an Event was used to control the shift dependent actions. An Event executes a set of actions or computer code based on a signal or time interval. The time interval was used and is tied to the duration of shift length. Each time the duration of shift is reached (i.e. 120 minutes) the event "fires" and the associated functions are executed. This Event resets a number of collections for the next shift and resets the random assignment of patients to nurses. The experimental design of the simulation changes two key parameters, the injection of JIT information effect and the impact of the attributes of the nurse, patient and medications agents.

The Event consecutively changes the state of one of the two items every model cycle; the model cycle is defined as the length of shift times twelve or twelve shift iterations, which is about 7,000, passes through the MAP. The number of samples selected was 7,000 with a power of 0.80, a standard deviation of 0.302, the overall response value, and a difference of 0.01. This has the effect of controlling each condition of JIT Information and Attributes to get a measure of their effects described in Table 3. 8. The false-false condition is, in-effect, the control, the true-false state measures the effect of all of the attributes without being affected by the information, the false-

[41] http://thehospitalleader.org/an-average-hospital-is/

[42] https://www.amnhealthcare.com/latest-healthcare-news/rn-to-patient-hospital-staffing-ratios-update/

true state provides the effect of just information without influence from the attributes, and true-true is a composite of both information and agent attributes.

Nurse Environment

Following startup and the initial Event in Main, which sets the stage for the rest of the model's execution, the other environments begin their processes. Figure 3. 8, duplicated here for convenience, represents the state charts and their interaction for Nurse. There are three general sets of states. The first set includes the off-shift and nonMapActivity states of the mapProcessStatechart. This environment begins its process when nurses process in through the off-shift state. This state functions as a holding area for nurse agents prior to and after their active shift. Connected to off-shift is the state nonMapActivity which receives nurse agents prior to going to off-shift and coming from off-shift. The transitions to off-shift are actioned by the same messages. Note that the transition from the compound state to off-shift ensures that an agent in the compound state at the designated shift change time (e.g. 120 minutes) will be immediately moved to off-shift in order to ensure all current shift agents are transitioned to off-shift at the appropriate time.

The compound state is the next set of states. These states represent the actual MAP process. The first two states are interim states. The preMapProcess receives nurse agents from nonMapActivity. The mapProcess state receives the nurse agents after a slight delay and allocates them to either continue through the MAP process or diverts them to the missed dose state based on a random event at a 1% rate. This 1% rate is derived from the available literature on the frequency of missed doses early in the MAP process. The mapProcess is a gateway state that is the location where the attributes, and overall coordination of the MAP process is done.

Table 3. 7: Primary Main startup functions

Startup Function	Description
nurseAgentShiftColllectionCompiler();	Creates collection (array) of all nurses
nursesInShiftCollectionFunction();	Creates collection of nurses by shift
nurseConnectionsByShiftMainEXPERIMENT();	Creates netwrok connections to patients by shift
NurseExperienceAllocation();	Randomly assigns levels of experience to nurse agents
addNurseExperienceCollectionFunction();	Creates collection of nurses by experience
numberOfMedsPerPatientGenerationFunction();	Randomly assigns (via network) medications to a patient agent
numberOfMedsPerPatientCounterFunction();	Tracks the number of medications per patient
nurseMedDistributionCheckCollectionBuildFunction();	Creates collection for tracking administartion of medications by patient
medicationCounter();	Counts the total number of medications
nurseMedDistCCounterCollectionStarter();	Creates tracking collection for distribution of medications by nurse
shiftMedCounterCollectionBuildFunctionMain();	Creates collection for tracking medication adminstration by medicatin per shift
randomConnectionsFunction1();	Builds the intial random connections between patient and nurse agents
medicationToPatientNetwork();	Tracks the connection between patients and nurses
totalMedSumPerNurseFunction();	Counts the total number of medications assigned to nurse via connected patients
numberOfNursesInEachShift();	Calculates the number of nurses for each shift
MedPerPatientCollectionFunction();	Builds the list of meds for each patient
medCountingPerPatientCollectionBuildingFunction();	Builds the collectin counter for trcking meds process for each patient
bigCheckingFunction();	V&V function that provides visual (i.e. run-time messages) for model execution

Table 3. 8: JIT and Attribute state changes during model execution

		JIT Information	
		Off	On
Attributes	Off	False-false	True-false
	On	False-true	True-true

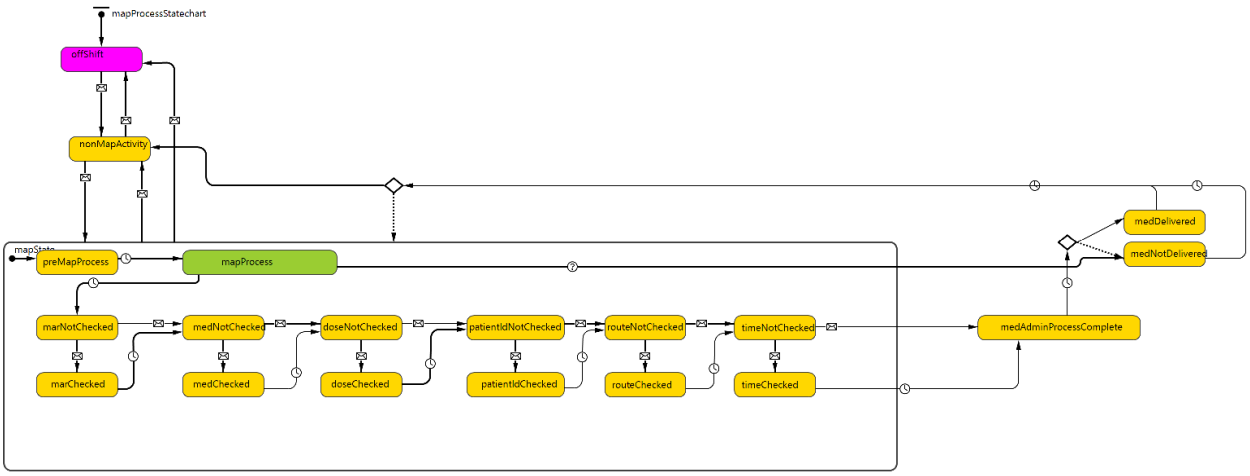


Figure 3. 8: Nurse state map

The core of the MAP process is embodied by the next state sets. A nurse agent enters the next MAP state, marNotChecked. Within this state a randomTrue() function is used to determine the fate of the next step of the agent. If the function returns a True then the nurse proceeds to the marChecked state indicating that the MAR was checked correctly. If the function returns a false then the MAR was not checked correctly for this medication. The likelihood of a True occurring can be a deterministic value set at 0.975 or a deterministic value tied to a beta distribution as described earlier. The deterministic value is an approximation based on the overall MAE error rate of approximately 88%. The beta distribution is somewhat more tailored. The remaining five state sets proceed identically to the marCheck state sets. Table 3. 9 details the likelihood of error occurrence from a number of different literature sources [29, 409-414]. A beta distribution (Equation 3.2) was developed to approximate these values. AnyLogic has a truncated beta function; this was set to range between 0.5 and 0.99 (50% and 99%). This function does not have a means to insert the median or average value or standard deviation. The various factors (p, q, shift and stretch) were input to approximate the desired values (see previous figure). In the case of this model, the beta function is designed as an extreme value probability function to align with the typical occurrence of MAEs. The deterministic version is used in obtaining the values for this study as noted below.

$$\frac{x^{\alpha-1} * (1-x)^{\beta-1}}{B(\alpha,\beta)}$$

$$where\ B(\alpha,\beta) = \frac{\Gamma(\alpha) * \Gamma(\beta)}{\Gamma(\alpha+\beta)}$$

Where Γ is the gamma function: $\Gamma(n) = (n-1)!$
α & $\beta > 0$ represent shape variable

The agent proceeds from within the compound state to the medAdminProcessComplete state which is an interim state prior to medication delivery. As the nurse agent exits the medAdminProcessComplete state, it passes through a decision node which directs the nurse to having either delivered the medication or not delivered the medication. This is also determined by a randomTrue() function and similar to previous discussions, the model allows for either a stochastic probability of 0.95 or a beta distribution as determined above. The deterministic version is used in obtaining the values for this study.

Table 3. 9: Likelihood of MAE by cause

	Dose Omitted	Wrong Dose	Wrong Time	Wrong Patient	Wrong Route	Wrong Drug
	8.1%	37.1%	12.5%	2.0%	17.7%	5.7%
	20.0%	24.1%	3.0%	1.9%	1.0%	1.0%
	16.0%	12.0%	26.0%	0.0%	1.5%	1.0%
	10.6%	10.0%	16.9%	1.0%	1.0%	1.0%
	50.0%	7.6%	2.7%		0.7%	1.0%
	5.0%	4.1%	9.0%		1.0%	2.0%
	1.1%	7.7%	8.7%			
	14.4%	0.0%	13.9%			
	5.0%	11.7%	10.0%			
			11.6%			
Mean	14%	13%	11%	1%	4%	2%
SD	14%	11%	6%	1%	6%	2%

After the medication delivery states, the nurse agent is evaluated to determine if all the medications it was assigned has been administered. This is done via using array counters that compare the list of medications per patient per nurse that have been delivered to what has been assigned. Table 3. 10 provides an example of how the model determines if the nurse agent has completed medication administration. Recall that each patient is assigned a specific number of medications. The nurse will start with the first patient in its array, in this example it is patient number 12 which is assigned 9 medications. It will continue going through the cycle of the MAP process until the nurse has delivered 9 medications; each time it goes through a cycle it will compare the assigned number to the delivered number. When the Assigned value for a particular patient equals the Delivered number for that patient, the nurse will move on to the delivery of medications for the next patient. In the example below, the nurse agent has one more medication to deliver to patient 63 before the nurse moves to patient 88. When the entire array of Assigned values and the counter array of Delivered are equal, the nurse is diverted from re-entering the compound state for MAP to the nonMapActivity state where it awaits to go off-shift.

The AnyLogic functions Events() are used as timers to determine when a particular shift should be dispatched to, or brought from home. Events() are functions that can be controlled by times are signals. These functions turn on at pre -determined intervals to execute specific tasks (in the form of computer code or other AnyLogic functions).

Table 3. 10: Example of medication distribution counter

Patient Number	12	18	35	63	88
Assigned	9	8	6	2	5

Patient Number	12	18	35	63	88
Delivered	9	8	6	1	0

Patient Environment

The patient states reflect the two primary considerations for the patient: where it resides in the overall MAP process and has experienced an ADR (Figure 3. 9). The patient moves between the preMAP and postMAP state by receiving communication from its current nurse. This communication also informs the patient if it has received its medication or not. In a separate set of states, the patient possibly experiences an ADR as a result of receiving a medication. This is determined probabilistically based on the likelihood of a MAE resulting in an ADR as referenced in the literature. The patient cycles back to its previous state after it reaches the postMAP and ADR states.

The number of medications assigned to each patient is determined through an AnyLogic table function that establishes the number of medications ranging from two to nine. A function then randomly assigns a value from the table function to a patient.

Medication Environment

The state for medication is discussed in the relevant V&V section. After medication agents move from the premed (pre-Medication administration) to the other states, they reside in that state until the end of the state. Agents move from preMed to the other states by receiving communication from the patient. Figure 3. 10 reiterates the statecharts for the medication agent.

Medication Severity and Difficulty distributions are determined by the AnyLogic custom distribution function. Medication Severity values are set at a frequency of 30%, 40% and 30% for low, medium and high severity respectively. Difficulty in delivering medication is set at a frequency of 40%, 45% and 15% for minimal, intermediate and significant difficulty respectively. Each value is assigned a likelihood of error (0.95, 1.0, 1.1) which is used in calculating the overall probability of MAE occurrence.

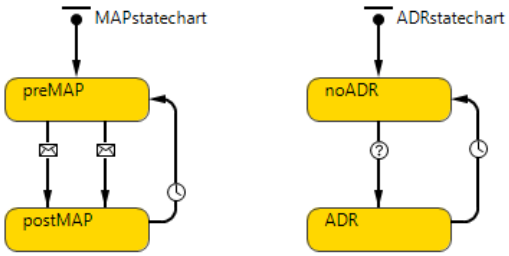


Figure 3. 9: Patient statecharts

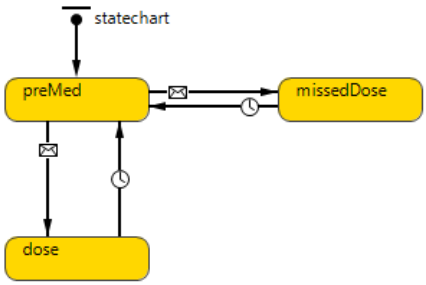


Figure 3. 10: Medication statechart

Selection of Modeling Software System

AnyLogic® Professional from the AnyLogic Company, was selected as the development platform for the computer simulation model. AnyLogic is a robust, comprehensive multi-method modeling tool that supports agent-based modeling, discrete event simulation and systems dynamics modeling. A unique feature of AnyLogic is that it has the ability to integrate each of these modeling methods in a given model should the need arise. It is built upon the Eclipse integrated development tools (IDE) using java. As such, it has superior flexibility for creating specialized computer code and it will work across various computer operating system platforms.

AnyLogic has a well-developed graphical user interface (GUI) that speeds the software development process. The basic program structure is created by dragging icons from the menu on to an agent's palette (Figure 3. 11). Agent states are created by dragging the state icons on to an agent environment and inserting flow connections for the changes of state. This approach provides for the verification of the logical connection between agent states.

AnyLogic provides a depth and breadth of functionality for the design and construction of ABM models. The program provides easy creation of the typical functionality of variables, parameters, and states (Figure 3. 12). In addition, it supports the ability to insert standard probability distribution functions (PDFs), create custom PDFs, and develop and insert functions (segments of customized java code).

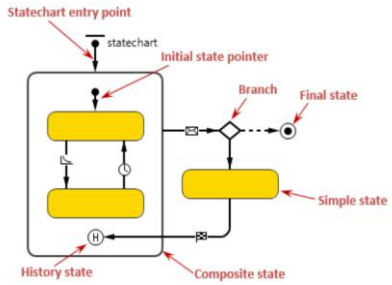


Figure 3. 11: Description of AnyLogic graphic programming[43]

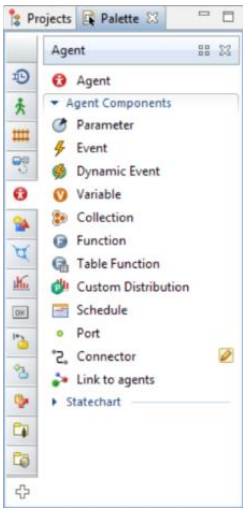


Figure 3. 12: AnyLogic graphic programming palette

[43] Images included under title 17 section 107 U.S. Copyright Law Fair Use Doctrine as educational material distributed for use without profit. Ref: https://help.anylogic.com/index.jsp?topic=%2Fcom.anylogic.help%2Fhtml%2Fstatecharts%2FStatecharts.html

Java code may be inserted into many of the programming icons of AnyLogic allowing for customization including creation of unique actions of the element. The AnyLogic professional version has added features for enhanced debugging, extended user interface functions, and easier integration with output files.

The features of AnyLogic include the advanced user interface, being implemented on an open development (Eclipse) java platform, having a relatively large user base and structured help and support, includes an extensive predefined library of functions and elements.

Model Verification and Validation

Verification and validation (V&V) of agent-based modeling poses unique challenges with ABM's compared to other more established approaches, such as discrete event and statistical models. ABM approaches, somewhat like artificial neural networks (ANN), have intrinsic "black-box" features that increase the difficulty in understanding what transpires during the simulation. ABM is still a relatively recent newcomer as a modeling and simulation tool; there are a limited number of formalized tools for the V&V of ABM models. The available literature suggests a process-oriented approach confirming the structure of the model logic and the alignment of the design with the desired output as an approach for V&V of ABM simulation models. This is the approach used for the V&V of the MAP model. Figure 3. 13 provides a graphic of the general consideration used in the V&V effort.

Considerable effort was invested in ensuring the model was delivering the information that was required, that the information was correct. That is "that the model was built right" and "that the right model was built". To revisit the model's purpose, it is intended to generate the likelihood of a potential MAE per nurse for each medication that is delivered for each patient. Various factors affect the likelihood or probability of the overall MAE based on the attributes of the nurse, the medication, the patient and if any information was provided to the nurse via the JIT intervention of information (i.e. information injection).

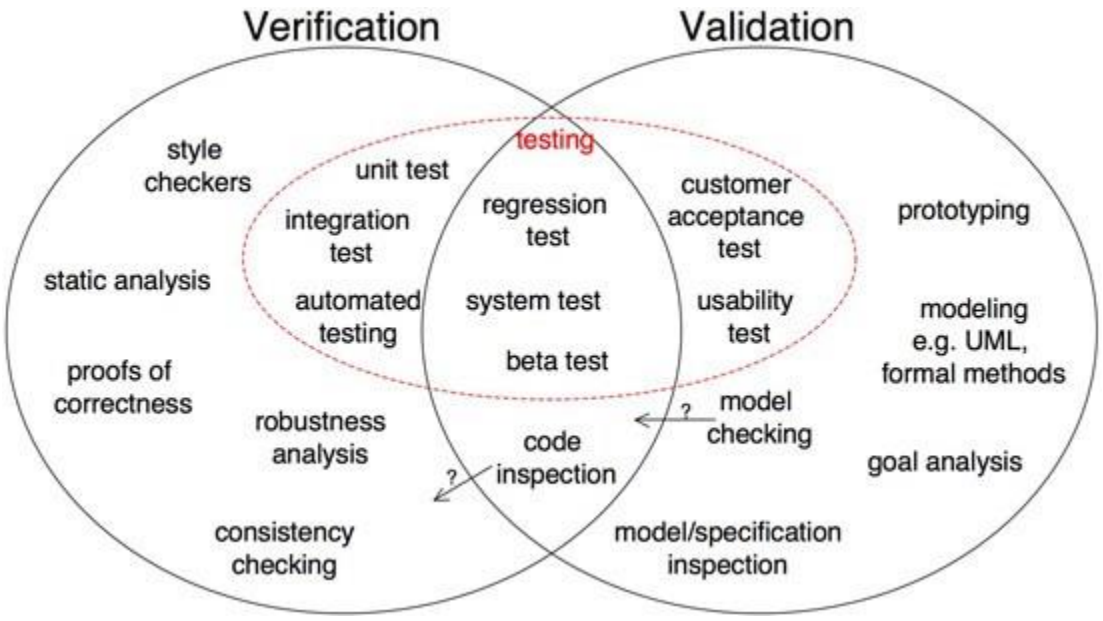


Figure 3. 13: Verification and Validation description[44]

[44] http://www.easterbrook.ca/steve/2010/11/the-difference-between-verification-and-validation/

Verification – Building the Model Right

Two approaches were used to support the verification of the model: static analysis of the system where the structure of the computer code is evaluated, and dynamic analysis which assesses the model based on exercising and observing model behavior (dynamic verification).

Based on the available literature and clinical trial, the following Model Requirements Specification - Functional/Operational Requirements have been established. The overall design of the model is set forth in the definition of the requirements. These requirements are outlined as follows:

- Accurately reflects the MAP steps of the 5-rights of medication administration
- Traces the steps of the MAP for each nurse
- Provides an accurate statistical representation of the probability of each step of the MAP
- Provides a consolidated likelihood or probability index of MAE
- Provides MA tacking at the nurse-patient-medication level
- Allows for the changes in agent behavior as determined by agent attributes
- The medication MAP is configured for adjustable time frames based on minutes for time units
- The model should account for the ability to have multiple nurse shifts
- The patient-nurse ratio should be able to be controlled
- The nurses should be randomly assigned to the patients they are caring for during each shift of the run
- The medications for each patient should be consistent through each run
- There should be a mechanism to allow for a missed dose
- The probabilities of the likelihood of error are independent for each step of the MAP process
- Provides a probabilistic indication of MAE and ADR for each medication administration
- There is a mechanism to account for the individual medication administration events at both the nurse and patient level

The AnyLogic platform provides a straight forward mechanism for the high-level static verification of the model. The graphical design allows for a comprehensive review of the logic of the programming. Once the states for each of the agent types have been defined, they are placed on the respective canvas. The flow of the agent through the mode, along with the intended action, can be visualized by stepping through each of the states. This high-level verification or tracing of the program flow also sets the stage for designing the requisite definition of parameters, variables, functions, etc. to more specifically construct the model's operations. The flow for each of the agent types was evaluated for logic and alignment with desired outcomes. As was mentioned previously, this was done by tracing the agent flow through the various agent states and connections. Figure 3. 14, Figure 3. 15 and Figure 3. 16 provide the high-level architecture of the three agent types defined for this model.

The verification of the nurse flow can be done by tracing the respective diagram. The nurse enters the initial state and passes through a number of initial "staging" states. The nurse agent then moves to the compound state for the medication administration process. Again, the nurse agent passes through a number of initial stages. At the mapProcess state, the programming logic dictates that the nurse will either omit giving the medication or continue down the map process. From this point, the MAP activities proceed through each step of the MAP. Each of these steps function as a binary switch based on the likelihood of either performing the step correctly or not performing it correctly. As described in the functional requirements, the process is linear with no recursive elements nor is a later state occurrence a function of the likelihood of an earlier state. At the completion of the MAP section, the nurse agent proceeds out of the compound state. The nurse agent then goes through a decision step that once again allows the nurse agent to complete the medication administration or terminate it. The purpose of this step is to accommodate the likelihood of a failure to administer a medication during the earlier states of the map. Once the nurse passes through the decision element, it passes through the medication delivered or medication not delivered state then routes around to another model decision element. This element evaluates if the nurse agent has completed the administration for each of the medications it has been assigned via the patients it is connected to. If the nurse has not completed all of its medication deliveries, it re-enters the compound state and goes through the map process until the list of medications that it is assigned matches the list that it has delivered. Once

the agent nurse delivers all of its medications, it passes the upper decision node and moves to the postMAP state where it awaits a signal to start the entire process again based on the shift change time. At the end of the shift the nurse agents are directed back to the off-shift state either via the nonMapActivity state of the overall mapState compound state in the unlikely event a nurse agent is in the compound state when the shift changes.

This logic aligns with the flow chart by Ghenadenlik et. al. that represents the medication administration process as referenced in the literature review.

With the focus being on the nurse agent model the other environments are comparatively simpler.

The patient agent presents a much simpler set of states. There are two fundamental properties of concern for the patient agent; did the patient agent receive the medication and did an Adverse Drug Reaction occur after a particular medication was received? The MAP state chart receives a message from the nurse state chart indicating whether a dedication was or was not received and then it transitions from the preMAP state to the postMAP state. The patient agent then cycles back to the preMAP state to wait for another message from the nurse state chart.

The ADRStatechart is also simple with the patient agent moving between noADR and ADR states. The movement between states is a function of the patient having received a medication as determined from the MAPstatechart and a probability of a patient experiencing an ADR as determined by a probability function elsewhere in the code.

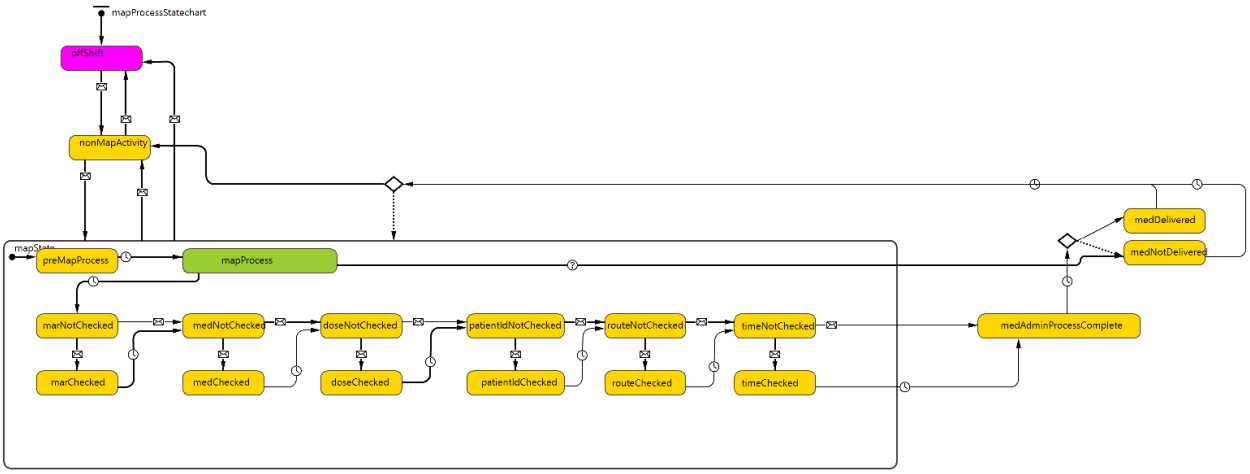


Figure 3. 14: Nurse statecharts

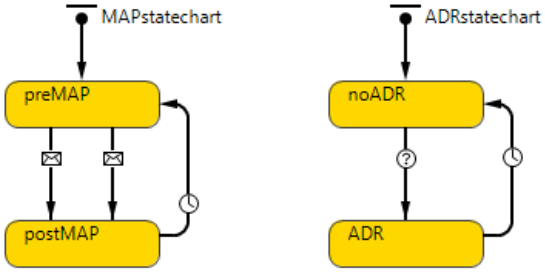


Figure 3. 15: Patient statecharts

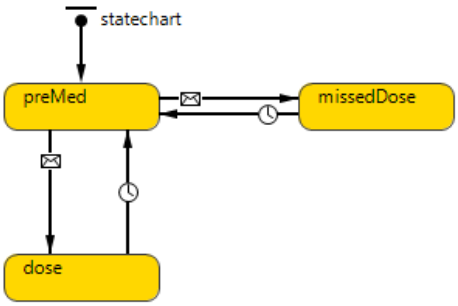


Figure 3. 16: Medication statechart

The medication statechart logic represents a trio of states. The first state is a holding state where medications reside prior to the administration. The medication can go to one of two states depending on the message received from the nurse state chart. The medication can either move to the dose state which indicates the medication was administered or it can go to the missedDose state indicating that the medication was not administered.

A large portion of the code is inherently verified by the structure of the AnyLogic program and its real-time error checking and debugging capability. The graphic representation of AnyLogic elements and their representation is pre-coded and automatically entered into the program when icons are dragged from the pallet to the canvas.

AnyLogic automatically debugs the model at run time as the model compiles, checking for any syntax errors. Functional errors that result during execution of the code result in run-time errors. When these occurred during the development of this model, it was the result of overflow errors of the arrays used for validation and control of the program: in essence the model would be trying to overfill an array for any number of reasons.

Model run-time verification was built into the programming plan. The key elements for verification of this model were to ensure that the correct number of medications passed through the administration process, that the medications were aligned correctly with the nurse and patient based on the patient and nurse network assignments, and that the nurses and patients were randomly reassigned to each other at the change of each shift.

To ensure random association between patients and nurses between each shift, all the connections and nurses were broken for a particular nurse shift, the patients were placed randomly into an array and then selected at random without replacement from the array and assigned to each nurse based on a distribution that calculated patient load for each nurse. The randomness of patient assignment to nurses was validated by doing both scatter plots and run tests.

The verification of the random assignment of patients to nurses was done by collecting the assignments for each shift via collection of the patient index into an array for each individual nurse. These arrays were then compared for randomness by using a runs test. The runs tests were performed by analyzing 24 consecutive nurse-patient assignments for each nurse. The P-values in Table 3. 11 indicate that nurse-patient combinations are random, ranging from 0.053 to 0.923. Note that the runs test is a function of the sequence in which the values are placed within the array so it is only a general indication of randomness for the purposes of this model.

Table 3. 11: Random test

Random Runs Test							
Nurse	Observed	Expected	P-Value	Nurse	Observed	Expected	P-Value
0	66	57.46	0.106	20	72	69.32	0.645
1	52	51.5	0.92	21	97	84.99	0.063
2	81	78.95	0.742	22	46	50.49	0.364
3	78	74.41	0.552	23	71	72.33	0.823
4	59	56	0.565	24	49	45.49	0.455
5	55	50.98	0.419	25	54	57.39	0.521
6	89	91.96	0.66	26	49	45.49	0.455
7	65	54.98	0.053	27	97	90.16	0.303
8	62	56.93	0.335	28	51	54.5	0.497
9	89	80.99	0.204	29	55	48.37	0.17
10	52	47.91	0.396	30	45	44.8	0.965
11	62	56.93	0.335	31	89	88.44	0.932
12	47	52.11	0.308	32	80	86.9	0.291
13	89	88.36	0.923	33	91	85.95	0.437
14	50	50.98	0.844	34	81	79.8	0.847
15	81	78.5	0.687	35	37	37.57	0.893
16	43	50.45	0.132	36	46	55	0.082
17	83	75	0.187	37	91	85.95	0.437
18	73	75.42	0.691	38	50	51.46	0.771
19	63	62.5	0.927	39	40	46.91	0.146

The verification of the functionality of the influences of both the nurse attributes and injection of information can best be seen by a graph of the composite probability outcomes which is a measure of overall effect on each individual medication administration event. The graph in Figure 3. 17 demonstrates four distinct phases. The furthest left phases are with no influence by either the nurse attributes or added information, this is affectionately referred to as the zombie effect; that is, the nurse agents proceed through the MAP process with no variance being created by information or attributes. The next phase, to the right, demonstrates the influence of the information injection; the effect is a significant compression of the variance since additional information increase performance pushing the likelihood of completing tasks correctly towards 1.0. The third from the left demonstrates the effects variance from the addition of nurse attributes creating wider variance swings since nurse behavior and effects of patient load and medication influences are broader. The segment furthest to the right show influences from both information injection and nurse attributes thus indicating graphically that there is some effect from these influences.

Another aspect to consider for verification of the model is establishing the performance of the medication distribution methodology. That is, verifying that the computer code allows for the nurse agent to interact with the intended patient agent and the intended medication. Considerable effort went in to building in a verification schema during computer code development, including the following.

- Built a base array for each nurse that contained their currently assigned patient
- Built a base array for each patient that contained the assigned medications
- Used tracking arrays that counted the number of medications process by patient and nurse

- Compared the tracking array with the base array
- Indicate that an execution error has occurred if there is misalignment during simulation execution

Using this approach, the computer code is self-monitoring. It is comparing the nurse-patient assignment and medication-patient assignment to the medication administration progress being made during the execution of the simulation.

Specific verification functions were developed to support the verification process including:

- Nurse-patient connections status
- Patient-medications connections status
- Nurse shift assignment
- Allocation of medications per patient per nurse
- Random assignment of patients to nurses by shift
- Assignment of medications to patients
- Transition of nurses into and out of the MAP process
- Completion of MAP process by each nurse
- Assignment of attributes to nurse
- Stepwise progression of nurse through the MAP process
- Individual tracking of patient-nurse-medication admiration status
- Transitions between shifts
- Message passing between agents (nurses, patients and medications) along with the time of the message
- Random nurse loading function

These functions were monitored either after sample simulation runs or during model execution to verify that the model was executing according to the functional design criteria and expected results for the model output. For the sake of comparison of different simulations, a fixed seed was used to limit random variance between simulations. During computer code development, another mechanism that was used for verification was runtime messages and pauses to visually inspect output and messages. Specifically, a traceln() function was used at key code segments to return string or object values for inspection. Functions were developed (e.g. threadStopPause(), pressAnyKeyToContinue()) to temporarily pause or stop program execution for detailed evaluation of tracking information. Figure 3. 18 is a snippet of traceln() output used to verify computer code during run-time.

Validation – building the right model

The fundamental requirement of this simulation model is to, in some fashion: 1) replicate the MAP process aligned with the probability of error occurrence found in the literature, and; 2) indicate the effect that JIT information might have. The validation process, for the purposes of this effort, is in many ways an extension of the verification process.

The validation of the model is ultimately determined by evaluating the actual output of the model against the expected values. As described in the verification section, the overall composite probability of MAE is a good general indicator of the performance of this model since this output is a function of the individual probability inputs from each of the MAP steps as well as the effects of the variance of nurse and medication attributes.

Revisiting Figure 3. 17, the significant changes in error probabilities, as the model progresses, indicates the effect of inclusion of information or nurse attributes. Figure 3. 19 indicates changes in the inclusion of information or nurse attributes during specific time sequences. The graph aligns with the design expectation that when information is added, the likelihood of error should decrease. When variance in the attributes of nurse agents are included, the variance in the likelihood of error increases. When both nurse attributes and information is included in the simulation, the probability range is broader than with just information but narrower than either the attributes/no information or neither information/attributes, also as expected.

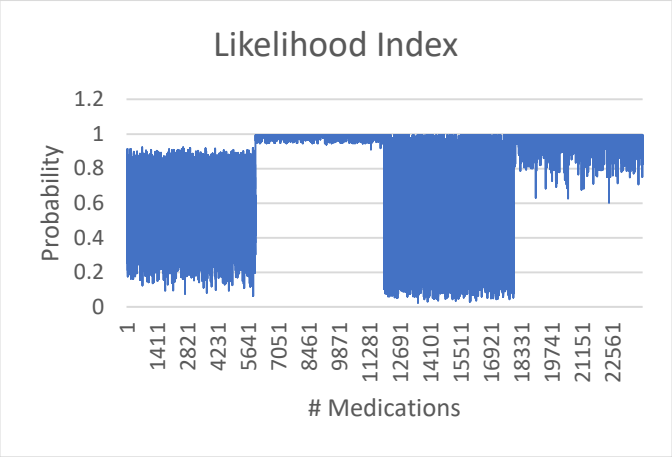


Figure 3. 17: Graph of overall correct Medication Administration likelihood

Figure 3. 18: Run-time messages for V&V

```
testCollection [14, 22, 10, 23, 37, 19, 35, 24, 27, 8, 37, 47, 15, 10, 18, 40, 45,
20, 17, 33, 34, 9, 25]
sum of all meds:  569
 test fired
bigCheckingFunction
medication count    569
medicationCollection [1, 1, 1,…]
collectionBuilderForMedications
Total Meds by Patients (in startup): 569
medication count    569
medicationCounterCollection [0, 0, 0,…]
collectionCounterBuilderForMedications
A SLIGHT PAUSE ONLY 5 SECONDS - TAKE 3 DEEP BREATHS
!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!!
!!!!!!!
byShiftNurseMedsFunction

totalMedSumPerNurseParameterFunction
```

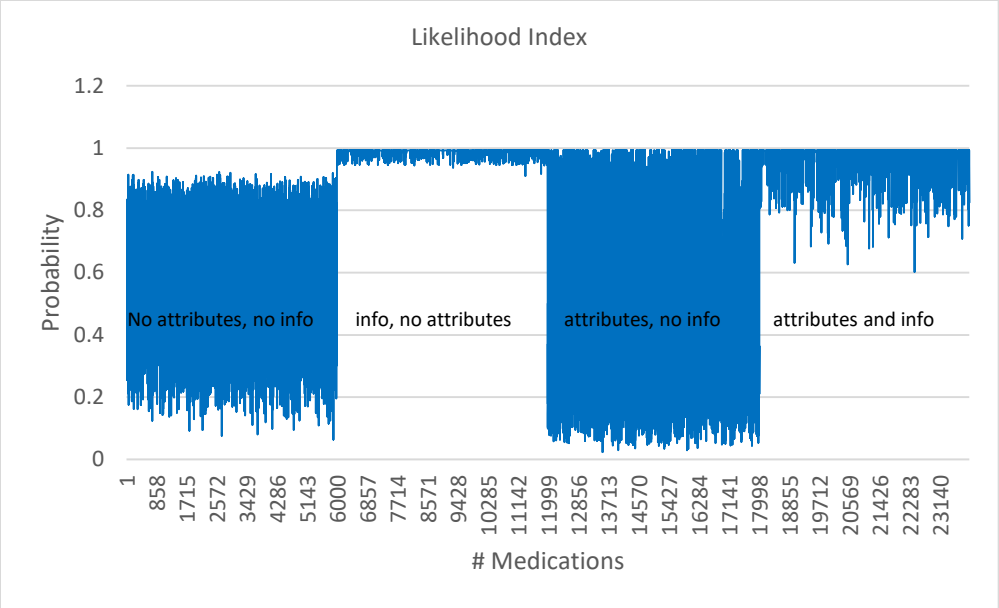


Figure 3. 19: Factors influencing likelihood of successful medication administration

Many of the variables in the model "auto-generate" their value, in that, a random or probability function determines what the variables' value is as the simulation executes. A tool was developed to help validate the model which collected the key monitoring variables into a large spreadsheet. This allowed visual inspection of each variable during each time step of model execution. Table 3. 13 shows the variables contained on this spreadsheet. Seventy-one separate variables were tracked. This tool allows assessing the validity of the model as it relates to the interaction of the various variables at a low level. Based on use of this tool, the assessment is that the model performs as expected with high confidence.

Evaluation of the occurrence of MAP errors during the medication process (i.e. the 5-right steps) provides insight on the validity of the computer code and operation of each of these elements. By checking the occurrence of calculated errors and comparing them against the standard error rate put into the model indicates if the model is executing correctly. Table 3.12 provides the output of this comparative assessment. The calculated value should be between 90-95 percent. Each of these values falls within that range.

Animation was used to graphically represent network connection changes (nurse-patient connections) during shift changes. At each shift change, the animation of the network map was redrawn indicating the planned random disconnecting and reforming of nurse-patient connections.

The relative effect of the JIT information effect and agent attributes is validated during each simulation run for each level of information injection.

Table 3. 12: Percentage occurrence of errors in MAP steps

marCheckP	Count	Percent	CumCnt	CumPct	**medCheckP**	Count	Percent	CumCnt	CumPct
0	46	9.20	46	9.20	0	39	7.80	39	7.80
1	454	90.80	500	100.00	1	461	92.20	500	100.00
N=	500				N=	500			

doseCheckP	Count	Percent	CumCnt	CumPct	**patientCheckP**	Count	Percent	CumCnt	CumPct
0	49	9.80	49	9.80	0	35	7.00	35	7.00
1	451	90.20	500	100.00	1	465	93.00	500	100.00
N=	500				N=	500			

routeCheckP	Count	Percent	CumCnt	CumPct	**timeCheckP**	Count	Percent	CumCnt	CumPct
0	48	9.60	48	9.60	0	38	7.60	38	7.60
1	452	90.40	500	100.00	1	462	92.40	500	100.00
N=	500				N=	500			

Table 3. 13: Key model elements for assessing model performance (V&V) agent attributes

Key metrics	Data type	Type	Description
VariableControlIndicator			
Main.nextId	integer	v	counter for total passes through the system
Nures ID (this.getIndex())	integer	agent	index of current nurse
variableControlIndicator	string	v	composite indicator showing the collective status of information injection and the godVariable: that is, it indicates if these functions are "turned on"
informationInjection	boolean	v	turns on or of the function for information injection benefit "true" indicates the function multiplier is on
godFunctionControlVariable	boolean	v	turns on or of the function for godVariable affect "true" indicates the function multiplier is on
currentShift	shift	v	the currently active shift (2 shifts total)
time()	time	v	current model time
this.patientsPerNurse	integer	p	number of patients per nurse
this.getIndex()	integer	agent	index of current nurse
this.currentPatient	integer	p	the connected patient that the nurse is giving the medication to
activePatient	integer	v	the connected patient that the nurse is giving the medication to
this.medsPerNurse	integer	p	total medications per nurse
this.nurseMedDisributionCounter	integer	p	this provides the current counter for the number of meds a nurse has administered
this.patientLink	integer	p	this identifies the current patient for a given nurse
medLinkConnections.size()	integer	p	this is the size of the array for monitoring each medication being administered
this.medicationsLink()	integer	p	This identifies the current medication being given to the patient
Main.medicationTotalSum	integer	v	total number of medications in a shift
this.marCheckP	boolean	v	indicates if the MAR has been checked
this.medCheckP	boolean	v	indicates if the med has been checked (is it the correct med)
this.doseChckP	boolean	v	indicates if the dose has been checked correctly
this.patientCheckP	boolean	v	indicates if the patient has been verified
this.routeCheckP	boolean	v	indicates if the route has been provided correctly
this.timeCheckP	boolean	v	indicates that the med has been given at the correct time
medicationsLink	integer	p	This identifies the current medication being given to the patient
medsPerPatientGiven	integer	p	per patient counter for medications given to each patient

Table 3. 13: Key model elements for assessing model performance (V&V) agent attributes (continued)

medsPerPatientMissed	integer	p	per patient counter for medications NOT given to each patient
selectionOfNumberOfMeds()	integer	p	medications per patient
ADRPerPatient	integer	p	counter for ADR per each patient
this.patientsPerNurse	integer	p	the total number of patients for each nurse
this.medsPerNurse	integer	p	the total number of medications for each nurse
this.interruption	double	p	probability of interruption occurring
informationInjectionBenefit	double	v	multiplier value that is applied to each 5-right probability so the likelihood of that activity increases
godVariable	double	v	integrated probability of occurrence of nurse, patient and medication attributes
this.missedDoseV	boolean	v	direct missing of dose
Main.nursesInCurrentShift	integer	v	number of nurses in current shift
totalStatsCalcV	double	v	multiplication of probability of each of the probability parameters
medSeverity	MedicationSeverity	p	indicator of relative hazard of medication of current medication being administered
medDifficulty	MedicationDifficulty	p	indicator of difficulty in correct administration of the medication of current medication being administered
informationInjection	boolean	v	was information injected
medsperPatient	integer	p	number of medications of current patient
nurseExperience	integer	p	relative indicator of nurse experience, education and proficiency
fatigueOutput	double	v	measure of level of fatigue based on duration of time into the shift
medicationLoad	double	v	factor influencing impact of medication load
interruption	boolean	v	did an interruption occur
patientLoadOutput	double	v	factor influencing impact of patient load
lengthOfShift	time	v	duration of each shift
MAR Checked	double	p	Probability of MAR being checked by nurse agent
Med Checked	double	p	Probability of Med being checked by nurse agent
Dose Checked	double	p	Probability of Dose being checked by nurse agent
Patient ID Checked	double	p	Probability of Patient being checked by nurse agent
Route Checked	double	p	Probability of Route being checked by nurse agent
Time Checked	double	p	Probability of Time being checked by nurse agent

p=parameter, v=variable, o=option list

The model, judging by the performance from a number of perspectives, appears to have acceptable performance in terms of executing in the fashion that it was designed for. The output of each of the key variable was assessed and the ranges of output are in the limits of what would be expected form the design parameters. Multiple sample runs were performed with different parameters and the results were consistent and within the expected values. The assessment is that the MAP model meets the expectations for verification and validity.

Key Assumptions and limitation

Several assumptions were made as part of the development and conduct of this research. These key assumptions were explored to consider the potential impact and are noted below

Clinical Trial

A fundamental premise of the clinical portion of this research is that the application of JIT information via the smartphone app translates directly to actionable steps based on the understanding or knowledge conveyed by the JIT information. This implies several operational assumptions:

In the context of this research it was assumed that information and knowledge are in essence synonymous. The conveyance of information via the app is assumed to provide the appropriate contextual framework leading to the appropriate action. The reporting on this research has used the term information to represent not only the data that is passed to the end user in a JIT fashion, but also with the right contextual framework that provides understanding for whatever task might be appropriate. In short it was assumed that when the content of the app was delivered to the nurse they had the requisite capability to understand the relevance of the information and respond.

The test subjects were specifically selected for this research because the represented a general uniformity of training, background and experience with regard to nursing skills. This was based on the academic and practical training they had received up to participation in this study. While this is believed to be generally true it is also understood that as individuals each of the participants brings with them different capabilities that could differ from the standard assumption. Similarly, the clinical portion of this research used students that were executing the MAP scenario as part of a class, it is assumed that being part of the class did alter the outcome of the clinical trial.

This research used, as a key resource the University of Tennessee HITS facility. HITS had the benefits of providing a controlled clinic-like environment that was a virtual environment for both a hospital setting and patient encounter. As a simulation the assumption is that it conducting the scenario in this environment does not adversely impact the subjects' behaviors.

Computer Simulation

Any computer simulation is a limited representation of the function(s) it is trying to represent. It is reported George Box, the renowned statistician had said "All models are approximations. Essentially, all models are wrong, but some are useful. However, the approximate nature of the model must always be bourn in mind".

The use of an information multiplier is used to sequential increase the effect of information on the statistical likelihood of error outcome. While this multiplier is simply an indexing represent a notional effect of information, it is assumed that this approach represents how incremental increasing of information would perform.

As an agent-based model, various attributes were assigned to the agents used as part of the model's structure. The attributes selected for the agents used represent attributes in the research literature that impact medication administration performance. Little research has been done on the interaction of these attributes in an actual clinical setting much less a computer simulation. Furthermore, computer modeling of human behavior has

inherent limitations. The subset of attributes used in this simulation is assumed to provide and adequate representation of those that effect MAE performance.

Medication Administration is a complex adaptive process influenced by many factors including the practitioner administering the medication, the patient, the medication, procedures, other health providers influencing the process both directly and indirectly, related computer systems, family members, and the medication itself. By design, this simulation included a subset of these factors. While these other factors can impact the MAP, the working assumption is that the current model is a reasonable approximation of the MAP.

Limitations

The sample size for the clinical study was determined by the class size of the course used that the subjects were drawn from. The size of the sample provided adequate numbers of test subjects as confirmed by the sample size analysis.

Student nurses were used as test subjects. This provided the benefit of a relatively uniform education level and experience base

Because the scenario used for the clinical trial was part of a Nursing class, its design needed to include both educational component as well as addressing the research objective

The use of the HITS facility provided a controlled environment that allowed direct, unobtrusive observation. However, with this environment it did not have other influences that would occur in an actual clinical setting.

For the clinical portion of the research, small groups or teams of nursing students carried out the scenario and the student nurses interacted during the execution of the MAP scenario. This clearly influenced their performance during the MAP scenario.

Chapter 4
Analysis

Scope and Analysis

Analysis Introduction

Various data analyses were performed on the two components of this research, first, the CCS which defines what the impact of JIT information on MAP might be through a clinical trial, and second, developing an ABM that uses data from the literature and the CCS to simulate the MAP. The data set for the CCS is modest and is based on the number of subjects divided between the control and treatment groups. In contrast, the data set obtained from the model simulations is extensive and composed of multiple trials, control and treatment groups.

Model Analysis

The primary function of this model is to simulate the process of medication administration by nurses. The overall measure of nurse performance is a composite statistic, defined as the Likelihood Index (LI), which indicates the likelihood of the nurse agents' successful completion of the MAP. Recall from an earlier section that this single statistic is a function of many other variables within the model which contributes to the output for each medication processed through the medication administration process by the nurse agent. The model was constructed to provide a broad collection of data output on the operation of the simulation. Figure 4. 1 represents the combination of inputs, effects, probabilistic effects and how the combine via the MAP process steps to form the likelihood output.

The analysis will focus on validating the performance of the model through evaluation of simulation outputs and its alignment with values found in the related literature and the clinical case studies performed as part of this research. The analysis of the model first considers the overall system level model performance, followed by considering specific output functions and then focusing on a more detailed analysis of a specific trial representative of the model's operation.

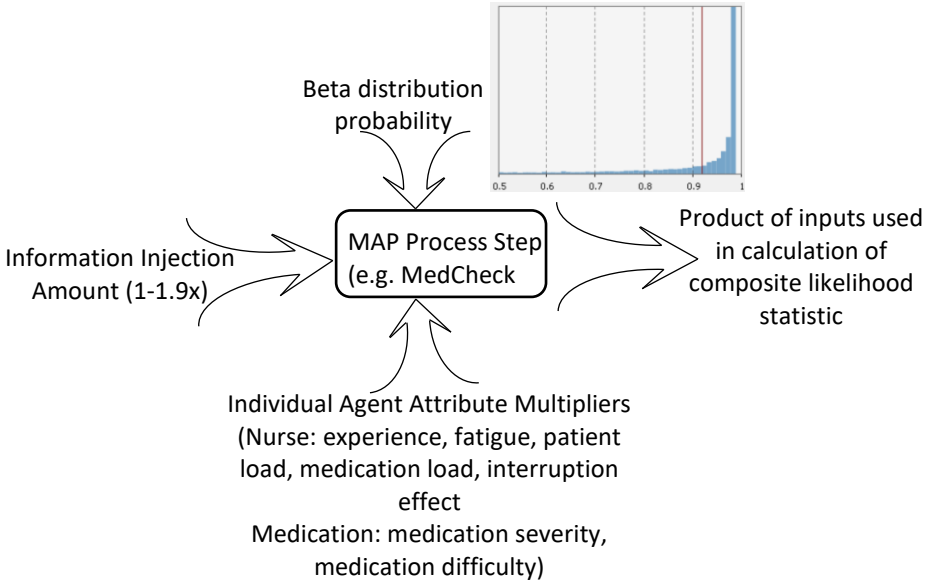


Figure 4. 1: Model elements contributing to overall data outputs for the model

Analysis of the model includes assessing the output of control variables data generated during the runs of the simulation against the variable representing the model conditions for the agents while executing the administration of medications. Comparative and descriptive statistical analysis is used to demonstrate model functioning and to compare expected versus actual performance of the model. The variable control analysis establishes overall benchmark performance of both the role of adding JIT information and gauging the effects of inserting the attributes of agents into the model.

The level of information injection is examined for each of the control-variables (false-false, false-true, true-false, true-true). The analysis of the model uses the composite performance indicator, Likelihood Index as the overall performance metric.

The true-true group, the group of simulations with both information injection and agent attributes being active, contains the data sets of interest for comparing the performance of the model relative to the clinical case study and actual clinical settings. Said another way, whereas the other control-variables are internal controls to validate model performance, true-true generates data that is intended to represent "real-world" nurse performance for administering medications. The information-medication trials are evaluated as with the control-variables; a representative trial is selected, as noted later for more detailed statistical evaluation.

Specifically, the effect from agent attributes is calculated by the product of the values assigned for each attribute:

Attribute Variable = exp*fatigue*patientLoad*medicationLoad*interruptionEffect*diff*medicationSeverity.

exp = nurse experience: overall experience of a nurse including education, years of experience and practical knowledge
fatigue = nurse fatigue: overall effect of fatigue based on hours worked for a nurse
patientLoad = patient load: number and difficulty of patients for a nurse
medicationLoad = medication load: number of medications
interruptionEffect = effect of interruption measured in hours worked
diff = medication difficulty: inherent difficulty of administering a medication
medicationSeverity = potential effect of a medication that would influence medication administration

The overall composite statistic is:

Likelihood Index = Information Injection value * beta distribution value* attributeVariable.

General Data Consideration:

Likelihood index[45] = $Information\ Injection\ Value \times beta\ distribution\ value\ _s \times \prod_{n=1} \prod_{p=1} \prod_{m=1} Attribute\ Variable_{npm}.$

Where n=nurse agent number, m = the subset of medications belonging to patient p for nurse n, s = each consecutive step in the MAE process

Recall that each nurse agent, patient agent and medication agent, form a combination of agents that function similarly to a small network. This small triplet network enters into the MAP and shuffles its way down the process chain stopping at each functional box where the likelihood of successfully completing that particular step is calculated. At the end of this process chain, the nurse agent returns to the beginning of the process where it figures out if the patient agent it is currently dealing with has any more medications to process, if it does, it starts down the path with the new medication; if not, it switches to its next patient to start the process anew. This is graphically represented in Figure 4. 2. The variables that are used in assessing the operation of the model are detailed in Table 4. 1.

[45] Also referred to as statsCalcP

Table 4. 1: Key variables in monitoring MAP model operations and assessing agent performance

Variable/Factor	**Description**
Primary Dependent Variable	
Likelihood Index (LI)	Overall likelihood of nurse successfully completing each MAP element
Primary Independent Variables	
Information Injection	Measure of JIT information provided to the agent in completing the overall MAP
Agent Attributes	Combination of contributions influencing the behavior and performance of individual agents to each MAP element
Contributory Variables	
MarCheckVariable	Likelihood of a nurse checking the mar for each patient
MedCheckVariable	Likelihood of a nurse checking the medication for each patient
DoseCheckVariable	Likelihood of a nurse checking the dose for each patient
PatientCheckVariable	Likelihood of a nurse checking the ID for each patient
RouteCheckVariable	Likelihood of a nurse checking the route for each patient
TimeCheckVariable	Likelihood of a nurse checking the time for each patient
Interruption	Nurse agent attribute for determining the impact of interruption
Medication Severity	Medication agent attribute for the impact of medication on likelihood of error
Medication Difficulty	Medication agent attribute for the impact of medication on likelihood of error
Nurse Experience	Nurse agent attribute for determining the impact of the level of nurse experience
Variable/Factor	**Description**
Patient Load	Nurse agent attribute for determining the impact of the number of patients per nurse
Medication Load	Nurse agent attribute for determining the impact of the number of medications per nurse
Nurse Fatigue	Nurse agent attribute for determining the impact of the level of nurse agent fatigue
Comparative Factors	
Log	Continuous count of the number of medications that have passed through the MAP
Time	Continuous measure of the time elapsed of the MAP process during the simulation

Table 4. 1: Key variables in monitoring MAP model operations and assessing agent performance (continued)

Variable/Factor	**Description**
Shift Number	Continuous measure of the number of shifts during a simulation
Patients per nurse	The number of patients assigned to individual nurse agents
Nurse ID	The unique number identifier of individual nurse agents
Current Shift	The shift the simulation is currently in
Medications per Nurse	the sum of the number of medications a nurse agent has based on the patients it is assigned
Model Parameters	
Length of Shift	The duration of each period of the shift
Number of Nurses	Total number of nurses entered into the model at the simulation
Number of Medications	The total number of medications passing through the MAP during a shift-established by model
Number of Patients	Total number of patients entered into the model at the simulation

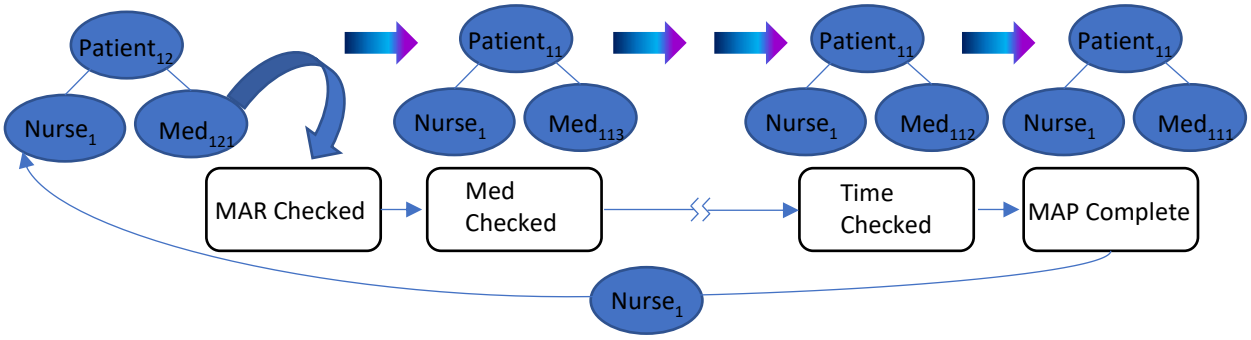


Figure 4. 2: Creation and flow of data generated by the model

A comprehensive simulation was designed as an approach in evaluating the MAP model. The simulation was structured to cover the essential operating parameters of the model, namely: amount of information injection, total number of medications, and duration of the MAP process by shift. The variables, the operating parameters are designed into the model and they vary within these boundaries based on predefined probability functions as described in the Materials and Methods section. The model allows for change, the overall number of nurses and patients are kept at one hundred and twenty respectively to allow the average nurse:patient ratio to be maintained at 1:5 (nurses to patients) as referenced in the literature.

The simulation iterates through various levels of information injection levels. The increments were: 1, 1.1, 1.3, 1.5, 1.7. 1.9. These levels were selected based on previous trial simulations that indicated this spread was adequate to demonstrate sufficient detail on the effect of the increase of information and its effects on the dependent variable. The 1.9 maximum was selected based on the trial simulation output that demonstrated this value reached a high level of saturation of effect of information on model performance. That is, at a multiplier of 1.9 for information injection, the Likelihood index was at 0.999 or greater for more than 97.5% of the medications processes. Meaning that there was a near 100% chance of at least 97.5% of the medications being administered. While higher levels of likelihood would be attainable, the plausibility of reaching this level in actual clinical application is unlikely.

Time duration for the MAP and the total amount of medication for each shift was also used as a measure in evaluating the model. The full data set represents two levels of total medication amounts, within three shift durations. The nominal amounts of 500 and 600 for total medications to be distributed was established by reviewing the literature for the average medications per patient for an acute care setting. As noted earlier, the actual medications per patient is determined stochastically. This property is also the reason that the actual medications amounts range from 598 to 503 for the low value and 595 to 600 for the high value. The total number of meds cannot be manually set by the user at run-time, rather the probability distribution function must be modified and tested until close to the desired total number of medications is reached. The fact that I hit 600, exactly the desired number, twice, was a testament to my blind good luck.

The shift duration was developed empirically through running multiple simulations to observe what durations provided the best clarity on the effect of shift duration boundary conditions. Durations of 120, 300 and 480 minutes were selected as the best candidate times. Table 4. 2 provides a summary table of the total medication number and shift duration combinations.

The model is constructed to provide three separate control groups, each with a different function, and one active measure. The collection of these values is referred to as *variable-control*. These control groups allow for examination of the independent effects of the delivery of JIT information and the attributes of the agents and other model effects. Table 4. 3 summarizes the various controls and active measure groups: the first three columns are control and the final column on the right is the effects group. The “false” indicates that the particular information injection or agent attributes are not being used. So, “false-false” indicates that neither information injection nor agent attributes are used during that portion of the simulation. This serves as the baseline to, in essence, evaluate the agent performance without any effects from attributes or information. The “false-true” control indicates model behavior with attributes functioning, but without information. Similarly, the “true-false” indicates that information injection is engaged and agent attributes are not being used. The value “true-true” is the portion of the simulation where the effects of both information injection and nurse attributes are being evaluated. *It is important to note that the active measure (i.e. the true-true variable-control) is the variable-control state that represents the desired output for measuring the influence of both the information injection and agent attributes – it is the output from this variable control that generates the information that is used in evaluating agent performance*. The other variable-controls provide baseline indication of model performance to ensure the model is performing as expected. The Information Injection Level indicates the level or intensity of the information provided to the nurse agent. In the Table 4. 4 you will note that 1.0 indicates no information is provided or used by the nurse agent, while 1.9 indicates a maximal amount is used.

Table 4. 2: Total medications per shift and shift duration combinations (medications-duration

			Shift Duration (minutes)		
			Short	Medium	Long
			120	300	480
No. Meds	Low	500	498-120	503-300	501-480
	High	600	595-120	600-300	600-480

Table 4. 3: Description of variable control variables

Variable Control variable values	Description/Function
false-false	Overall control value, the information injection and use of agent attributes is turned off
false-true	Control for information injection, agent attributes is turned on, information is turned off
true-false	Control for agent attributes, information is turned on, agent attributes is turned off
true-true	Experimental value with information injection and agent attributes both turned on. This measures the impact of information under the condition of the agents exhibiting active attributes

Table 4. 4: Distribution of variable controls by information injection level and functional description

		Information Injection on/off and Agent Attributes on/off			
		no info/no attribute	no info/attribute	info/no attribute	info/attribute
Info Injection Level	1.0	false-false	false-true	true-false	true-true
	1.1	false-false	false-true	true-false	true-true
	1.3	false-false	false-true	true-false	true-true
	1.5	false-false	false-true	true-false	true-true
	1.7	false-false	false-true	true-false	true-true
	1.9	false-false	false-true	true-false	true-true

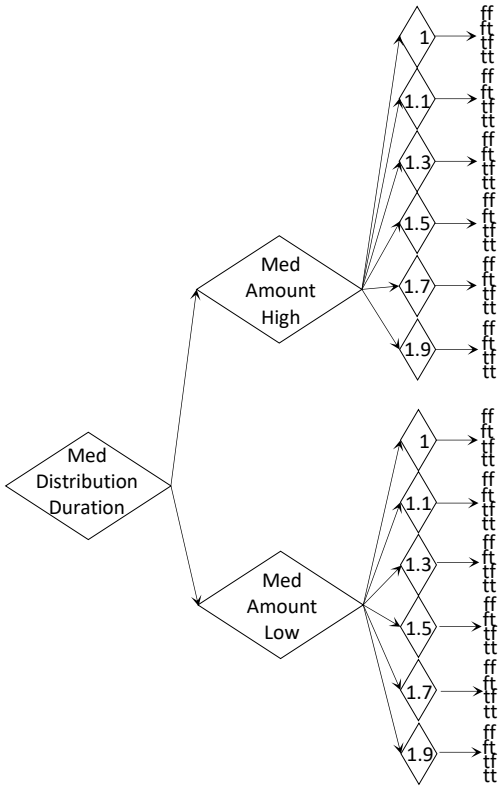
The length of shift is used as a basis for calculating the variable-control selection and information injection durations for the length of the simulation run for a particular value for information injection. As an example, assume a shift length of 480 minutes is set. As demonstrated in the top part of the diagram of Figure 4. 4, the model will go through 12 shift changes after which it changes to the next step of variable-control moving from false-false, true-false, false-true and then true-true. After the simulation iterates through each of the four variable-control states, it will then change to the next level of information injection and complete the same cycle. Variable-control selection is calculated by using (length of shift) * 12 and information injection duration is determined by (length of shift) * 48. So, in the example simulation shown in Figure 4. 4, a 480-minute length of shift spans 5,760 minutes and 23,040 minutes for variable-control duration and information injection duration respectively. Another way to consider this is that there are four variable-control states for each level of information injection. The variable-control states represent three separate experimental control groups and the active measure. Each level of variable-control state is made up of 12 shifts. The shift durations are set at the start of the model based on the goal of the simulation. The graphic in figure 4.4, portrays the sequencing of time related model elements.

One perspective of how the simulation trials can be represented by the categorical tree map is shown in Figure 4. 3 which combines the information injection and variable control variables. Starting on the right-hand side of the diagram, there are three different control runs (ff, ft, tf) and one response run (tt) for each level of information injection represented in the diamonds. These are each done for a high (600 medications) and low (500) amount of medications. Each of these are repeated for three different time durations (120, 300 and 480 minutes).

The simulation designed for the analysis generated a data set of 945,570 rows with more than 100 fields. That is over nine million data elements. This large data set contains each of the six trials. The analysis initially assesses the overall data set allowing a comparative assessment of the various information injection levels, shift lengths and controls on model outcomes. Following this assessment, a representative trial set was selected for the assessment of the variables for agent attributes and their effect on the overall likelihood of medication error. Three factors influenced the selection of the sub-dataset for the final selection:

1) The consistency of the data throughout the ranges of each of the shift duration/medications per shift/information injection combinations
2) The use of the data set(s) that reflected the application of the agent attributes and injection of information
3) Balance of the influence of the other factors across the data subset such as shifts, medication loading per nurse, agent attribute effects and others

As a first step in the analysis, the data was evaluated to explore the model's overall behavior by assessing key elements of the model. A distribution analysis, shown in Table 4. 5, indicates minor differences between the number of data elements within the time/med categories and the variable-control fields. The expected result would be that each row would be the same value among each of the columns. Some of the differences between rows, the meds per shift-minutes per shift column, are a result of the slightly different number of medications for each of the trials. Two notable differences are for the 120-minute runs and the true-true variable-control column. The 120-minute shifts have differences among each of the columns, while the remaining shifts have consistent values for each of the columns except for the true-true column, with the exception of the 503-300 trial. The difference for 501-480 and 600-300 is 23 medications, and the difference for 600-480 is 28 medications. The differences were evaluated for these three trials and were determined to be a truncation of the last several rows of data resulting from the means of data transfer. The reason for the differences at the 498-120 and 595-120 will be explored in a future section. Each of the data subsets was generally congruent with the literature on MAE performance and the clinical case study, and the 503-300 data-subset more closely fit with the criteria.



This tree diagram represents the approach to using High and Low medication (Med) amounts as part of the trial schema. Trials are run for the High (~600) and Low (~500) Med amounts. Each trial goes through the same levels of information injection (triangles) and control groups (ff, ft, tf, tt). This is duplicated for each of the three shift durations analyzed.

Figure 4. 3: Sequence of shifts, processing controls and information injection

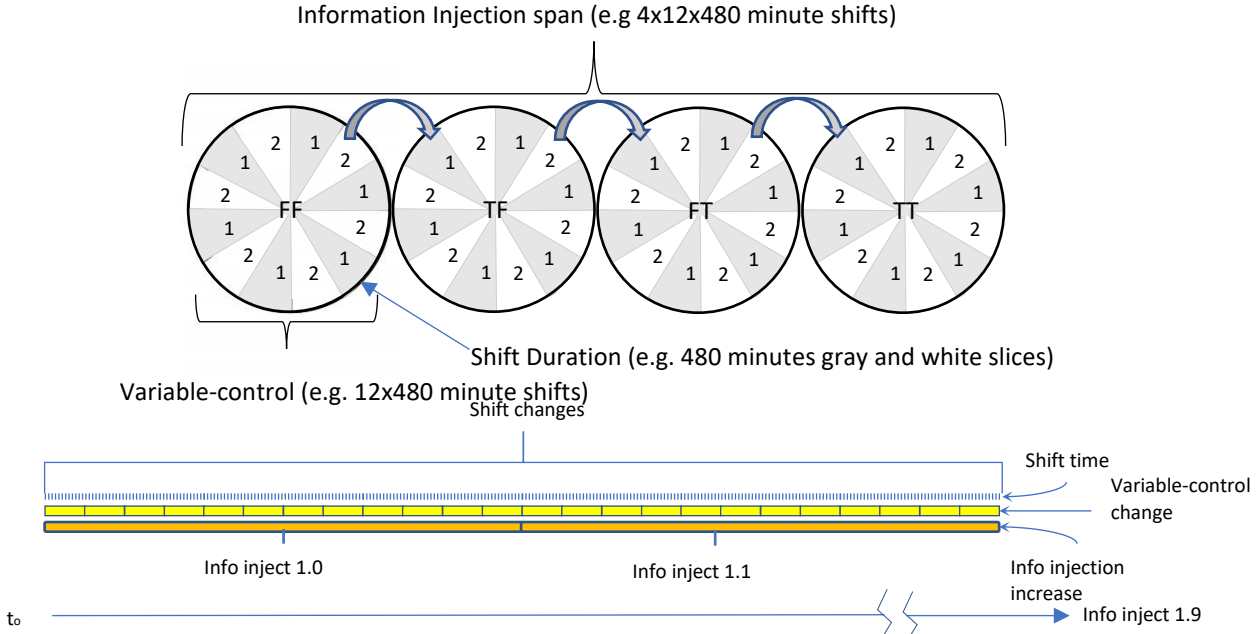


Figure 4. 4: Depiction of the relationship of the variable-control, shift duration and information injection variable during simulation execution

Table 4. 5: Counts of medications processed during separate trials for control and response groups

Med-min	false-false	false-true	true-false	true-true
498-120	35734	35837	35628	35677
501-480	36072	36072	36072	36049
503-300	36216	36216	36216	36216
595-120	42053	42647	41480	41836
600-300	43200	43200	43200	43177
600-480	43200	43200	43200	43172

Med-min represents the number of medications per shift and the number of minutes per shift respectively. Note the relative consistencies of the values except for the 120-minute durations.

Figure 4. 5 evaluates the number of medications that have gone through the MAP considering the spread, information injection amount and shift. The shorter shift duration, 120 minutes as highlighted in the figure, shows the most variance. The remaining elements show only a slight change in the largest amount of information injection, 1.9, with the exception of 503-300 which 12,072 medications processed for both shifts and all levels of information injection.

The evaluation of the distribution of the dataset was done by performing a contingency analysis using JMP 13. The analysis was partitioned by the duration/medication load and information injection amounts in order to provide a more detailed assessment. Since there are two shifts, the contingency analysis was done for both shifts. Of the three durations used, 120, 300, and 480 minutes, the 120-minute duration results in the MAP process execution being terminated due to lack of time for completion, that is, nurse agents could not deliver all their medications because they ran out of time in the simulation for both shifts. The highlighted areas in Figure 4. 5 show the incomplete delivery for the 120-minute period, particularly for the higher number of medications. The 300 and 480-minute durations completed their medication deliveries for shift one, shift two saw only the 300-minute duration at the 503 medication level completing the deliveries. The last shift of the overall shift, shift 288, had slightly fewer medications processed for the 501-480, 600-480, 600-300 simulations of 23, 28, and 23 medications respectively. The fewer medications processed is a function of the operations of the model.

While medications per nurse and duration of shift impact the likelihood of completing the administration of medication, the overall input variable for the likelihood of administration effort is the information injection function. As noted above, this variable is the input that modifies the effect or benefit of providing JIT information to the nurse agent administering during the administration process. The information injection function acts as a multiplier that modifies the individual probabilities of each of the check variables (e.g. marCheck, medCheck, etc.). For example, if the value of marCheck, as assigned by the probability distribution function is 0.721231, and the current information injection variable value is 1.5, the probability changes to 1.081846. Clearly a probability cannot be more than 1, so the simulation modifies any value greater than 1 to 0.999. The value 0.999 was selected as the high-end value to ensure no spurious events occurred in the simulation due to the unlikely occurrence of a probability of 1. Plus, in a real-world event, the likelihood of a 100% chance lack of error does not exist.

The other variable to consider is the attribute multiplier. This variable is a composite effect of all the various attributes that influence the behavior (likelihood to make an error) for each nurse. Similar to the information injection function, the attribute variable functions by modifying the overall check probability by multiplying it by a value that has the effect of changing the overall occurrence of that particular check probability. Unlike the information injection function, the attribute multiplier is a function of various modifying values.

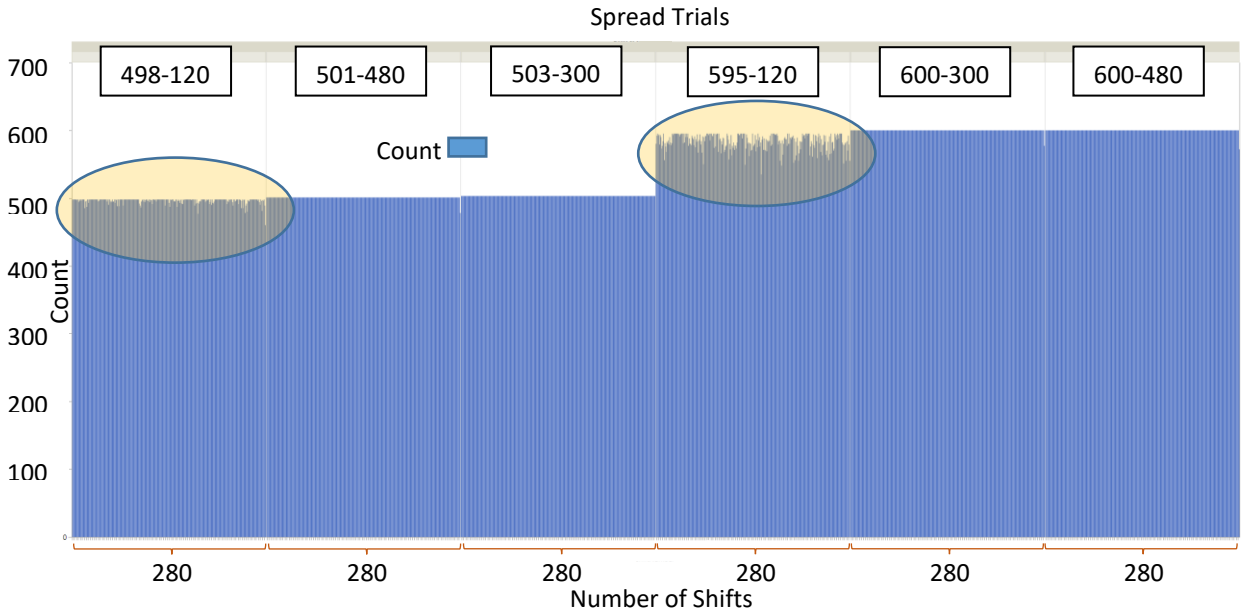


Figure 4. 5: frequency analysis of medications processed, individual trials by shift number

The model is constructed to run controls for each level of information injection. The controls selectively "turn on" and "turn off" the injection of information and attributes for the agents. This demonstrates the effects of each of these factors on the nurse agents' performance. The description of the controls is provided in Table 4. 4. As will be noted, there are three separate control conditions, one data generation run for each iteration of the simulation (i.e. for each level of information injection ranging from 1.0-1.9)

Table 4. 5 analyzes the association between two variables, the information injection (the amount of information that is provided to the nurse) and the status of agent attributes and if the information injection is on or off. The overall frequency of each of the conditions should be generally equal. Differences could result from truncated medication administration periods due to limited time, or a greater number of medications distributed based on more medications in a particular shift.

Multiple simulation runs were constructed with each having a defined duration and similar numbers of medications to administer. As with the previous example simulations, there were low numbers of medications and greater numbers of medications. Six model runs were designed to evaluate the model performance with varying lengths and different numbers of medication. The actual numbers of medications vary between runs due to the random selection of the number of medications. Table 4.6 lists the number of medications and time period in minutes for each of the six simulations.

In these runs, in contrast to the previews model runs used for analysis, the number of medications were not set at a specific scale. In the previous test runs, medications were set at five or six medications per patient to limit variance. Rather, the distribution was kept at the native value in the model and the values were randomly selected during model instantiation.

Table 4. 6: Distribution of medications randomly assigned to patients during Lo and Hi medication trials

	No. Medications per Patient	
index	Lo	Hi
1	2	2
2	3	4
3	4	6
4	5	7
5	7	8
6	9	9

The Lo column is the number of medications that are randomly assigned to patients for the Lo medication trials (500 medications per shift). Similarly, the Hi column represents the count of medications assigned randomly assigned to patients during the Hi (600 medications per shift) trials.

The medication distribution for Lo and Hi number of medications per patient are seen in Table 4. 6. The total number of medications per shift is set in the model by modifying the medications per patient distribution. The Lo column totals 30, divided by six items in the column results in an average of five medications per patient. Likewise, for the Hi column the total is 36 with an average of six. There are 100 patients in each shift resulting in an expected value of 500 and 600 medications per shift respectively. As noted previously, the actual number of medications in any simulation run might differ slightly from the expected value since the selection of medications per patient is stochastic, following a uniform distribution. The medication distribution or the Lo and Hi values used are noted in Table 4. 7.

Over 950,000 rows of data consisting of 10 million data elements, make up the full data set representing two levels of total medication amounts, three shift durations, each having three internal control groups and the response group for agent attributes and information injection levels. These levels and conditions result in 48 different sub-datasets. A representative data subset was selected for the assessment of the variables for agent attributes and their effect on the overall likelihood of medication error (Figure 4. 6). Three factors influenced the selection of the sub-dataset for the final selection:

1) The consistency of the data throughout the ranges of each of the shift duration/medications per shift/information injection combinations
2) The use of the data set(s) that reflected the application of the agent attributes and injection of information
3) Balance of the influence of the other factors across the data subset such as shifts, medication loading per nurse, agent attribute effects, and etcetera.

As will be seen, each of the data subsets was congruent with the literature MAE performance and the clinical case study, the 503-300 data-subset more closely fit with the criteria outlined above.

Analysis of Clinical Case Study Data

While the sequence of steps in a standard MAP follows a specific sequence, as in Figure 4. 7, in practice the steps can occur in a variety of sequences based on the preferences of the nurse and the particular condition being experienced at that time. This set of standard steps was used to build a set of variables to track MAP performance for the clinical simulations.

The activities of each nurse team were tracked through the MAP clinical simulation process using a set of variables that measured performance for each individual step of the process. Table 4.8 provides the list and description of variables used in the tracking of the medication administration steps followed by the nurses during the MAP clinical simulations

Table 4. 7: Matrix of trial runs for shift duration and no. of medications per shift

		No. of medications	
		Lo	Hi
Administration/shift time (minutes)	480	501	600
	300	505	600
	120	498	595

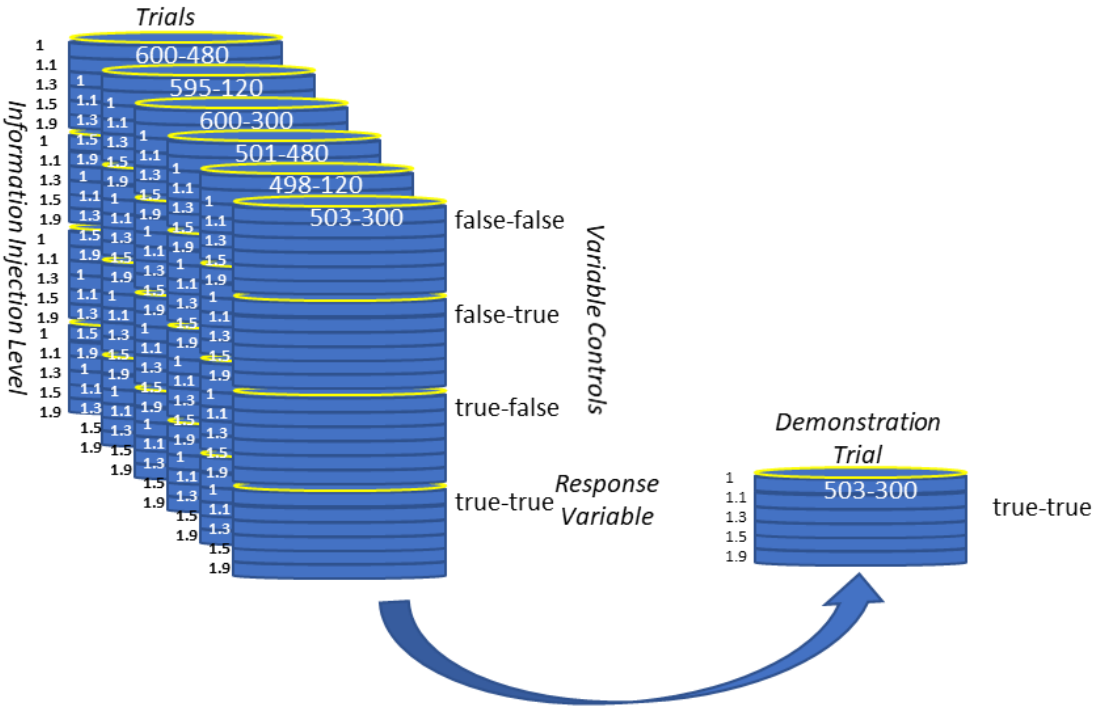


Figure 4. 6: Data reduction/down-select of demonstration trial for specific analysis

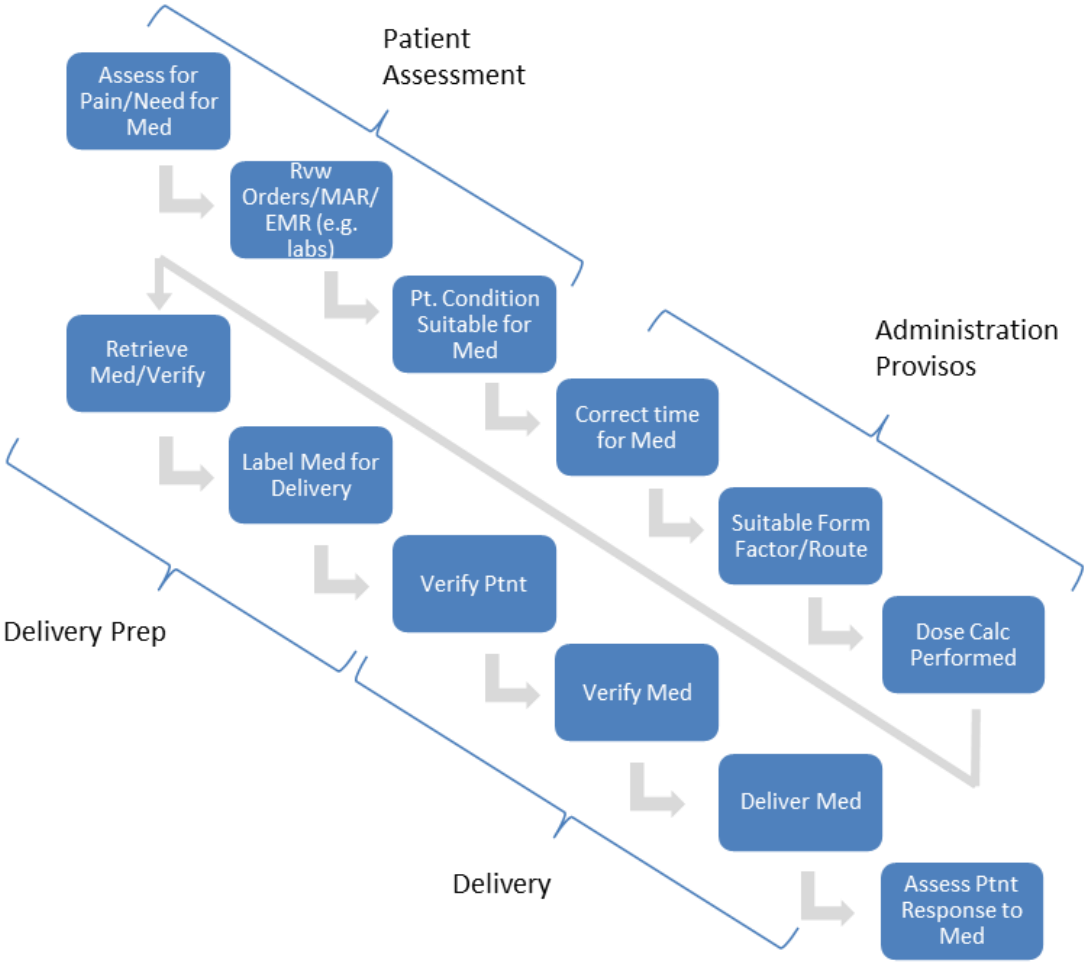


Figure 4. 7: Notional MAP sequence steps for correct medication administration

Table 4. 8: List of clinical case study tracking variables

Clinical Trial Variables	Variable Description
Pain Assessed/Med Needed	Patient evaluated to determine level of pain or need for medication based on physiological or observed condition
Dose Checked	Medication dose validated and appropriate dose calculated
Correct Dose Calculation	Dose calculated by nurse is correct
Med Delivered	Medication administered appropriately
Patient Checked	Patient Identification checked
Med Checked	Medication type, form and other characteristics validated as correct
Correct Med Delivered	The correct medication type, form, and dose were administered
Labs Checked	Patient laboratory values checked in the EMR
Labs Understood	Laboratory values and associated implications understood and appropriate actions taken
Route Checked	Delivery approach (e.g. oral, injection, tablet, liquid) validated
Time Checked	Timeframe validated for correct medication administration
Full/Stopped	MAP process terminated
MAR Checked	Medication Administration Record reviewed
Near Miss	Nurse actions were on path to error but corrected before an error occurred
Med Delivered Correctly	All of the requirements for correct medication administration have been complied with
Used App	JIT application used
Info	Qualitative assessment of degree to which JIT app was used
Liked	Post simulation indication of app benefit
Performance	Overall performance measure of nurse performance in administering medication defined as successful or unsuccessful

Table 4. 9: Clinical study tracking variable by group frequency table

		Group		
Clinical Study Tracking Variable		Control	Treatment	Total
Med Needed	No	0	0	0
	Yes	18	20	38
Dose Checked	No	4	10	14
	Yes	14	10	24
Correct Dose Calc	No	10	15	25
	Yes	18	5	23
Med Delivered	No	1	10	11
	Yes	17	10	27
Patient Check	No	5	10	15
	Yes	13	10	23
Med Checked	No	1	10	11
	Yes	17	10	27
Correct Med Deliv	No	2	10	12
	Yes	16	10	26
Labs Checked	No	12	9	21
	Yes	6	11	17
Labs Understood	No	7	9	16
	Yes	11	11	22
Route Checked	No	7	12	19
	Yes	11	8	19
Time Checked	No	2	0	2
	Yes	16	20	36
Mar Checked	No	0	0	0
	Yes	18	20	38

A frequency analysis of the response by variable for the control and treatment groups is provided in Table 4.9. It can be generally observed that overall performance improves in the treatment group. Specific interpretation on a by-variable basis is difficult because an outcome in the treatment group is the termination of the scenario based on the recognition by the nurse that the medication dose is in error and/or the patient's laboratory values are inappropriate. This early termination can occur at any stage of the scenario and as a result the process steps downstream from the termination event do not occur. While the fact that termination occurred was recorded, the point at which it occurred and which process steps were affected was not.

Various methodologies were used in analyzing the CCS data. The methods selected were appropriately vetted based on the data type and population size. The data was retrieved from standard score sheets used to collect the data. It was collected into a spreadsheet and the descriptive statistics were generated. As described later the population was relatively small. The primary methods selected were:

- Binary logistic (logit) regression,
- Chi square,
- T test.

The collection of the data was validated via reviewing of the video and audio recordings. Each scenario was reviewed three times. The data for each viewing was compared. For the scorings that resulted in different values the section of the video was reviewed again to determine a final score.

The qualitative aspects of the assessment, principally the test subject's assessment of the performance of the app and suggestions for improvements were collated but are not reported as part of this study. The input was used from the control group regarding the challenges in performing the training scenario to help in the design of the app.

Several commercial statistics software computer programs were used in the analysis of the clinical data. The software used was: JMP® 13.2.0, SPSS® 25, Minitab® 18 and Microsoft Excel® 2016. Each program offered specific characteristics for certain analyses. The large data set created some unique challenges for the software. Excel is limited to one-million rows: the data set had about 950,000, This made the manipulation cumbersome. Minitab was used for subsets of the data since it did not load the entire model data set. SPSS and JMP both were able to load the large data set.

JMP was used primarily for the analysis of the computer simulation data set while SPS was used primarily for the clinical data set. The logit evaluations and other analysis was more streamlined. The style of the tables in SPSS differs slightly from JMP. This difference was maintained in order to highlight the difference between the clinical analysis and the computer simulation data analysis

Appendix 1 holds detailed tables for the analysis for the interested reader including tables 4. 58 through 4. 64.

Table 4. 10: Summary of clinical case study data

			Performance	
		JIT app usage	Unsuccessful	Successful
Control		No app use	16	2
	Pre-Train	No app use	6	0
		Limited app use	2	0
		Significant app use	0	3
Treatment				
	Post-Train	No app use	0	0
		Limited app use	2	0
		Significant app use	0	7

The evaluation of the data from the clinical case study will assess the association of the use of JIT information delivered via a smartphone application on the overall success of completing the scenario. Success in the case of the scenario could be accomplished via a variety of decision paths by the student nurse. The overall outcome being measured is; of the control group (no information app), how many nursing students successfully complete the scenario, contrasted with the intervention group that used the app and their success rate. A chi-square test is used to indicate the likelihood of association between use of the smartphone app, implying JIT use of information based on the structure of the scenario, and a successful outcome.

There are two data groups, the control group and the treatment group, as will be detailed more fully in the section covering analysis of this portion of the data. The treatment group is broken down further into a pre-training group and a post-training group. Pre-training/post-training refers to providing brief structured training on the use of the app prior to the subjects performing the scenario. There were 18 subjects in the control group and 20 in the treatment group. Table 4. 10 summarizes the clinical case study (CCS) data.

While performance of the subjects for each step of the MAP process was collected, the key measures for the clinical case study are whether the app was used and the resulting performance of the test subject. In the control group, 16 subjects were unsuccessful in executing the MAP process correctly leaving two that performed correctly. Overall, the pre-treatment group had eight unsuccessful trials in executing the MAP process of which two used the app; three successfully completed the scenario. In contrast, the post-training group demonstrated seven subjects that completed the scenario successfully with two subjects being unsuccessful in their efforts.

Analysis

There are a number of interesting and challenging facets in analyzing this data generated from the simulations. The sample sizes are large, and highly skewed. This skewness is expected and inherent to the beta probability distribution used along with the structure of the model: the significant positive skew is by design replicating the profile of mediation administration in an actual clinical setting. Because of the skew, the data does not fit a normal profile and is a mix of balanced and unbalanced data. Much of the data is stochastic and, the design of the model determines the value of the model's variables during run-time. The inference is that it is generally not possible to control most of the model's variables to evaluate the impact of one variable on another variable.
Both parametric and nonparametric analysis was used in analyzing the data in consideration of the lack of normality. Guidance in the literature suggest larger sample sizes provide flexibility in using parametric measure for non-normal data; representatives of these tests were included in the assessment. Another motivation for including parametric tests is their ability to perform better on data with different population sizes, as is the case with this data. Several comparative methodologies are used, chiefly, the Tukey-Kramer Honest Significant Difference (HSD), Dunn's Method and the Steel-Dwass test.

Summary

A variety of statistical approaches are used in analyzing the model output. The approaches evaluated the data obtained from within each simulation run (I.e. the control and test groups) and among the simulations performed for each level of medication loading and shift duration combination.

Analysis methods included:

- Analysis of variance within each simulation and among the simulation trials
- Analysis of means
- Equal Variances
- All pairs (or joint pairs) parametric and non-parametric assessments
- Chi-square tests

Tukey-Kramer HSD

A Tukey-Kramer HSD (Honest Significant Difference) pairwise comparison Connecting Letters Report provides a concise indication of the comparative similarity among the means. The Tukey-Kramer range test is a parametric test but is robust for non-normal distributions and reportedly provides a more powerful approach when doing an all pairwise comparison when compared to the t-test. The Tukey-Kramer method considers the differences

between and among the individual means (pairwise comparison) decided by the estimated standard deviation of the mean. While not needed for this sample set, the Tukey-Kramer method compensates for unequal sample sizes by calculating the standard deviation for each pair comparison.

Examination of the paired groupings indicates the 480-minute scenarios and the 120FixedLo have means that appear similar.

$$HSD = \frac{\bar{x}_i - \bar{x}_j}{\sqrt{\frac{MSw}{n}}}$$

$\bar{x}_i, \bar{x}_j$: sample means where x_i greater than x_j

MSw: mean square within

n: sample size

Steel-Dwass (all pairs)

The Steel-Dwass (SD) is another nonparametric test. As with Wilcoxon it uses rank. The Steel Dwass method performs the multiple comparisons while controlling the overall experiment-wise error rate: in essence, it is the non-parametric equivalent to the Tukey-Kramer All-Pairs method. The, Steel Dwass procedure in JMP *is reported to* allow unequal treatment sizes. Each pair of treatments is compared by ranking only the observations in the two treatments of the comparison, calculating the mean rank for each treatment, and then computing the "Score Mean Difference", which is the difference in ranks with a continuity correction applied. The standardized statistic is asymptotically normal. Steel Dwass is also reportedly good for large sample sizes.

Dunn Method - All Pairs for Joint Ranks

The Dunn's method, also known as Bonferroni t, performs a comparison of each pair, similar to the Steel-Dwass All Pairs option. The Dunn method computes ranks for all the data, not just the pair being compared. The reported p-value reflects a Bonferroni adjustment which, in essence, is dividing the group alpha by the number of comparisons which reduces the per comparison level of alpha. It is, in essence, creating an orthogonal set of contrasts. The Dunn test is appropriate for unequal sample size and as a posthoc test, it is used to pinpoint which are means significantly different from others.

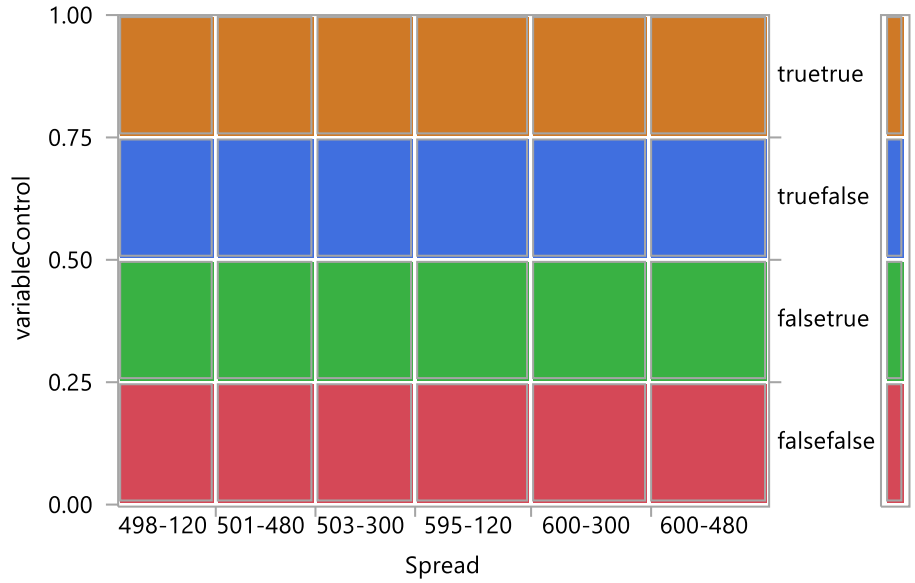
Evaluation of data balance

A factor that is considered in analyzing data from various trials is data balance. Data balance is defined as the number of elements in each trail. The balance of the data can affect the outcome of comparative statistical tests Data sets begin compared that have near equal numbers of elements are "balanced" those with unequal numbers are unbalanced.

The contingency test results provided a Likelihood ratio of 0.5716 and a Pearson Coefficient of 0.5709 this p value is greater than the threshold alpha of 0.05 leading to the conclusion that there is not enough evidence to support the null value assumption that there is a relationship between these two variables. This result matches the expected outcome from the design of the model for the overall comparison of differences in trials.

Assessing the balance of the data within a trial and across the variable control values, the data is largely balanced on a percentage basis (Table 4. 11 and Table 4. 12). The greatest deviation from balance is noted in the 120-minute trials. Regarding the remaining trials, with the exception of the 503-300 trial, the only difference is with the true-true variable control. The very last iteration has a slight decrease in the number of medications processed resulting in 1/100th of one-percent point difference, less than 30 data elements; as a result, these trials are considered near-balanced. The 503-300 trial data is balanced.

When analyzed among the trials, the data is unbalanced primarily due to the differences in the medications per shift.



The mosaic plot in Figure 4. 8 is striking in the visual similarity among the elements. As noted elsewhere, there is only a modest percentage difference between comparable entries

Figure 4. 8: Contingency analysis of variable control by spread mosaic plot

Table 4. 11: Contingency table evaluating unbalanced data - spread by variable control

Count Row %	false-false	false-true	true-false	true-true	Total
498-120	35734 25.01	35837 25.08	35628 24.94	35677 24.97	142876
501-480	36072 25.00	36072 25.00	36072 25.00	36049 24.99	144265
503-300	36216 25.00	36216 25.00	36216 25.00	36216 25.00	144864
595-120	42053 25.03	42647 25.38	41480 24.69	41836 24.90	168016
600-300	43200 25.00	43200 25.00	43200 25.00	43177 24.99	172777
600-480	43200 25.00	43200 25.00	43200 25.00	43172 24.99	172772
Total	236475	237172	235796	236127	945570

Table 4. 12: Tests for contingency matrix evaluating unbalance data

Contingency tests

N	DF	-LogLike	RSquare (U)
945570	15	6.6986494	0.0000

Test	ChiSquare	Prob>ChiSq
Likelihood Ratio	13.397	0.5716
Pearson	13.406	0.5709

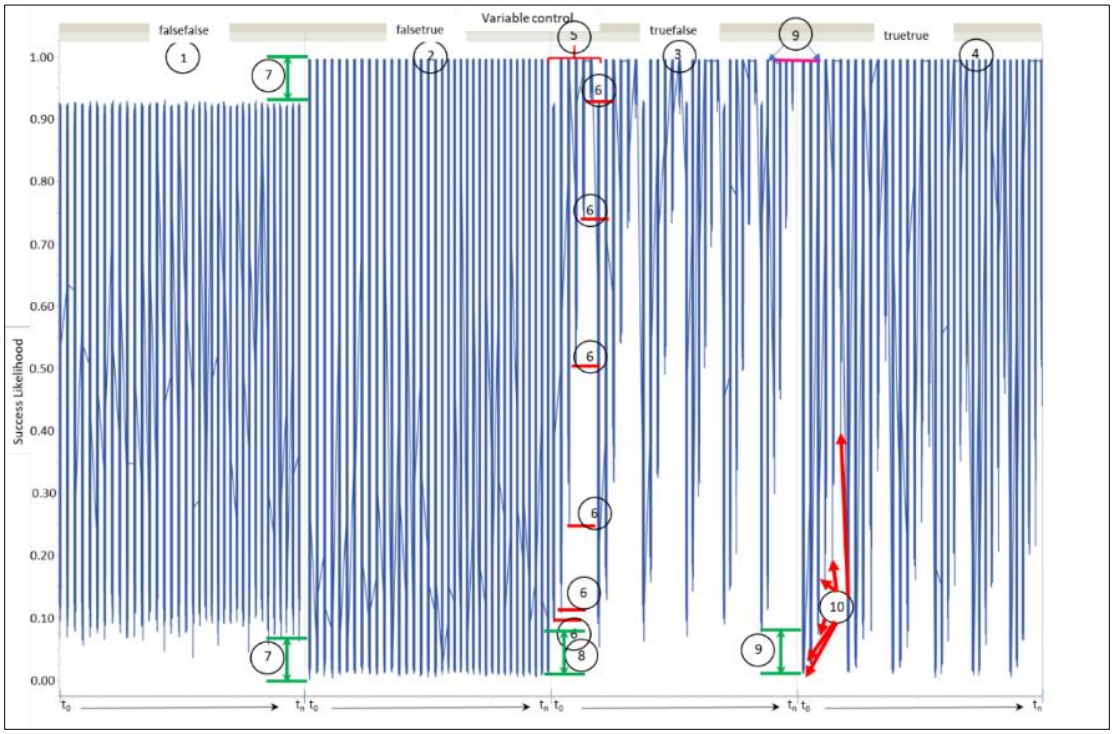


Figure 4. 9: Representative graph of success Likelihood by variable control demonstrating controls and response data

Figure 4. 9 is a graphical representation of the data profile of a representative simulation. The description of each phase is labeled with a corresponding number label:

1. This represents the false-false control section. Note the smaller range on the vertical axis which is a result of decreased variance from the agents not having attributes and no information being applied which decreases the maximum likelihood of success.
2. This section is a control section and it is the false-true section of the simulation which "turns on" the unique attributes of each agent but does not have additional information. The larger range, when
3. Compared to the initial section, this is a function of the increased variance from the application of attributes to the agents.
4. Section 3 represents another control section referred to as true-false. This section does not have the agent attributes functioning but includes the JIT information injection feature.
5. The final section, section 4, has both agent attributes and JIT information injection functioning. This section is the key section representing the fully functional model demonstrating the simulated performance of nurse, patient and medication agents.
6. Label 5 indicates the change in pattern which is a result of the injection of information. The decreasing range along each step of this, progressing upward in a saw tooth pattern, indicates the effect of increasing levels of information.
7. Label 6 indicates the increasing levels of performance, that is, the improving likelihood of success along progressive increases in information.
8. The change in variance induced attributes is indicated by level 7.
9. The decrease in variance created by removing the influence of agent attributes is indicated by label 8, as the simulation transitions from false-true to true-false.
10. The increase in variance from the presence of attributes being re-instituted for true-true is indicated by label 9.
11. Label 10, similar to label 6, indicates the improvement in the Likelihood Success Factor as the information level is increased from no information to the maximum amount (6 increments).

Figure 4. 9 serves as a segue into the specific analyses of the model starting with the three control sections and the test or demonstration section. Each of the sections for each simulation run from false-false through true-false, the simulation incorporating agent attributes and information true-true for each level of medication loading. Shift duration is also analyzed to understand the dynamics of the model and the degree to which it appropriately represents the clinical case study results.

Evaluation of Control Value False-False

The first evaluation considers the overall total likelihood index (i.e. this is the totalStatsCalcP variable representing the composite statistic for the likelihood of the nurse agent successfully completing the MAP) for each of the trials (number of medications-shift duration) with no effects introduced from either information or agent attributes (i.e. the false-false variable control). Without the effects of attributes or additional information the expectation would be that the mean values and variances should be consistent among the trials. If there were a variance between trial data sets that would indicate an influence introduced by the model or an undefined effect from the shift duration or total number of medications per shift. Oneway analysis was performed using JMP. As would be expected, Figure 4. 10 indicates uniformity across the trials. The analysis of variance (ANOVA), having a probability for the whole model test of 0.7381 indicates there is no significant difference among the mean values within the model. Further analysis on pairwise comparisons was done using both the Tukey-Kramer HSD and the Steel-Dwass Method. Both methods indicated no significant differences between the means of the trials at an alpha = 0.05 which provides the connecting letters report.

The results of the equal means and variance tests align with the original supposition that the variances would be equal. Figure 4. 11 and Figure 4. 12 provides the detail of the test results. Specifically, the figures indicate that the means and variances are similar. The conclusion, based on the relative uniformity of the data, is that the model is generating consistent results through various shift durations and medication amounts when controlling for the effects of attributes and information. Note in Figure 4.11 that the vertical axis has a quite small difference

between the lower decision limit (LDL) and upper decision limit (UDL): this difference of less than five one-thousandths highlights the similarity of the values.

The output of the ANOVA provided a p value is greater than the alpha = 0.05 leading to the acceptance of the null hypothesis that the means are equal. Inspection of the mean and standard deviation for each of the trials for this control group supports the ANOVA that there is no significant difference of the means

To summarize the analysis for the variable control value of false-false, there is no influence from either the application from agent attributes nor from information. Based on this, the expected likelihood index values would reflect a uniform range, near equivalent means and variances. Any differences would be a result of the stochastic distributions within the model. This particular set of simulations made up of the each of the different shift durations and medication amounts with both the information injection and agent attributes set at having no influence, establishes the baseline from which the other potential influences from increasing the effects of information or application of agent attributes might be determined. The analysis of the associated output from these simulations implies equivalent means and variances among the trial groups and therefore aligns with the expected outcomes.

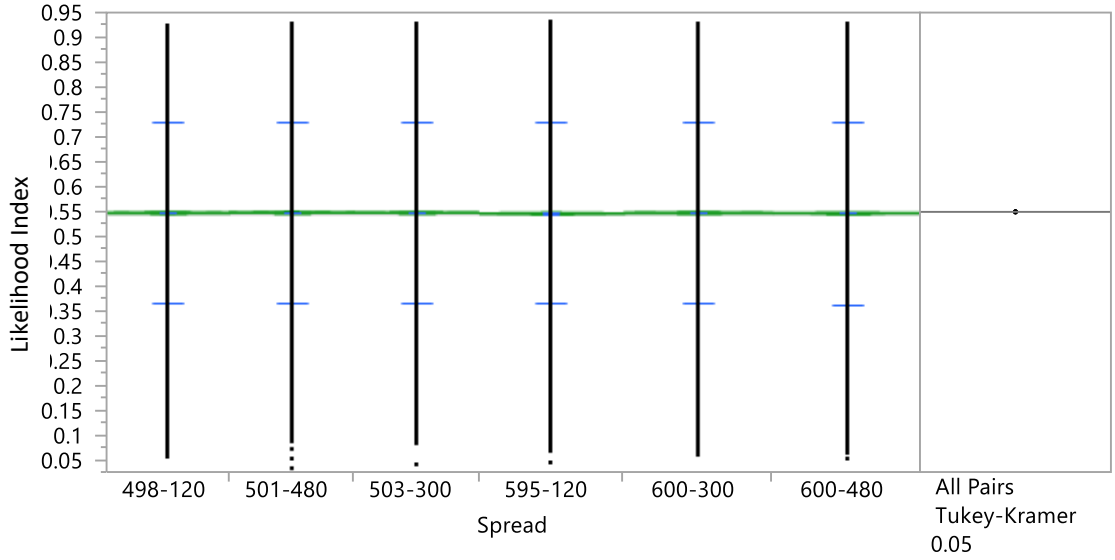


Figure 4. 10: Oneway analysis of likelihood index (LI) by spread variable Control=false-false, information injection=1

Table 4. 13: Connecting letters report for Tukey-Kramer HSD and Steel Dwass all pairs

Trial	Tukey	Steele
501-480	A	A
503-300	A	A
498-120	A	A
600-300	A	A
600-480	A	A
595-120	A	A

Corresponding with the ANOVA the pairwise comparison of the falsefalse variable control demonstrated that there appears to be no significant difference among the means. comparison (Levels not connected by same letter are significantly different)

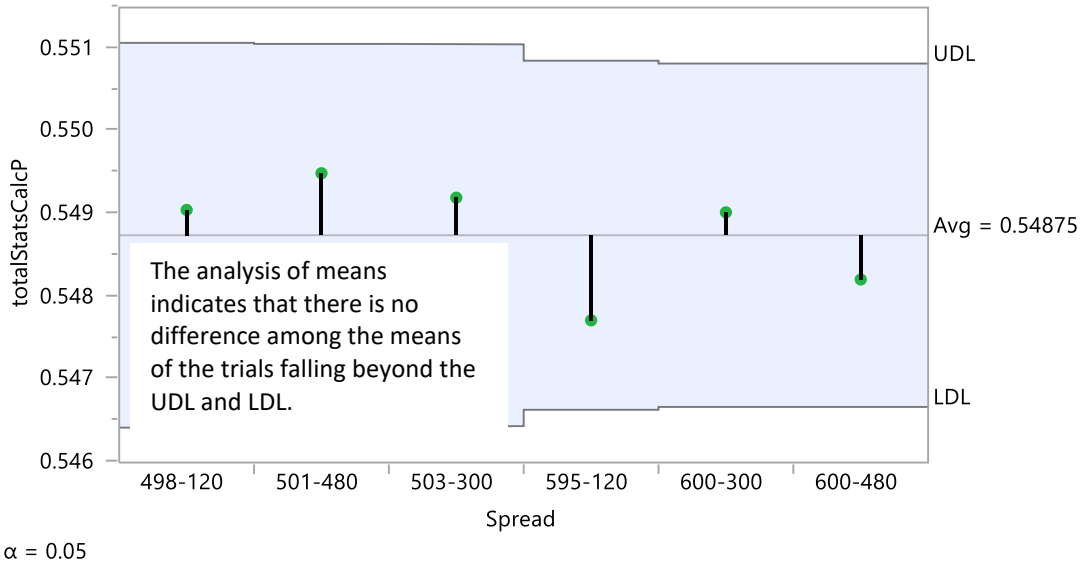
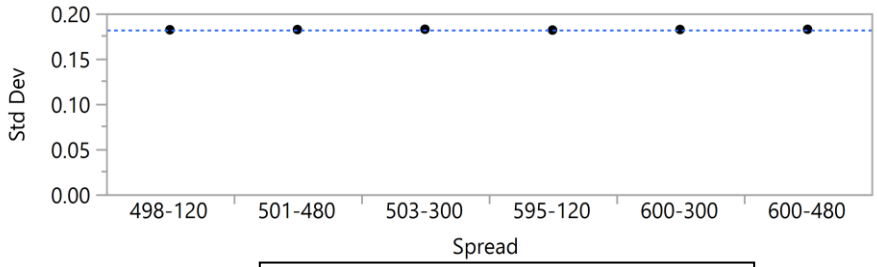


Figure 4. 11: Tests for equal means



The equal variance tests indicate, based on p>0.05, that the null is accepted and that the variances are equal.

Equal variance test	Prob > F
O'Brien[.5]	0.8100
Brown-Forsythe	0.3657
Levene	0.3638
Bartlett	0.9335
Welch's	0.7373

Figure 4. 12: Equal variance tests for variable control false-false information injection level = 1

To summarize the analysis for the variable control value of false-false, there is no influence from either the application from agent attributes nor from information. Based on this, the expected likelihood index values would reflect a uniform range, near equivalent means and variances. Any differences would be a result of the stochastic distributions within the model. This particular set of simulations made up of the each of the different shift durations and medication amounts with both the information injection and agent attributes set at having no influence, establishes the baseline from which the other potential influences from increasing the effects of information or application of agent attributes might be determined. The analysis of the associated output from these simulations implies equivalent means and variances among the trial groups and therefore aligns with the expected outcomes.

Evaluation of Control Value False-True

The next trial data set explores the effects of incorporating agent attributes on the overall likelihood of success probabilities. The introduction of agent attributes introduces significant variance by creating differences among the agents. In contrast with the false-false data set, this shows a significant difference between the trial datasets as indicated by the ANOVA p value of less the 0.0001 (recall that false-false had an ANOVA p value equal to 0.7381). Figure 4. 13 evinces an overall mean of 0.39632; a lower mean than the mean of 0.548748 for the previous control. In addition to the overall means being different, there is also a difference noted among the individual means between the two simulation runs. The Tukey-Kramer HSD and Steel Dwass pairwise comparison have similar results indicating differences among various sets of the means. The summary of the results in

Table 4. 15 shows similar means between trials with 300-minute shift times and 120-minute shift times.
The results of the equal means and variances tests indicate unequal variances among the trials. Figure 4. 14 and Figure 4. 15 provides detail of the test results.

The expectation was that the inclusion of agent attributes would contribute to increasing overall variance within and among the trials. This result was borne out with the assessment of the differences among the means and greater variances in the system. This indicates that the addition of attributes has the desired effect of creating diversity in the agents and how the effect the overall system.
There is a decrease in the overall mean response from 0.54875 in the falsefalse control group to 0.39632 for the false-true control group as expected due to the depression of performance by the application of attributes.

The p value calculated by the ANOVA is <0.001, is less than the alpha = 0.05 leading to the rejection of the null hypothesis that the means are equal.

Corresponding with the ANOVA p value, the pairwise comparison of the false-true variable control demonstrated that there appears to be significant differences among the means. In this comparison, 503-300 and 600-300 are similar as are 498-120 and 595-120 (In contrast the 480-minute trials (501-480 and 600-480) is different within itself and from the other trials, see Table 4. 14). In contrast the 480-minute trials (501-480 and 600-480) is different within itself and from the other trials.

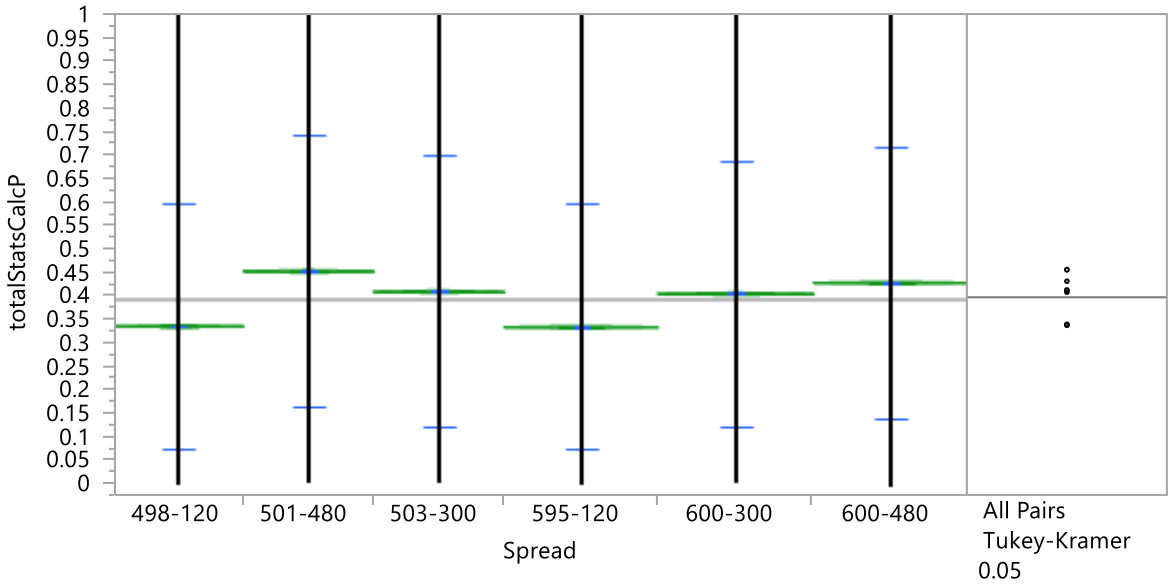


Figure 4. 13: Oneway Analysis of Likelihood Index (totalStatsCalcP) By Spread variableControl=false-true, information injection=1

Table 4. 14: Connecting letters report for Tukey-Kramer HSD and Steel Dawes all pairs comparison

Level	Tukeys				Steel			
501-480	A				A			
600-480		B				B		
503-300			C				C	
600-300			C				C	
498-120				D				D
595-120				D				D

(Levels not connected by same letter are significantly different). Levels not connected by same letter are significantly different.

Table 4. 15: Connecting letters report for II = 1 variable control = true-false

Level	Tukey		Steel		Dunn	
501-480	A		A		A	
498-120	A		A		A	
503-300	A		A		A	
595-120	A	B	A	B	A	B
600-300	A	B	A	B	A	B
600-480		B		B		B

In Table 4. 15 the Tukey-Kramer HSD and two non-parametric tests, Steel Dwass and Dunn, for joint ranking indicate largely similar values with 600-480 being significantly different from the largest grouping.

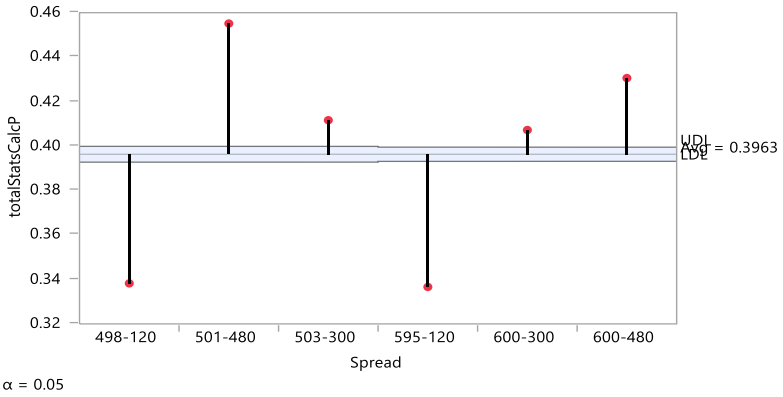
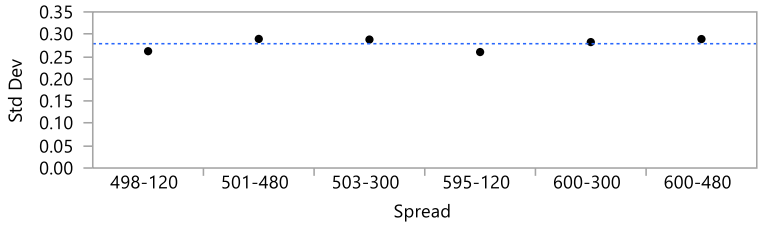


Figure 4. 14: Tests for equal variances and means

The analysis of means indicates that there is a difference among the means of the trials falling beyond the UDL and LDL.



Test	Prob > F
O'Brien[.5]	<.0001*
Brown-Forsythe	<.0001*
Levene	<.0001*
Bartlett	<.0001*
Welch's	<.0001*

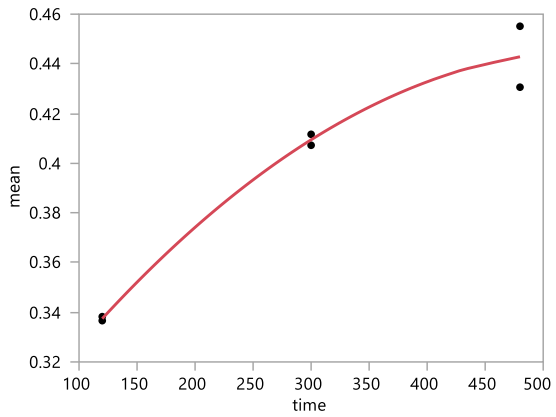
The equal variance tests indicate, based on p>0.05, that the null is rejected and the variances are among the trials.

Figure 4. 15: Equal variance tests for variable control false-true information injection level = 1

The false-true control controls the information injection to the value of 1. This means no additional information input and the agent attributes is set to "on" meaning the agents' attributes are active and are influencing their behavior and therefore their effect on the likelihood index. The presumptive effect of incorporating the agent attributes would be to increase the overall variance of the model by creating a wider spectrum of potential outcomes or deviations from the beta distribution conditioning the base behavior of the agent. As an example, without the attributes function, the agent behaves like an automaton zombie with its behavior strictly limited in a very narrow band; the addition of attributes expands the potential breadth of behaviors and as a result an increase in the variance of the likelihood index.

The analysis of the output for false-true demonstrates a considerable increase in variance from the false-false baseline as expected. Each of the medication-shift time trials indicate differing variations between the means of the likelihood index values for the trials, as well as deviations from the overall mean of the false-true runs. The pairwise comparisons indicate unequal means among the trials with 501-480 and 600-480 being unique unto themselves. 503-300 and 600-300 are similar to each other as are 498-120 and 595-120, but, differing from the other trials. The means for 501-480 and 600-480 are higher and, the standard deviation is also larger. While the reason for this is not entirely clear, some plausible causes could include a random effect generated by the model,

or less likely, an effect of shift length. Note that while there is a difference in the means between the 300 and 480 shift durations, the difference is less than 0.05. In contrast, the difference between the 300 and 480 shift durations is considerably greater with the mean of the 120-shift duration at 0.3 and the other durations greater than 0.4. This difference can be rationalized by considering the chart in
Figure 4. 5 which plots the frequency of medication administrations by shift. Of note is the saw tooth pattern for the 120-minute shift durations indicating the full number of medications per shift are not being administered. We are assuming this could decrease the likelihood index. However, as mentioned previously, there could be a duration dependent relationship between shift duration and the likelihood index that is not entirely understood at this point which warrants further investigation. Further evaluation of potential time dependency reveals a potential linear relationship between shift duration and the overall mean of the LI for the given shift duration. The plot of residuals reveals potential heteroscedasticity. The graph of Figure 4. 16 plots the curve for the consecutive shift durations from 120-480 minutes for the false-true control which holds include agent attributes but has no effect from information injection. This indicates a relationship of improved performance given longer shift times. The R-square value is 0.973849 with the p value for the intercept and variable "time" have p values of <0.0001 and 0.0019 respectively.



Polynomial Fit Degree=2
mean = 0.3215651 + 0.0002929*time - 5.9518e-7*(time-300)^2

Figure 4. 16: Graph and analysis of mean Likelihood Index for shift duration levels for the false-true control

The (time-300)^2 factor had a p value of 0.1169. Consideration of this relationship must be conditioned by several factors: there are only three shift durations which should guard a firm conclusion of a relationship and, the relationship is projected for the mean values of the LI. To be noted is graph Figure 4. 17 demonstrating an increase in residual difference versus predicted indicating a divergence of actual versus predicted. The vertical bars represent all the medications administered in that specific shift duration.

Evaluation of Control Value True-False

The next step in the analysis is to evaluate the third control group where the level of information changes and the agent attributes are not included in the simulations. The expectation is that the mean of the Likelihood index for each level of information injection should gradually increase as the amount of information increases. The variance remaining relatively constant as the amount of information injected into the system is progressively increased. At the initial level of information injection of 1.0, with no additional information being provided to the nurse agent, each trial is relatively equivalent. Of note is the difference in the 600-480 trial in comparison to the other trials having the indication that the mean is modestly lower than the other trial mean values. This is not completely unexpected, the pairwise comparison tests indicate that the 680-480 trial is not shown to have significant difference with two other values. A comparative frequency analysis was done of the individual response values, the 600-480 trial indicates a slight positive skew of 0.04 while the other trials indicate a slight negative skewness. This slight shift in the histogram implies larger values resulting from the probability distributions for the trials other than the 600-480 trial. Since the data is not normally distributed, the analysis of means (ANOM) for variances with Levene was used. This method provides a robust test that compares the group means of the *absolute deviations from the median* (ADM) to the overall mean ADM. The use of ANOM for Variances with Levene (ADM) if it is suspected that the data is non-normal. ANOM for Variances with Levene (ADM) is a nonparametric analog of the ANOM for Variances analysis.

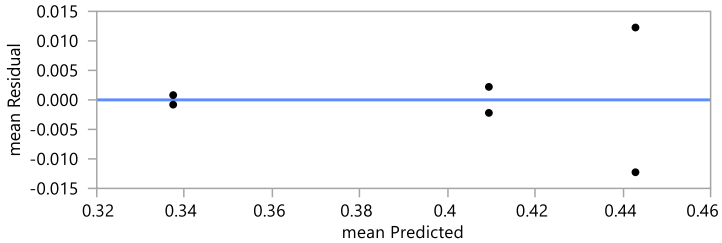
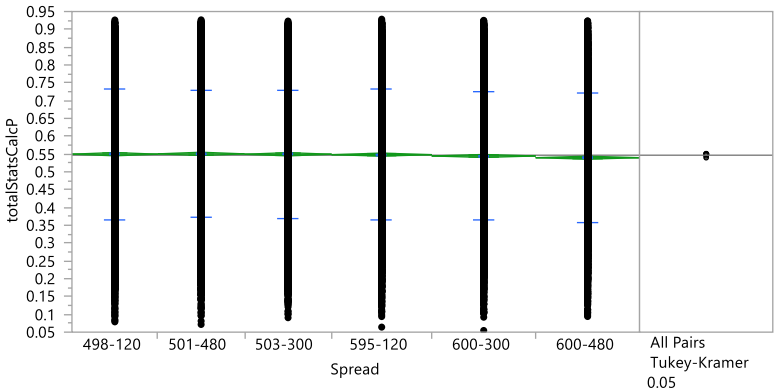
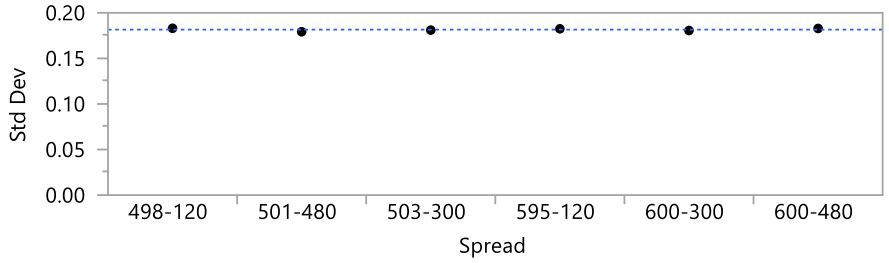


Figure 4. 17: Residual by predicated plot of trial LI means



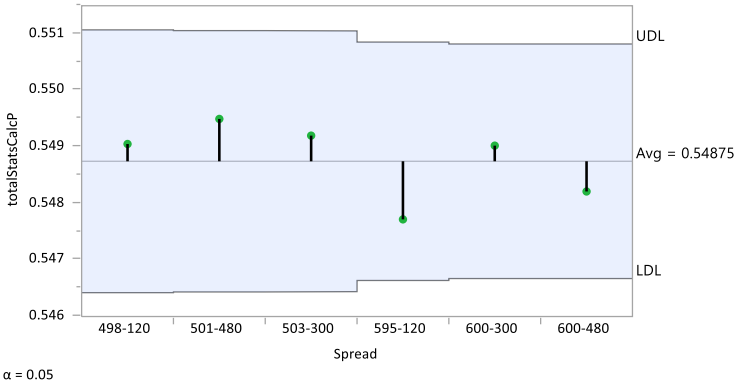
The plots of the individual trials in Figure 4. 18 should be roughly equal and similar to the falsefalse trial.

Figure 4. 18: Oneway analysis of likelihood index by medication amount/shift duration variablecontrol=true-false, information injection=1



Test	Prob > F
O'Brien[.5]	0.1892
Brown-Forsythe	0.1463
Levene	0.151
Bartlett	0.5079

Figure 4. 19: Analysis of means for true-false=1, for II trials



Analysis of means using ANOM in Figure 4. 19 for variances with Levene (absolute deviation from mean/median) indicates that all values fall within the decision limits.

Figure 4. 20: Tests that the variances are equal for true-false II=1

Figure 4. 20 and the associated table indicates that the variances are equal for the simulated trials. In particular, the Levene test is noted because its use is appropriate for testing variances from non-normal distributions. All p values reported are greater than the alpha of 0.05 concluding that the null hypothesis that the group variances are equivalent.

In analyzing the control group for the effect of information injection controlling for agent attributes (i.e. excluding the effects for attributes), the effect of information injection increase can be summarized by Figure 4. 21 which plots the change in the mean of likelihood of error avoidance and the associated decrease of its standard deviation. This figure shows the average values for the combination of trials. This composite graph provides a density map of the medications delivered for each information level (colored vertical cloud), along with the associated box plot. A curve tracing the predicted average for each information level as well as a curve indicating the rate of change of the standard deviation are also included.

The density map for injection level 1 shows the point cloud spread of the likelihood of error avoidance (i.e. likelihood of success) for each medication that has gone through the MAP process. The trial to the far left, as the internal control for this set, demonstrates grouping similar to that for the false-false control. The expectation is that it would have the lowest overall mean of the trial sets which is represented by the beginning of the mean trial curve. Table 4. 61 provides the detailed data set in the appendices.

Considering the Oneway analysis in Figure 4. 22, the overall mean can be observed slowly increasing as the level of information injection increases from 1.1 to 1.9 as is expected. The data in each of the trials gets compressed closer

to 1 as the injection of information increases the LI demonstrating the increase in MAP performance by the nurse agent. The blue hash marks, representing the confidence interval, get progressively smaller as the II increases. The analysis of means used the same approach as described previously, using the ANOM variances-Levene (ADM). The values for each of the trials falls well within the boundaries of the upper and lower decision limits (Figure 4. 23). This highlights the minimal disturbance in the variance and small standard deviations. This set of trials is similar in the amount of variance as the false-false control set of trials. As such, it is expected that the addition of information does not increase the amount of variance.

The analysis of means/medians employing both parametric and non-parametric tests proceeded similarly to that done for the false-true trial. The connecting letters report indicates that each of the medication amount/shift duration trials have medians/means that are not significantly different, matching the expectation for the model design for this control (detail in appendix Table 4.61 to Table 4.64). The Dunn method for joint ranking was not included in the connected letters report, the results are consistent with the Tukey-Kramer and Steel Dwass reports.

Measurement for equal variance shown in Figure 4. 24 and Table 4. 65 indicates variance equality tests that generally show that the variances are equal. Particular attention is given to the Welch's due to the unequal sample sizes of the trials which well suited for unequal sample sizes and indicates the variances appear similar.

No linear relationship was noted between the medication/shift duration trials. Oneway analysis was performed on the true-false trials across the information injection levels 1.1-1.9. Tukey HSD and Dunn's test were performed (Table 16 shows the Tukey and Steel test). All values are greater than 0.5 with most values approaching 1.0 and indicating that the means appear to be equal implying no linear relationship exists (abridged output is provided in Table 4.66 in the appendix).

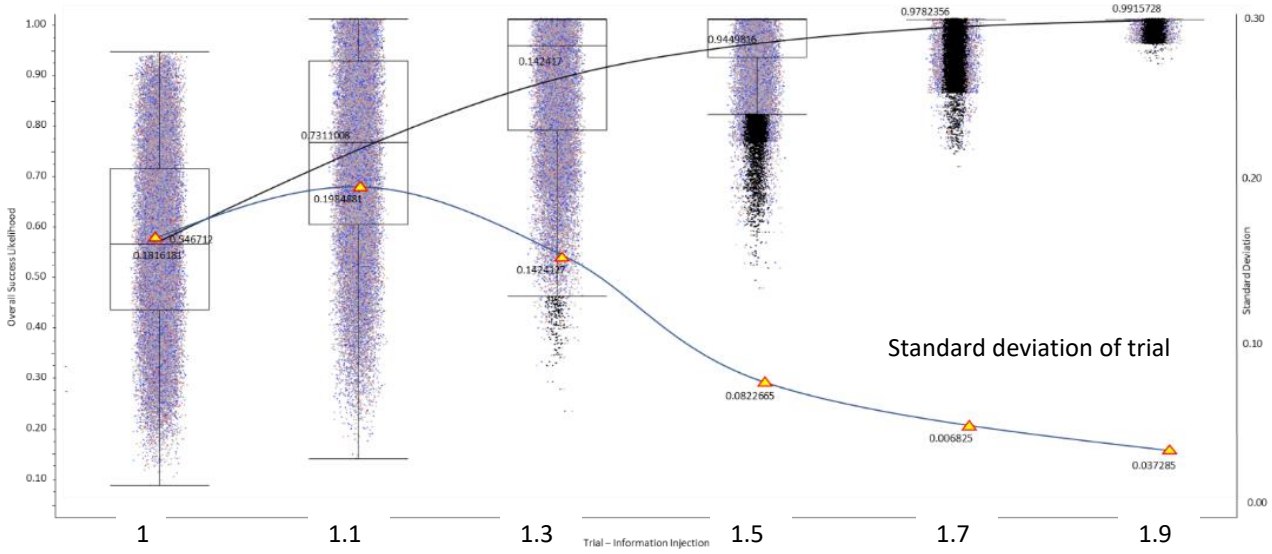


Figure 4. 21: True-false composite boxplot for true-false

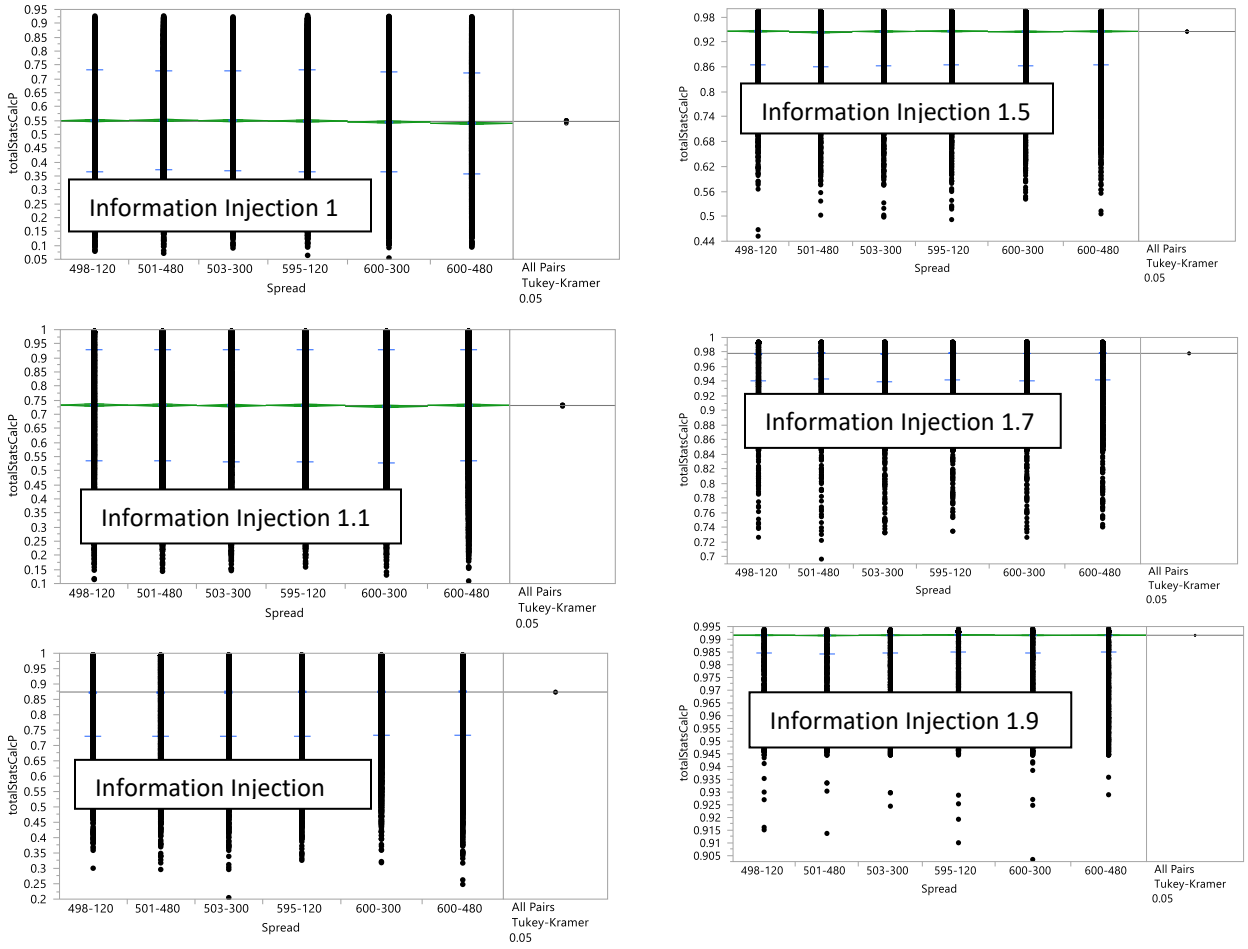


Figure 4. 22: Oneway analysis of likelihood index by medication amount/shift duration variablecontrol=true-false, information injection=1 through 1.9.

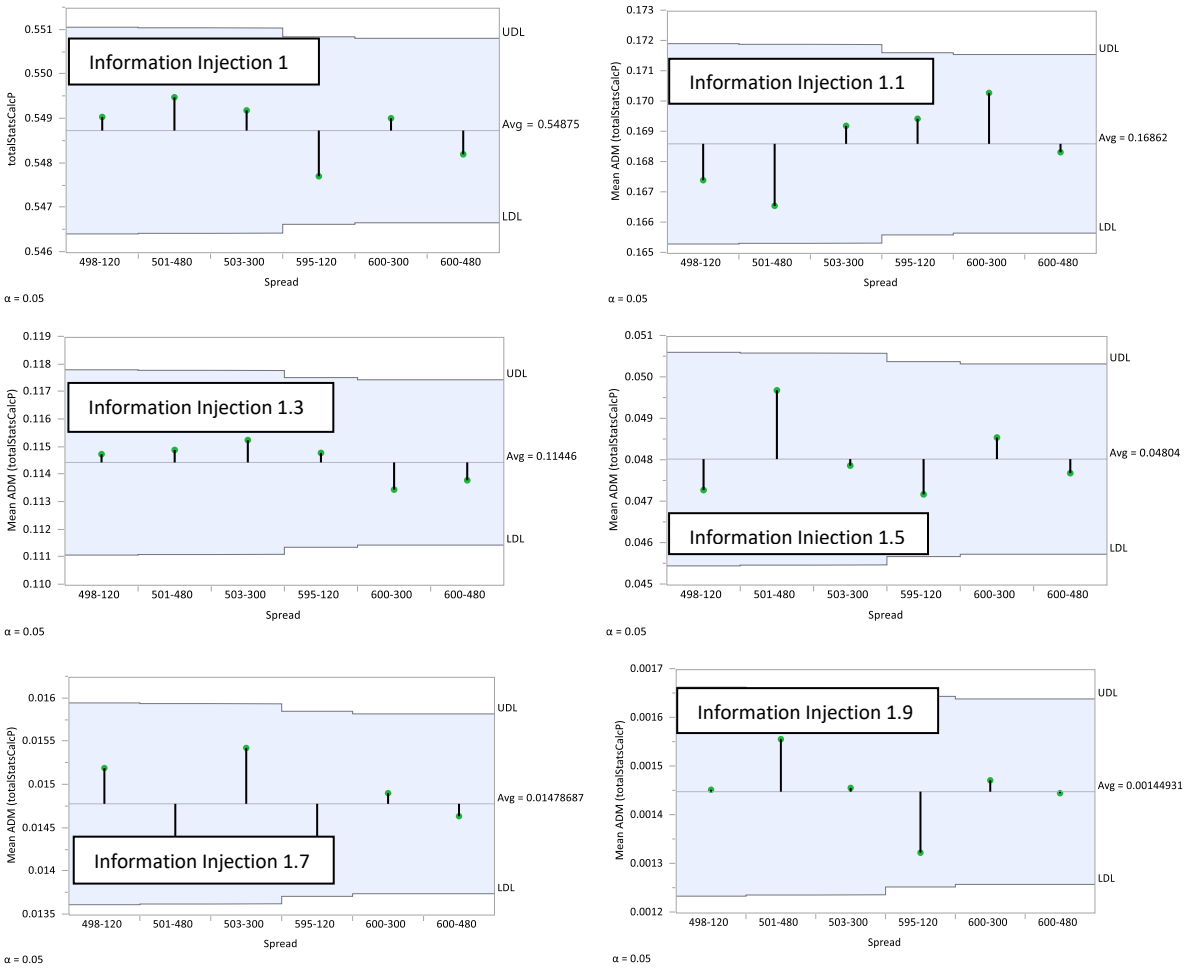


Figure 4. 23: Analysis of means for true-false=1-1.9, for II trials

Table 4. 16: Connecting letters report for true-false trial

	1		1		1.1	1.1	1.3	1.3	1.5	1.5	1.7	1.7	1.9	1.9
Level	Tukey		Steel		Tukey	Steel	Tukey	Steel	Tukey	Steel	Tukey	Steel	Tukey	Steel
501-480	A		A		A	A	A	A	A	A	A	A	A	A
498-120	A		A		A	A	A	A	A	A	A	A	A	A
503-300	A		A		A	A	A	A	A	A	A	A	A	A
595-120	A	B	A	B	A	A	A	A	A	A	A	A	A	A
600-300	A	B	A	B	A	A	A	A	A	A	A	A	A	A
600-480		B		B	A	A	A	A	A	A	A	A	A	A

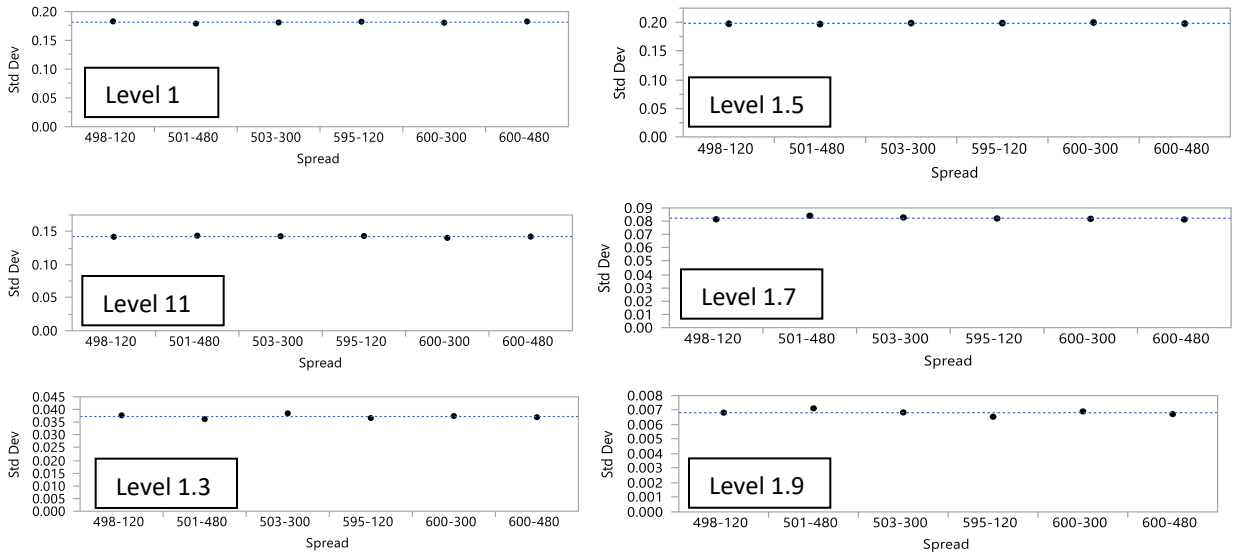


Figure 4. 24: Equal variance graphs for each information level for true-false

Evaluation of Control Value True-True

The true-true set of trials represents the data generated by the model when both the information injection and agent attributes effects are active. Whereas the other variable control simulation groups were intended to serve as the controls to measure the effects of the individual items of information injection and agent behavior, this variable control produces the results that are intended to resemble the behavior of the actual MAP process along with the influences of providing JIT information and as such is the data group of central interest to this study.

The expectation is that the output should resemble the combination of both the information injection and agent attribute control groups. The mean of the Likelihood index for each level of information injection should gradually increase as the amount of information increases. The variance, being impacted by the effect of the agent attributes, should be greater than that found when just the information injection effects were present. The variance should decrease as the amount of information provided increases.

The internal control labeled Information Injection 1 has no effects from information injection nor agent attributes. In contrast to the true-false equivalent internal control, it is noted that there is a difference among the means for each of the trials groups. However, when compared to the false-true group it appears that the variance approximately the same. With no additional information being provided to the nurse agent each trial is relatively equivalent. A more direct way to visualize this is in Table 4. 67 in the appendix. Comparing the false-true and true-false sets of columns, the means are large for the true-false, this is the effect of information injection increasing the overall success of medication administration. The variance decreases for the true-false in comparison to the false-true. The true-true group more closely resemble the false-true group which coincides what one would expect based on the construction of the model.

The ANOM values indicate dissimilar means among the medication amount/shift duration trials for true-true=1. This is corroborated by the Tukey, Steel and Dunn tests. Note that the 120-minute and 300-minute trials are determined to be equivalent amongst themselves. The 480-minute trials are not equivalent based on these tests. Not surprisingly, this matches the true-false control group. The variance equivalency tests have p values less than

the alpha of 0.05 leading to the rejection of the null hypothesis leading to the conclusion that a significant difference exists between the values.

While the initial impression would be that the mean values for the LI values for each of the medication/shift duration trials for true-true would be an average of the false-true/true-false variable controls, upon further reflection the resemblance of the true-true internal control to the false-true internal control makes sense based on the design of the model. The information injection effect has, in essence a null effect, the agent attribute effect induces residual variance. Combining the two effects leads to the results seen in the true-true control.

The composite boxplot in Figure 4. 25 provides an overall visualization of the influence of inserting JIT in the simulation. Moving from left to right the mean and median increase at an increasing rate while at the same time the standard deviation decreases at a relatively linear rate. Noting the trend of the LI values, as with the similar true-false graph, the values increase the congregation around the maximum LI value of one as the information injection value increases. This is a result of increasing the probability of the agent successfully completing each of the MAP process stages as a function of the increased level of information.

Several differences worthy of note in a side by side comparison of the true-true and true-false composite box plots.

1) The curves representing the mean have different initial slopes and rates of change. The true-true curve begins with a shallower slope implying a slower increase in the benefit from additional information, but, accelerates somewhat more at higher information levels. The terminus of the true-false curve is slightly higher than the true-true curve. This coincides with the expectation that the true-true scenarios have significantly more variability due to the influence of agent attributes thus have a broader range of success outcomes. The log-dash light green curve on the bottom plot represents the standard deviation for the true-false curve overlaid on top of the true-true for easier comparison.

2) The standard deviation curve for true-true has higher values and a steady linear decrease in contrast to the true-false standard deviation curve. As with the mean values, the standard deviation is heavily influenced by the variance induced by agent attributes. With no effect of agent attributes, the true-false standard deviation curve starts at a moderately low level and descends as the injection of information increases. The descent is moderated at the upper end of the injection of information amounts as a result of the likelihood of success being driven to high levels by the effect of the LI multiplier. The effect is similar for the true-true curve with the difference being that the standard deviation in this case has the effect of agent attributes making the values larger while the starting and ending points are at higher levels due to the presence of agent attributes driving the variance up. The short-dash light green curve on the bottom plot represents the standard deviation for the true-false curve overlaid on top of the true-true for easier comparison.

3) In comparing the graphs along each of the information injection levels, the difference in the spread or range of the individual data points can be noted. Each dot represents the likelihood of a medication being administered successfully. The wider spread in the data for true-true starting with the information injection level of 1 represents the influence of the effect of agent attributes on the nurse agent's performance in administering medications. The difference in the boxplot dimensions indicate this divergence continuing along the axis.

The bottom axis of both curves represents a categorical variable so the spacing is equal for each unit. This makes for easier visualization of the data but must be considered when doing quantitative interpretation. Specifically, the interval between 1 and 1.1 is less than 1.1 and 1.3. This has the effect of making it seem like the early parts of the curve have faster rates of change than later parts of the curve. The vertical axis is numerical therefore the interpretation requires no additional treatment. A numerical version of the x-axis is provided later in the document (Figure 4. 35) for comparison by the interested reader.

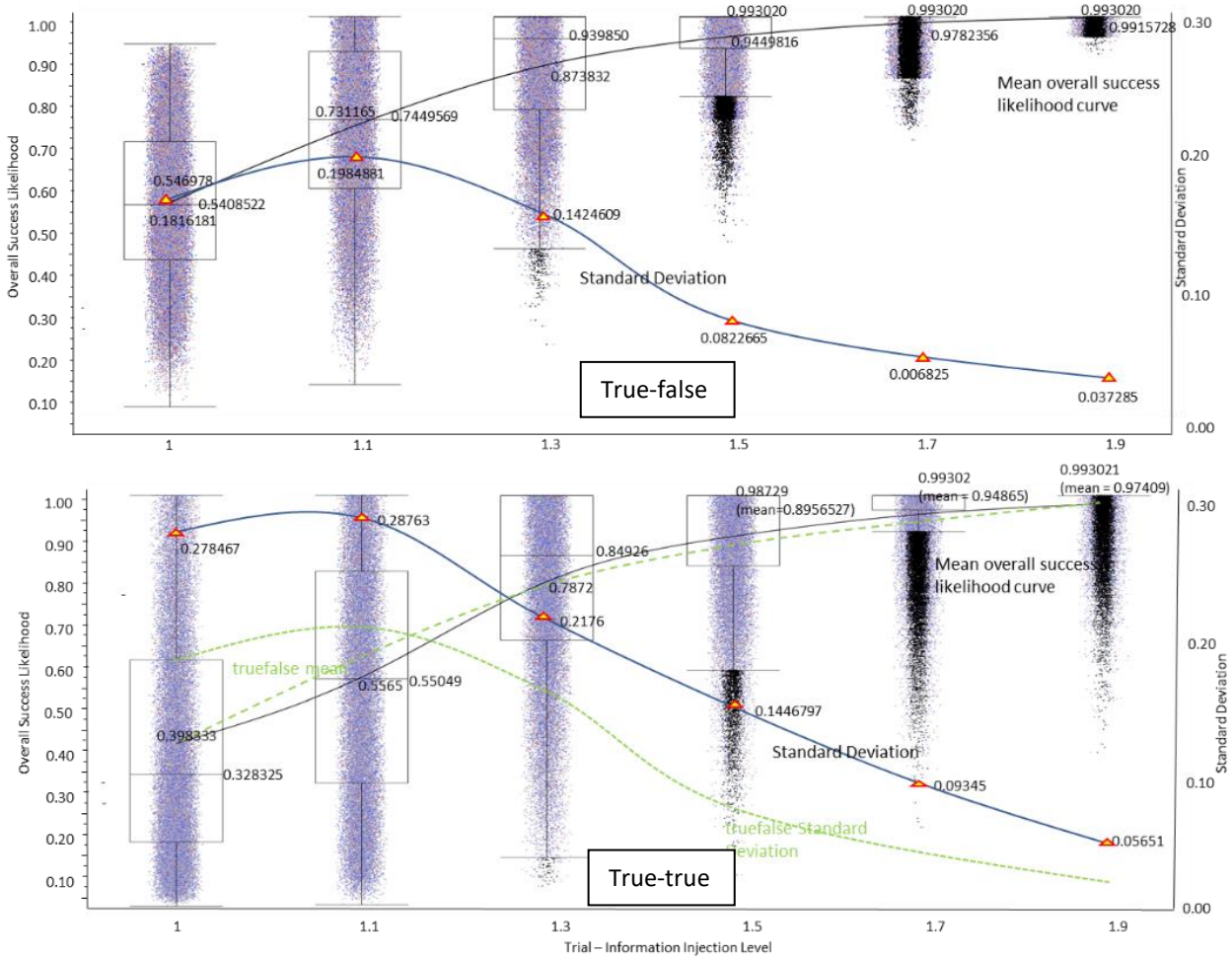


Figure 4. 25: Composite boxplot of information level vs likelihood of success probability for true-false and true-true

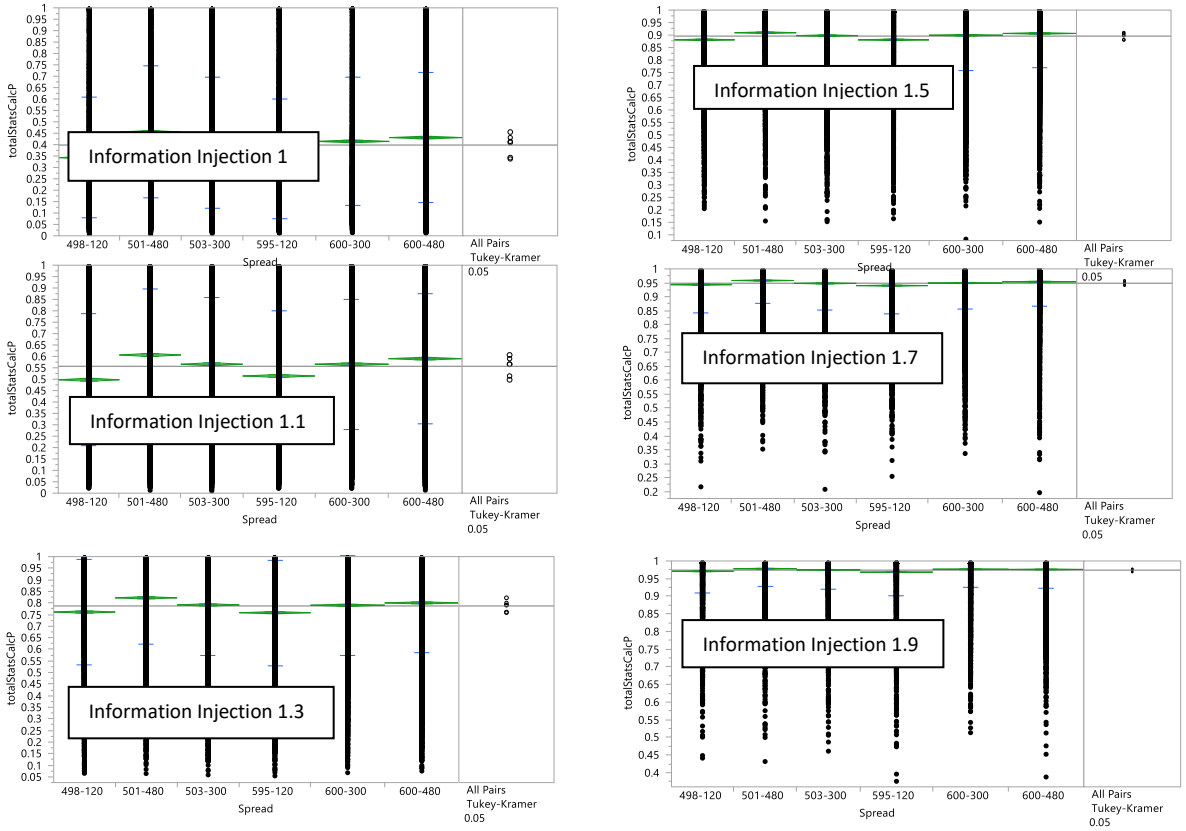


Figure 4. 26: Oneway analysis of likelihood index by medication amount/shift duration variablecontrol= true-true, Information Injection=1

Figure 4. 26 represents the mean, standard deviation and the all pairs Tukey-Kramer test for similarity of means. As would be expected, it is similar to the similar true-false graphs in terms of the increase in mean values and decrease in variance as the level of information increases. There is more divergence among the trials which dissipates as the level of information applied is increased.

The means comparison in Figure 4. 27 provide the analysis of similar means. Review of these methods shows the means across the trials becoming statistically similar as they reach the 1.9 information injection level. This is a result of as the information level increases, the likelihood of success increases (that is, agent performance increasing), and approaches the limit of 100% success.

The parametric Tukey-Kramer test and the non-parametric Steel Dwass and Dunn's methods show similar although not identical results (Table 4-17, 4-67, 4-68, 4-69) Any differences in the parametric versus non-parametric method can be ascribed to the nature of the data being skewed (non-normal). The connecting letters report for in Table 4.17 for the Tukey-Kramer and Steel Dwass methods are similar for information injection values 1-1.5. There is a difference between the methods for the 1.7 level and then they converge back together for the 1.9 level; as described previously this is attributed to the effect of skewness and non-normality effects on the two tests.

The conclusion on model performance as it relates to this portion of the analysis is that the model behaves in a fashion that coincides with both the intent of the design and what would be expected in terms of the performance or a nurse in an actual setting. The relatively slight differences in the levels of performance, as measured by LI, are moderate by the increases in the amount of information provided.

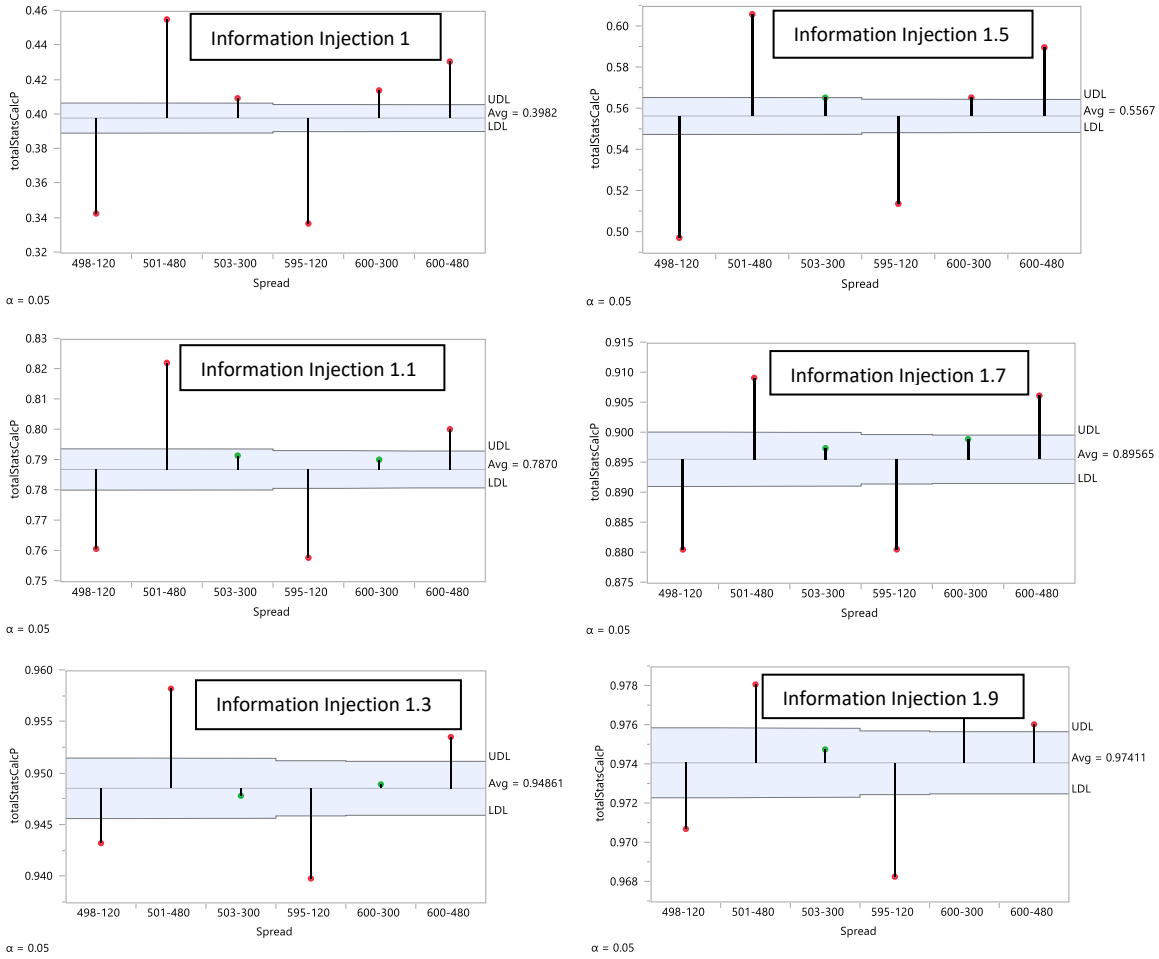


Figure 4. 27: Analysis of means for true-true=1-1.9, for II trials

The output for the ANOM tests coincides with the other evaluations highlighting the difference in means among the medication/shift duration trials. Of note is trial 503-300 which consistently stays within the decision limits for each of the information levels. The 600-300 trial also stays within the decision limit boundaries with the exception of the 1.9 information level. The 120-minute duration trials fall outside the boundaries throughout the range of information levels: the likely cause of this is the consistent lack of completion of the MAP process for man of the medications which is assumed to be due to the shorter shift durations.

The 480-minute trials also fall out of the decision limits. The cause of this remained elusive until a more detailed examination revealed that the overall means of the 480-minute runs are uniformly and significantly above the other means. Since the ANOM is calculated based on the population mean, the divergence of the 480-minute trials, outside of the decision limits, can be rationalized on their higher mean values-thus making their departure from the population mean greater. Understanding this, the implication is that the longer shift duration leads to a higher likelihood of success. Examining the other medication amount/shift duration, LI mean values showcases this concept: the longer the shift duration the higher the overall LI mean. This concept falls in line with the logic that allowing more time to complete MAP tasks will lead to higher overall success in the MAP process. Note that one artifact of the method of the graph in Figure 4. 28 is the shape of the curve at the left which reflects a polynomial feature. This is because of the treatment of the information injection values as nominal rather than continuous; the actual shape of the curve more resembles a curve of a polynomial degree 2 .

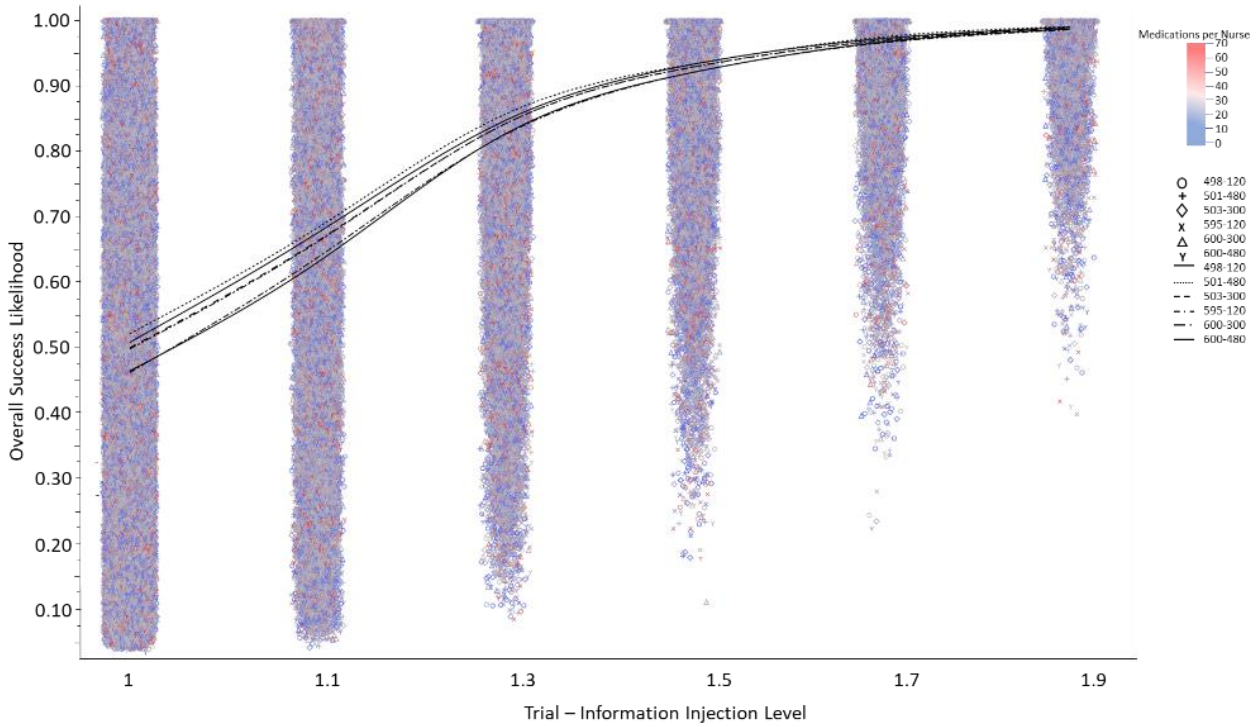


Figure 4. 28: Comparison of LI means by information injection level

The connecting letters report in Table 4. 18 shows that the Tukey and Steel analysis show that II levels of 1 and 1.1 are similar indicating that there are four groups of means with 501-480, 600-480, 600-300 and 503-300, and, 498-120 and 595-120 trials each having common mean values. At II level 1.5 and 1.9 are also similar among the two methods. II levels. II level 1.3 differs for the two analysis methods at the 120-minute trials. At the 1.7 II level the 300 and 120-minute trials also differ among the analysis methods. The detail is provided in Table 4.66 through Table 4.70 in the appendix. The differences between the results of the two methods are ascribed to the effect of the data on parametric versus non-parametric factors. Note that the two non-parametric tests are similar. The conclusion is that given the nature of the data that the non-parametric tests are more representative of the similarities of means.

An evaluation of equal variances was performed. The expectation based on the model design, would be that the variances would change over the course of information increase. As the Figure 4.29 and Table 4.71 in the appendix demonstrates, the p values are less than the 0.05 alpha value and indicate that the null hypothesis for the variances being equal should be rejected.

As noted previously, the true-true data set attempts to represent the performance of nurses in administering medications. It is intended to model a number of key attributes of nurses and medications. The role of JIT information is the key variable being assessed. Based on the overall performance of the model as assessed by the statistically relevant changes in the response variable it can be concluded that the model responds as expected and effectively demonstrates the performance of the agents and the positive effect of the insertion of information into the MAP process.

As noted previously, there are a number of key characteristics that can be derived from the simulation. The predicative nature of the rate of change of performance from information injection could prove valuable for future optimization studies. The observation that the rate of change of performance slows at higher information levels and that issues related to time and medication load are mitigated provides interesting options for improved performance in a clinical setting.

Table 4. 17: Connecting letters report for true-true for LI means by trial

	Level	501-480	600-480	600-300	503-300	498-120	595-120
1	Tukey	A					
			B				
				C	C		
						D	D
	Steel	A					
			B				
				C	C		
						D	D
	Level	501-480	600-480	600-300	503-300	595-120	498-120
1.1	Tukey	A					
			B				
				C	C		
						D	
							E
	Steel	A					
			B				
				C	C		
						D	
							E
		501-480	600-480	503-300	600-300	498-120	595-120
1.3	Tukey	A					
			B	B	B		
						C	C
	Steel	A				A	A
			B	B	B		
		501-480	600-480	600-300	503-300	595-120	498-120
1.5	Tukey	A	A				
				B	B		
						C	C
	Steel	A	A				
				B	B		
						C	C
		501-480	600-480	600-300	503-300	498-120	595-120
1.7	Tukey	A					
			B				
				C	C		
					D	D	
						E	E
	Steel	A					
			B	B	B		
						C	C
		501-480	600-300	600-480	503-300	498-120	595-120
1.9	Tukey	A	A	A			
			B	B	B		
						C	C
	Steel	A	A	A			
			B	B	B		
						C	C

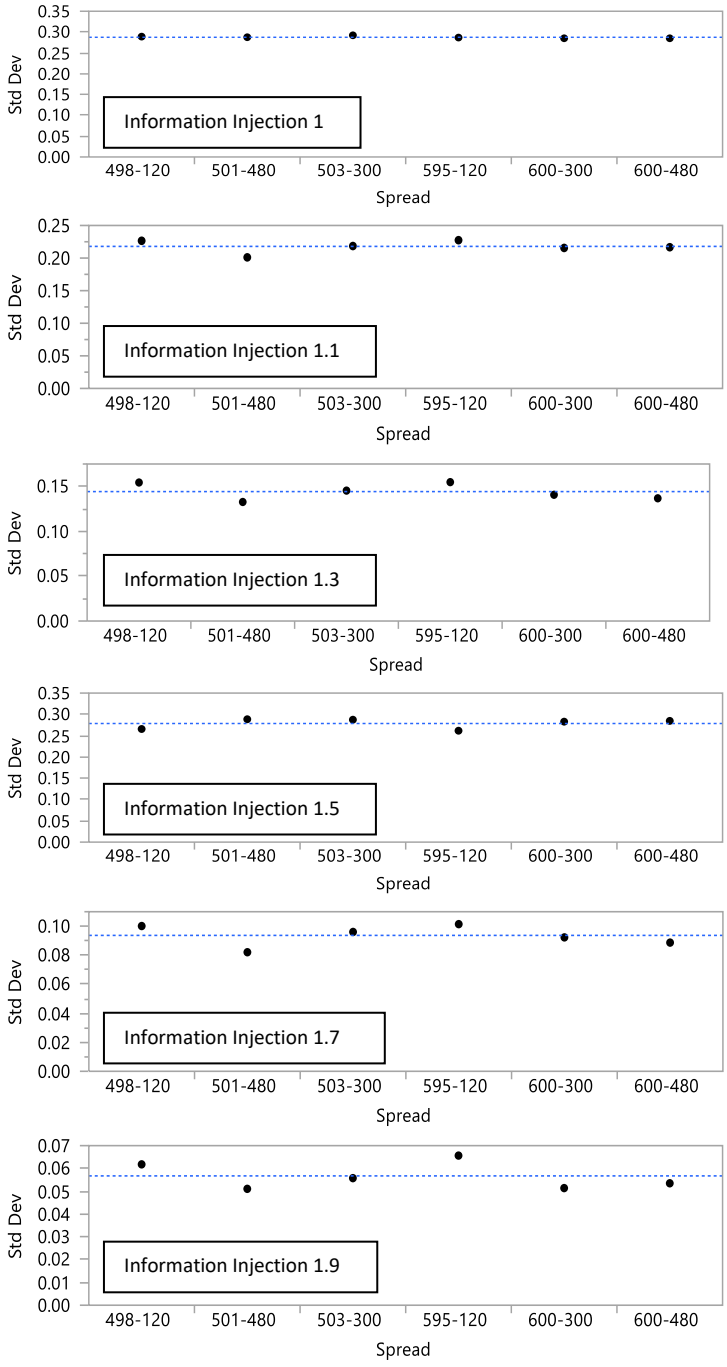


Figure 4. 29: Equal variance assessment true-true

Notional Model Replicate

One way to assess the performance of the information injection portion of the model is to attempt to replicate this function outside of the model. A 100-element data set was developed by first developing a random number set, and then transformed via application of a beta distribution. As with the actual model, the input values were truncated at 0.5 for the lower level and 0.999 for the upper level. The graphical representation in Figure 4. 30 is similar to that generated by the simulation. As with the simulation, as the multiplier representing the information injection function increases from 1 to 1.9 the same effects occur; the variance decreases and the values progressively congregate at or below the maximum threshold of 0.999.

The analysis below indicates similar results to the MAP simulation; variances differ as the multiplier increases. The variance comparison tests all confirm differences in variances exists (Figure 4.31). The pairwise comparison of means supports the observation of differing means among the groups. The Tukey- Kramer test indicates similarities between three sets of pairs (Table 4. 19). The non-parametric test indicates conflicting results with the Dunn's method indicating more values with p values greater than 0.05. The Dunn's test can be very conservative test, especially if there are a larger number of comparisons (Table 4. 21).

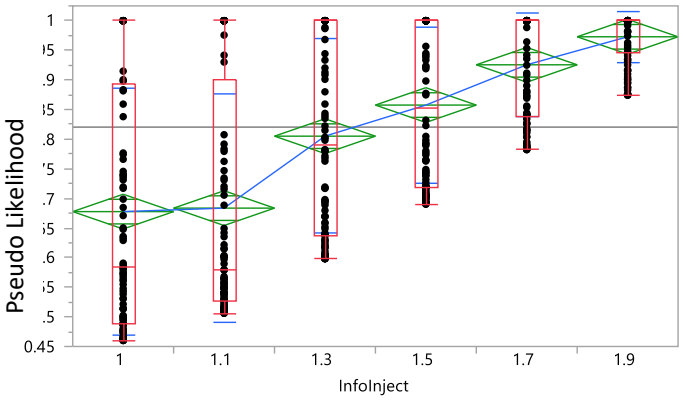


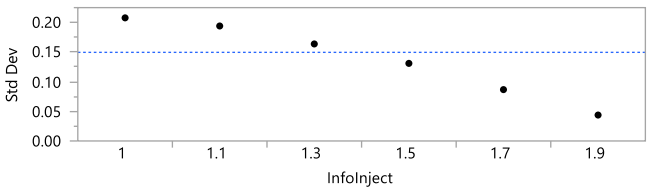
Figure 4. 30 represents similar behavior to the data created from the MAP simulation with reduction of variance and compression to 0.999 as the information injection multiplier increases

Figure 4. 30: Oneway analysis of Pseudo likelihood index by information injection level

Table 4. 18: Analysis of variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
InfoInject	5	7.498820	1.49976	67.0773	<.0001*
Error	594	13.281087	0.02236		
C. Total	599	20.779908			

The ANOVA and variance tests in Table 4. 18 indicates a difference in variance between the 1-1.9 levels.



Test	F Ratio	Prob > F
O'Brien[.5]	54.1760	<.0001*
Brown-Forsythe	30.4187	<.0001*
Levene	80.2816	<.0001*
Bartlett	48.4441	<.0001*

Figure 4. 31: Pseudo likelihood tests that the variances are equal

Table 4. 19: Comparisons for all pairs using Tukey-Kramer HSD

		Tukey	Steel Dwass	Dunn
Level	- Level	p-Value	p-Value	p-Value
1.1	1	0.9998	0.7766	1
1.3	1	<.0001*	<.0001*	0.0004
1.3	1.1	<.0001*	<.0001*	0.0013
1.5	1	<.0001*	<.0001*	<.0001
1.5	1.1	<.0001*	<.0001*	<.0001
1.5	1.3	0.1308	0.0434*	1
1.7	1	<.0001*	<.0001*	<.0001
1.7	1.1	<.0001*	<.0001*	<.0001
1.7	1.3	<.0001*	<.0001*	0.0002
1.7	1.5	0.0172*	0.0012*	0.1864
1.9	1	<.0001*	<.0001*	<.0001
1.9	1.1	<.0001*	<.0001*	<.0001
1.9	1.3	<.0001*	<.0001*	<.0001
1.9	1.5	<.0001*	<.0001*	0.0002
1.9	1.7	0.2227	0.0057*	0.9314

As one measure, these results provide confidence that the effect of the information multipliers is independent of the data set that it is used upon and, that the effects, such as decreasing variance and compression of the results at the 0.999, can be replicated.

Analysis of 503 True-True Values

While a detailed analysis of each of the medication amount/shift duration simulations could be analyzed, a data set best representing the group of simulations is being used for the detailed analysis. A method of data reduction was considered. After appropriate review the selection of a representative data was done as a means to get a representative set of data. Each of the trials were considered and evaluated. Using the criteria defined earlier, the 503-300 simulation run was selected for the detailed variable review. Recall the three factors used for the selection of the data set were:

1) The consistency of the data throughout the ranges of each of the shift duration/medications per shift/information injection combinations
2) The use of the data set(s) that reflected the application of the agent attributes and injection of information
3) Balance of the influence of the other factors across the data subset such as shifts, medication loading per nurse, agent attribute effects, and so on.

The data set generated from this simulation run demonstrated the following characteristics:
Homogenous sizes of the sub data sets, such as the variable control values (i.e. true-true, false-false, true-false, false-true), information injection trials and medication amount/shift duration. The data sets have uniform frequency counts for medications processed without regard to the division of the data set. For example, the frequency of medications processed for each of the information injection levels was 6026, the shift splits were identical at 18,108, and each of the MAP process steps is 6036. This uniformity provides more options for selecting statistical analysis tools which allows more straightforward interpretations.

The 503-300 is consistent with the expected design output from the model as noted in the earlier analyses. The data set appropriately responds to influences of agent attributes and the injection of information as demonstrated in the previous data analysis. The 503-300 data set consistently performs within the boundaries of the expected

limits. Comparison of LI means by information injection level provides a representation of this in the form of tracking the means across the II levels.

Analysis of MAP Process Step

A key element of the model is the six MAP process steps that represent the sequential set of actions the nurse agent takes as it works to complete the medication administration process. These steps are designed as independent steps and the outcome of one step does not influence the action of any other step. While in an actual clinical setting, there could be some influence or interaction, no studies have been identified that draw such a correlation.

Table 4. 20 highlights the frequency of the nurse agent successfully completing each respective MAP process step as the level of information used changes. The table shows that as the level of information goes up, the success rate increases. The number of successful completions starts at the level set by the beta distribution of about 85%, while the success rate increases for each level of information increase, reaching near 100% at the 1.9 information level.

The graph in Figure 4. 32 illustrates the increase in likelihood for each process step across the information increase amounts. Consistent with the model design, each of the steps is similar in their change along the information increase profile. The slight variation can be explained by the stochastic nature of the beta distribution.

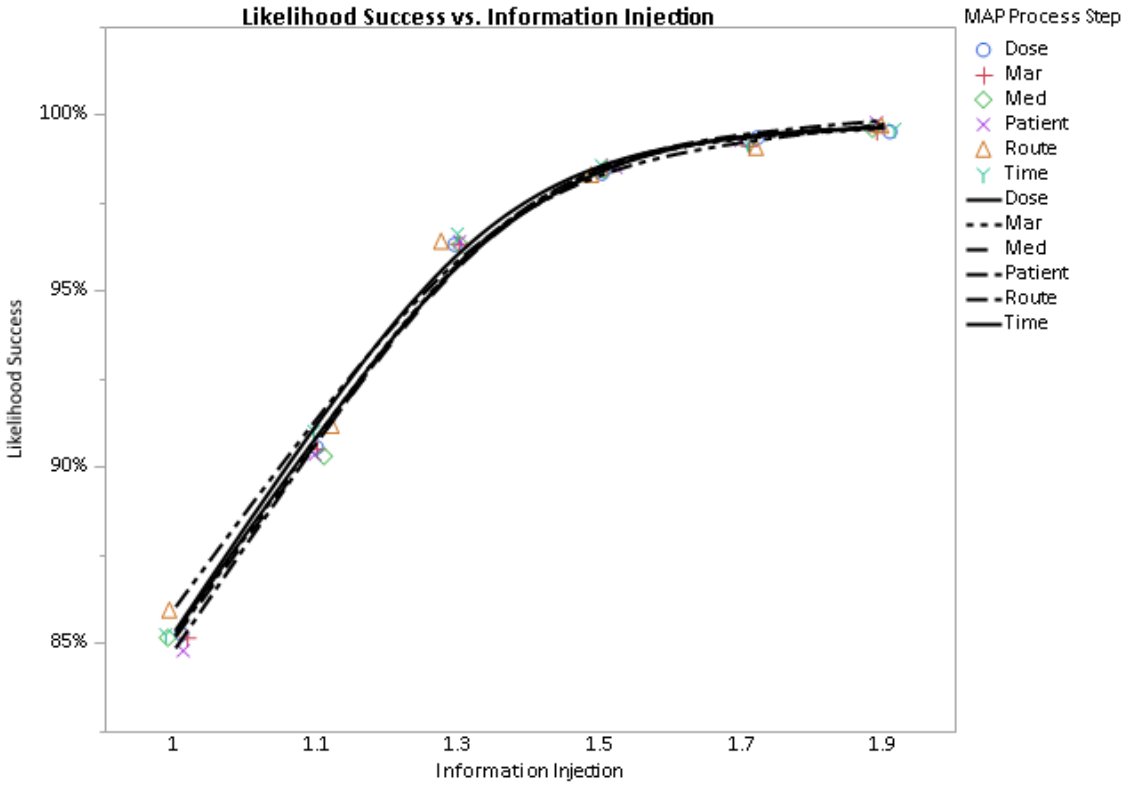


Figure 4. 32: Graph of likelihood of successful completion of MAP process step

Table 4. 20: Frequency of success/failure of completion of each step of the MAP Process

Patient check				
Information Injection	N(FALSE)	Row %(FALSE)	N(TRUE)	Row %(TRUE)
1	918	15.21%	5118	84.79%
1.1	582	9.64%	5454	90.36%
1.3	217	3.60%	5819	96.40%
1.5	90	1.49%	5946	98.51%
1.7	44	0.73%	5992	99.27%
1.9	13	0.22%	6023	99.78%
Med check				
Information Injection	N(FALSE)	Row %(FALSE)	N(TRUE)	Row %(TRUE)
1	896	14.84%	5140	85.16%
1.1	585	9.69%	5451	90.31%
1.3	223	3.69%	5813	96.31%
1.5	94	1.56%	5942	98.44%
1.7	45	0.75%	5991	99.25%
1.9	24	0.40%	6012	99.60%
Dose check				
Information Injection	N(FALSE)	Row %(FALSE)	N(TRUE)	Row %(TRUE)
1	890	14.74%	5146	85.26%
1.1	570	9.44%	5466	90.56%
1.3	222	3.68%	5814	96.32%
1.5	100	1.66%	5936	98.34%
1.7	39	0.65%	5997	99.35%
1.9	29	0.48%	6007	99.52%
MAR check				
Information Injection	N(FALSE)	Row %(FALSE)	N(TRUE)	Row %(TRUE)
1	895	14.83%	5141	85.17%
1.1	572	9.48%	5464	90.52%
1.3	220	3.64%	5816	96.36%
1.5	88	1.46%	5948	98.54%
1.7	52	0.86%	5984	99.14%
1.9	27	0.45%	6009	99.55%
Route check				
Information Injection	N(FALSE)	Row %(FALSE)	N(TRUE)	Row %(TRUE)
1	849	14.07%	5187	85.93%
1.1	533	8.83%	5503	91.17%
1.3	217	3.60%	5819	96.40%
1.5	103	1.71%	5933	98.29%
1.7	57	0.94%	5979	99.06%
1.9	19	0.31%	6017	99.69%
Time check				
Information Injection	N(FALSE)	Row %(FALSE)	N(TRUE)	Row %(TRUE)
1	891	14.76%	5145	85.24%
1.1	542	8.98%	5494	91.02%
1.3	204	3.38%	5832	96.62%
1.5	87	1.44%	5949	98.56%
1.7	48	0.80%	5988	99.20%
1.9	25	0.41%	6011	99.59%

An analysis was done to compare each of the process steps to validate this assumption of the model build. Similar to the previous analyses performed, a comparison of means/medians was performed. Both parametric and non-parametric tests were done to ensure consistency of results and limit the likelihood of type 2 errors (Table 4.73 in appendix). The analysis confirms that the Model's MAP process steps are analogous as observed in Table 4. 23. The mean likelihood of success values; the values for each of the information levels among the Map Process steps are noted to be similar (Table 4. 72 in the appendix).

Agent Attribute Analysis

For an agent-based modeling system, the attributes imbued upon the agents play an important role in the operation of the model. For this particular model, a number of attributes were designed to influence the behavior of the nurse and medication agents. The quantitative influence of these attributes was described earlier. Table 4. 21 provides the relative breakdown of the occurrence of each attribute in terms of percent and frequency. The table below illustrates the relative contribution of each of the agent attributes for each of the information injection levels. The value for N represents the number of medications administered during the respective information injection level and the Col% refers to the percentage of the elements of each attribute in a given information injection level. In essence, the N value infers the number of nurses in a category and is a function of the number of medications a nurse agent might have in that particular category.

The model construction intends that the agent attributes would have consistent values over each information injection level. As Table 4. 22 shows, the values for each category of agent attribute remains relatively constant across the information injection range.

Table 4. 21: Descriptive statistics of agent attributes by information injection level

	Information Injection Level											
	1		1.1		1.3		1.5		1.7		1.9	
nurseExperience	N	Col %	N	Col %	N	Col %	N	Col %	N	Col %	N	Col %
moderate	3591	59.49	3637	60.26	3735	61.88	3585	59.39	3577	59.26	3575	59.23
novice	1292	21.40	1283	21.26	1330	22.03	1319	21.85	1328	22.00	1279	21.19
senior	1153	19.10	1116	18.49	971	16.09	1132	18.75	1131	18.74	1182	19.58
fatigueStatus												
FALSE	3206	53.11	3083	51.08	3015	49.95	3012	49.90	3022	50.07	3000	49.70
TRUE	2830	46.89	2953	48.92	3021	50.05	3024	50.10	3014	49.93	3036	50.30
interruption												
FALSE	2812	46.59	2839	47.03	2835	46.97	2873	47.60	2855	47.30	2840	47.05
TRUE	3224	53.41	3197	52.97	3201	53.03	3163	52.40	3181	52.70	3196	52.95
medicationSeverity												
low	2402	39.79	2399	39.74	2404	39.83	2399	39.74	2400	39.76	2405	39.84
medium	1964	32.54	1965	32.55	1965	32.55	1968	32.60	1968	32.60	1967	32.59
high	1670	27.67	1672	27.70	1667	27.62	1669	27.65	1668	27.63	1664	27.57
medicationDifficulty												
difficult	909	15.06	914	15.14	910	15.08	912	15.11	910	15.08	913	15.13
intermediate	2858	47.35	2855	47.30	2856	47.32	2856	47.32	2865	47.47	2854	47.28
minimal	2269	37.59	2267	37.56	2270	37.61	2268	37.57	2261	37.46	2269	37.59
PatientLoadOut												
high	1517	25.13	1516	25.12	1501	24.87	1434	23.76	1559	25.83	1744	28.89
low	1533	25.40	1403	23.24	1224	20.28	1297	21.49	1262	20.91	1476	24.45
med	2986	49.47	3117	51.64	3311	54.85	3305	54.75	3215	53.26	2816	46.65

Table 4. 22: Average impact values of agent attributes by information injection level

	1	1.1	1.3	1.5	1.7	1.9
medSeverity	1.025961	1.025895	1.026019	1.025919	1.025944	1.02606
medDifficulty	1.030061	1.029987	1.03007	1.03002	1.02992	1.030028
nurseExperience	0.998849	0.998617	0.997026	0.998451	0.998368	0.999196
fatigueOutput	0.953115	0.951077	0.94995	0.949901	0.950066	0.949702
interruptionOutput	0.9327	0.933263	0.93318	0.933973	0.933597	0.933284
patientLoadOutput	1.012434	1.013494	1.014728	1.013014	1.015374	1.016667

Table 4. 23: Variable Importance: agent attributes variable importance independent resampled inputs summary report for *averaged* II values

Column	Main Effect	Total Effect
Interruption	0.230	0.246
Med Severe	0.174	0.211
Med Diff	0.158	0.190
Patient Load	0.114	0.113
Fatigue	0.145	0.161
Experience	0.05	0.062

Each agent attribute category is assigned a numerical value that influences the performance or behavior of the nurse agent. The relative contribution of the assigned numerical values of each of the categories within an attribute creates, in essence, a weighted value, that leads to an overall average value for the attribute. Table 4. 22 lists these values for each attribute by information injection value. A value greater than one implies a positive contribution to the likelihood index, and conversely a value less than one implies a negative benefit for that particular attributes contribution to the likelihood index. The values should remain relatively constant with only modest changes in attribute values changing for each information injection level due to other random changes in the model during simulation runs. Figure 4. 33 provides a graphical representation of each of these values by attribute and information injection level (the axis labeled Data can be interpreted as the Likelihood inde*x). Note that the change in values are at the level of only several thousandths, which is insignificant in terms of the impact to the overall model.*

The agent attributes operate in a way that is consistent with the design of the model and contribute in ways that are expected with overall model performance. The attributes contribute in a measured way and as evidenced in the false-true control group have a significant impact on the likelihood index in spite of the small values each individual agent attribute conveys to the overall multiplier that modifies the likelihood index.

Evaluation of Likelihood Index

The Likelihood Index (LI) is the overall measure of the success of a nurse agent completing the MAP process without errors. Errors are defined as not successful accomplishing each of the MAP steps in whole or in part. The MAP is a composite statistic that reflects the influences of each of the agent attributes and stochastic model features. There is an LI value for each medication that goes through the administration process.

Figure 4. 34 demonstrates the change progression as the information levels migrate from low (1.1) to high (1.9). As would be anticipated, the frequency shifts from a diffuse pattern to be heavily concentrated at the maximum level of 1.0. The frequency distribution clearly shifts to higher values along the II profile. As noted in previous analyses, the standard deviation measurably decreases for each II increase as well. The geometric mean was included as an evaluation parameter because of the polynomial increase of the LI function. While its rate of

change is different than the mean, the overall interpretation of the effect of information on the LI does not change.

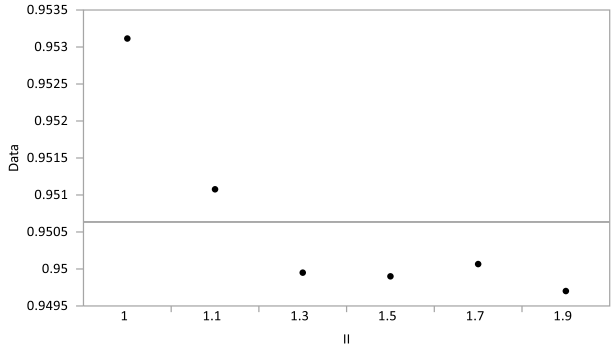
Figure 4. 35 represents an overlay plot with the mean value represented by the curvilinear line. As with the earlier analysis, the means and medians increase in a linear fashion that is approximated by a polynomial function. The boxplot overlay demonstrates the variance that is typical for this plot. The higher value of the medians is expected since there is a significant number of values at the higher end of the LI. The values at the lower end depress the mean. Table 4. 74 provides detailed information on the mean, median, standard deviation and range information in support of Figure 4. 35 in the appendix.

The colored dots represent the nurse agents, the range of performance, the congregation of colors indicates the binning of nurse agents in certain performance areas resulting from the performance characteristics generated by their respective attributes.

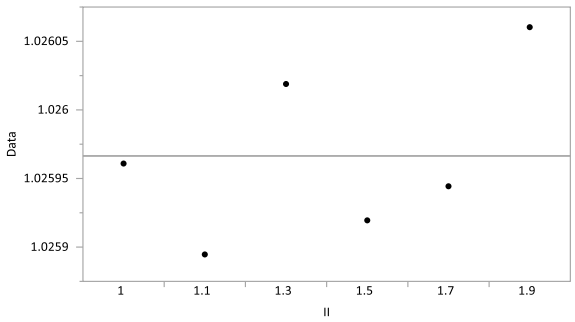
A line was fitted for the purposes of examining the potential predictive capability (Figure 4. 36). The line fit for this function has an R-Square of over 0.99 and each of the coefficients has p values below the 0.05 threshold indicating that there is enough evidence for each of the coefficients to be valid. The use of the linear relationship is observational at this point and a subject for future study, the use of this function could possibly be used to optimize the information injection value against other objective criteria such as cost and risk.

The relative impact of agent attributes was assessed by performing least squares analyses. The purpose of this analysis is to get an overall impression of the relative effects or impacts of the agent attributes on the outcome. The previous analyses indicated that there is no covariant nature with the attributes. The nature of the data, its significant amount of skew and non-normal distribution makes detailed analysis and interpretation problematic. However, for the purposes of understanding the relative impacts of the attributes on the LI output, a least squares analysis will be suitable. The initial analysis performed considered the overall performance of the attributes without inclusion of the individual effects of information injection.

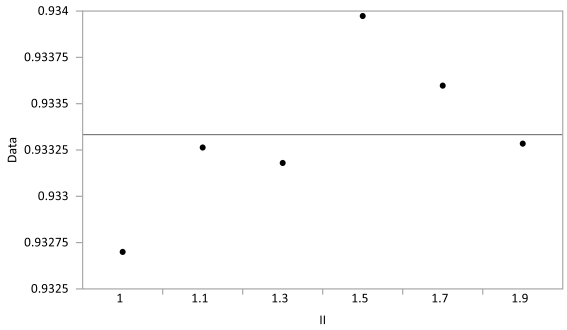
Data by II Label=fatigueOutput



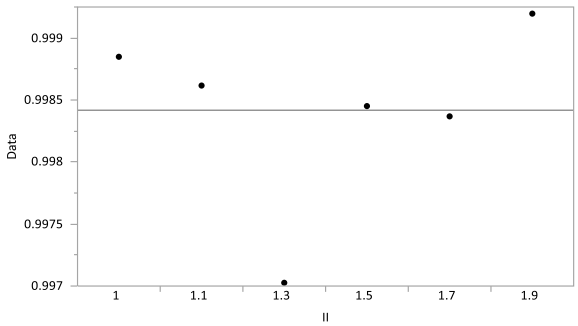
Data by II Label=medSeverityV



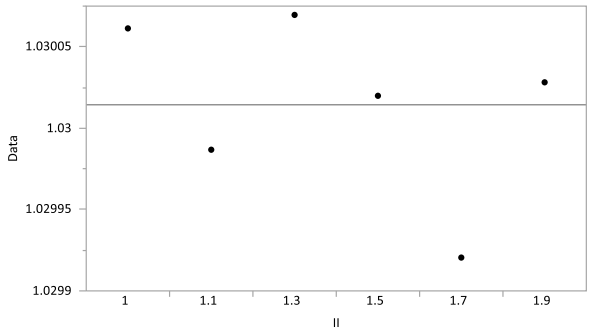
Data by II Label=interruptionOutput



Data by II Label=nurseExperienceV



Data by II Label=medDifficultyV



Data by II Label=patientLoadOutput

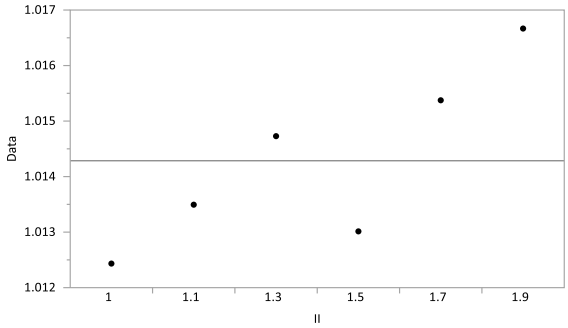
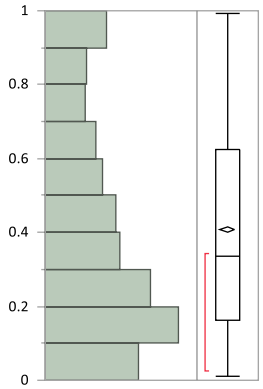


Figure 4. 33: Oneway analysis of agent attribute values, data = the multiplier value for the particular attribute

Distributions II=1

Likelihood Index

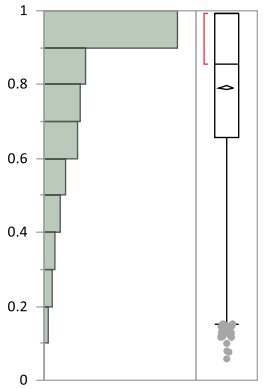


Summary Statistics

Mean	0.4096544
Std Dev	0.2874504
N	6036
Median	0.337542
Geometric Mean	0.2972386

Distributions II=1.3

Likelihood Index

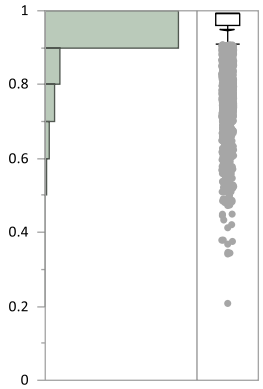


Summary Statistics

Mean	0.7916199
Std Dev	0.2184559
N	6036
Median	0.8554565
Geometric Mean	0.7492207

Distributions II=1.7

Likelihood Index

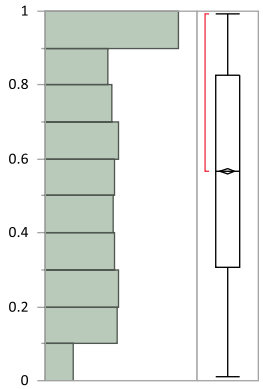


Summary Statistics

Mean	0.9478844
Std Dev	0.0960541
N	6036
Median	0.993021
Geometric Mean	0.9417622

Distributions II=1.1

Likelihood Index

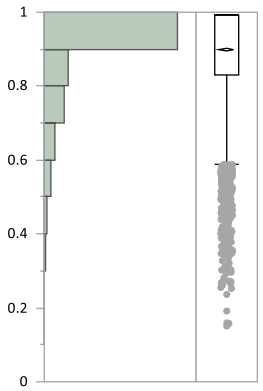


Summary Statistics

Mean	0.5655787
Std Dev	0.2922344
N	6036
Median	0.5684525
Geometric Mean	0.4653085

Distributions II=1.5

Likelihood Index

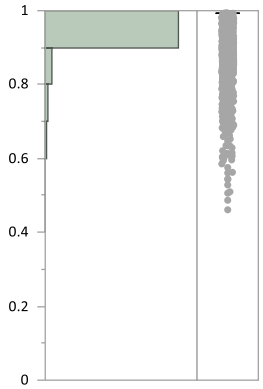


Summary Statistics

Mean	0.8975023
Std Dev	0.1453512
N	6036
Median	0.993021
Geometric Mean	0.8820871

Distributions II=1.9

Likelihood Index



Summary Statistics

Mean	0.9747863
Std Dev	0.0557428
N	6036
Median	0.993021
Geometric Mean	0.9728778

Figure 4. 34: Summary statistics for 503-300 likelihood index by information injection level

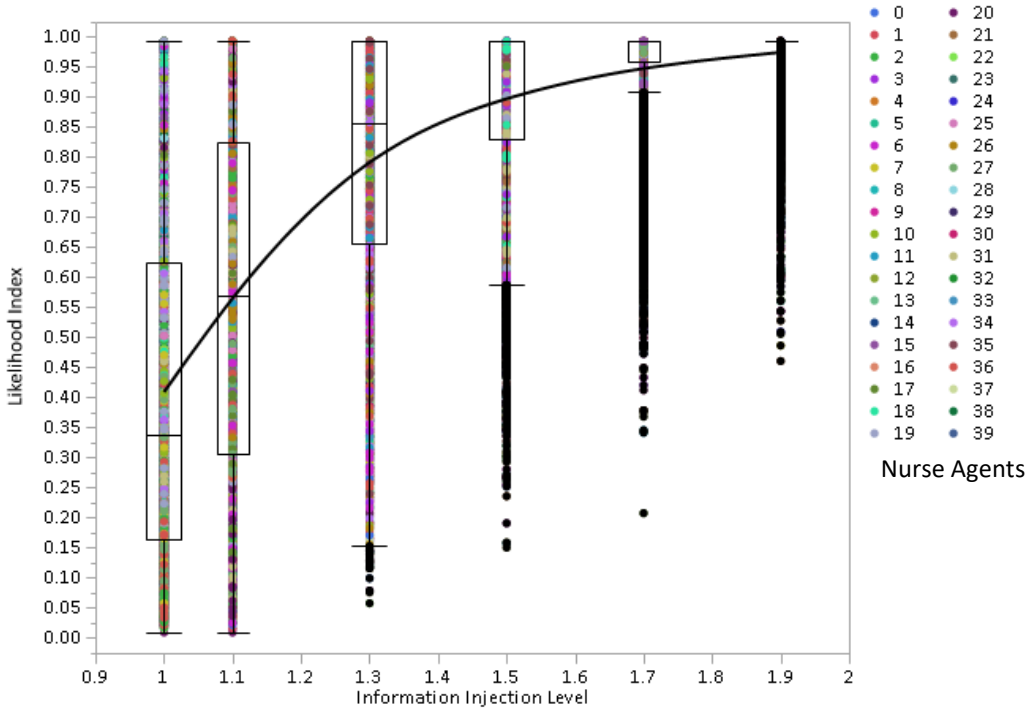
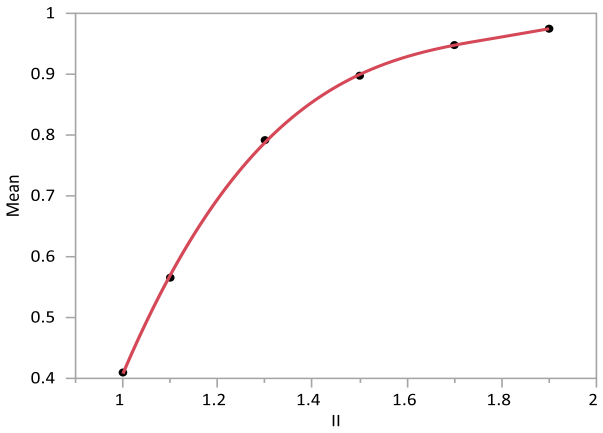


Figure 4. 35: Graph of likelihood index with mean values for LI by II and boxplot overlay for 503 true-true



Polynomial Fit Degree=3

Mean = 0.1328971 + 0.5154363*II - 1.0169364*(II-1.41667) ^{2} + 0.885933*(II-1.41667)^{3}

Figure 4. 36: Bivariate fit of mean of LI by II for 503-300 trial

A measure of variable performance was done using JMP Fit Model. Table 4.24 provides the list of each of the agent attributes and the relative contribution of each to the changes in the model averaged over each of the II levels. Interruption has the greatest effect at 0.241 for the Main Effect which is an importance index that reflects the relative contribution of that factor alone, not in combination with other factors. The Total Effects value is 0.257 which is an importance index that reflects the relative contribution of that factor both alone and in combination with other factors. The other attributes descend in level of contribution with the experience of the nurse having the least in terms of its effect in terms of impact to changes in the LI given a change in experience. Table 4.26 provides a comparison for information injection at the level of 1 through 1.9. Two things can be drawn from these tables:

1) that the impact of individual attributes to the LI is different; and
2) the magnitude of contribution can change as the II changes. Overall, the relative impact remains about the same among the attributes.

Based on the analysis and in accordance with previous analysis, each of the attributes were found to have effect values of less than the alpha value of 0.05 indicating that they do have an effect on the outcome of the model. The analysis of each attribute value was performed two of the analyses are shown in Table 4.75 in the appendix. The first data column shows the resultant effect of the attributes averaged across all II values, the second column shows these results for the II value equal to 1.9. For the averaged II values only moderate nurseExperience is shown to have no effect.

Nurse Agent Detail

The model tracks medication administration at nurse agent for each individual medication. This allows the evaluation of the performance of each nurse agent. Figure 4. 37 charts the performance path of each of the 40 nurse agents in this simulation. The breadth of performance at II level 1 results from the difference in agent attributes established by the model at the start of the simulation. As the simulation proceeds to higher levels of information, the nurse agent moves up the Likelihood Index scale. It is worthy of note that despite the wide divergence of nurse performance at the early II levels, the nurse agents approach the same level of performance at levels 1.7 and 1.9. This has an interesting implication; with the higher levels of appropriate JIT information, overall nurse agent performance increases to approximately the same levels without regard to their respective attributes. The conclusion is that JIT information mitigates the negative effects of attributes as well as random errors and enhances MAP performance.

As with the bivariate fit for the overall mean shown in Figure 4. 35, lines can also be fit for each nurse agent. The axis in this case are nominal instead of ordinal. As a result it is expected that the rate of change will be somewhat different than that calculated early for the ordinal/categorical scale.

Table 4. 24: Variable Importance: agent attributes variable importance independent resampled inputs summary report for II = 1 through 1.9

	Main Effect						Total Effect					
	1	1.1	1.3	1.5	1.7	1.9	1	1.1	1.3	1.5	1.7	1.9
Fatigue	0.136	0.159	0.148	0.168	0.157	0.102	0.149	0.173	0.17	0.186	0.174	0.115
Interruption	0.265	0.25	0.214	0.252	0.263	0.137	0.278	0.263	0.235	0.269	0.281	0.15
Med Diff	0.148	0.153	0.18	0.161	0.174	0.228	0.161	0.167	0.202	0.179	0.191	0.241
Med Severe	0.18	0.2	0.227	0.158	0.188	0.214	0.192	0.214	0.248	0.176	0.205	0.227
Experience	0.047	0.045	0.031	0.046	0.04	0.073	0.06	0.058	0.05	0.061	0.057	0.086
Patient Load	0.143	0.11	0.082	0.11	0.081	0.157	0.156	0.124	0.104	0.128	0.099	0.169

(Green highlighting Table 4. 24 indicates the largest contributing factor)

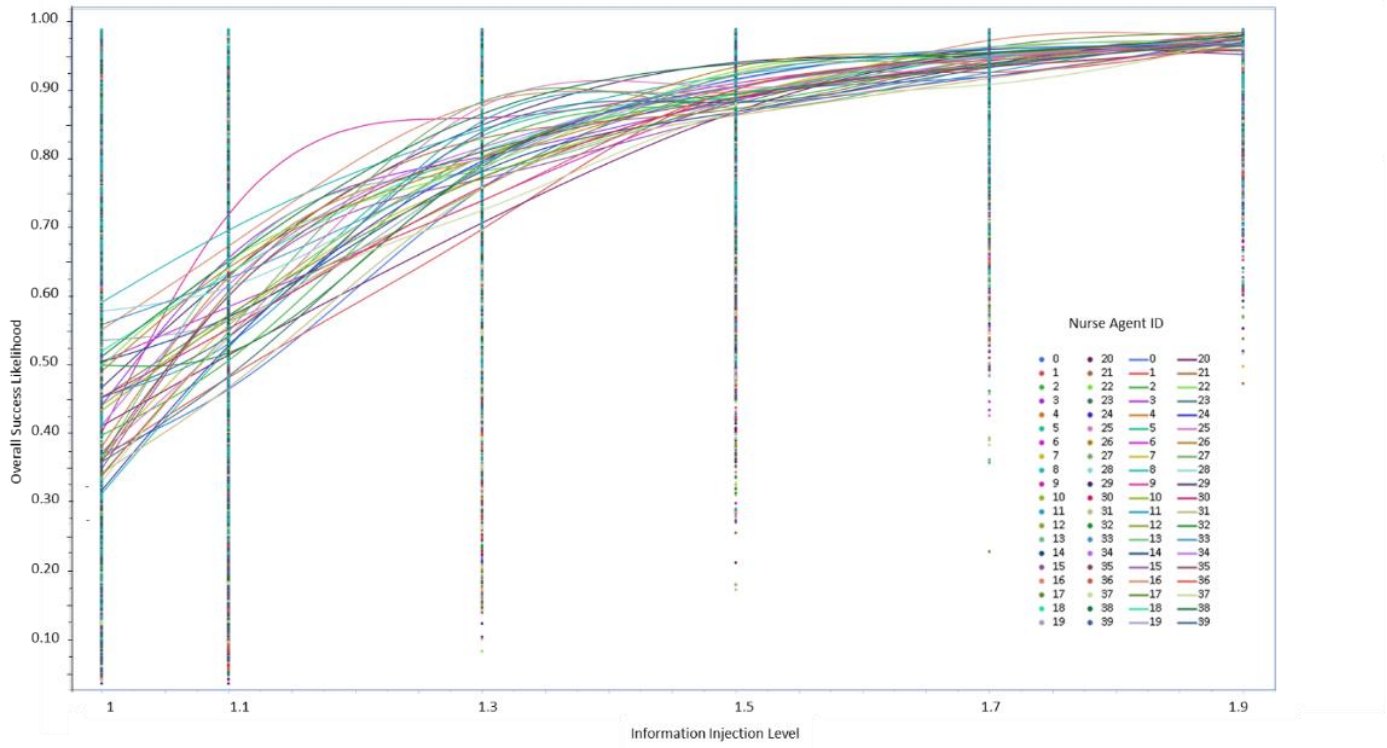


Figure 4. 37: Representation of the performance of each nurse agent as measured by LI for each II level

Clinical Case Study

Overview and initial analysis

The clinical case study (CCS), as described in the materials and Methods section, used a classic controlled clinical trial approach to evaluate the benefit, if any, of JIT on improving the likelihood of success in the MAP process. The results of the CSS are tabulated in Table 4. 26. The scenario was designed to assess the performance of each of the MAP steps, as well as overall performance in medication delivery. One of the successful outcomes, and in fact the optimal one, was termination of the process prior to completing all the steps since early recognition of overdosing of acetaminophen was a key factor in use and interpretation of the available information. This early termination of the process makes it somewhat difficult to make direct conclusions on successful completion of each of the MAP steps listed in Table 4. 25 since early termination would lead to a number of the MAP steps which would not be completed. However certain general observations can be made.

1. Initial interfacing with the patient is done by all the nurse groups
2. All of the groups used the MAR to access information, but with a varying degree of success, implying information could play a role in overall successful completion of the process
3. Use of JIT information early in the process leads to increased performance
4. Use and deciphering of information, such as laboratory results, can be enhanced by JIT information
5. Use of JIT information, via the app, was enhanced by providing more specific training on its use, which also infers that the amount of information that is available influences overall performance success

Table 4. 26 summarizes the results of the CSS with a total of 38 observations in the population. Eighteen of the observations were the control group, with the remaining 20 being the response group. The response group has sub-groups for pre-training and post-training with use of the JIT app: there are eleven observations in the pre-training group and nine observations in the post-training app.

Table 4. 25: Compilation of clinical case study data for each MAP process step

	Pain Assessed		Patient Checked		MAR Checked		Med Checked		Dose Checked		Correct Dose Calculation		Performance	
Trial	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Succ	Unsucc
Control	18	0	13	5	18	0	17	1	14	4	8	10	2	16
Post-train	9	0	2	7	9	0	2	7	2	7	2	7	7	2
Pre-train	11	0	8	3	11	0	8	3	8	3	3	8	3	8

	Time Checked		Labs Checked		Labs Understood		Route Checked		Used App		Full/Terminated		Performance	
Trial	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Terminated	Full	Succ	Unsucc
Control	16	2	6	12	2	16	11	7	0	18	2	16	2	16
Post-train	9	0	7	2	7	2	2	7	9	0	7	2	7	2
Pre-train	11	0	4	7	4	7	6	5	6	5	3	8	3	8

Table 4. 26: Summary of data for clinical case study on benefit of JIT for MAP successful completion

			Performance		
Group	Subgroup	*JIT app usage*	*Unsuccessful*	*Successful*	*Row totals*
Control		No app use	16	2	18
		Sub totals	*16*	*2*	*18*
Treatment		No app use	6	0	6
	Pre-Train	Limited app use	2	0	2
		Significant app use	0	3	3
		Sub totals	*8*	*3*	*11*
		No app use	0	0	0
	Post-Train	Limited app use	2	0	2
		Significant app use	0	7	7
		Sub totals	*2*	*7*	*9*
		Totals	*26*	*12*	*38*

Power and Sample Size

Retrospective analysis was performed to evaluate the power and sample size for the clinical case study. JMP k Means was used to do the estimated calculations. A pooled standard deviation for unequal sample sizes was developed using the following equation:

$$s_{pooled} = \sqrt{\frac{(n_1 - 1) * s_1^2 + (n_2 - 1) * s_2^2 + \cdots (n_k - 1) * s_k^2}{n_1 + n_2 + \cdots + n_k - k}}$$

k = number of samples

n_k = population in each sample

s_k = standard deviation for sample population

s_{pooled} = pooled standard deviation

The standard deviations contributing to the pooled estimate were obtained by doing a one-way estimate of MAP performance by trial. The means and standard deviations for this are highlighted in Table 4. 27. Note that Post-Train is the largest mean indicating the best performance in terms of the highest likelihood of success.

Table 4. 27: Means and standard deviations of Oneway analysis of performance by trial for power and sample size evaluation

Level	Number	Mean	Std Dev
Control	18	0.111111	0.323381
Post-Train	9	0.777778	0.440959
Pre-Train	11	0.272727	0.467099

This table uses the numeric values of 0 (false) and 1 (true) to calculate the mean and Std Dev as an indication of the central tendency and dispersion of the values

The resulting pooled standard deviation equals 0.458778. The calculated sample size for a power of 0.8 is 29. The individual sample size is estimated by n/k leading to 29/3 or about 10 per level. This is compared to an actual sample size of 11 for pre-training and 9 for post-training. Using this same methodology, a power of 0.78 results in a sample size projection of 27 or 9 samples per level. Based on this assessment, the sample size of each group is suitable for making statistically relevant conclusions, particularly considering the constraints of other factors of the research design.

Overall, 26 (77.6% of the total) of the participants were *not* successful in completing the MAP, 12 or 23.4% were successful. Within the Unsuccessful category, 62% were from the control group, 30% were from the pre-training (pre-train) group and the remainder were from the post-training (post-train) group. Conversely, 58% of the successful category were made up of the post-train Treatment group, with 25% and 17% respectively from the post-train Treatment group and Control group.

Table 4. 28 provides a tabulation of the percent contributions for the Control and Treatment groups for both the Successful and Unsuccessful completion of the MAP by the nurses. The first column represents the percentage of a groups MAP successful performance relative to the rest of the groups. For example, of all the successful completions, the Control Group contributed 16.67% of them and they did not use the app. The logic for the second column is similar but refers to unsuccessful attempts. Columns 3 and 4 represent the contribution to the overall percentage. Again, as an example, the post-training treatment group had 18.4% of the 38 groups successfully complete the exercise with significant use of the app, whereas only 7.9% of the pre-training group performed in the same way.

With that as background, several observations can be made using Table 4. 28 and Table 4.26:

1) The majority of successes, <73%, used the app to a significant extent
2) Training (or familiarity with the app) appears to play some role in the app use
3) The use of information appears to contribute to greater success rates between the Control group and Treatment group
4) The degree to which the app is used (i.e. the amount of JIT information) seems to influence the success rate; the more JIT information yields greater success. Said differently, limiting JIT information leads to lower MAP performance

Table 4. 28: Percent contributions for the control and treatment groups for both the successful and unsuccessful completion of the MAP by the nurses

			Relative Percent of MAP Performance		Percent of Overall Total	
Group		INFO	Column 1 Column %(Success)	Column 2 Column %(Unsuccess)	Column 3 % of Total(Success)	Column 4 % of Total(Unsucc)
Control		No app use	16.67%	61.54%	5.26%	42.11%
		Limited app use	-	-	-	-
		Significant app use	-	-	-	-
Treatment	Post-train	No app use	0.00%	0.00%	0.00%	0.00%
		Limited app use	0.00%	7.69%	0.00%	5.26%
		Significant app use	58.33%	0.00%	18.42%	0.00%
	Pre-train	No app use	0.00%	19.23%	0.00%	13.16%
		Limited app use	0.00%	7.69%	0.00%	5.26%
		Significant app use	25.00%	3.85%	7.89%	2.63%
		Percent Totals	100%	100%	31.57%	68.42%

Detailed Analysis

To evaluate overall response to the use of JIT information, a binary logit model scoring against if the nurse successfully performed the MAP (variable=Performance) and measuring the effect of the use of JIT information in the form of the app. The model used all 38 observations. Of the total observations, 26 were unsuccessful, 12 were successful (Table 4. 29). Of the 12 that completed successfully, 10 used the app to some degree. Of the 26 unsuccessful, four used the app in some fashion (Table 4. 28 above). The model converged appropriately.

Table 4. 30 provides a null model set that illustrates and assumes no effect from the covariate of using the app leads to 68.4% classification accuracy. Furthermore, the frequency of 26 and 12 are represented as statistically significantly different from one another in Table 4. 31 shown by the significance of the Walds test. The interpretation of the Exp(B) interpretation is that there is a 53.8% greater likelihood of not being successful without outside intervention[46]. The Variables Not in eqn. row of this table shows that USEDAPP, the variable identifying whether or not the nurse used the app, is significant at the alpha=0.05 level.

With the previous information setting the stage for what the results are with no effect from using the app, the information in Table 4. 32 shows the output from the binary logistic regression performed after the treatment (i.e. information supplied). The use of the app increases the predicted likelihood of successfully completing the MAP as seen below in the bottom right section of Table 4. 32. Based on the analysis, the number of unsuccessful events *predicted* is 21 versus the 26 observed in the actual outcomes. The number of statistically predicted successful completions increases to 10 from 0 in the control. The model failed to predict 2 outcomes, that is there were 2 cases observed and the model did not predict and it also failed to predict 2 successful events. The 10 predicted successful events associate well with the value in the Treatment cases which is also 10. The predictive capacity by using the app increases by a significant 12% over the null model.

The USEDAPP variable is statistically significant at the 0.05 alpha value as provided by the Wald statistic (Table 4. 33). The odds ratios of 21.0 infers that the use of the JIT information app has a 21 times greater likelihood of successfully completing the MAP when using the app, controlling for other factors within the analysis.

Table 4. 29: Summary response profile for null model set for use of the app

Response Profile		
Ordered Value	Performance	Total Frequency
1	0: Unsuccessful MAP	26
2	1: Successful MAP	12

Table 4. 30: Classification Table

			Selected Cases[b] Predicted Performance		
	Observed		Unsuccessful	Successful	Percentage Correct
Step 0	Performance	Unsuccessful	26	0	100.0
		Successful	12	0	0.0
	Overall Percentage				68.4

[46] https://www.youtube.com/watch?v=zdJhydkcqv4

Table 4. 31: Variables in the equation step 0

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-.773	.349	4.908	1	.027	.462
	Variables Not in eqn.	USED APP			1	.000	

Table 4. 32: Crosstabulation of performance vs. info use for chi-square

			Information Use		
			no	yes	Total
Performance	unsuccessful	Observed Count	5	0	5
		Expected Count	1.7	3.3	5.0
	success	Observed Count	0	10	10
		Expected Count	3.3	6.7	10.0
Total		Observed Count	5	10	15
		Expected Count	5.0	10.0	15.0

Table 4. 33: Classification table for inclusion of USEDAPP

			Selected Cases Predicted Performance		
	Observed		Unsuccessful	Successful	Percentage Correct
Step 1	Performance	Unsuccessful	21	5	80.8
		Successful	2	10	83.3
	Overall Percentage				81.6

Table 4. 34: Variables in the equation step 1

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	USED APP	3.045	.921	10.935	1	.001	21.000
	Constant	-2.351	.740	10.096	1	.001	.095

In order to determine if the degree to which the app was used, and therefore the amount of information used, made a difference in the outcomes, the amount of usage of the app was measured during the MAP process. This data is based on a qualitative assessment of the degree to which the nurses used the app during the performance of the scenario and was recorded as "no use", "limited use", or "significant use". *Since the comparison is being done on the degree to which the app is used, data from the control group was removed and only the treatment group was evaluated. The "no use" observations were also excluded since the comparison is being focused on the "limited use" and "significant use" observations.* A chi-square analysis was done using SPSS v.25 and was performed between the response variable (performance) and information use (InfoUse)(Table 4. 34).

As seen in Table 4. 34, the observed count for not being successful in performance of the MAP and using the lower amount of information was 5, whereas the expected count of no association, that is no association between performance information use, would be 1.7. The expected value for being successful in completing the MAP with no information is 3.3, however, the observed value was that there were zero occurrences. In further evaluation of the table, the observed count for being successful in the MAP while using information was 10, while the expected value would be 6.7. There were no observations of being successful completing the MAP at the higher levels of information usage.

The chi-square results, in Table 4. 35, indicate statistically significant results at the alpha = 0.05 level as noted in Asymptotic Significance column, which is the significance value indicator. Examining the Fisher's Exact test with a significance value below 0.05, indicates that the null hypothesis is not valid and therefore there is an association between information use at the higher level and performance in the MAP. That is, performance is dependent on the amount of information used.

Examining results for nominal association in Table 4. 36, Phi is used since the test was for a 2x2 chi-square. The significance value is less than the alpha value of 0.05 and the effect value is 1.000. This high effect size can be explained by examining the detailed data for Performance and Info Use; there is direct correspondence between the amount of information used and successful performance resulting in the high level of association.
The relationship between duration of the process and overall success was noted earlier. Duration of the process is directly influenced by its early termination. To evaluate this, the control group and each of the treatment group's duration of performance was considered. The average duration for the control group was 11:43 (minutes). The average duration for the treatment group was 9:06 with the post-training group being 8:13 and the pre-training group duration averaging 9:49. The durations were also examined by successful and unsuccessful performance; successful performance observations had an average duration of 7:32 and unsuccessful averaged 11:38. Two-sample t-tests were performed on both the duration by trial and performance durations and the p-values were below the 0.05 alpha confirming that a significant difference does exist. This leads to the conclusion in case that JIT information lead to earlier decision making, as well as, an overall increase in successful performance.

Table 4. 35: Chi-square results for performance vs. info use

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	15.000[a]	1	.000		
Continuity Correction	10.838	1	.001		
Likelihood Ratio	19.095	1	.000		
Fisher's Exact Test				.000	.000
N of Valid Cases	15				

Table 4. 36: Symmetric measures test for association for performance * info use for chi-square.

		Value	Approximate Significance
Nominal by Nominal	Phi	1.000	.000
	Cramer's V	1.000	.000
N of Valid Cases		15	

Analysis of JIT information effects on scenario duration

A more detailed analysis of the differences of durations among the trial groups validates these findings. Four separate T tests were performed to compare the overall treatment group with the control and to compare each of the treatment subgroups (pre and post training) with the control group. Time was converted to a decimal format using excel in order to simplify the analysis. Table 4. 37 provides the summary tables of all the T-Test combinations. Each of the p values are less than the alpha=0.05 with the exception of the T test of the pre and post training. This is likely the influence of the JIT intervention.

Table 4. 38 provides a one-way ANOVA of the durations for each of the groups. The p value of 0.0081 indicates a significant difference between the values. Figure 4. 38 provides a graphical representation of the values for each of the groups which highlights the differences in means and standard deviations. The analysis of means in Figure 4. 39 indicates that the control and post training groups fall outside the UDL/LDL, demonstrating the effect of the JIT information on the duration of the scenario execution.

Figure 4. 40 highlights the mean and standard deviation for the control group and overall treatment groups. Table 4. 39 is the ANOVA for this comparison and indicates statistically significant differences between the groups at an α=0.05 versus the p value of 0.0047. The Analysis of Means in Figure 4. 41 indicates divergence of both groups from the calculated UDL/LDL emphasizing the difference in durations of the two groups.

The design of the simulation scenario had the use and understanding of lab results as a key factor in successful performance. Considering the frequency of checking labs first (Table 4. 40), the control group had the lab checked seven times versus missing checking the labs 11 times. A chi-square test (Table 4. 41) comparing the association of the control/treatment groups with checking of lab results indicates that this is significant at the 0.05 alpha value; there is, in fact, a statistically significant difference between how the control group and treatment group checked on lab results. The Crammer's V result is 0.315 indicating a medium level effect size implying that using the JIT app had a moderate effect on checking the labs.

The next consideration is the effect the JIT might have on the understanding of the lab results and what influence it might have on the outcome of the MAP process. As with the activity of checking the lab results, a chi-square test was performed. The observed versus expected table (Table 4. 42) indicates the difference in the occurrence of the control and treatment group's values; as expected, fewer in the control group understood the lab results. The following table, Table 4.43, provides the Chi-square results. Here the results are more dramatic. The association of the control/treatment groups with understanding of lab results indicates that this is significant at the 0.05 alpha value; there is, in fact, a statistically significant difference between how the control group and treatment group for the understanding of lab results. The Crammer's V result is 0.462 indicating a moderate to large effect size implying that the consideration of using the JIT app had a moderate effect on checking the labs.

Table 4. 37: T test calculations for time comparison

Control-Post training T test

Trial	N	Mean	StDev	SE Mean
Control	18	0.488	0.115	0.027
Post train	9	0.343	0.120	0.040

T-Value	DF	P-Value
3.01	15	0.009

Pre train-Post training T test

Trial	N	Mean	StDev	SE Mean
Post Train	9	0.343	0.120	0.040
Pretrain	11	0.4090	0.0915	0.028

T-Value	DF	P-Value
-1.37	14	0.193

Pre train-Control T test

Descriptive Statistics: Duration

Trial	N	Mean	StDev	SE Mean
Control	18	0.488	0.115	0.027
Pretrain	11	0.4090	0.0915	0.028

T-Value	DF	P-Value
2.05	24	0.05

All Treatments-Control T test

Trial Total	N	Mean	StDev	SE Mean
Control	18	0.488	0.115	0.027
Treatment	20	0.379	0.108	0.024

T-Value	DF	P-Value
3.01	34	0.005

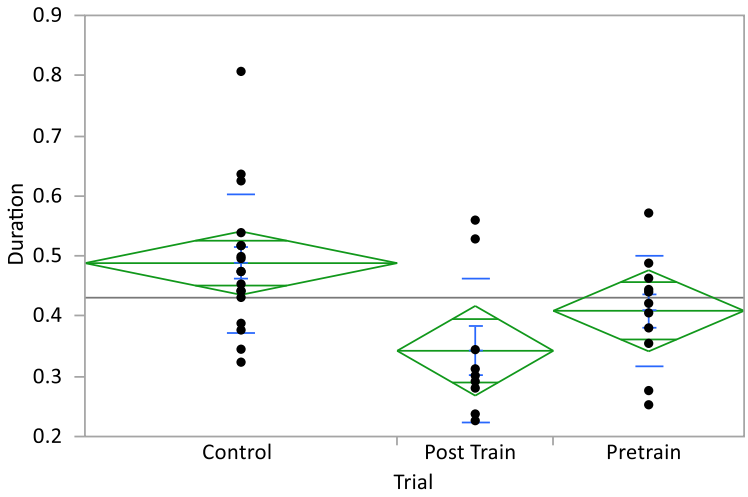


Figure 4. 38: Mean and standard deviation for duration by trial

Table 4. 38 : Analysis of variance for duration by trial

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Trial	2	0.13473575	0.067368	5.5519	0.0081*
Error	35	0.42469931	0.012134		
C. Total	37	0.55943507			

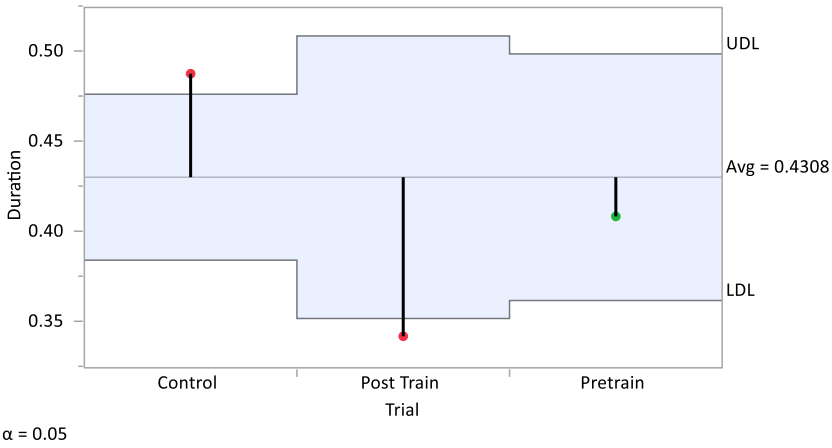


Figure 4. 39: Analysis of means for duration by trial

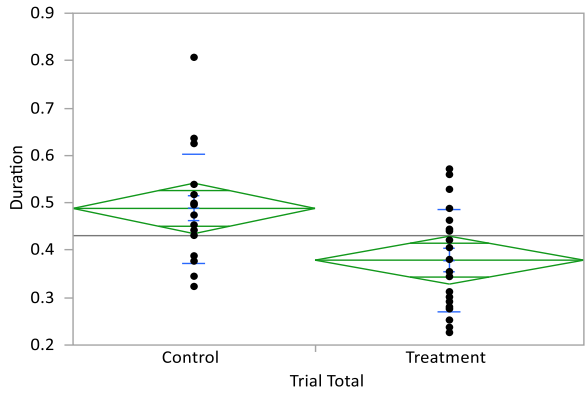


Figure 4. 40: Mean and standard deviation for Duration by Total Trial

Table 4. 39: Analysis of Variance for Duration by Total Trial

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Trial Total	1	0.11283748	0.112837	9.0958	0.0047*
Error	36	0.44659758	0.012405		
C. Total	37	0.55943507			

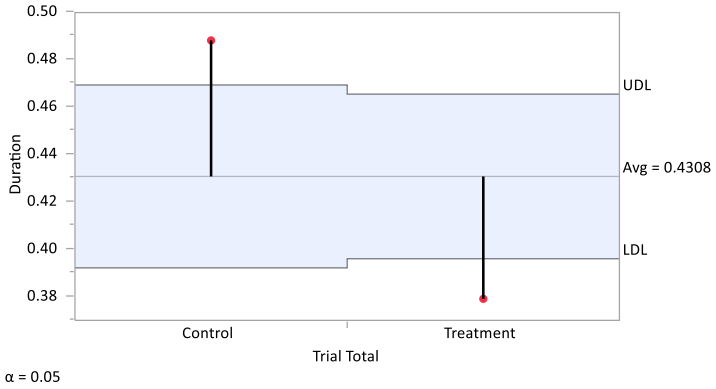


Figure 4. 41: Analysis of means for duration by total trial

Table 4. 40: Labs checked crosstabulation

			Control vs. Treatment		
			Control	Treatment	Total
Labs Checked	No	Observed Count	11	6	17
		Expected Count	8.1	8.9	17.0
	Yes	Observed Count	7	14	21
		Expected Count	9.9	11.1	21.0
Total		Observed Count	18	20	38
		Expected Count	18.0	20.0	38.0

Table 4. 41: Chi-square test comparing control/treatment group with occurrence of checking lab results

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)	Point Probability
Pearson Chi-Square	3.709[a]	1	.05	.101	.05	
Fisher's Exact Test				.101	.05	
N of Valid Cases	38					

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 8.05.

Table 4. 42: Labs understood crosstabulation

			Control vs. Treatment Control	Treatment	Total
Labs Understood	No	Observed Count	16	9	25
		Expected Count	11.8	13.2	25.0
	Yes	Observed Count	2	11	13
		Expected Count	6.2	6.8	13.0
Total		Observed Count	18	20	38
		Expected Count	18.0	20.0	38.0

Table 4. 43: Chi-square test comparing control/treatment group with occurrence of understanding lab results

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	8.108[a]	1	.004		
Fisher's Exact Test				.006	.005
N of Valid Cases	38				

Table 4. 44: Used app and labs understood crosstabulation

			USED APP No	Yes	Total
Labs Understood	No	Observed Count	21	4	25
		Expected Count	15.1	9.9	25.0
	Yes	Observed Count	2	11	13
		Expected Count	7.9	5.1	13.0
Total		Observed Count	23	15	38
		Expected Count	23.0	15.0	38.0

Table 4. 45: Chi-square test comparing Understanding labs and use of the JIT app

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	16.854[a]	1	.000		
Fisher's Exact Test				.000	.000
N of Valid Cases	38				

One final analysis was done considering the interrelationship of use of the app on understanding the lab results. The results are presented in Table 4. 44 and Table 4. 45. As can be seen, and what would be expected from the previous analyses, is that there is an association between use of the app and the understanding of the lab results. The p value is well below the 0.05 alpha threshold and the Crammer's V is calculated at 0.666 indicating a large effect of use of the app on the understanding of the lab results.

A binary logit regression was performed and provided a p value of <0.001, and odds ratio (Exp(B)) of 38.33 and Nagelkerke R square of 0.561. These results indicate a significant benefit provided by use of the smart phone app in understanding the laboratory results (detailed results in Appendix 1).

Analyzing Control Group versus Treatment Group

The evaluation of Control vs. Treatment groups yielded the results seen below. In this analysis there is no discrimination between pre and post-training. Table 4.46 provides the null model which uses no predictive variables (i.e. does not include the effect of treatment, or, it is an intercept only model). This table indicates what the expected results would be. Without the effect of treatment, the prediction would be that 26 of the observations would result in unsuccessful completion of the MAP and 12 of the attempts would result in successful attempts. The null model provides 68.4% predictive capability.

The only variable considered in the model is the consideration of treatment versus non-treatment (control). Table 4. 47 illustrates what significance the Treatment value will play when it is entered into the logistic regression. At an alpha of 0.05, the significance of Treatment allows us to reject the null hypothesis that there is not an influence contributed by the Treatment.

Table 4. 48 considers the performance of the logistic regression with inclusion of the Treatment variable, the significance value of 0.008, which is less than the alpha of 0.05, indicates that the influence of the Treatment is a good predictor for the regression results.

The output also provides a Nagelkerke R^2 of 0.240. This value shows how much of the variance in the dependent variable is a result of the effect of the Treatment variable in the regression. In this instance, 24% of the variance is explained by the role of Treatment. While not extremely large, the effect is substantial enough to be of value.

The classification table results after incorporating treatment indicates better prediction of the individual outcomes, while the overall predictive capability of 68.4% remains the same as the null hypotheses (Table 4. 49)

Based on this analysis, the conclusion can be made that the effect of the variable Treatment (addition of information) does have a statistically significant effect on the MAP outcome. Furthermore, the coefficient of 2.079 indicates that there is a significant effect between the control group and the treatment group in terms of the MAP being accomplished correctly. As noted previously, this analysis considers just the effect of overall use of the app and does not include pre- and post-training effect. As noted in the assumption and limitations section the use of information in this context conveys the implication that the insertion of information includes the ability to effectively translate it into action.

Table 4. 46: Classification table for effect of treatment

			Predicted		
			PERFORMANCE		Percentage Correct
	Observed		Unsuccessful	Successful	
Step 0	PERFORMANCE	Unsuccessful	26	0	100.0
		Successful	12	0	0.0
	Overall Percentage				68.4

Table 4. 47: Variables not in the equation for treatment

			Score	df	Sig.
Step 0	Variables	Treatment	6.631	1	.010
	Overall Statistics		6.631	1	.010

Table 4. 48: Omnibus tests of model coefficients for treatment

		Chi-square	df	Sig.
Step 1	Step	7.114	1	.008
	Block	7.114	1	.008
	Model	7.114	1	.008

Analysis of Training Effect

A chi-square test was performed to determine if an association exists between the amount of training and the successful completion of the MAP. Table 4. 50 provides the cross tabulation of the chi-square test, the expected count, that is, the responses we would get if there is no association, are 5.5 for each value of performance for Pre-training. The expected count for Post-training is 4.5 for each value of performance. The observed counts are notably different than the expected counts.

Table 4. 51, the Asymptotic Significance which serves as the p-value 0.025, is clearly less than the α=0.05 therefore, the level training effect is statistically significant and there is an association between training level and performance. The likelihood ratio is also significant at a value of 0.021. The Fisher's Exact test of 0.07 is however not significant, at an alpha of 0.05. The differences in significance could be a function of sample size, with two of three indicators implying significance, the assumption is that the differences are significant. This assumption is corroborated later in the binary linear regression analysis. The Phi value of 0.503 indicates that the amount of training has a strong effect on performance.

Binary logistic regression was also performed to help understand the training effect further. The initial null model (Table 4. 54) predicts a 50% chance of prediction with no predictor variables in the model.

Table 4.52 shows the null table. Table 4. 53 shows the result in the classification table with the inclusion of the predictor variable of training. The value increases to 75% compared to the 50% of the classification table without the inclusion of the predictor variable. The only variable considered in the logistic regression is pre versus post training. Table 4. 54 illustrates what the significance of the Training value is in the logistic regression. At an alpha of 0.05, the significance of Training at 0.025 allows us to reject the null hypothesis that there is not an influence contributed by the Training.
Table 4. 55 considers the performance of the logistic regression with inclusion of the Training variable, the significance value of 0.021, which is less than the alpha of 0.05, indicates that the influence of the Training is a good predictor for the regression results.

Table 4. 49: Effect of treatment variable (Control versus Treatment groups)

								95% C.I. for EXP(B)	
		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 1[a]	Treatment	2.079	.873	5.671	1	.017	8.000	1.445	44.297
	Constant	-2.079	.750	7.687	1	.006	.125		

Table 4. 50: Crosstabulation for training * PERFORMANCE

			PERFORMANCE		
			Unsuccessful	Successful	Total
Training	Pre-training	Observed Count	8	3	11
		Expected Count	5.5	5.5	11.0
	Post-training	Observed Count	2	7	9
		Expected Count	4.5	4.5	9.0
Total		Observed Count	10	10	20
		Expected Count	10.0	10.0	20.0

Table 4. 51: Chi-square test for training amount effect on performance

		Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square		5.051	1	.025		
Continuity Correction		3.232	1	.072		
Likelihood Ratio		5.300	1	.021		
Fisher's Exact Test					.070	.035
Linear-by-Linear Association		4.798	1	.028		
N of Valid Cases		20				
Nominal by Nominal	Phi	.503		.025[c]		
	Cramer's V	.503		.025[c]		

Table 4. 52: Classification table for effect of training effect without predictor variable

			Predicted PERFORMANCE		Percentage Correct
	Observed		Unsuccessful	Successful	
Step 0	PERFORMANCE	Unsuccessful	0	10	.0
		Successful	0	10	100.0
	Overall Percentage				50.0

Table 4. 53: Classification table for effect of training effect with predictor variable

			Predicted PERFORMANCE		Percentage Correct
	Observed		Unsuccessful	Successful	
Step 1	PERFORMANCE	Unsuccessful	8	2	80.0
		Successful	3	7	70.0
	Overall Percentage				75.0

Table 4. 54: Variables not in the equation for training

			Score	df	Sig.
Step 0	Variables	Training	5.051	1	.025
	Overall Statistics		5.051	1	.025

Table 4. 55: Omnibus tests of model coefficients for training

		Chi-square	df	Sig.
Step 1	Step	5.300	1	.021
	Block	5.300	1	.021
	Model	5.300	1	.021

The output also provides a Nagelkerke R^2 of 0.310 (Table 4. 56). This value shows how much of the variance in the dependent variable is a result of the effect of the Treatment variable in the regression. In this instance, 31% of the variance is explained by the role of Treatment. While not extremely large, the effect is substantial enough to be of value.

The odds ratio and coefficient are displayed in Table 4. 52. The odds ratio of 9.333 implies a magnitude of over nine times greater likelihood of having a successful outcome of MAP completion with a beta coefficient of 2.234.

Based on this analysis, the conclusion can be made that the effect of the variable Training (pre vs post training) does have a statistically significant effect on the MAP outcome. Furthermore, the coefficient of 2.234 indicates that there is a significant effect between the control group and the treatment group in terms of the MAP being accomplished correctly.

Recapitulation

The goal of the clinical case study was to ascertain what role JIT information might play in affecting nurse performance in the MAP process. The fundamental conclusion can be made, based on the analysis of clinical case study information, that the use of the app and the associated access to JIT information increased the likelihood of success of the MAP.

The results and observations from the analyses demonstrates the following:

- The treatment group, using an app providing JIT information, had overall improved MAP outcomes measured than the control group which had no access to the JIT app.
- There is a direct association between using an app providing JIT information and improvement in the outcome of the MAP process.
- The difference in MAP outcomes for pre and post-training was statistically significant, post-training having better performance, and it can be used as an indicator that the degree to which information is used improves outcomes.
- Early termination of the scenario by the nurse to check with the physician on the proper dosage influenced the completion of other steps of the MAP process.
- Use of the app improved the checking of lab values and the understanding of the implications of lab values and lead to improved decision making for the MAP.

Table 4. 56: R-Square coefficient for training

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	22.426[a]	.233	.310

Table 4. 57: Effect of training variable

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I. for EXP(B) Lower	Upper
Step 1	Training	2.234	1.049	4.530	1	.033	9.333	1.193	72.991
	Constant	-.981	.677	2.099	1	.147	.375		

The CCS used a modest sized cohort to assess the role of providing JIT information in MAP performance. The size of the groups (control and treatment) and the sub-group (pre and post training subgroup within the treatment group) were evaluated retrospectively and were determined to be of appropriate size to have sufficient power of 0.8 to provide meaningful statistics, although the post-training sub-group was at the margin of meeting the number of samples.

A primary goal of the CCS was to inform the development of the agent-based modeling effort and to confirm the hypothesis that JIT information would be effective in increasing the effort of administering medication. The foregoing analyses does provide credence to the hypothesis that the application of JIT information is significant in improving overall MAP success. While the methodology was not designed to identify the effect of information on each step, it has been proven to increase performance in several key process steps. While one must be cautious generalizing the benefit of JIT information for all of the MAP steps, it would not be unreasonable to assume that information specifically tailored for each MAP process step would have some positive effect in reducing medication administration error and improving MAP success rates.

Chapter 5
Summary of Findings

Revisit of the Goal

There are two separate but related parts of this research effort; a clinical case study that assesses the effect of JIT information on the successful completion of the administration of medication, and the construction, verification validation of an agent-based model that represents the nurse MAP. The primary purpose of the clinical trial was to provide the underpinning confirmation of the impact of JIT on nurse performance. The intent of building an ABM was to first establish that an ABM could be constructed that effectively reflected nurse performance during the medication administration process, and then to use the agent-based computer model to assess the effect of JIT information on the likelihood of success in the MAP.

Clinical Case Study

A clinical study was developed to assess the effect of JIT information via a smartphone app on the performance of administering medication by nurses. The study used student nurses in their senior year and the HITS lab to perform a specifically designed scenario for the administration of medication. This approach provided controlled experimental conditions that allowed direct monitoring via audio and video of the test subjects performance: the physical environment, the scenario, and the "patient" mannequin were identical for each test run. The scenario was detailed, scripted, rehearsed and conducted in the same fashion for each run. Using student nurses afforded consistency of each of them having approximately the same level of experience; the scenario was performed by small groups of two to three nurses. The testing took place over two semesters, the fall semester of 2015 and the spring semester of 2016. The clinical study was performed in accordance with IRB guidelines. There was a total of 38 runs of the scenario, eighteen of which served as the control group and were not provided the JIT smartphone app but had access to all other information including the EMR/MAR. The remaining 20 runs were the treatment/response group, which used the smartphone JIT app. The response group was also divided into the pre-training group, which was provided a brief overview of the app and the post training group which was given the same overview, but a worksheet to complete while using the app.

The clinical evaluation for the effect of JIT information on the MAP demonstrated that the information obtained via the app increased the likelihood of the nurse performing the MAP correctly in contrast to the control group which did not have access to information via the app. Furthermore, the degree to which the app was used provided different outcomes. Increased use of the app resulted in improved likelihood of success. The initial assessment, comparing the control group to the treatment group, demonstrated increased likelihood of successful MAP performance with an odds ratio of 8.00 implying an 8-fold increase in likelihood of successful MAP completion when considering the Treatment variable.

While all of the treatment groups had access to the use of information via the app, not all of the subjects used it, or if they did use it some did not use it effectively. If one considers those who used the app versus those who did not, the results show significant improvement in performance for those that used the app. The use of the app results in an odds ratio of 21 for increased performance of using the app, and the beta constant of 3.045 when the dependent variable is successful at completion of the MAP process, thereby demonstrating increased nurse performance for those that used the app.

The treatment group had two sub groups, the pre-training group and the post-training group. The pre-training group was given a brief verbal overview and approximately 15 minutes to use the JIT app prior to the participating in the scenario. The post-training group was also provided the verbal overview but also completed a worksheet that required them to use the JIT app. The amount of training had a statistically significant impact on performance, influencing both the use of the JIT app as well as increasing their likelihood of success in performance of the medication administration scenario. The chi-square and likelihood ratio results of 0.02 indicate statistical significance at the α=0.05. The binary logistic regression provided a significance level of 0.33 and an odds ratio of 9.33.

Other insights have been gained from the clinical portion of the research. An observation obtained from evaluating the performance of the control group was the lack of use and understanding of the patient's laboratory results. In the clinical scenario used, laboratory results provided key information on the correct decision path. The response group demonstrated increased review with a chi-square significance value of 0.05 and a better understanding, with a chi-square significance of 0.00, for the laboratory results.

The use of the app resulted in shorter scenario times indicating the nurses were reaching decisions more quickly when information from the app was used. Both the t test and ANOVA confirmed a statistically significant difference in the duration of the scenarios between the control and treatment groups. The implication is that the JIT information can serve as an effective decision-making aid helping to guide the nurse to better informed decisions more quickly.

A primary goal of the CCS was to inform the development of the agent-based modeling effort and to confirm the hypothesis that JIT information would be effective in increasing the effort of administering medication. The foregoing analyses does provide credence to the hypothesis that the application of JIT information is significant in improving overall MAP success: specifically, the app was successful in transferring information to the user and the information improved overall performance in MAP execution. While the methodology was not designed to identify the effect of information on each step, it has been proven to increase performance in several key process steps. While one must be cautious generalizing the benefit of JIT information for all of the MAP steps, it would not be unreasonable to assume that information, specifically tailored for each MAP process step, would have some positive effect in reducing medication administration error and improving MAP success rates.

Medication Administration Process Model

A computer simulation that modeled the nurse related process of medication administration was developed using the program AnyLogic. An agent-based modeling approach was used because it afforded the ability to have multiple interactions among a variety of entities and allowed for incorporation of multiple attributes and a dynamic structure for the interactions amongst the objects within the model.

Three agent types were used in the model: nurses, patients and medications. Each agent type had a set of attributes that conveyed individuality to each particular agent. The attributes modified the agent's behavior and influenced their performance while executing the MAP. The numbers of nurse and patient agents where held constant while the number of medication agents were allowed to change depending on the attributes of the patients and nurses. The interactions between patients and nurses changed over time as the simulation ran, the number of patients a nurse agent would have was assigned randomly at the start of the simulation run. The number and type of medications assigned to a patient was assigned randomly based approximately on a uniform distribution. Nurse agents were assigned to one of two shifts; shift duration was the length of time a nurse agent was allowed to distribute medications to their allotted patients.

The MAP portion of the model was made up of each of the key MAP steps medication check, MAR check, dose check, patient check, route check, and time check. In a figurative sense, for every medication, a nurse agent would pass sequentially through each of this process steps. A probability engine inside each step would determine the likelihood of successful completion of each step. At the end of all of the steps a composite Likelihood Index would be calculated that determined the overall probability of the nurse agent's successful completion of the overall medication administration process. The effect of agent attributes and the impact of JIT information was controlled as part of the overall simulation process.

The validation and verification of the model was performed using a variety of methods. Numerous tracking variables were built into the model in order to track its execution and ensure that the model's processes performed as intended. Considerable effort was placed on statistical analysis of simulation output to verify the model's performance.

Six simulations were designed to evaluate model performance and to represent the influence of JIT information on nurse agent performance. A combination of shift durations and total medication amounts (which influences medications per nurse) was used. Three different durations and two levels of total medication amounts were

selected, giving a total of six scenarios that were run and analyzed. The levels for duration and total medications were selected to represent amounts that were believed to stress the model, as well as appropriately reflect levels that represent amounts found in a typical acute care setting.

Each of the six scenarios performed largely as expected. The shorter duration shift time reflected a higher rate of incomplete medication runs and lower overall likelihood of success probabilities. As duration increased, the overall probability of success increased. As the number of total medications increases, the overall likelihood of success decreases. The lower time amount was found to have considerable "jitter" in the response due to incomplete delivery of medications which was due to the short time period.

The influence of JIT information was done via a multiplier. As with the clinical trial, information had a dramatic effect on nurse agent performance. The rate of increase followed a polynomial increase, with the rate of performance increase, decreasing as more information was inserted into the system. As the overall performance increases, the associated standard deviation decreases by roughly a proportionate amount. This is expected since as more information is injected into the system, overall performance congregates near 1.00 which depresses the variance.

With all six simulations, there were over 950,000 lines of data with each line having over 100 variables resulting in 95 million data elements. It was necessary to reduce the data set to a manageable amount for more detailed analysis. One simulation was selected that best represented model performances. This selection was based on a comparative assessment within and among the six simulations based on a specific set of selection criteria.

The data was appropriately tortured for this more detailed analysis. The specific influence from each of the agent attributes, the performance at each MAP process step, as well as overall model performance was analyzed. Several specific conclusions can be reached from this analysis. As the amount of information increases, the effect of agent attributes on overall performance decreases, reaching the point of no discernable impact at the highest level of information. The implication here is that information can mitigate the negative effects of attributes such as inexperience, fatigue, higher patient loads and medication complexity on performance.

Another consideration, discerned from the detailed analysis, is that the effect of information behaves in a predictable pattern. This can be used to support building a predictive model to project outcomes based on changes in attributes and the addition of information.

Each of the individual process steps was analyzed in terms of the effect of information on the overall likelihood of success. The observation is that, for this model, each of the steps behaves similarly. This result is expected since the model design did not add any feature that would create differences among the process steps.

Of note is the ability of the model to consider the performance of each individual nurse agent. The performance of each agent can be mapped over the profile of increasing information injection in order to see the response of the individual as information increases. Of particular interest is the effect of information on the individual agents as the information increases. While not the purpose of this study, it is possible that this ability can be used to optimize how information can be used to improve MAP processes in consideration of costs and other factors.

In summary, the MAP computer simulation model and the data from the clinical case study align: the model accurately reflects nurse performance and appropriately represents the effect of JIT information. The model provides utility in being able to discern overall nurse agent performance as well as individual performance of nurse agents. While not explored in detail, the model appears to have inherent predictive capability as well as the ability to support optimization of the MAP process.

Future Work

This area of research provides rich opportunities for additional pursuit. As with this research effort, the consideration of future work foals within two main categories: the use of simulated clinical environment like the HITS lab to perform clinical trials and the use of computer simulation to provide a richer understanding of real world phenomena and to explore a diversity of scenarios. Ideally these two facets would be combined.

Clinical Simulation Environment

The HITS lab is an excellent resource to perform modest clinical trials. Resource limitations make it difficult to use multiple patients (mannequins) or test subjects. Expansion of these resources would provide a richer environment to perform a wide array of clinical trials with a greater degree of experimental control while eliminating many of the barriers faced in using an actual clinical setting.

As a first step constructing the clinical trial to provide differing levels of information to the test subjects in order to specifically assess the role of the amount of information injected into the performance of the MAP would be valuable. This could be accomplished be either providing additional categories of information for different test groups or providing increasing content for each category of information.

It can be envisioned to use a larger HITS-like environment with larger numbers of patients to more realistically represent an acute care setting. The scenarios could be enhanced to allow multiple medications along with various ward types (pediatrics, medical-surgical, oncology, etc.).

While student nurses proved to be well-suited for this study, repeating this research with nurses with various levels of experience and training would broaden the value of this research. In the same vain, using multiple medications over a greater period of time would also add a richness to this research.

Reconstructing the scenario to be open-ended, that is, to allow various integrated scenarios using multiple medications to run simultaneously would more closely mimic actual MAP operations.

Computer Simulation

The development of the MAP computer model, developed for this research effort, provides insight on areas for additional development. ABM is an excellent simulation tool for the MAP. Augmenting this with additional agent types and more interaction among the agents would provide a model that has increased capability for prediction and optimization.

While prediction and optimization were not part of this research, it would be a natural next step. The ability to use objective functions to measure the value and optimize to gain better efficiencies in terms of risk, cost and utilization of resources would be of direct benefit to the health care community.

Expanding the model's agents' emergent attributes and properties would provide an enhanced approach to simulate the complex system of MAP. Also, in line with this and the concept of complex adaptive systems would be integration of a MAP computer model with outside influences ranging from other hospital functions, such as a pharmacy operation, to other more general influences such as procedures, policies and economic drivers.

Broader Context

The use of JIT information appears to improve outcomes in high consequence environments where human performance plays a key role. Areas where immediate decision making regarding factors influencing health and safety and rapid response, particularly where small mistakes can cascade to have a large impact could benefit from a JIT information approach. Applications including nuclear, aviation, chemical processing, finance, and healthcare are likely candidate areas. Conceivable small apps developed for specific purposes could provide the same positive benefit as was identified with this research. Furthermore, the application of artificial intelligence into the apps could aid in identifying incipient errors and provide timely course correction without being obtrusive.

References

1. James, J.T., *A New, Evidence-based Estimate of Patient Harms Associated with Hospital Care.* Journal of Patient Safety, 2013. **9**(3): p. 122-128.

2. Makary, M.A. and M. Daniel, *Medical error—the third leading cause of death in the US.* BMJ, 2016. **353**.
3. Administration, U.S.F.a.D. *Medication Errors Related to Drugs*. [cited 2016 5/6/2016]; Available from: http://www.fda.gov/drugs/drugsafety/medicationerrors/.
4. Keers, R.N., et al., *Causes of medication administration errors in hospitals: a systematic review of quantitative and qualitative evidence.* Drug safety, 2013. **36**(11): p. 1045-1067.
5. Kohn, L.T., J.M. Corrigan, and M.S. Donaldson, *To err is human:: building a Safer Health System*. Vol. 6. 2000: National Academies Press.
6. Ash, J.S., M. Berg, and E. Coiera, *Some unintended consequences of information technology in health care: the nature of patient care information system-related errors.* Journal of the American Medical Informatics Association, 2004. **11**(2): p. 104-112.
7. Kossman, S.P. and S.L. Scheidenhelm, *Nurses' perceptions of the impact of electronic health records on work and patient outcomes.* Computers Informatics Nursing, 2008. **26**(2): p. 69-77.
8. Laramee, A.S., et al., *A comparison of nurse attitudes before implementation and 6 and 18 months after implementation of an electronic health record.* Computers Informatics Nursing, 2012. **30**(10): p. 521-530.
9. Palojoki, S., et al., *An analysis of electronic health record-related patient safety incidents.* Health informatics journal, 2016.
10. Holroyd-Leduc, J.M., et al., *The impact of the electronic medical record on structure, process, and outcomes within primary care: a systematic review of the evidence.* Journal of the American Medical Informatics Association, 2011. **18**(6): p. 732-737.
11. Fanjiang, G., et al., *Building a Better Delivery System:: A New Engineering/Health Care Partnership*. 2005: National Academies Press.
12. Ernst, A.T., et al., *Staff scheduling and rostering: A review of applications, methods and models.* European journal of operational research, 2004. **153**(1): p. 3-27.
13. Burke, E.K., et al., *The state of the art of nurse rostering.* Journal of scheduling, 2004. **7**(6): p. 441-499.
14. Carayon, P., et al., *Work system design for patient safety: the SEIPS model.* Quality and Safety in Health Care, 2006. **15**(suppl 1): p. i50-i58.
15. Keyserling, W.M., T.J. Armstrong, and L. Punnett, *Ergonomic job analysis: a structured approach for identifying risk factors associated with overexertion injuries and disorders.* Applied Occupational and Environmental Hygiene, 1991. **6**(5): p. 353-363.
16. Brailsford, S., et al., *An analysis of the academic literature on simulation and modelling in health care.* Journal of simulation, 2009. **3**(3): p. 130-140.
17. Jacobson, S.H., S.N. Hall, and J.R. Swisher, *Discrete-event simulation of health care systems*, in *Patient flow*. 2013, Springer. p. 273-309.
18. Jahangirian, M., et al., *Simulation in health-care: lessons from other sectors.* Operational Research, 2010. **12**(1): p. 45-55.
19. Urban, C. and B. Schmidt. *PECS–Agent-Based Modelling of Human Behaviour*. in *Emotional and Intelligent–The Tangled Knot of Social Cognition, AAAI Fall Symposium Series, North Falmouth, MA. www. or. unipassau. de/5/publik/urban/CUrban01. pdf*. 2001.
20. Keohane, C.A., et al., *Quantifying nursing workflow in medication administration.* Journal of Nursing Administration, 2008. **38**(1): p. 19-26.
21. FDA, U., *Federal Food, Drug and Cosmetics Act*, ed. U.S.F.a.D. Administration. Vol. FD&C Act, sec. 201(g)(1). 2017.
22. Hughes, R., *Administration Safety. In: Hughes RG, editor. Patient Safety and Quality: An Evidence-Based Handbook for Nurses.* 2008, Agency for Healthcare Research and Quality (US: Rockville (MD).
23. Lisby, M., et al., *How are medication errors defined? A systematic literature review of definitions and characteristics.* International Journal for Quality in Health Care, 2010. **22**(6): p. 507-518.
24. Wolf, Z.R., *Medication errors and nursing responsibility.* Holistic Nursing Practice, 1989. **4**(1): p. 8-17.
25. Roy, V., P. Gupta, and S. Srivastava, *CHAPTER-14 MEDICATION ERRORS: CAUSES & PREVENTION.* Health administrator, 2006. **19**(1): p. 60-64.

26. Ghenadenik, A., et al., *Potential risks associated with medication administration, as identified by simple tools and observations.* The Canadian journal of hospital pharmacy, 2012. **65**(4): p. 300.
27. Teixeira, T.C.A. and S.H.D.B. Cassiani, *Root cause analysis: evaluation of medication errors at a university hospital.* Revista da Escola de Enfermagem da USP, 2010. **44**(1): p. 139-146.
28. Health, U.D.o. and H. Services, *National action plan for adverse drug event prevention.* Washington, DC, 2014.
29. Tang, F.I., et al., *Nurses relate the contributing factors involved in medication errors.* Journal of clinical nursing, 2007. **16**(3): p. 447-457.
30. Ulanimo, V.M., C. O'Leary-Kelley, and P.M. Connolly, *Nurses' perceptions of causes of medication errors and barriers to reporting.* Journal of nursing care quality, 2007. **22**(1): p. 28-33.
31. Flynn, E.A., *A Brief History of Medication Errors.* American Pharmaceutical Association, 1999: p. 1-6.
32. Berdot, S., et al., *Drug administration errors in hospital inpatients: a systematic review.* PLoS One, 2013. **8**(6): p. e68856.
33. Patterson, E.S., R.I. Cook, and M.L. Render, *Improving patient safety by identifying side effects from introducing bar coding in medication administration.* Journal of the American Medical Informatics Association, 2002. **9**(5): p. 540-553.
34. Bates, D.W., et al., *Relationship between medication errors and adverse drug events.* Journal of general internal medicine, 1995. **10**(4): p. 199-205.
35. Negash, G., Y. Kebede, and S. Hawaze, *Medication errors in the adult emergency unit of a tertiary care teaching hospital in Addis Ababa.* Archives of Pharmacy Practice, 2013. **4**(4): p. 147.
36. Brady, A.-M., A.-M. Malone, and S. Fleming, *A literature review of the individual and systems factors that contribute to medication errors in nursing practice.* Journal of Nursing Management, 2009. **17**(6): p. 679-697.
37. Beyea, S.C., R.W. Hicks, and S.C. Becker, *Medication errors in the OR—a secondary analysis of Medmarx.* AORN journal, 2003. **77**(1): p. 122-134.
38. Kalisch, B.J. and M. Aebersold, *Interruptions and multitasking in nursing care.* Joint Commission Journal on Quality and Patient Safety, 2010. **36**(3): p. 126-132.
39. Biron, A.D., C.G. Loiselle, and M. Lavoie-Tremblay, *Work interruptions and their contribution to medication administration errors: an evidence review.* Worldviews on Evidence-Based Nursing, 2009. **6**(2): p. 70-86.
40. Hall, L.M., et al., *Interruptions and pediatric patient safety.* Journal of pediatric nursing, 2010. **25**(3): p. 167-175.
41. Sears, K. and W.M. Goodman, *Risk Factors for Increased Severity of Paediatric Medication Administration Errors.* Healthcare Policy, 2012. **8**(1): p. 109.
42. Wolf, Z.R., R. Hicks, and J.F. Serembus, *Characteristics of medication errors made by students during the administration phase: a descriptive study.* Journal of Professional Nursing, 2006. **22**(1): p. 39-51.
43. Pauly-O'Neill, S., *Beyond the five rights: Improving patient safety in pediatric medication administration through simulation.* Clinical Simulation in Nursing, 2009. **5**(5): p. e181-e186.
44. Stratton, K.M., et al., *Reporting of medication errors by pediatric nurses.* Journal of pediatric nursing, 2004. **19**(6): p. 385-392.
45. Wakefield, B.J., et al., *Organizational culture, continuous quality improvement, and medication administration error reporting.* American Journal of Medical Quality, 2001. **16**(4): p. 128-134.
46. Layde, P.M., et al., *Patient safety efforts should focus on medical injuries.* JAMA, 2002. **287**(15): p. 1993-1997.
47. Sawhney, R., *Proactivley Mitigating Risk by Managing Leading Indicators of Incidents*. 2015, University of Tennessee.
48. Myers, J.A., F. Dominici, and L. Morlock, *Bayesian Hierarchical Models for Analysis of Medication Errors.* 2010.
49. Jones, S.W., *Reducing medication administration errors in nursing practice.* Nursing Standard, 2009. **23**(50): p. 40-46.
50. McBride-Henry, K. and M. Foureur, *Medication administration errors: understanding the issues.* 2006.
51. Pape, T.M., *Searching for the final answer: factors contributing to medication administration errors.* The Journal of Continuing Education in Nursing, 2001. **32**(4): p. 152-160.

52. Young, J., M. Slebodnik, and L. Sands, *Bar code technology and medication administration error.* Journal of patient safety, 2010. **6**(2): p. 115-120.
53. Westbrook, J.I., et al., *Association of interruptions with an increased risk and severity of medication administration errors.* Archives of Internal medicine, 2010. **170**(8): p. 683-690.
54. Kliger, J., et al., *Empowering frontline nurses: a structured intervention enables nurses to improve medication administration accuracy.* Joint Commission Journal on Quality and Patient Safety, 2009. **35**(12): p. 604-612.
55. Borel, J.M. and K.L. Rascati, *Effect of an automated, nursing unit-based drug-dispensing device on medication errors.* American Journal of Health-System Pharmacy, 1995. **52**(17): p. 1875-1879.
56. Smalley, H.E., *Hospital management engineering : a guide to the improvement of hospital management systems*. 1982, Englewood Cliffs, N.J.: Englewood Cliffs, N.J. : Prentice-Hall.
57. Valdez, R.S., E. Ramly, and P.F. Brennan, *Industrial and Systems Engineering and Health Care: Critical Areas of Research*. 2010, Rockville, MD: Agency for Healthcare Research and Quality.
58. Smith, M., et al., *Best care at lower cost: the path to continuously learning health care in America*. 2013: National Academies Press.
59. Young, T., S. McLean, and J., *Some Challenges Facing Lean Thinking in Healthcare.* Int Health Care 21 Print. **5**(2009 SRC - GoogleScholar): p. 309-10.
60. Justin, W. and J., *Lean Healthcare: Rhetoric, Ritual and Resistance.* Soc Sci Med 71 Print. **7**(2010 SRC - GoogleScholar): p. 1332-40.
61. Noon, C.E.H., Charles T.; Cote, Murray J., *Understanding the Impacts of Variation in the Delivery of Healthcare Services.* Healthc Manag. **48**(2): p. 82-97.
62. Butler, V., et al., *Applying science and strategy to operating room workforce management.* Nursing Economics, 2012. **30**(5): p. 275.
63. Piggott, Z., Weldon, Erin; Strome, Trevor; Chochinov, Alecs., *"Application of Lean Principles to Improve Early Cardiac Care in the Emergency Department.* CJEM 13 Print. **5**(2011 SRC - GoogleScholar): p. 325-32.
64. Johnson, M., et al., *Improving Patient Flow through the Emergency Department.* Journal of Healthcare Management 57 Print, 2012. **4**(2012 SRC - GoogleScholar): p. 236-43.
65. Leo, S. and Q. Patient, *Pamela; Sato, Brendon; Richmond, Barbara; Stahnke, Lennis. "Using Lean Principles to Improve and Workflow in Histololy and Anatomic Pathology.* Adv Anat Pathol 17 Print. **3**(2010 SRC - GoogleScholar): p. 215-21.
66. DelliFraine, J.L., J.R. Langabeer, and I.M. Nembhard, *Assessing the evidence of Six Sigma and Lean in the health care industry.* Quality Management in Healthcare, 2010. **19**(3): p. 211-225.
67. Nicolay, C.R., *Systematic Review of the Application of Quality Improvement Methodologies from the Manufacturing Industry to Surgical Healthcare.* British Journal of Surgery 99 Print. **3**(2012 SRC - GoogleScholar): p. 324-35.
68. Chakravorty, S.S., *Where process-improvement projects go wrong.* World Street Journal (January 2010), 2005.
69. Ching, J.M., et al., *Using lean to improve medication administration safety: in search of the "perfect dose".* Joint Commission journal on quality and patient safety, 2013. **39**(5): p. 195-204.
70. Esimai, G., *Lean Six Sigma reduces medication errors.* Quality progress, 2005. **38**(4): p. 51.
71. Hicks, B., *Lean information management: Understanding and eliminating waste.* International journal of information management, 2007. **27**(4): p. 233-249.
72. Stainback, I. and J. Ruric, *A New Lean Model: Improving Race Team Performance through Team-Driver Communication Efficacy.* 2010.
73. Kerschberg, L. and H. Jeong, *Just-in-time knowledge management*, in *Professional Knowledge Management*. 2005, Springer. p. 1-18.
74. Hall, A. and G. Walton, *Information overload within the health care system: a literature review.* Health Information & Libraries Journal, 2004. **21**(2): p. 102-108.
75. Davenport, T.H. and J. Glaser, *Just-in-time delivery comes to knowledge management.* Harvard business review, 2002. **80**(7): p. 107-11, 126.
76. Chueh, H. and G.O. Barnett, *"Just-in-time" clinical information.* Academic Medicine, 1997. **72**(6): p. 512-7.
77. Ghosh, B. and J.E. Scott, *Comparing knowledge management in health-care and technical support organizations.* Information Technology in Biomedicine, IEEE Transactions on, 2005. **9**(2): p. 162-168.

78. Wulff, K., et al., *Medication administration technologies and patient safety: a mixed-method systematic review.* Journal of Advanced Nursing, 2011. **67**(10): p. 2080-2095.
79. Alsunaidi, A., *Unit Dose System*. 2014, SlideShare.
80. Boyle, C.M., et al., *Missed doses an evaluation in two drug distribution systems.* The Australian Journal of Hospital Pharmacy, 1998. **28**(6): p. 413-416.
81. Cousein, E., et al., *Effect of automated drug distribution systems on medication error rates in a short-stay geriatric unit.* Journal of evaluation in clinical practice, 2014. **20**(5): p. 678-684.
82. Martin, E.D., N.G. Burgess, and C.J. Doeck, *Evaluation of an automated drug distribution system in an Australian teaching hospital.* The Australian Journal of Hospital Pharmacy, 2000. **30**(4): p. 141-145.
83. Murray, M.D., . *Automated Medication Dispensing Devices.* Making health care safer: A critical analysis of patient safety practices, 2001. **111**.
84. Chapuis, C., et al., *Automated drug dispensing system reduces medication errors in an intensive care setting.* Critical care medicine, 2010. **38**(12): p. 2275-2281.
85. Sinnemäki, J., et al., *Automated dose dispensing service for primary healthcare patients: a systematic review.* Systematic reviews, 2013. **2**(1): p. 1.
86. Zheng, Y., et al., *Automated bedside dispensing machine may significantly reduce nurses' medication administration errors in inpatient settings.* International Journal of Nursing Studies, 2016. **61**: p. 173-175.
87. DeYoung, J.L., M.E. Vanderkooi, and J.F. Barletta, *Effect of bar-code-assisted medication administration on medication error rates in an adult medical intensive care unit.* Am J Health Syst Pharm, 2009. **66**(12): p. 1110-5.
88. Anderson, S. and W. Wittwer, *Using Bar-Code Point-of-Care Technology for Patient Safety.* Journal for Healthcare Quality, 2004. **26**(6): p. 5-11.
89. Voshall, B., et al., *Barcode medication administration work-arounds: a systematic review and implications for nurse executives.* J Nurs Adm, 2013. **43**(10): p. 530-5.
90. Koppel, R., et al., *Workarounds to barcode medication administration systems: Their occurrences, causes, and threats to patient safety.* Journal of the American Medical Informatics Association, 2008. **15**(4): p. 408-423.
91. Phillips, M. and E. Berner, *Beating the system--pitfalls of bar code medication administration.* Journal of healthcare information management: JHIM, 2003. **18**(4): p. 16-18.
92. Bowers, A.M., et al., *Impact of Bar-code Medication Administration on Medication Administration Best Practices.* Computers Informatics Nursing, 2015. **33**(11): p. 502-508.
93. Hassink, J.J.M., M.M.P.M. Jansen, and P.J. Helmons, *Effects of bar code-assisted medication administration (BCMA) on frequency, type and severity of medication administration errors: a review of the literature.* European Journal of Hospital Pharmacy: Science and Practice, 2012. **19**(5): p. 489-494.
94. Gooder, V., *Nurses' perceptions of a (BCMA) bar-coded medication administration system: a case-control study.* Online Journal of Nursing Informatics (OJNI), 2011. **15**(2).
95. Song, L., B. Park, and K.M. Oh, *Analysis of the Technology Acceptance Model in Examining Hospital Nurses' Behavioral Intentions Toward the Use of Bar Code Medication Administration.* CIN: Computers, Informatics, Nursing, 2015. **33**(4): p. 157-165.
96. Holden, R.J., et al., *That's nice, but what does IT do? Evaluating the impact of bar coded medication administration by measuring changes in the process of care.* International journal of industrial ergonomics, 2011. **41**(4): p. 370-379.
97. Poon, E.G., et al., *Effect of bar-code technology on the safety of medication administration.* New England Journal of Medicine, 2010. **362**(18): p. 1698-1707.
98. Sakushima, K., et al., *Time trend of injection drug errors before and after implementation of bar-code verification system.* Technology and health care, 2015. **23**(3): p. 267-274.
99. Dwibedi, N., et al., *Effect of bar-code-assisted medication administration on nurses' activities in an intensive care unit: a time-motion study.* Am J Health Syst Pharm, 2011. **68**(11): p. 1026-31.
100. Henneman, P.L., et al., *Bar-code verification: reducing but not eliminating medication errors.* Journal of Nursing Administration, 2012. **42**(12): p. 562-566.
101. Simborg, D.W., *Promoting electronic health record adoption. Is it the correct focus?* Journal of the American Medical Informatics Association, 2008. **15**(2): p. 127-129.

102. Franklin, B.D., et al., *The impact of a closed-loop electronic prescribing and administration system on prescribing errors, administration errors and staff time: a before-and-after study.* Quality and Safety in Health care, 2007. **16**(4): p. 279-284.
103. Mekhjian, H.S., et al., *Immediate benefits realized following implementation of physician order entry at an academic medical center.* Journal of the American Medical Informatics Association, 2002. **9**(5): p. 529-539.
104. Appari, A., et al., *Medication administration quality and health information technology: a national study of US hospitals.* Journal of the American Medical Informatics Association, 2012. **19**(3): p. 360-367.
105. Husch, M., et al., *Insights from the sharp end of intravenous medication errors: implications for infusion pump technology.* Quality and Safety in Health Care, 2005. **14**(2): p. 80-86.
106. Keohane, C.A., et al., *Intravenous medication safety and smart infusion systems: lessons learned and future opportunities.* Journal of infusion nursing, 2005. **28**(5): p. 321-328.
107. Ohashi, K., et al., *Benefits and risks of using smart pumps to reduce medication error rates: a systematic review.* Drug safety, 2014. **37**(12): p. 1011-1020.
108. Chao, C.-C., J.-M. Yang, and W.-Y. Jen, *Determining technology trends and forecasts of RFID by a historical review and bibliometric analysis from 1991 to 2005.* Technovation, 2007. **27**(5): p. 268-279.
109. Peris-Lopez, P., et al., *A comprehensive RFID solution to enhance inpatient medication safety.* international journal of medical informatics, 2011. **80**(1): p. 13-24.
110. Yen, Y.-C., N.-W. Lo, and T.-C. Wu, *Two RFID-based solutions for secure inpatient medication administration.* Journal of medical systems, 2012. **36**(5): p. 2769-2778.
111. Sun, P.R., B.H. Wang, and F. Wu, *A new method to guard inpatient medication safety by the implementation of RFID.* Journal of medical systems, 2008. **32**(4): p. 327-332.
112. Zhu, X., S.K. Mukhopadhyay, and H. Kurata, *A review of RFID technology and its managerial applications in different industries.* Journal of Engineering and Technology Management, 2012. **29**(1): p. 152-167.
113. Yao, W., C.-H. Chu, and Z. Li. *The use of RFID in healthcare: Benefits and barriers*. in *RFID-Technology and Applications (RFID-TA), 2010 IEEE International Conference on*. 2010. IEEE.
114. Coustasse, A., et al., *Benefits and barriers of implementation and utilization of radio-frequency identification (RFID) systems in transfusion medicine.* Perspectives in Health Information Management, 2015. **12**(Summer).
115. Ajami, S. and R. Arab-Chadegani, *What are the most important barriers to implement Radio Frequency Identification Device (RFID) in healthcare system.* J Inform Tech Soft Engg S, 2013. **7**: p. 2.
116. Berg, T.A., Li, X. P., *Realt-Time Technology for Tracking Providers and Patients*. 2012, Y-12 National Nuclear Complex: Y-12 National Nuclear Complex. p. 25.
117. Mcnikle, M. *10 things you hate about your EMR* 2011 [cited 2016 November, 21]; Available from: http://www.healthcareitnews.com/news/10-things-you-hate-about-your-emr.
118. Mulanax, A., et al., *Electronic Health Record Recognition Of Safety Issues By The Interprofessional Team During Simulated Rounds In The Intensive Care Unit*, in *A22. TECHNOLOGY FOR DISEASE IDENTIFICATION AND MANAGEMENT IN PULMONARY AND CRITICAL CARE*. 2016, Am Thoracic Soc. p. A1099-A1099.
119. Moss, J. and E.S. Berner, *Evaluating clinical decision support tools for medication administration safety in a simulated environment.* Int J Med Inform, 2015. **84**(5): p. 308-18.
120. Rothman, B., J.C. Leonard, and M.M. Vigoda, *Future of electronic health records: implications for decision support.* Mount Sinai Journal of Medicine: A Journal of Translational and Personalized Medicine, 2012. **79**(6): p. 757-768.
121. Prgomet, M., et al., *Impact of commercial computerized provider order entry (CPOE) and clinical decision support systems (CDSSs) on medication errors, length of stay, and mortality in intensive care units: a systematic review and meta-analysis.* Journal of the American Medical Informatics Association, 2016: p. ocw145.
122. Powell, A.C., A.B. Landman, and D.W. Bates, *In search of a few good apps.* Jama, 2014. **311**(18): p. 1851-1852.
123. Yang, Y.T. and R.D. Silverman, *Mobile health applications: the patchwork of legal and liability issues suggests strategies to improve oversight.* Health Affairs, 2014. **33**(2): p. 222-227.
124. Boulos, M.N.K., et al., *Mobile medical and health apps: state of the art, concerns, regulatory control and certification.* Online journal of public health informatics, 2014. **5**(3).

125. Misra, S., T.L. Lewis, and T.D. Aungst, *Medical application use and the need for further research and assessment for clinical practice: creation and integration of standards for best practice to alleviate poor application design.* JAMA dermatology, 2013. **149**(6): p. 661-662.
126. Divall, P., J. Camosso-Stefinovic, and R. Baker, *The use of personal digital assistants in clinical decision making by health care professionals: a systematic review.* Health informatics journal, 2013. **19**(1): p. 16-28.
127. Murfin, M., *Know your apps: an evidence-based approach to evaluation of mobile clinical applications.* The Journal of Physician Assistant Education, 2013. **24**(3): p. 38-40.
128. Mickan, S., et al., *Evidence of effectiveness of health care professionals using handheld computers: a scoping review of systematic reviews.* Journal of medical Internet research, 2013. **15**(10): p. e212.
129. Ventola, C.L., *Mobile devices and apps for health care professionals: uses and benefits.* Pharmacy and Therapeutics, 2014. **39**(5): p. 356.
130. Aungst, T.D., *Medical applications for pharmacists using mobile devices.* Annals of Pharmacotherapy, 2013. **47**(7-8): p. 1088-1095.
131. O'Neill, K., et al., *Applying surgical apps: Smartphone and tablet apps prove useful in clinical practice.* Bull Am Coll Surg, 2013. **98**(11): p. 10-18.
132. Yoo, J.-H., *The meaning of information technology (IT) mobile devices to me, the infectious disease physician.* Infection & chemotherapy, 2013. **45**(2): p. 244-251.
133. Lapkin, S., et al., *The effectiveness of interventions designed to reduce medication administration errors: a synthesis of findings from systematic reviews.* Journal of Nursing Management, 2016. **24**(7): p. 845-858.
134. Greengold, N.L., et al., *The impact of dedicated medication nurses on the medication administration error rate: a randomized controlled trial.* Archives of Internal Medicine, 2003. **163**(19): p. 2359-2367.
135. Gonzales, K., *Medication administration errors and the pediatric population: a systematic search of the literature.* Journal of pediatric nursing, 2010. **25**(6): p. 555-565.
136. Biron, A.D., M. Lavoie-Tremblay, and C.G. Loiselle, *Characteristics of Work Interruptions During Medication Administration.* Journal of Nursing Scholarship, 2009. **41**(4): p. 330-336.
137. Trbovich, P., et al., *Interruptions During the Delivery of High-Risk Medications.* Journal of Nursing Administration, 2010. **40**(5): p. 211-218.
138. Prakash, V., et al., *Mitigating errors caused by interruptions during medication verification and administration: interventions in a simulated ambulatory chemotherapy setting.* BMJ Qual Saf, 2014. **23**(11): p. 884-92.
139. Nguyen, E.E., P.M. Connolly, and V. Wong, *Medication Safety Initiative in Reducing Medication Errors.* Journal of Nursing Care Quality, 2010. **25**(3): p. 224-230.
140. Colligan, L. and E.J. Bass, *Interruption handling strategies during paediatric medication administration.* BMJ quality & safety, 2012. **21**(11): p. 912-917.
141. Colligan, L., et al., *Designing for distractions: a human factors approach to decreasing interruptions at a centralised medication station.* BMJ Qual Saf, 2012. **21**(11): p. 939-47.
142. Raban, M.Z. and J.I. Westbrook, *Are interventions to reduce interruptions and errors during medication administration effective?: a systematic review.* BMJ Qual Saf, 2014. **23**(5): p. 414-21.
143. O'Shea, E., *Factors contributing to medication errors: a literature review.* Journal of clinical nursing, 1999. **8**(5): p. 496-504.
144. Tissot, E., et al., *Observational study of potential risk factors of medication administration errors.* Pharmacy world and science, 2003. **25**(6): p. 264-268.
145. Pape, T.M., *Applying airline safety practices to medication administration.(CE Series).* Medsurg Nursing, 2003. **12**(2): p. 77-95.
146. Pape, T.M., et al., *Innovative approaches to reducing nurses' distractions during medication administration.* J Contin Educ Nurs, 2005. **36**(3): p. 108-16; quiz 141-2.
147. Tamuz, M. and M.I. Harrison, *Improving patient safety in hospitals: contributions of high-reliability theory and normal accident theory.* Health services research, 2006. **41**(4p2): p. 1654-1676.
148. Tissot, E., et al., *Medication errors at the administration stage in an intensive care unit.* Intensive care medicine, 1999. **25**(4): p. 353-359.
149. Hughes, R.G. and M.A. Blegen, *Medication administration safety.* 2008.

150. Carlton, G. and M.A. Blegen, *Medication-related errors: a literature review of incidence and antecedents.* Annual review of nursing research, 2006. **24**(1): p. 19-38.
151. Seki, Y. and Y. Yamazaki, *Effects of working conditions on intravenous medication errors in a Japanese hospital.* Journal of nursing management, 2006. **14**(2): p. 128-139.
152. Blegen, M.A., C.J. Goode, and L. Reed, *Nurse staffing and patient outcomes.* Nursing research, 1998. **47**(1): p. 43-50.
153. Aiken, L.H., et al., *Hospital nurse staffing and patient mortality, nurse burnout, and job dissatisfaction.* Jama, 2002. **288**(16): p. 1987-1993.
154. Kane, R.L., et al., *The association of registered nurse staffing levels and patient outcomes: systematic review and meta-analysis.* Medical care, 2007. **45**(12): p. 1195-1204.
155. Laschinger, H.K.S. and M.P. Leiter, *The impact of nursing work environments on patient safety outcomes: The mediating role of burnout engagement.* Journal of Nursing Administration, 2006. **36**(5): p. 259-267.
156. Needleman, J., et al., *Nurse-staffing levels and the quality of care in hospitals.* New England Journal of Medicine, 2002. **346**(22): p. 1715-1722.
157. Ball, J.E., et al., *'Care left undone'during nursing shifts: associations with workload and perceived quality of care.* BMJ quality & safety, 2013: p. bmjqs-2012-001767.
158. Blegen, M.A., et al., *Baccalaureate education in nursing and patient outcomes.* Journal of Nursing Administration, 2013. **43**(2): p. 89-94.
159. Aiken, L.H., et al., *The effects of nurse staffing and nurse education on patient deaths in hospitals with different nurse work environments.* Medical care, 2011. **49**(12): p. 1047.
160. Orbæk, J., et al., *Patient safety and technology-driven medication–A qualitative study on how graduate nursing students navigate through complex medication administration.* Nurse education in practice, 2015. **15**(3): p. 203-211.
161. Keers, R.N., et al., *Impact of interventions designed to reduce medication administration errors in hospitals: a systematic review.* Drug Saf, 2014. **37**(5): p. 317-32.
162. Rosin, T., *Nurse scheduling, staffing issues continue to afflict hospitals: 8 key statistics* Bcker's Hospital Review, 2016(October 14, 2016).
163. Wright, P.D. and S. Mahar, *Centralized nurse scheduling to simultaneously improve schedule cost and nurse satisfaction.* Omega, 2013. **41**(6): p. 1042-1052.
164. Green, L.V., S. Savin, and N. Savva, *"Nursevendor problem": Personnel staffing in the presence of endogenous absenteeism.* Management Science, 2013. **59**(10): p. 2237-2256.
165. Maenhout, B. and M. Vanhoucke, *An integrated nurse staffing and scheduling analysis for longer-term nursing staff allocation problems.* Omega, 2013. **41**(2): p. 485-499.
166. Pape, T.M., *Applying airline safety practices to medication administration.* Medsurg Nurs, 2003. **12**(2): p. 77-93; quiz 94.
167. Prakash, V., et al., *Mitigating errors caused by interruptions during medication verification and administration: interventions in a simulated ambulatory chemotherapy setting.* BMJ quality & safety, 2014: p. bmjqs-2013-002484.
168. Alsulami, Z., S. Conroy, and I. Choonara, *Double checking the administration of medicines: what is the evidence? A systematic review.* Archives of disease in childhood, 2012: p. archdischild-2011-301093.
169. Kullberg, A., J. Larsen, and L. Sharp, *'Why is there another person's name on my infusion bag?'Patient safety in chemotherapy care–A review of the literature.* European Journal of Oncology Nursing, 2013. **17**(2): p. 228-235.
170. HFES. *Definitions of Human Factors and Ergonomics*. [cited 2016 November 22]; Available from: https://www.hfes.org/Web/EducationalResources/HFEdefinitionsmain.html.
171. Lightsey, B., *Systems engineering fundamentals*. 2001, DTIC Document.
172. Beuscart-Zephir, M.-C., S. Pelayo, and S. Bernonville, *Example of a Human Factors Engineering approach to a medication administration work system: Potential impact on patient safety.* International Journal of Medical Informatics, 2010. **79**(4): p. E43-E57.
173. Koppel, R., et al., *Role of computerized physician order entry systems in facilitating medication errors.* Jama, 2005. **293**(10): p. 1197-1203.
174. Wetterneck, T.B., et al., *Factors contributing to an increase in duplicate medication order errors after CPOE implementation.* Journal of the American Medical Informatics Association, 2011. **18**(6): p. 774-782.

175. Harrison, M.I., R. Koppel, and S. Bar-Lev, *Unintended consequences of information technologies in health care—an interactive sociotechnical analysis.* Journal of the American medical informatics Association, 2007. **14**(5): p. 542-549.
176. Poissant, L., et al., *The impact of electronic health records on time efficiency of physicians and nurses: a systematic review.* Journal of the American Medical Informatics Association, 2005. **12**(5): p. 505-516.
177. Leape, L.L., et al., *Systems analysis of adverse drug events.* Jama, 1995. **274**(1): p. 35-43.
178. Leape, L.L., *Error in medicine.* JAMA: Journal of the American Medical Association, 1994.
179. Hughes, R.G., P. Carayon, and A.P. Gurses, *Nursing workload and patient safety—a human factors engineering perspective.* 2008.
180. Gurses, A.P. and P. Carayon, *Performance obstacles of intensive care nurses.* Nursing research, 2007. **56**(3): p. 185-194.
181. SPISSO, J., et al., *Improved quality of care and reduction of housestaff workload using trauma nurse practitioners.* Journal of Trauma and Acute Care Surgery, 1990. **30**(6): p. 660-665.
182. Carayon, P. and A.P. Gürses, *A human factors engineering conceptual framework of nursing workload and patient safety in intensive care units.* Intensive and Critical Care Nursing, 2005. **21**(5): p. 284-301.
183. Wright, P.D., K.M. Bretthauer, and M.J. Côté, *Reexamining the nurse scheduling problem: Staffing ratios and nursing shortages.* Decision Sciences, 2006. **37**(1): p. 39-70.
184. Pearson, A., et al., *Systematic review of evidence on the impact of nursing workload and staffing on establishing healthy work environments.* International Journal of Evidence-Based Healthcare, 2006. **4**(4): p. 337-384.
185. Skrutkowski, M., et al. *Impact of a pivot nurse in oncology on patients with lung or breast cancer: symptom distress, fatigue, quality of life, and use of healthcare resources*. in *Oncology nursing forum*. 2008.
186. Rogers, A.E., *The effects of fatigue and sleepiness on nurse performance and patient safety.* 2008.
187. Litvak, E., et al., *Managing unnecessary variability in patient demand to reduce nursing stress and improve patient safety.* The Joint Commission Journal on Quality and Patient Safety, 2005. **31**(6): p. 330-338.
188. Han, K., et al., *Job stress and work schedules in relation to nurse obesity.* Journal of Nursing Administration, 2011. **41**(11): p. 488-495.
189. Shamian, J., et al., *Nurse absenteeism, stress and workplace injury: what are the contributing factors and what can/should be done about it?* International Journal of Sociology and Social Policy, 2003. **23**(8/9): p. 81-103.
190. Kanai-Pak, M., et al., *Poor work environments and nurse inexperience are associated with burnout, job dissatisfaction and quality deficits in Japanese hospitals.* Journal of clinical nursing, 2008. **17**(24): p. 3324-3329.
191. Rogers, A.E., W.-T. Hwang, and L.D. Scott, *The effects of work breaks on staff nurse performance.* Journal of Nursing Administration, 2004. **34**(11): p. 512-519.
192. Anthony, K., et al., *No interruptions please: impact of a no interruption zone on medication safety in intensive care units.* Critical Care Nurse, 2010. **30**(3): p. 21-29.
193. Kalisch, B.J. and M. Aebersold, *Interruptions and multitasking in nursing care.* The joint commission journal on quality and patient safety, 2010. **36**(3): p. 126-132.
194. Kliger, J., et al., *Empowering frontline nurses: a structured intervention enables nurses to improve medication administration accuracy.* Jt Comm J Qual Patient Saf, 2009. **35**(12): p. 604-12.
195. Armitage, G., *Human error theory: relevance to nurse management.* Journal of nursing management, 2009. **17**(2): p. 193-202.
196. Rothschild, J.M., et al., *The Critical Care Safety Study: The incidence and nature of adverse events and serious medical errors in intensive care.* Critical care medicine, 2005. **33**(8): p. 1694-1700.
197. Taxis, K. and N. Barber, *Causes of intravenous medication errors: an ethnographic study.* Quality and Safety in Health Care, 2003. **12**(5): p. 343-347.
198. Mayo, A.M. and D. Duncan, *Nurse perceptions of medication errors: what we need to know for patient safety.* Journal of nursing care quality, 2004. **19**(3): p. 209-217.
199. Ridley, R.T., *The relationship between nurse education level and patient safety: An integrative review.* Journal of Nursing Education, 2008. **47**(4): p. 149-156.

200. Collins, S.E. and C.A. Mikos, *Evolving taxonomy of nurse practice act violators.* Journal of Nursing Law, 2008. **12**(2): p. 85-91.
201. Jukkala, A.M., et al., *Developing a standardized tool to improve nurse communication during shift report.* Journal of nursing care quality, 2012. **27**(3): p. 240-246.
202. Sidlow, R. and R.J. Katz-Sidlow, *Using a computerized sign-out system to improve physician–nurse communication.* The joint commission journal on quality and patient safety, 2006. **32**(1): p. 32-36.
203. Leonard, M., S. Graham, and D. Bonacum, *The human factor: the critical importance of effective teamwork and communication in providing safe care.* Quality and Safety in Health Care, 2004. **13**(suppl 1): p. i85-i90.
204. Fero, L.J., et al., *Critical thinking ability of new graduate and experienced nurses.* Journal of advanced nursing, 2009. **65**(1): p. 139-148.
205. Martin, C., *The theory of critical thinking of nursing.* Nursing education perspectives, 2002. **23**(5): p. 243-247.
206. Fero, L.J., et al., *Critical thinking skills in nursing students: comparison of simulation-based performance with metrics.* Journal of Advanced Nursing, 2010. **66**(10): p. 2182-2193.
207. Eisenhauer, L.A., A.C. Hurley, and N. Dolan, *Nurses' reported thinking during medication administration.* Journal of Nursing Scholarship, 2007. **39**(1): p. 82-87.
208. Leape, L.L., *A systems analysis approach to medical error.* Journal of evaluation in clinical practice, 1997. **3**(3): p. 213-222.
209. Chaudhury, H., A. Mahmood, and M. Valente, *The effect of environmental design on reducing nursing errors and increasing efficiency in acute care settings: A review and analysis of the literature.* Environment and Behavior, 2009.
210. Burlington, D.B., *Human factors and the FDA's goals: improved medical device design.* Biomedical instrumentation & technology/Association for the Advancement of Medical Instrumentation, 1995. **30**(2): p. 107-109.
211. Berman, A., *Reducing medication errors through naming, labeling, and packaging.* Journal of medical systems, 2004. **28**(1): p. 9-29.
212. Cohen, M.R., *The role of drug packaging and labeling in medication errors.* Medication errors, 2007: p. 111.
213. Endestad, T., et al., *Package design affects accuracy recognition for medications.* Human Factors: The Journal of the Human Factors and Ergonomics Society, 2016. **58**(8): p. 1206-1216.
214. McGrayne, S.B., *The theory that would not die: how Bayes' rule cracked the enigma code, hunted down Russian submarines, & emerged triumphant from two centuries of controversy*. 2011: Yale University Press.
215. Power, D.J., *Decision support systems: a historical overview*, in *Handbook on Decision Support Systems 1*. 2008, Springer. p. 121-140.
216. Wu, H.W., P.K. Davis, and D.S. Bell, *Advancing clinical decision support using lessons from outside of healthcare: an interdisciplinary systematic review.* BMC medical informatics and decision making, 2012. **12**(1): p. 1.
217. EPA, *Decision support Tools-Development of a Screening Matri for 20 Specific Software Tools*, O.o.S.R.a.T. Innovation, Editor. 2005.
218. HeathIT.gov. *Clinical Decision Support*. [cited 2016 August 11]; Available from: https://www.healthit.gov/policy-researchers-implementers/clinical-decision-support-cds.
219. Berner, E.S., *Clinical decision support systems*. 2007: Springer.
220. Greenes, R.A., *Clinical decision support: the road ahead*. 2011: Academic Press.
221. Versel, N., *10 Innovative Clinical Decision Support Programs*, in *Information Week Healthcare*. 2011, Information Week.
222. Bates, D.W., et al., *Ten commandments for effective clinical decision support: making the practice of evidence-based medicine a reality.* Journal of the American Medical Informatics Association, 2003. **10**(6): p. 523-530.
223. Kawamoto, K., et al., *Improving clinical practice using clinical decision support systems: a systematic review of trials to identify features critical to success.* Bmj, 2005. **330**(7494): p. 765.
224. Theera-Ampornpunt, N. *Clinical Decision Support Systems*. 2014 [cited 2016 9/11/16]; Available from: http://www.slideshare.net/nawanan/clinical-decision-support-systems-35858765.

225. systems, D.s. July 2006, 2005 [cited 2016 August 13]; Available from: http://www.openclinical.org/dss.html.
226. Improvement., I.f.H. *Overview of CDS Five Rights*. 2015 [cited 2016 August 11]; Available from: https://healthit.ahrq.gov/ahrq-funded-projects/clinical-decision-support-initiative/chapter-1-approaching-clinical-decision/section-2-overview-cds-five-rights.
227. Lucas, P., A. Abu-Hanna, and M. AMC-UvA, *Prognostic Models in Medicine: Artificial Intelligence and Decision Analytic Approaches.*
228. Lahsasna, A., et al., *A Transparent Fuzzy Rule-Based Clinical Decision Support System for Heart Disease Diagnosis*, in *Knowledge Technology*. 2012, Springer. p. 62-71.
229. Yang, J.-B., et al., *Belief rule-base inference methodology using the evidential reasoning approach-RIMER.* IEEE Transactions on systems, Man, and Cybernetics-part A: Systems and Humans, 2006. **36**(2): p. 266-285.
230. Lisboa, P.J. and A.F. Taktak, *The use of artificial neural networks in decision support in cancer: a systematic review.* Neural networks, 2006. **19**(4): p. 408-415.
231. Zellner, B.B., et al., *A cost-minimizing diagnostic methodology for discrimination between neoplastic and non-neoplastic brain lesions: utilizing a genetic algorithm1 scientific reports.* Academic radiology, 2004. **11**(2): p. 169-177.
232. Schreiber, P. *Applications of genetic algorithms*. in *CECIIS-2008*. 2008.
233. Gonzalez, C. and J. Meyer, *Integrating Trends in Decision-Making Research.* Journal of Cognitive Engineering and Decision Making, 2016: p. 1555343416655256.
234. Endsley, M.R., et al., *Cognitive engineering and decision making: An overview and future course.* Journal of Cognitive Engineering and Decision Making, 2007. **1**(1): p. 1-21.
235. Kushniruk, A.W., *Analysis of complex decision-making processes in health care: cognitive approaches to health informatics.* Journal of biomedical informatics, 2001. **34**(5): p. 365-376.
236. Kahneman, D. and A. Tversky, *Choices, values, and frames*. 2000: Cambridge University Press.
237. Wang, Y. and G. Ruhe, *The cognitive process of decision making.* 2007.
238. Andersen, D.L. and D.F. Andersen, *Theories of decision making: an annotated bibliography.* 1977.
239. Klein, G., *Naturalistic decision making.* Human Factors: The Journal of the Human Factors and Ergonomics Society, 2008. **50**(3): p. 456-460.
240. Endsley, M.R., *The role of situation awareness in naturalistic decision making.* 1997.
241. Simon, H.A., *Theories of decision-making in economics and behavioral science.* The American economic review, 1959. **49**(3): p. 253-283.
242. De Martino, B., et al., *Frames, biases, and rational decision-making in the human brain.* Science, 2006. **313**(5787): p. 684-687.
243. Kohle-Ersher, A., et al., *Evaluating the barriers to point-of-care documentation for nursing staff.* CIN: Computers, Informatics, Nursing, 2012. **30**(3): p. 126-133.
244. Ishii, H., *The tangible user interface and its evolution.* Communications of the ACM, 2008. **51**(6): p. 32-36.
245. Lumsden, J., *Handbook of research on user interface design and evaluation for mobile technology*. Vol. 1. 2008: IGI global.
246. Johnson, J., *Designing with the mind in mind: simple guide to understanding user interface design guidelines*. 2013: Elsevier.
247. Fruhling, A.L., S. Raman, and S. McGrath, *Mobile Healthcare User Interface Design Application Strategies.* Telehealth and Mobile Health, 2015: p. 363.
248. Staggers, N. and D. Kobus, *Comparing response time, errors, and satisfaction between text-based and graphical user interfaces during nursing order tasks.* Journal of the American Medical Informatics Association, 2000. **7**(2): p. 164-176.
249. Page, T., *Usability of text input interfaces in smartphones.* Journal of Design Research, 2013. **11**(1): p. 39-56.
250. Junglas, I., C. Abraham, and B. Ives, *Mobile technology at the frontlines of patient care: Understanding fit and human drives in utilization decisions and performance.* Decision Support Systems, 2009. **46**(3): p. 634-647.
251. Wyatt, T. and P. Krauskopf, *E-health and nursing: using smartphones to enhance nursing practice.* Online Journal of Nursing Informatics (OJNI), 2012. **16**(2).

252. Mosa, A.S.M., I. Yoo, and L. Sheets, *A systematic review of healthcare applications for smartphones.* BMC medical informatics and decision making, 2012. **12**(1): p. 1.
253. Krishna, S., S.A. Boren, and E.A. Balas, *Healthcare via cell phones: a systematic review.* Telemedicine and e-Health, 2009. **15**(3): p. 231-240.
254. Lopez, K.D., et al., *Integrative review of clinical decision support for registered nurses in acute care settings.* Journal of the American Medical Informatics Association, 2016: p. ocw084.
255. Wu, J.-H., S.-C. Wang, and L.-M. Lin, *Mobile computing acceptance factors in the healthcare industry: A structural equation model.* International journal of medical informatics, 2007. **76**(1): p. 66-77.
256. Wu, L., J.-Y. Li, and C.-Y. Fu, *The adoption of mobile healthcare by hospital's professionals: An integrative perspective.* Decision Support Systems, 2011. **51**(3): p. 587-596.
257. Pejovic, V. and M. Musolesi, *Anticipatory mobile computing: A survey of the state of the art and research challenges.* ACM Computing Surveys (CSUR), 2015. **47**(3): p. 47.
258. Barnsteiner, J., *Teaching the culture of safety.* The Online Journal of Issues in Nursing, 2011. **16**(3).
259. Sintchenko, V., et al., *Handheld computer-based decision support reduces patient length of stay and antibiotic prescribing in critical care.* Journal of the American Medical Informatics Association, 2005. **12**(4): p. 398-402.
260. Linan, M.K., D. Sottara, and R.R. Freimuth. *Creating Shareable Clinical Decision Support Rules for a Pharmacogenomics Clinical Guideline Using Structured Knowledge Representation*. in *AMIA Annual Symposium Proceedings*. 2015. American Medical Informatics Association.
261. Sottara, D., et al. *The Health eDecisions Authoring Environment for Shareable Clinical Decision Support Artifacts*. in *Challenge+ DC@ RuleML*. 2014.
262. Framework, S.I. *Standards and Interoperability Framework HealthIT*. 2016 [cited 2016 September, 8]; https://www.healthit.gov/policy-researchers-implementers/standards-interoperability-si-framework]. Available from: http://www.siframework.org/.
263. Rees, S., C. Moloney, and H. Farley, *Mobile Learning Initiatives in Nursing Education.* Handbook of Mobile Teaching and Learning, 2015: p. 275-289.
264. Phillippi, J.C. and T.H. Wyatt, *Smartphones in nursing education.* Computers Informatics Nursing, 2011. **29**(8): p. 449-454.
265. Holroyd, C.B. and M.G. Coles, *The neural basis of human error processing: reinforcement learning, dopamine, and the error-related negativity.* Psychological review, 2002. **109**(4): p. 679.
266. Gehring, W.J., et al., *A neural system for error detection and compensation.* Psychological science, 1993. **4**(6): p. 385-390.
267. Leonard, T.C., *Richard H. Thaler, Cass R. Sunstein, Nudge: Improving decisions about health, wealth, and happiness.* Constitutional Political Economy, 2008. **19**(4): p. 356-360.
268. Ariely, D., *The Upside of Irrationality: The Unexpected Benefits of Defying Logic*. 2011: Harper Perennial. 368.
269. Ariely, D., *The Upsdie of Irrationality: The Unexected Benefits of Defying Logics*. 2011: Harper Perennial.
270. Kahneman, D., *Thinking Fast and Slow*. 2013: Farrar, Straus and Giroux. 499.
271. Su, L., *Why studying human behavior is a critical component of patient safety.* Current problems in pediatric and adolescent health care, 2015. **45**(12): p. 367-369.
272. Reason, J., *Human error: models and management.* Bmj, 2000. **320**(7237): p. 768-770.
273. Senders, J.W. and N.P. Moray, *Human error: Cause, prediction, and reduction*. 1991: L. Erlbaum Associates Hillsdale, NJ.
274. Reason, J., *Understanding adverse events: human factors.* Quality in health care, 1995. **4**(2): p. 80-89.
275. Hollnagel, E., *Looking for errors of omission and commission or the hunting of the Snark revisited.* Reliability Engineering & System Safety, 2000. **68**(2): p. 135-145.
276. Reason, J., *A life in error: from little slips to big disasters*. 2013: Ashgate Publishing, Ltd.
277. Wiegmann, D., et al., *Human error and general aviation accidents: A comprehensive, fine-grained analysis using HFACS*. 2005, DTIC Document.
278. Sheridan, T.B., *Human error in nuclear power plants.* Technology Review, 1980. **82**(4): p. 22-33.
279. Leape, L.L. and D.M. Berwick, *Five years after To Err Is Human: what have we learned?* Jama, 2005. **293**(19): p. 2384-2390.

280. McKenna, F.P., *The human factor in driving accidents an overview of approaches and problems.* Ergonomics, 1982. **25**(10): p. 867-877.
281. Deacon, T., P. Amyotte, and F. Khan, *Human error risk analysis in offshore emergencies.* Safety science, 2010. **48**(6): p. 803-818.
282. Heinrich, H.W., et al., *Industrial accident prevention: A safety management approach*. 1980: McGraw-Hill Companies.
283. Bird, F. and G. Germain, *Practical Loss Control Leadership: The Consevation of People, Property, Process and Profits.* 1989.
284. Reason, J., *Human error*. 1990: Cambridge university press.
285. Weigmann, D.A. and S.A. Shappell, *Human factors analysis of postaccident data: Applying theoretical taxonomies of human error.* The International Journal of Aviation Psychology, 1997. **7**(1): p. 67-81.
286. Endsley, M.R. *Design and evaluation for situation awareness enhancement*. in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*. 1988. SAGE Publications.
287. Endsley, M.R., *Level of automation effects on performance, situation awareness and workload in a dynamic control task.* Ergonomics, 1999. **42**(3): p. 462-492.
288. McGee, D.l. *Cognitive Errors in Decision Making*. 2015 [cited 2016 Ptober 25]; Available from: http://www.merckmanuals.com/professional/special-subjects/clinical-decision-making/cognitive-errors-in-clinical-decision-making.
289. O'HARE, D., et al., *Cognitive failure analysis for aircraft accident investigation.* Ergonomics, 1994. **37**(11): p. 1855-1869.
290. Shappell, S.A. and D.A. Wiegmann, *A human error approach to accident investigation: The taxonomy of unsafe operations.* The International Journal of Aviation Psychology, 1997. **7**(4): p. 269-291.
291. Zhang, J., et al., *A cognitive taxonomy of medical errors.* Journal of biomedical informatics, 2004. **37**(3): p. 193-204.
292. Singh, H., A.N. Meyer, and E.J. Thomas, *The frequency of diagnostic errors in outpatient care: estimations from three large observational studies involving US adult populations.* BMJ quality & safety, 2014: p. bmjqs-2013-002627.
293. Smith, D.J., *Reliability, maintainability and risk 8e: Practical methods for engineers including reliability centred maintenance and safety-related systems*. 2011: Elsevier.
294. Practice, I.f.S.M. *Selecting the best error-prevention "tools" for the job*. 2006 [cited 2016 October 11, 2016]; Available from: https://www.ismp.org/newsletters/ambulatory/archives/200602_4.asp.
295. Paparella, S., *Choosing the Right Strategy for Medication Error Prevention—Part II.* Journal of Emergency Nursing, 2008. **34**(3): p. 238-240.
296. Press, D., *Guidelines for Failure Mode and Effects Analysis (FMEA), for Automotive, Aerospace, and General Manufacturing Industries*. 2003: CRC Press.
297. DeRosier, J., et al., *Using health care failure mode and effect analysis™: the VA National Center for Patient Safety's prospective risk analysis system.* The Joint Commission Journal on Quality and Patient Safety, 2002. **28**(5): p. 248-267.
298. IHI, I.f.H.I. *Failure Modes and Efffects Analysis Tool*. 2015 [cited 2015 December 28, 2015]; Available from: http://www.ihi.org/resources/pages/tools/failuremodesandeffectsanalysistool.aspx.
299. Ambekar, S.B., A. Edlabadkar, and V. Shrouty, *A review: implementation of Failure Mode and Effect Analysis.* International Journal of Engineering and Innovative Technology (IJEIT), 2013. **2**(8): p. 37-41.
300. Smith, D.L., *FMEA: preventing a failure before any harm is done.* isixsigma magazine, march, 2004.
301. Inoue, H. and S. Yamada, *Failure mode and effects analysis in pharmaceutical research.* International Journal of Quality and Service Sciences, 2010. **2**(3): p. 369-382.
302. Dhillon, B., *Methods for performing human reliability and error analysis in health care.* International Journal of Health Care Quality Assurance, 2003. **16**(6): p. 306-317.
303. Filip, F.-c. *Theoretical Research on the Failure Mode and Effects Analysis (FMEA) Method and Structure*. in *4th International Conference on Manufacturing Engineering, Quality and Production Systems*. 2011.
304. Liu, H.-C., L. Liu, and N. Liu, *Risk evaluation approaches in failure mode and effects analysis: A literature review.* Expert systems with applications, 2013. **40**(2): p. 828-838.
305. Beauregard, M.R. and R.J. Mikulak, *The basics of FMEA*. 2009: CRC Press.

306. Spath, P. *FMEA Failure Scoring Schemes*. 2013 Dec 29, 2015]; Presentation]. Available from: https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&cad=rja&uact=8&ved=0ahUKEwiNo4-VgIHKAhUB3mMKHV6oBaYQFgghMAA&url=http%3A%2F%2Fwww.tnpatientsafety.com%2FLinkClick.aspx%3Ffileticket%3DfRKzWHOzThw%3D&usg=AFQjCNGyl8BAl4LnecCdJW2chYdoIxYoRA&sig2=aNTVDDipl0meq5GRuQcYww&bvm=bv.110151844,d.cGc.
307. Braband, J., *Improving the risk priority number concept.* Journal of System Safety, 2003. **39**(3): p. 21-23.
308. Gilchrist, W., *Modelling failure modes and effects analysis.* International Journal of Quality & Reliability Management, 1993. **10**(5).
309. Krouwer, J.S., *An improved failure mode effects analysis for hospitals.* Archives of pathology & laboratory medicine, 2004. **128**(6): p. 663-667.
310. Alizadeh, S.S., et al., *Failure modes and effects analysis (FMEA) technique: a literature review.* Scientific Journal of Review, 2015. **4**(1): p. 1-6.
311. Wang, Y.-M., et al., *Risk evaluation in failure mode and effects analysis using fuzzy weighted geometric mean.* Expert Systems with Applications, 2009. **36**(2): p. 1195-1207.
312. Ben-Daya, M. and A. Raouf, *A revised failure mode and effects analysis model.* International Journal of Quality & Reliability Management, 1996. **13**(1): p. 43-47.
313. Bowles, J.B. *An assessment of RPN prioritization in a failure modes effects and criticality analysis*. in *Reliability and Maintainability Symposium, 2003. Annual*. 2003. IEEE.
314. Tay, K.M. and C.P. Lim, *On the use of fuzzy inference techniques in assessment models: part II: industrial applications.* Fuzzy Optimization and Decision Making, 2008. **7**(3): p. 283-302.
315. Tay, K.M. *On fuzzy inference system based failure mode and effect analysis (FMEA) methodology*. in *Soft Computing and Pattern Recognition, 2009. SOCPAR'09. International Conference of*. 2009. IEEE.
316. Kahraman, C., İ. Kaya, and Ö. Şenvar, *Healthcare failure mode and effects analysis under fuzziness.* Human and Ecological Risk Assessment: An International Journal, 2013. **19**(2): p. 538-552.
317. Kenett, R.S., *Cause-and-Effect Diagrams.* Wiley StatsRef: Statistics Reference Online, 2007.
318. HealthcareCatalyst, *Healthcare: A Better Way the New Era of Opportuntiy*. 2014.
319. Meng Tay, K. and C. Peng Lim, *Fuzzy FMEA with a guided rules reduction system for prioritization of failures.* International Journal of Quality & Reliability Management, 2006. **23**(8): p. 1047-1066.
320. Chin, K.-S., A. Chan, and J.-B. Yang, *Development of a fuzzy FMEA based product design system.* The International Journal of Advanced Manufacturing Technology, 2008. **36**(7-8): p. 633-649.
321. Xu, K., et al., *Fuzzy assessment of FMEA for engine systems.* Reliability Engineering & System Safety, 2002. **75**(1): p. 17-29.
322. Kumru, M. and P.Y. Kumru, *Fuzzy FMEA application to improve purchasing process in a public hospital.* Applied Soft Computing, 2013. **13**(1): p. 721-733.
323. Garcia, P.A. and R. Schirru, *A fuzzy data envelopment analysis approach for FMEA.* Progress in Nuclear Energy, 2005. **46**(3): p. 359-373.
324. Guimarães, A.C.F. and C.M.F. Lapa, *Fuzzy FMEA applied to PWR chemical and volume control system.* Progress in Nuclear Energy, 2004. **44**(3): p. 191-213.
325. Yang, Z., S. Bonsall, and J. Wang, *Fuzzy rule-based Bayesian reasoning approach for prioritization of failures in FMEA.* Reliability, IEEE Transactions on, 2008. **57**(3): p. 517-528.
326. Abdelgawad, M. and A.R. Fayek, *Risk management in the construction industry using combined fuzzy FMEA and fuzzy AHP.* Journal of Construction Engineering and Management, 2010. **136**(9): p. 1028-1036.
327. Huang, D., T. Chen, and M.-J.J. Wang, *A fuzzy set approach for event tree analysis.* Fuzzy sets and systems, 2001. **118**(1): p. 153-165.
328. Andrews, J.D. and S.J. Dunnett, *Event-tree analysis using binary decision diagrams.* IEEE Transactions on Reliability, 2000. **49**(2): p. 230-238.
329. Cohen, M. *Risk-Informed Interventions in Community Pharmacy: Implementation and Evaluation (Text Version)*. 2009 [cited 2016 October 12, 2016]; Available from: http://archive.ahrq.gov/news/events/conference/2009/cohen/index.html.
330. Murthy, S. *Selected real-world applications [decision tree]*. 1995 [cited 2016 Oct 12, 2016]; Available from: http://www.cbcb.umd.edu/~salzberg/docs/murthy_thesis/survey/node32.html.

331. Baraldi, P. and E. Zio, *A combined Monte Carlo and possibilistic approach to uncertainty propagation in event tree analysis.* Risk Analysis, 2008. **28**(5): p. 1309-1326.
332. Deeter, J., *Human reliability analysis in healthcare: Application of the Cognitive Reliability and Error Analysis Method (CREAM) in a hospital setting.* 2012.
333. Hollnagel, E., *Cognitive reliability and error analysis method (CREAM)*. 1998: Elsevier.
334. Heise, D.R., *Causal analysis*. 1975: John Wiley & Sons.
335. Turney, R., *Risk Assessment in the Process Industries*. 1996: Institute of Chemical Engineers, IChemE; 2r.e. edition 177.
336. Arsham, H. and A. Kahn, *"What-if" analysis in computer simulation models: A comparative survey with some extensions.* Mathematical and Computer Modelling, 1990. **14**: p. 101-106.
337. Sanders, R., *The Pareto principle: its use and abuse.* Journal of Services Marketing, 1987. **1**(2): p. 37-40.
338. Erik Hollnagel. *Cognitive Reliability and Error Analysis Model (CREAM)*. [cited 2016 October 12]; Available from: http://www.hf.faa.gov/workbenchtools/default.aspx?rPage=Tooldetails&subCatId=41&toolID=7.
339. Reason, J., *Generic error-modelling system (GEMS): A cognitive framework for locating common human error forms.* New technology and human error, 1987. **63**: p. 86.
340. Marx, D. and A. Slonim, *Assessing patient safety risk before the injury occurs: an introduction to sociotechnical probabilistic risk modelling in health care.* Quality and Safety in Health Care, 2003. **12**(suppl 2): p. ii33-ii38.
341. Wreathall, J. and C. Nemeth, *Assessing risk: the role of probabilistic risk assessment (PRA) in patient safety improvement.* Quality and Safety in Health Care, 2004. **13**(3): p. 206-212.
342. Keller, W. and M. Modarres, *A historical overview of probabilistic risk assessment development and its use in the nuclear power industry: a tribute to the late Professor Norman Carl Rasmussen.* Reliability Engineering & System Safety, 2005. **89**(3): p. 271-285.
343. Shappel, S.A. and D.A. Wiegmann, *The human factors analysis and classification system--HFACS*. 2000, US Federal Aviation Administration, Office of Aviation Medicine.
344. U.S. Department of Tranportation, F.A.A. *Human Factors Analyisi and Classification System (HFACS)*. [cited 2016 Octiber 12]; Available from: http://www.hf.faa.gov/workbenchtools/default.aspx?rPage=Tooldetails&toolID=112.
345. Chen, L., *Agent-based modeling in urban and architectural research: A brief literature review.* Frontiers of Architectural Research, 2012. **1**(2): p. 166-177.
346. Macal, C.M. and M.J. North, *Tutorial on agent-based modelling and simulation.* Journal of simulation, 2010. **4**(3): p. 151-162.
347. Santos, M.F., F. Portela, and M. Vilas-Boas. *Intcare: multi-agent approach for real-time intelligent decision support in intensive medicine*. in *3rd International Conference on Agents and Artificial Intelligence (ICAART)*. 2011. SciTePress.
348. Wobcke, W. and A. Dunn. *Agent-based modelling for risk assessment of routine clinical processes*. in *International Conference on Principles and Practice of Multi-Agent Systems*. 2010. Springer.
349. Bonabeau, E., *Agent-based modeling: Methods and techniques for simulating human systems.* Proceedings of the National Academy of Sciences, 2002. **99**(suppl 3): p. 7280-7287.
350. Giannakis, M. and M. Louis, *A multi-agent based framework for supply chain risk management.* Journal of Purchasing and Supply Management, 2011. **17**(1): p. 23-31.
351. Clancy, T.R. and C.W. DELANEY, *Complex nursing systems.* Journal of nursing management, 2005. **13**(3): p. 192-201.
352. Vázquez-Vélez, E., *Agent-based Models of Nurse Behavior to Evaluate the Medication Administration Process.*
353. Wall, F., *Agent-based modeling in managerial science: an illustrative survey and study.* Review of Managerial Science, 2016. **10**(1): p. 135-193.
354. CK-12. *Why Do We Need Agent-based Modeling?* . 2016 [cited 2016 October 13]; Available from: http://www.ck12.org/section/Introduction-%3A%3Aof%3A%3A-Agent-based-Modeling-%3A%3Aof%3A%3A-CK-12-Modeling-and-Simulation-for-High-School-Teachers%3A-Principles-Problems-and-Lesson-Plans/.
355. Hammond, R.A., *Considerations and best practices in agent-based modeling to inform policy.* 2015.
356. Gilbert, G.N., *Agent-based models*. 2008: Sage.

357. Garcia, R. and W. Jager, *From the Special Issue Editors: Agent-Based Modeling of Innovation Diffusion.* Journal of Product Innovation Management, 2011. **28**(2): p. 148-151.
358. *Chapter III: Statecharts based Behavior for Agent Based Modeling*. 2016 [cited 2016 October 16]; Available from: http://www.academia.edu/4151699/Chapter_III_Statecharts_based_Behavior_for_Agent_Based_Modeling.
359. Harel, D., *Statecharts: A visual formalism for complex systems.* Science of computer programming, 1987. **8**(3): p. 231-274.
360. Borshchev, A. and A. Filippov. *From system dynamics and discrete event to practical agent based modeling: reasons, techniques, tools*. in *Proceedings of the 22nd international conference of the system dynamics society*. 2004. Citeseer.
361. Grigoryev, I., *AnyLogic 7 in three days.* A quick course in simulation modeling, 2015.
362. Marsella, S.C., D.V. Pynadath, and S.J. Read. *PsychSim: Agent-based modeling of social interactions and influence*. in *Proceedings of the international conference on cognitive modeling*. 2004. Citeseer.
363. Pan, X., et al., *A multi-agent based framework for the simulation of human and social behaviors during emergency evacuations.* Ai & Society, 2007. **22**(2): p. 113-132.
364. Corchado, J.M., et al., *Intelligent environment for monitoring Alzheimer patients, agent technology for health care.* Decision Support Systems, 2008. **44**(2): p. 382-396.
365. Nealon, J. and A. Moreno, *Agent-based applications in health care*, in *Applications of software agent technology in the health care domain*. 2003, Springer. p. 3-18.
366. Laclavík, M., et al. *Agent-based simulation platform evaluation in the context of human behavior modeling*. in *International Conference on Autonomous Agents and Multiagent Systems*. 2011. Springer.
367. BRADY, A., A. MALONE, and S. Fleming, *A literature review of the individual and systems factors that contribute to medication errors in nursing practice.* Journal of nursing management, 2009. **17**(6): p. 679-697.
368. Helmreich, R.L., *Managing human error in aviation.* Scientific American, 1997. **276**(5): p. 62-67.
369. Helmreich, R.L., *On error management: lessons from aviation.* British Medical Journal, 2000. **320**(7237): p. 781.
370. Baker, K., J. Olson, and D. Morisseau, *Work practices, fatigue, and nuclear power plant safety performance.* Human Factors: The Journal of the Human Factors and Ergonomics Society, 1994. **36**(2): p. 244-257.
371. Nelson, W.R., et al., *Structured methods for identifying and correcting potential human errors in space operations.* Acta Astronautica, 1998. **43**(3): p. 211-222.
372. Schmidt, B., *The modelling of human behaviour*. 2000: Society for Computer Simulation International.
373. L'Hommedieu, T. and K. Kappeler, *Lean methodology in iv medication processes in a children's hospital.* American Journal of Health-System Pharmacy, 2010. **67**(24).
374. Hughes, R., *Patient safety and quality: An evidence-based handbook for nurses - Ch 35 Error Reporting and Disclosure*. Vol. 3. 2008: Citeseer.
375. Wakefield, D.S., et al., *Perceived barriers in reporting medication administration errors.* Best practices and benchmarking in healthcare: a practical journal for clinical and management application, 1995. **1**(4): p. 191-197.
376. Westbrook, J.I., et al., *What are incident reports telling us? A comparative study at two Australian hospitals of medication errors identified at audit, detected by staff and reported to an incident system.* International Journal for Quality in Health Care, 2015. **27**(1): p. 1-9.
377. Westbrook, J.I., et al., *Errors in the administration of intravenous medications in hospital and the role of correct procedures and nurse experience.* BMJ Quality and Safety, 2011. **20**(12): p. 1027-1034.
378. Dean, B. and N. Barber, *Validity and reliability of observational methods for studying medication administration errors.* American Journal of Health-System Pharmacy, 2001. **58**(1): p. 54-59.
379. Holden, L.M., *Complex adaptive systems: concept analysis.* Journal of advanced nursing, 2005. **52**(6): p. 651-657.
380. Tyson, P. *Emergence: Everday examples*. [cited 2018 June 23]; Available from: http://www.pbs.org/wgbh/nova/sciencenow/3410/03-ever-nf.html.
381. Scan, E., *Complex Adaptive Systems*, T.H. Foundation, Editor. 2010, The Evidence Scan.

382. K., S. *On the Edge of Chaos: Where Creativity Flourishes*. 2014 [cited 2018 June, 23]; Available from: https://www.kqed.org/mindshift/35462/on-the-edge-of-chaos-where-creativity-flourishes.
383. Begun, J.W., B. Zimmerman, and K. Dooley, *Health care organizations as complex adaptive systems.* Advances in health care organization theory, 2003. **253**: p. 288.
384. Rouse, W.B., *Health care as a complex adaptive system: implications for design and management.* Bridge-Washington-National Academy of Engineering-, 2008. **38**(1): p. 17.
385. Sturmberg, J.P., D.M. O'halloran, and C.M. Martin, *Understanding health system reform–a complex adaptive systems perspective.* Journal of Evaluation in Clinical Practice, 2012. **18**(1): p. 202-208.
386. Chaffee, M.W. and M.M. McNeill, *A model of nursing as a complex adaptive system.* Nursing Outlook, 2007. **55**(5): p. 232-241. e3.
387. Clancy, T.R., J.A. Effken, and D. Pesut, *Applications of complex systems theory in nursing education, research, and practice.* Nursing outlook, 2008. **56**(5): p. 248-256. e3.
388. Sitterding, M., *Clinical nurse specialist integration of complex adaptive systems theory to positively influence the achievement and sustainability of surgical site infection prevention.* Clinical Nurse Specialist, 2005. **19**(2): p. 82.
389. Nugus, P., et al., *Integrated care in the emergency department: a complex adaptive systems perspective.* Social science & medicine, 2010. **71**(11): p. 1997-2004.
390. Clancy, T.R., et al., *The benefits of standardized nursing languages in complex adaptive systems such as hospitals.* Journal of nursing administration, 2006. **36**(9): p. 426-434.
391. Paley, J., *Complex adaptive systems and nursing.* Nursing inquiry, 2007. **14**(3): p. 233-242.
392. Lane, R., N.A. Stanton, and D. Harrison, *Applying hierarchical task analysis to medication administration errors.* Appl Ergon, 2006. **37**(5): p. 669-79.
393. Wakefield, D.S., et al., *Understanding why medication administration errors may not be reported.* American Journal of Medical Quality, 1999. **14**(2): p. 81-88.
394. Patterson, E.S., M.L. Rogers, and M.L. Render, *Fifteen best practice recommendations for bar-code medication administration in the Veterans Health Administration.* The Joint Commission Journal on Quality and Safety, 2004. **30**(7): p. 355-365.
395. Matlow, A., et al., *How can the principles of complexity science be applied to improve the coordination of care for complex pediatric patients?* BMJ Quality & Safety, 2006. **15**(2): p. 85-88.
396. Ebright, P.R., *The complex work of RNs: Implications for healthy work environments.* Online Journal of Issues in Nursing, 2010. **15**(1).
397. Rogers, A., et al., *Role of registered nurses in error prevention, discovery and correction.* BMJ Quality & Safety, 2008. **17**(2): p. 117-121.
398. Hall, L.M., D. Doran, and G.H. Pink, *Nurse staffing models, nursing hours, and patient safety outcomes.* Journal of Nursing Administration, 2004. **34**(1): p. 41-45.
399. Duffield, C., et al., *Nursing staffing, nursing workload, the work environment and patient outcomes.* Applied nursing research, 2011. **24**(4): p. 244-255.
400. Kiekkas, P., et al., *Patient severity as an indicator of nursing workload in the intensive care unit.* Nursing in critical care, 2007. **12**(1): p. 34-41.
401. Runciman, W.B., et al., *Adverse drug events and medication errors in Australia.* International Journal for Quality in Health Care, 2003. **15**(suppl_1): p. i49-i59.
402. Kaushal, R., et al., *Medication errors and adverse drug events in pediatric inpatients.* Jama, 2001. **285**(16): p. 2114-2120.
403. Morimoto, T., et al., *Adverse drug events and medication errors: detection and classification methods.* BMJ Quality & Safety, 2004. **13**(4): p. 306-314.
404. de Oliveira Alves, C., F. Schuelter-Trevisol, and D.J. Trevisol, *Beers Criteria-based assessment of medication use in hospitalized elderly patients in southern Brazil.* Journal of family medicine and primary care, 2014. **3**(3): p. 260.
405. Gleason, K.M., et al., *Results of the Medications at Transitions and Clinical Handoffs (MATCH) study: an analysis of medication reconciliation errors and risk factors at hospital admission.* Journal of general internal medicine, 2010. **25**(5): p. 441-447.
406. Kanjanarat, P., et al., *Nature of preventable adverse drug events in hospitals: a literature review.* American Journal of Health-System Pharmacy, 2003. **60**(17): p. 1750-1759.

407. Lisby, M., L.P. Nielsen, and J. Mainz, *Errors in the medication process: frequency, type, and potential clinical consequences.* International Journal for Quality in Health Care, 2005. **17**(1): p. 15-22.
408. Elganzouri, E.S., C.A. Standish, and I. Androwich, *Medication Administration Time Study (MATS): nursing staff performance of medication administration.* Journal of Nursing Administration, 2009. **39**(5): p. 204-210.
409. Richard, N.K., et al., *Prevalence and Nature of Medication Administration Errors in Health Care Settings: A Systematic Review of Direct Observational Evidence.* Annals of Pharmacotherapy, 2013. **47**(2): p. 237-256.
410. Kozer, E., et al., *Variables associated with medication errors in pediatric emergency medicine.* Pediatrics, 2002. **110**(4): p. 737-742.
411. Westbrook, J.I., et al., *Errors in the administration of intravenous medications in hospital and the role of correct procedures and nurse experience.* BMJ Qual Saf, 2011. **20**(12): p. 1027-1034.
412. Ghaleb, M.A., et al., *The incidence and nature of prescribing and medication administration errors in paediatric inpatients.* Archives of Disease in Childhood, 2010: p. adc158485.
413. McBride-Henry, K. and M. Foureur, *Medication administration errors: understanding the issues.* Australian Journal of Advanced Nursing, The, 2006. **23**(3): p. 33.
414. Wong, I.C., et al., *Incidence and nature of dosing errors in paediatric medications.* Drug safety, 2004. **27**(9): p. 661-670.

Appendices

Appendix 1: Detailed tables from Chapter 4

Table 4. 58: Mean, median and standard deviation (SD) values for Figure 4. 28

Trial		1	1.1	1.3	1.5	1.7	1.9	Trial mean
498-120	mean	0.54957	0.73258	0.87278	0.94573	0.97782	0.99157	0.84501
	median	0.54435	0.74966	0.93588	0.99302	0.99302	0.99302	0.86816
	SD	0.18304	0.19773	0.14206	0.08151	0.03772	0.00683	0.10815
501-480	mean	0.55043	0.732	0.87296	0.94332	0.9788	0.99146	0.84483
	median	0.5445	0.74695	0.93807	0.99302	0.99302	0.99302	0.8681
	SD	0.17926	0.19715	0.14375	0.08416	0.03624	0.00712	0.10795
503-300	mean	0.54937	0.73087	0.87335	0.94514	0.97759	0.99157	0.84465
	median	0.54638	0.7441	0.94009	0.99302	0.99302	0.99302	0.86827
	SD	0.18105	0.19887	0.14292	0.08285	0.03852	0.00684	0.10851
595-120	mean	0.54825	0.73168	0.87381	0.94583	0.97865	0.9917	0.84499
	median	0.54328	0.74763	0.93973	0.99302	0.99302	0.99302	0.86828
	SD	0.18248	0.19884	0.14333	0.08211	0.03668	0.00655	0.10833
600-300	mean	0.54455	0.728	0.87494	0.94446	0.97811	0.99155	0.8436
	median	0.53644	0.74027	0.9412	0.99302	0.99302	0.99302	0.86616
	SD	0.18063	0.19995	0.14041	0.08184	0.03745	0.00691	0.10787
600-480	mean	0.5397	0.73187	0.87515	0.94532	0.97838	0.99158	0.84367
	median	0.53016	0.74114	0.94413	0.99302	0.99302	0.99302	0.86575
	SD	0.18286	0.19812	0.1423	0.08136	0.037	0.00673	0.10806
	Info level mean	0.54698	0.73117	0.87383	0.94497	0.97822	0.99157	
	Info level median	0.54085	0.74496	0.93985	0.99302	0.99302	0.99302	
	Info level SD	0.18155	0.19845	0.14246	0.08231	0.03727	0.00683	

Table 4. 59: Tukey report for true-false trial

		p-Value					
Level	- Level	1	1.1	1.3	1.5	1.7	1.9
501-480	498-120	0.9998	1	0.9993	0.5982	0.9991	0.9997
503-300	498-120	1	0.9992	0.9801	0.9988	0.9878	0.9811
503-300	501-480	0.9989	0.9998	0.9992	0.9513	0.9132	0.9175
595-120	498-120	0.9979	1	0.8929	0.9998	0.9674	0.2773
595-120	501-480	0.9799	1	0.9818	0.831	0.9982	0.1461
595-120	503-300	0.9996	1	0.9995	0.9971	0.6814	0.7348
600-300	498-120	0.6231	0.8484	0.945	1	1	0.9987
600-300	501-480	0.4293	0.8923	0.9947	0.5108	0.9931	0.9814
600-300	503-300	0.7056	0.969	1	0.9969	0.9966	0.9994
600-300	595-120	0.8522	0.9103	1	0.9211	0.9057	0.4564
600-480	498-120	0.0217	1	0.787	0.9991	0.9983	0.9993
600-480	501-480	0.0069	1	0.9398	0.9689	1	0.9868
600-480	503-300	0.0279	0.9998	0.9944	0.7321	0.8838	0.9987
600-480	595-120	0.0544	1	0.9999	1	0.9985	0.4199
600-480	600-300	0.5352	0.8818	0.9986	0.989	0.9884	1

Table 4. 60: Steel Dwass report for true-false trial

		Steel Dwass p-Value					
Level	- Level	1	1.1	1.3	1.5	1.7	1.9
501-480	498-120	0.9998	1	0.9993	0.5982	0.9991	0.9997
503-300	498-120	1	0.9992	0.9801	0.9988	0.9878	0.9811
503-300	501-480	0.9989	0.9998	0.9992	0.9513	0.9132	0.9175
595-120	498-120	0.9979	1	0.8929	0.9998	0.9674	0.2773
595-120	501-480	0.9799	1	0.9818	0.831	0.9982	0.1461
595-120	503-300	0.9996	1	0.9995	0.9971	0.6814	0.7348
600-300	498-120	0.6231	0.8484	0.945	1	1	0.9987
600-300	501-480	0.4293	0.8923	0.9947	0.5108	0.9931	0.9814
600-300	503-300	0.7056	0.969	1	0.9969	0.9966	0.9994
600-300	595-120	0.8522	0.9103	1	0.9211	0.9057	0.4564
600-480	498-120	0.0217	1	0.787	0.9991	0.9983	0.9993
600-480	501-480	0.0069	1	0.9398	0.9689	1	0.9868
600-480	503-300	0.0279	0.9998	0.9944	0.7321	0.8838	0.9987
600-480	595-120	0.0544	1	0.9999	1	0.9985	0.4199
600-480	600-300	0.5352	0.8818	0.9986	0.989	0.9884	1

Table 4. 61: Dunn report for true-false trial

		Dunn p-Value					
Level	- Level	1	1.1	1.3	1.5	1.7	1.9
501-480	498-120	1	1	1	1	1	1
503-300	498-120	1	1	1	1	1	1
503-300	501-480	1	1	1	1	1	1
595-120	498-120	1	1	1	1	1	1
595-120	501-480	1	1	1	1	1	1
595-120	503-300	1	1	1	1	1	1
600-300	498-120	1	1	1	1	1	1
600-300	501-480	0.967	1	1	1	1	1
600-300	503-300	1	1	1	1	1	1
600-300	595-120	1	1	1	1	1	1
600-480	498-120	0.0239	1	1	1	1	1
600-480	501-480	0.0083	1	1	1	1	1
600-480	503-300	0.0351	1	1	1	1	1
600-480	595-120	0.0699	1	1	1	1	1
600-480	600-300	1	1	1	1	1	1

Table 4. 62: True-false equal variance tests

Test	O'Brien[.5]		Brown-Forsythe		Levene		Bartlett		Welch's	
Information Injection Level	Prob > F	F Ratio	Prob > F	F Ratio	Prob > F	F Ratio	Prob > F	F Ratio	Prob > F	F Ratio
1	0.1892	1.4904	0.1463	1.6373	0.151	1.6194	0.5079	0.8588	0.0037	3.4878
1.1	0.7332	0.5569	0.3551	1.1053	0.3666	1.0845	0.8967	0.3274	0.7969	0.4726
1.3	0.4856	0.8914	0.9203	0.2873	0.791	0.4806	0.4508	0.9443	0.8925	0.3342
1.5	0.4428	0.9568	0.5333	0.8226	0.0668	2.0632	0.071	2.0305	0.5464	0.8043
1.7	0.2964	1.2206	0.4229	0.9886	0.0024	3.7029	<.0001	5.7911	0.4281	0.9803
1.9	0.6433	0.6738	0.561	0.784	0.0121	2.9234	<.0001	10.33	0.551	0.7978

Table 4. 63: Dunn method for joint ranking and Tukey Kramer HSD

		Tukey Kramer HSD					Dunn Method for Joint Ranking				
Level	**- Level**	**1.1**	**1.3**	**1.5**	**1.7**	**1.9**	**1.1**	**1.3**	**1.5**	**1.7**	**1.9**
498-120	501-480	1	0.9333	0.5982	0.9994	0.9613	1	1	1	1	1
498-120	503-300	0.9971	0.9516	0.9988	0.71	1	1	1	1	1	1
498-120	595-120	0.9998	0.9543	0.9513	0.4814	1	1	1	1	1	1
498-120	600-300	0.7761	0.9683	0.9998	0.9999	0.9662	1	1	1	1	1
498-120	600-480	1	0.9789	0.831	0.9019	1	1	1	1	1	1
501-480	503-300	0.9996	0.9878	0.9971	0.988	0.8948	1	1	1	1	1
501-480	595-120	1	0.9935	1	0.8094	0.3794	1	1	1	1	1
501-480	600-300	0.8583	0.997	0.5108	0.5893	0.8797	1	1	1	1	1
501-480	600-480	1	0.9986	0.9969	0.9571	0.7896	1	1	1	1	1
503-300	600-300	0.9622	0.9994	0.9211	0.9981	0.8955	1	1	1	1	1
595-120	503-300	0.9999	0.9999	0.9991	0.9978	0.9808	1	1	1	1	1
595-120	600-300	0.8806	1	0.9689	0.9665	1	1	1	1	1	1
600-480	503-300	0.9997	1	0.7321	0.9574	0.9389	1	1	1	1	1
600-480	595-120	1	1	1	0.8303	1	1	1	1	1	1
600-480	600-300	0.8518	1	0.989	0.9982	0.9999	1	1	1	1	1

Table 4. 64: Means and standard deviations comparing internal control simulations for false-true, true-false and true-true

	II=1 false-false		II=1 false-true		II=1 true-false		II=1 true-true	
Level	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
498-120	0.54802	0.181908	0.338235	0.261968	0.549566	0.183039	0.34291	0.265639
501-480	0.550751	0.181477	0.455126	0.289493	0.550433	0.179257	0.455272	0.28855
503-300	0.547369	0.180963	0.411632	0.288068	0.54937	0.181047	0.409654	0.28745
595-120	0.546668	0.18064	0.336618	0.260076	0.548249	0.182483	0.337111	0.261619
600-300	0.549679	0.182455	0.407224	0.28239	0.544548	0.180633	0.414181	0.282848
600-480	0.550432	0.183078	0.430598	0.289155	0.539702	0.182861	0.430885	0.284693

Table 4. 65: Tukey Kramer method for comparison of means for true-true

		p-Value					
Level	- Level	1	1.1	1.3	1.5	1.7	1.9
498-120	595-120	0.8439	<.0001*	0.973	<.0001*	0.3037	0.1479
501-480	498-120	<.0001*	<.0001*	<.0001*	0.0001*	<.0001*	<.0001*
501-480	503-300	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*	0.0169*
501-480	595-120	<.0001*	<.0001*	<.0001*	0.0007*	<.0001*	<.0001*
501-480	600-300	<.0001*	0.0165*	<.0001*	0.8495	<.0001*	0.6448
501-480	600-480	<.0001*	<.0001*	<.0001*	<.0001*	0.0481*	0.3135
503-300	498-120	<.0001*	<.0001*	<.0001*	<.0001*	0.0779	0.0013*
503-300	595-120	<.0001*	0.0137*	<.0001*	1	<.0001*	<.0001*
600-300	498-120	<.0001*	<.0001*	0.9993	<.0001*	0.0067*	<.0001*
600-300	503-300	0.9386	1	<.0001*	0.9914	0.9844	0.4554
600-300	595-120	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*
600-480	498-120	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*	0.9942
600-480	503-300	0.0002*	<.0001*	0.1997	0.0067*	0.0065*	<.0001*
600-480	595-120	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*	0.7889
600-480	600-300	0.0043*	<.0001*	0.0631	0.0304*	0.0383*	<.0001*

Table 4. 66: Steel Dwass method for comparison of means for true-true

		Steel Dwass p-Value					
Level	- Level	1	1.1	1.3	1.5	1.7	1.9
501-480	498-120	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*
503-300	498-120	<.0001*	<.0001*	<.0001*	<.0001*	0.0043*	0.0005*
503-300	501-480	<.0001*	<.0001*	<.0001*	0.0010*	<.0001*	0.0014*
595-120	498-120	0.9009	0.0085*	0.9894	1	0.3487	0.2129
595-120	501-480	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*
595-120	503-300	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*
600-300	498-120	<.0001*	<.0001*	<.0001*	<.0001*	0.0006*	<.0001*
600-300	501-480	<.0001*	<.0001*	<.0001*	0.0010*	<.0001*	0.0865
600-300	503-300	0.5891	1	0.9523	1	0.9995	0.7145
600-300	595-120	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*
600-480	498-120	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*
600-480	501-480	<.0001*	0.0114*	<.0001*	0.9716	0.0097*	0.0682
600-480	503-300	<.0001*	<.0001*	0.0783	0.0103*	0.0951	0.7806
600-480	595-120	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*
600-480	600-300	0.0032*	<.0001*	0.0025*	0.0115*	0.1556	1

Table 4. 67: Dunn method for comparison of means for true-true

		Dunn p-Value					
Level	- Level	1	1.1	1.3	1.5	1.7	1.9
501-480	498-120	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
503-300	498-120	<.0001	<.0001	<.0001	<.0001	0.0036	0.0003
503-300	501-480	<.0001	<.0001	<.0001	0.0012	<.0001	0.0031
595-120	498-120	1	0.0173	1	1	0.6222	0.2347
595-120	501-480	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
595-120	503-300	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
600-300	498-120	<.0001	<.0001	<.0001	<.0001	0.0005	<.0001
600-300	501-480	<.0001	<.0001	<.0001	0.0013	<.0001	0.1945
600-300	503-300	1	1	1	1	1	1
600-300	595-120	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
600-480	498-120	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
600-480	501-480	<.0001	0.0221	<.0001	1	0.0196	0.1451
600-480	503-300	<.0001	<.0001	0.1161	0.0133	0.1427	1
600-480	595-120	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
600-480	600-300	0.0043	<.0001	0.0033	0.0156	0.2607	1

Table 4. 68: Equal variance test for true-true

Test	O'Brien[.5]	Brown-Forsythe	Levene	Bartlett	Welch's
Information Injection Level	Prob > F	Prob > F	Prob > F	Prob > F	Prob > F
1	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*
1.1	0.0125*	0.0293*	0.0276*	0.3328	<.0001*
1.3	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*
1.5	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*
1.7	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*
1.9	<.0001*	<.0001*	<.0001*	<.0001*	<.0001*

Table 4. 69: Mean values for probabilities of process step success

	Information Injection Level					
MAP Process Step	1	1.1	1.3	1.5	1.7	1.9
probabilityOfMarCheck	0.854199	0.905865	0.96383	0.984696	0.992045	0.996209
probabilityOfMedCheck	0.853891	0.904806	0.964349	0.984378	0.992686	0.996488
probabilityOfDoseCheck	0.852195	0.907873	0.964104	0.984125	0.992369	0.996388
probabilityOfPatientCheck	0.853473	0.906854	0.963017	0.984379	0.991647	0.996476
probabilityOfRouteCheck	0.852448	0.906575	0.964041	0.983765	0.992063	0.99623
probabilityOfTimeCheck	0.852499	0.906331	0.964874	0.98435	0.992345	0.99611

Table 4. 70: Pairwise comparison of probability of success of MAP process steps
Methods: [1]Tukey-Kramer HSD, [2]Dunn's, [3]Steel-Dwass.

Information Injection Level		1.1			15			1.9		
Probability Pairwise Comparison		Tukey[1]	Dunn[2]	Steel[3]	Tukey	Dunn	Steel	Tukey	Dunn	Steel
Level	- Level	p-Value	p-Value	p-Value	p-Value	p-Value	p-Value	p-Value	p-Value	p-Value
DoseCheck	MarCheck	0.9721	1	0.9768	0.9783	0.348	0.1972	0.999	1	1
DoseCheck	MedCheck	0.8124	1	0.884	0.9998	1	0.9269	1	1	0.809
DoseCheck	MedDelivered	0.8942	1	0.9999	0.9977	1	0.8606	0.9995	1	0.863
DoseCheck	PatientCheck	0.9993	1	0.7414	0.9999	1	0.9784	0.9887	1	1
DoseCheck	RouteCheck	0.9973	1	0.9958	0.7881	1	0.7336	1	1	1
DoseCheck	TimeCheck	0.993	1	1	0.9999	1	1	1	1	0.8085
MarCheck	MedCheck	0.9991	1	0.9861	0.9691	1	0.8573	0.9887	1	1
MarCheck	MedDelivered	0.9999	1	1	0.9999	1	0.9254	0.9987	1	1
MedDelivered	MedCheck	1	1	0.9994	1	1	1	1	1	0.8114
PatientCheck	MarCheck	0.9994	1	0.9916	0.9252	1	0.9996	0.9924	1	1
PatientCheck	MedCheck	0.9692	1	0.9975	0.9966	1	0.7662	0.9471	1	0.9827
PatientCheck	MedDelivered	0.9899	1	0.9999	1	1	0.968	1	1	0.9694
PatientCheck	RouteCheck	1	1	0.9948	1	1	0.9999	1	0.6235	0.2946
PatientCheck	TimeCheck	1	1	0.9652	1	1	0.997	0.9986	1	0.9835
RouteCheck	MarCheck	0.9999	1	1	0.9248	1	1	1	1	0.9821
RouteCheck	MedCheck	0.9854	1	0.9699	0.9966	1	0.6716	0.9912	1	0.9993
RouteCheck	MedDelivered	0.9963	1	1	1	1	0.9866	0.9992	1	0.998
RouteCheck	TimeCheck	1	1	0.9999	0.9988	1	0.9989	0.9942	1	0.5215
TimeCheck	MarCheck	1	1	0.9971	1	1	0.9897	0.9552	1	0.9994
TimeCheck	MedCheck	0.9934	1	1	0.9334	1	0.9999	1	1	0.9993
TimeCheck	MedDelivered	0.9988	1	0.9999	0.9974	1	1	0.9999	1	0.9998

Table 4. 71: Descriptive statistics for II for 503-300

II	Mean	Median	SD	Min	Max
1	0.409654	0.337542	0.287450393	0.009452	0.993472
1.1	0.565579	0.568452	0.292234388	0.009297	0.994015
1.3	0.79162	0.855457	0.218455928	0.058107	0.994015
1.5	0.897502	0.993021	0.14535118	0.150787	0.994004
1.7	0.947884	0.993021	0.096054074	0.208027	0.994015
1.9	0.974786	0.993021	0.05574277	0.461074	0.994015

Table 4. 72: Least squares analysis of agent attributes – impact by II level 1 and 1.9 for 503-300

Term	Avg. II Prob>|t|	II = 1.9 Prob>|t|
interruption[FALSE]	<.0001*	<.0001*
interruption[TRUE]	<.0001*	<.0001*
medicationSeverity[low]	<.0001*	<.0001*
medicationSeverity[medium]	<.0001*	0.3155
medicationSeverity[high]	<.0001*	<.0001*
medicationDifficulty[difficult]	<.0001*	<.0001*
medicationDifficulty[intermediate]	0.0002*	0.2514
medicationDifficulty[minimal]	<.0001*	<.0001*
nurseExperience[moderate]	0.1149	0.9023
nurseExperience[novice]	<.0001*	<.0001*
nurseExperience[senior]	<.0001*	<.0001*
fatigueStatus[FALSE]	<.0001*	<.0001*
fatigueStatus[TRUE]	<.0001*	<.0001*
PatintLoadOut[high]	<.0001*	<.0001*
PatintLoadOut[low]	<.0001*	<.0001*
PatintLoadOut[med]	0.0296*	0.4959

True-false equal variance tests

Test	O'Brien[.5]		Brown-Forsythe		Levene		Bartlett		Welch's	
Information Injection Level	Prob > F	F Ratio	Prob > F	F Ratio	Prob > F	F Ratio	Prob > F	F Ratio	Prob > F	F Ratio
1	0.1892	1.4904	0.1463	1.6373	0.151	1.6194	0.5079	0.8588	0.0037	3.4878
1.1	0.7332	0.5569	0.3551	1.1053	0.3666	1.0845	0.8967	0.3274	0.7969	0.4726
1.3	0.4856	0.8914	0.9203	0.2873	0.791	0.4806	0.4508	0.9443	0.8925	0.3342
1.5	0.4428	0.9568	0.5333	0.8226	0.0668	2.0632	0.071	2.0305	0.5464	0.8043
1.7	0.2964	1.2206	0.4229	0.9886	0.0024	3.7029	<.0001	5.7911	0.4281	0.9803
1.9	0.6433	0.6738	0.561	0.784	0.0121	2.9234	<.0001	10.33	0.551	0.7978

Appendix 2: Medical Training Simulation ScenarioN404 6yo Pain Assess Tibia-Fibula Fx

Scenario developed by: Susan Henley Hébert, MSMS, RN, CHSE, Simulation Director/Clinical Faculty, Stephanie Hopper, BSN, RN, Learning Lab Coordinator, Deb Chyka, DNP, RN Clinical Assistant Professor, University of Tennessee, Knoxville , College of Nursing

Ms, Hébert is a Medical Simulation professional with extensive experience working with student nurses in the medical simulation environment she is a Certified Healthcare Simulation Educator, holds a Master of Science degree in Medical Simulation and has worked a registered nurse in pediatrics,

Dr. Deb Chyka earned a BSN, MSN, DNP in 1981,1985 and 2012 respectively from the University of Tennessee Health Science Center in Memphis, Tennessee. She has extensive experience in pediatric nursing, growth and development. As a faculty member for the UTK CON she is accomplished in nurse education and training.

File Name: N404 Pain Management in 6yo Fx Tibia/Fibula

Date: 11/15/15

Authors: Deb Chyka, Susan Fancher and Stephanie Hopper

Brief Summary: 6yo Pediatric male with tibia/fibula fx to be assessed and managed for pain.

Objectives:

Cognitive (Knowledge)	Technical (Skills)	Behavioral (Psychomotor)
Knowledge of safe dose for acetaminophen/kg for patient.	Calculates acetaminophen dose correctly.	Communicates effectively w/pt. with developmental appropriate communication for 6yo.
Knowledge of developmental stages of pediatric patient.	Prepares acetaminophen correctly.	Integrates parent assessment of medication administration into patient care.
Knowledge of different pediatric pain scales.	Administers acetaminophen using developmentally appropriate route of delivery.	Communicates effectively with healthcare provider in regards to unsafe dose.
	Follows medication rights (right patient, right med, right time, right route, right dose, etc.)	

Objectives of training scenario

Roles/Guidelines for Roles:

1. 2 Student Nurses

2. Simulated actor for mother

Supplies	Medication and Fluids	Manikins[sic]/Equipment
Oral Syringes and medication cups for liquid med	Oral tablets (chewable and non-chewable) and liquid Acetaminophen with scan labels	SimJr
Cup for water	D5 1/2NS + 20KCL @ 55ml/hr	Computer for Docucare(control group)
Incident reports	Ibuprofen liquid	Computer and Smart phone (intervention group)
External fixator for tibia/fibula fx		Pediatric pt room
Faces Pain scale		Medication scanner

Materials for training scenario

Scenario Prompt:

RN Report:

Frank is 6 y/o male who was brought in yesterday to the ER by Mom and Dad after falling off the trampoline at home three days ago. His parents did not realize the severity of the injury and thought he just had a bad bruise. They treated his injury with elevation, ice and Tylenol for pain. X-ray revealed a right tibia/fibula fracture. Pt had surgery yesterday to repair the fracture. Frank has a 22G angiocath in his right AC with D5 1/2NS with 20KCL infusing at 55 ml/hr. He has been getting scheduled morphine q2 hours and Tylenol q4hr PRN for breakthrough pain. Frank is complaining of pain. His mom just called right before report and I have not had a chance to assess his pain yet. I gave him his morphine an hour ago but he hasn't had Tylenol in 6 hours. Labs were drawn last night and they are in the computer but I haven't look at them yet.

VS: HR 118, RR 32, BP 121/56, Temp 37.7 C, Faces Pain Scale showing 4/5

Diagnostic Results:

Hepatic Panel: albumin 4.0; Alkaline phosphatase 200; ALT 84 (H); AST 43 (H)

Standardized Mother/Father Role:

- Comfort crying child - Rub patient's abdomen when comforting child, continue rubbing periodically throughout scenario so child can complain of abdominal pain

- If asked about abdominal pain mother says, “I don’t know, he hasn’t been complaining of his stomach hurting, just his leg…”
- Assist patient in identification of name/DOB and Pain scale if asked
- If RNs say they will get medicine ask “What are you giving him for his pain?”
    - If RN says “acetaminophen/Tylenol” → mother, “Ok good, that’s what I’ve been giving him at home.”
    - If questioned about Tylenol use at home (amount/frequency) mother to say “I’ve been giving him a couple spoonful’s whenever he complains of pain”
- If students bring Tylenol to give to child mother to say, “Is that all you’re giving him? I usually give him more than that at home.”
- If students bring ibuprofen (orange) mother to say, “The medicine I give him at home is grape flavored”

SCENARIO: SIMULATOR/Standardized Pt.:

MONITOR DISPLAY				ACCESS				Special Notes:
	ECG		BP		PIV site:		PICC site:	
	Sa02		ART line BP		Central Line:			
	RR				UVC/UAC:			
INTRAVENOUS FLUIDS								
	IV fluids:				Rate:			
	IV fluids:				Rate			
	TPN				Rate:			
MEDICATIONS								
OXYGEN SUPPLIES AT BEDSIDE								
	Self-inflating Bag/Mask		T-Piece resuscitator				Wall Oxygen/Suction with tubing	
	Nasal Cannula		Flow-inflating Bag/Mask				Vapotherm	

	Mechanical vent with settings:				CPAP
AIRWAY MANAGEMENT					
	Laryngoscope	Blade sizes:			
	ETT	Sizes:			
	LMA				
CARTS AND EQUIPMENT					
	Airway tote		Stethoscope		Radiant warmer
	Bulb syringe		Code cart		UVC kit
	Defibrillator		Portable I-stat		Needle thoracentesis kit
	Transilluminator		EZ IO kit		Pleurevac
	Needle aspiration kit		Chest Tube		Pigtail catheter
MISC ITEMS					
	Patient chart		Footprint page with BW		Code Sheet
	Antibiotic order sheet		Scenario		Blank order sheets
	Lab Results		X-Ray results		Tape
	Blood		Moulage:		Manikin attachments
	C-section drapes				

ROOM SET UP AND EQUIPMENT: R210

Debriefing Questions

1. **In 10 words or less what happened in the scenario?**
2. **What would you consider a strength in the scenario, what was a weakness?**
3. **Did the participants properly assess the pt's pain? If so, did they acknowledge the developmental stage of the child?**
4. **Did the participants correctly calculate the safe dosage range of the medication?**
5. **Did the participants complete the 5 rights of medication administration?**
6. **Did the participants administer the medication using a developmentally appropriate route for the pt?**
7. **In what ways did the participants use their knowledge of development to communicate with the pt?**
8. **Do you think the participants properly communicated with the pt's mother? If so, how?**
9. **Was SBAR used in reporting concerns to the healthcare provider?**
10. **How will your practice change after this scenario?**

Active Observer Checklist

1. Did the participants properly assess the patient's pain? What scale did they use? How did they incorporate the developmental age/stage of the child?

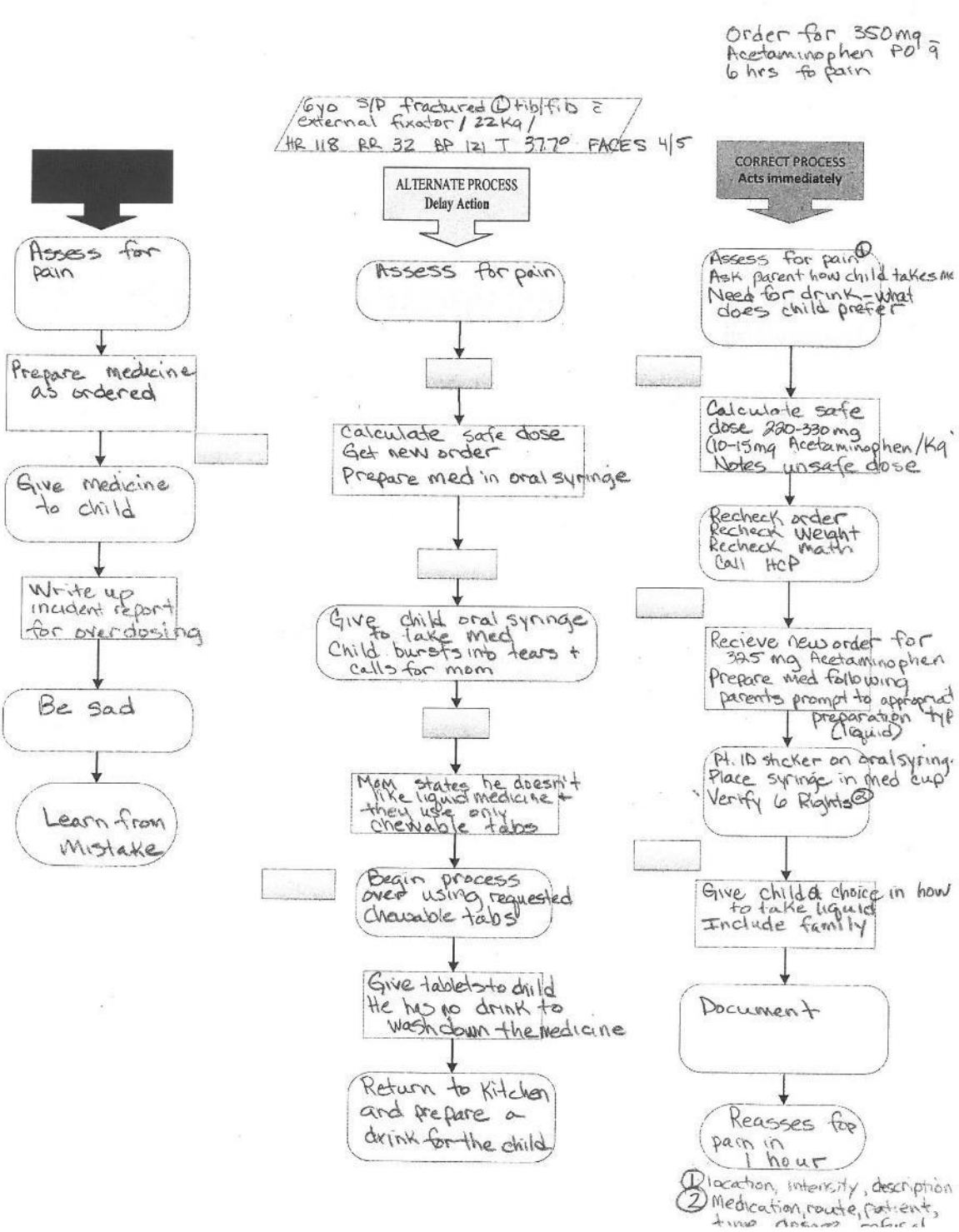
2. Did the participant ask the parent how the child takes medicine at home? Did the participant make sure there was a fresh drink for the child?

3. Did the participants accurately calculate the safe dosage range of the medication? Did the participant complete the 5 rights of medication administration?

4. Did the participants administer the medication using a developmentally appropriate route for the patient? Did the participant ask the parent if they wanted to administer the medication?

5. In what ways did the participants use their knowledge of development to communicate with the patient? Do you think the participants properly communicated with the patient's mother? If so, list some examples.

6. Was SBAR used in reporting concerns to the healthcare provider?



Training scenario flow chart

Debriefing Questions

1. **What just happened in the scenario?**
2. **How were the rights of medication administration carried out?**
3. **How was the right medication dose determined for this patient? How is the safe dose of acetaminophen determined for a child?**
4. **How do you follow the developmentally appropriate dose of medication for a child?**

5. **How did the nurses communicate effectively? With the child? With the parent? With the physician on the phone if they called?**

6. **What about this scenario will change the care you provide to patients in the future?**

Appendix 3: Score Sheet for Evaluation of Student Nurse Performance

Score Sheet for Evaluation of Student Nurse Performance

	1	2	3	4	5	6	7	8	9
	Pain level not assessed				Pain assessment attempted with some consideration of appropriate method				Pain accurately and effectively assessed using the right tool and method
Asses Pain/Med Need Ascertained									
	EMR Not Reviewed				EMR/MAR reviews in part/key information not checked (e.g. labs)				Comprehensive Review of EMR and query of questionable information
Review Orders/MAR/EMR (e.g. labs)									
	Pt. not assessed for ability to take med				Pt. observed and assumed suitable to take med				Explicit assessment of pt. ability to take med by prescribed dose, route, and

									contraindications
Asses Pt. condition suitable to rcv med									
	Right time for medication not assessed				Timing of medication checked but not verified				Medication time window validated
Chk Correct time for med									
	Form Factor not considered				Form factor/route corrected after dose preparation				Form factor validated via EMR and patient preference as appropriate
Suitable form factor/route									

	Need to do dose calculation not considered				Dose calc attempted but accuracy not confirmed. Follow-up not done*				Dose calc performed and double checked. Calc done correctly with correct follow-up action*
Dose Calculation									
	Med not verified				Med verified after dose is prepared				Med verified at beginning of administration process
Retrieve Med/Verify									
	Patient not re-verified prior to giving med				Patient re verified but correct process is not used				Patient reverified via bracelet, DOB
Verify Pt.									
	Med not re-verified at bedside				Med only partially re-verified				Med re-verified correctly (dose, route, patient, etc.)

Verify Med (at patient location)									
	Med not given to patient				Med administered inappropriately (partial dose, wrong or poor technique, etc.)				Med correctly administered to patient
Deliver Med									
	Administration of med not documented				Information partially documented				Med administration correctly entered into MAR
Document									

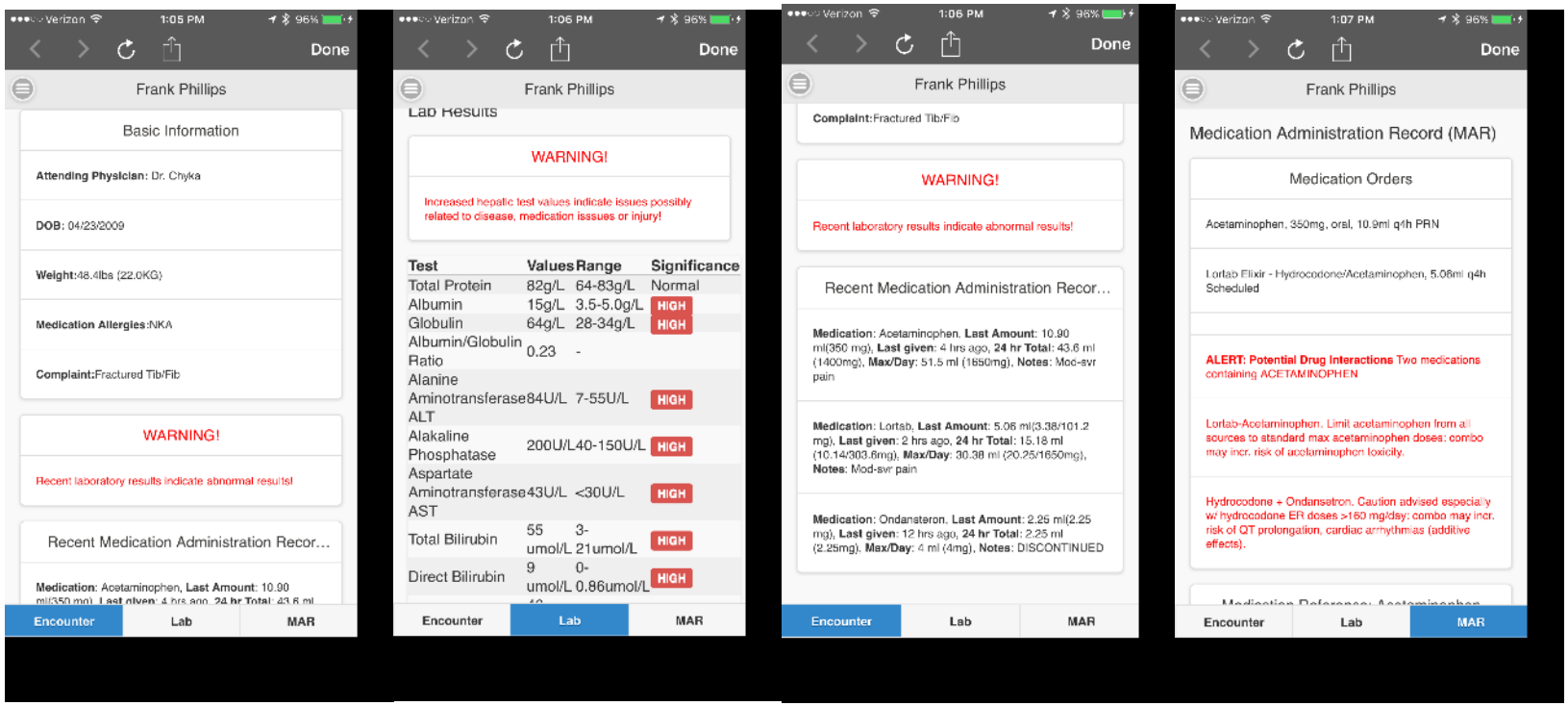
Example: Filled out data form

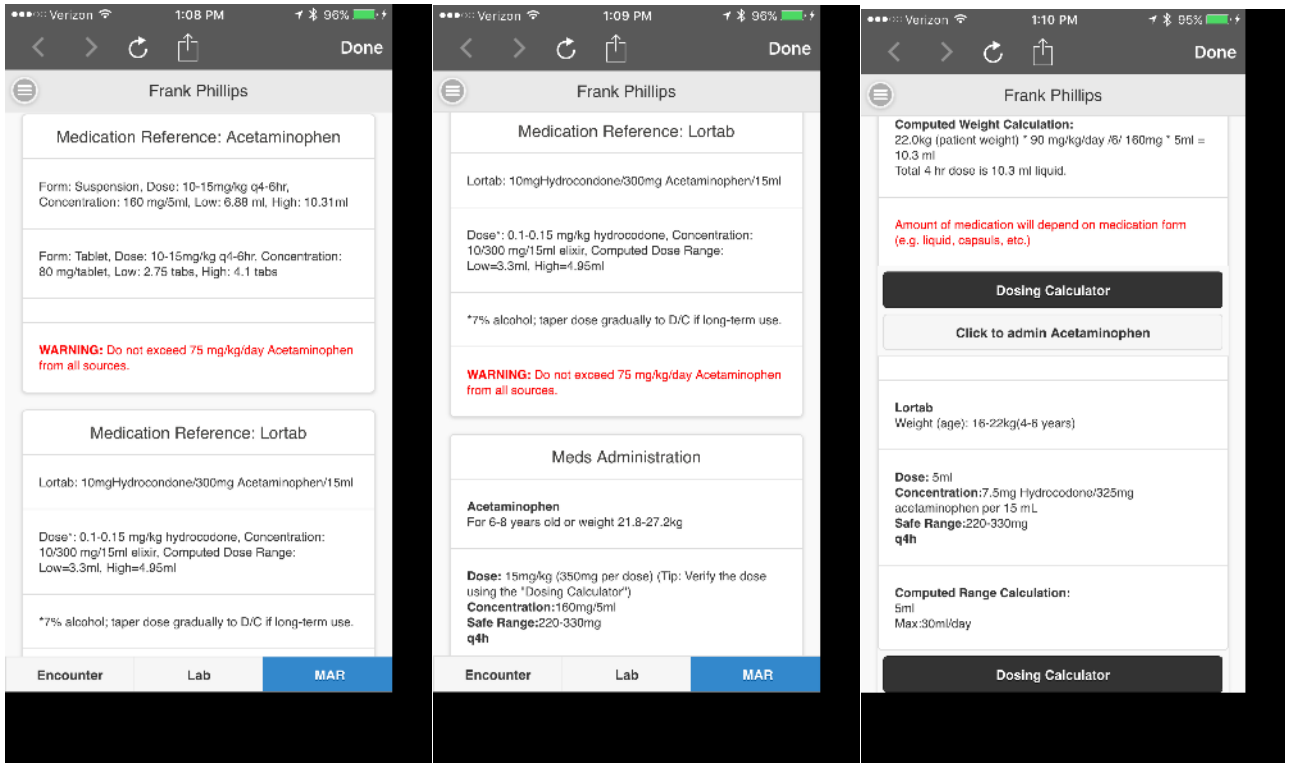
Duration 11:54. 2 Nurses										Stephanie Hopper as Mom
Session 9 (1)	1	2	3	4	5	6	7	8	9	
Asses Pain/Med Need Ascertained									9	Mentioned they were going to give Lortab. Got indication from mom that level was 6-8
Review Orders/MAR/EMR (e.g. labs)									9	Checking noted can't take Lortab but can take APAP
Asses Pt. condition suitable to rcv med									9	PT OK to receive med
Chk Correct time for med									9	Correct time verified
Suitable form factor/route									9	Retrieved Tylenol cups, did not query mom about form factor but did select suspension

Dose Calculation									9	Calculated correct dose, although they struggled with the calculation, they looked up the correct dose in the computer called MD
Retrieve Med/Verify									9	Giving APAP
Verify Pt.									9	Verified via scan and DOB and name from mom
Verify Med (at patient location)									9	Verified via mom and scan
Deliver Med									9	Provided med via syringe with drink
Document										
Considered Contraindications	1									Did not note Lortab contained APAP
Other Notes										

Appendix 4: MAE Error App Final Version for Nursing Student Simulation

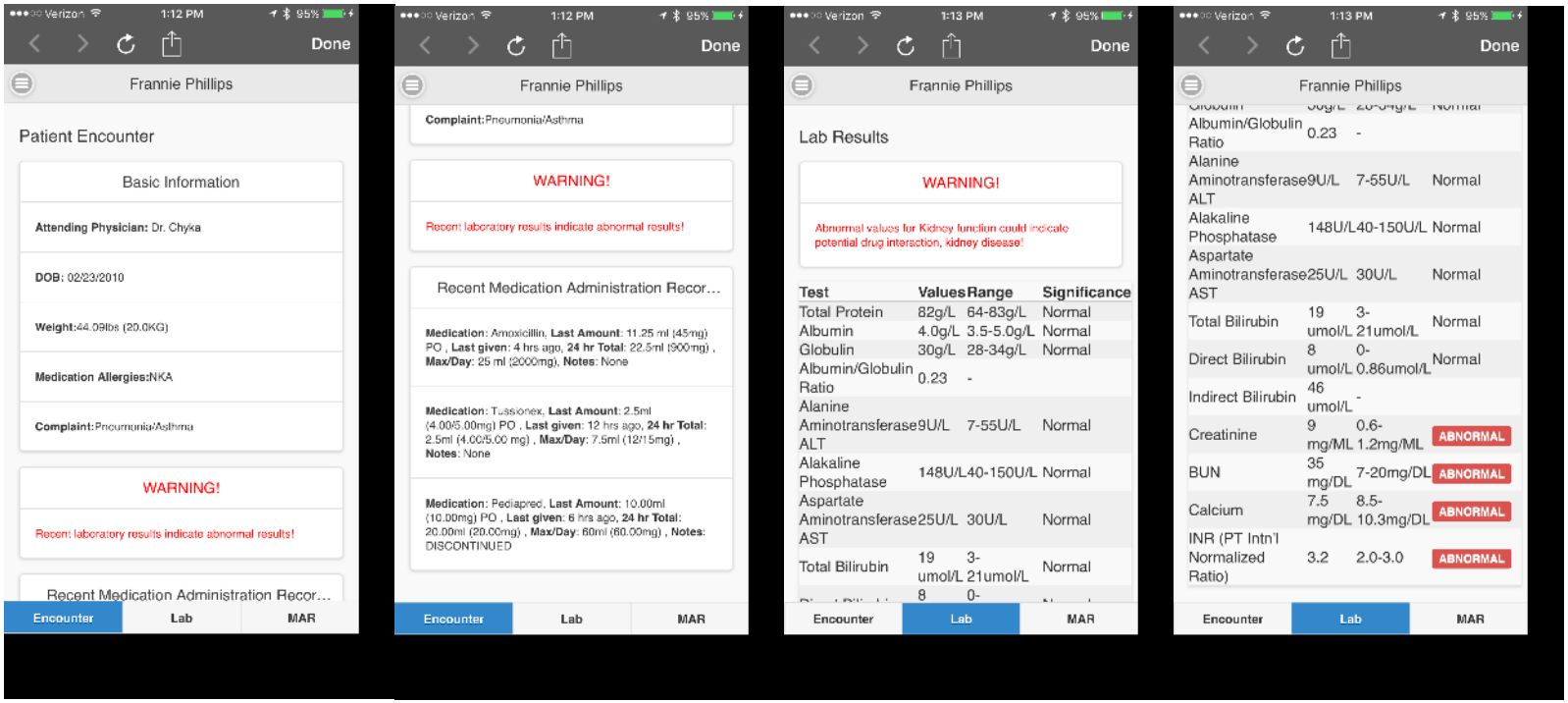
http://ilab.engr.utk.edu/hits/tberg/frank

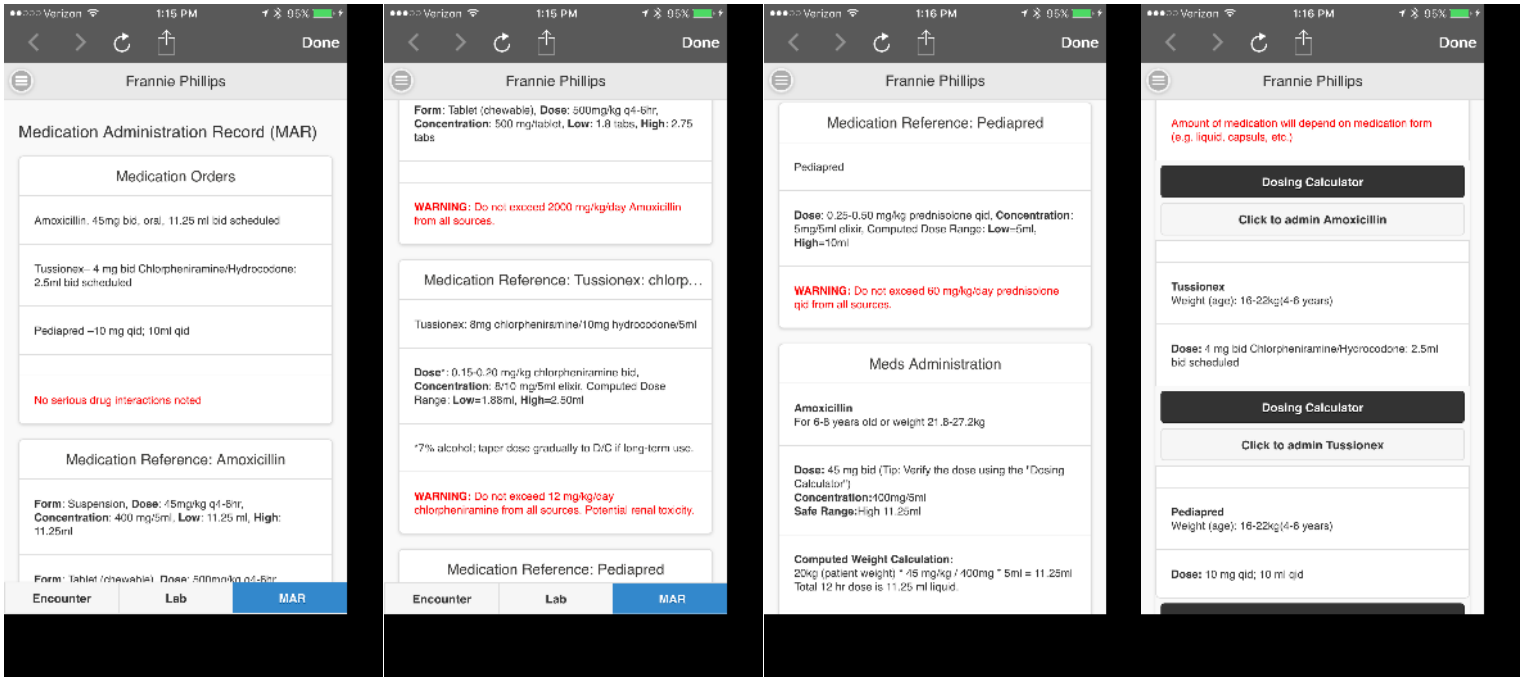




Appendix 5: MAE Error App Practice Version for Nursing Student Simulation

http://ilab.engr.utk.edu/hits/tberg/frannie





Appendix 6: Overview of APP for Student Nurses prior to simulation

APP OVERVIEW

Description of Smartphone App for Nursing Simulation

Overview

- Liked the simplicity and ease of use
- Provided the right amount of information
- Easier to use than the EHR
- The calculator was useful

We discovered that the app was simple and easy to use, practice on interpreting the information was needed

What Do They Mean – What Should You Do?

Our Goal: See if this app prevents MAEs

2 Steps

1. Overview of the App
2. Hands-on practice

Things to Remember

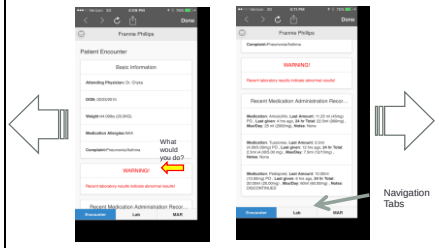
- Patient info
- Important information (e.g. new Lab Results)
- Most recent medications given
- Lab results & indications
- Med Orders
- Med Reference
- Handy Dandy Dose Calculator AND comparison to Ordered Amount

App Overview

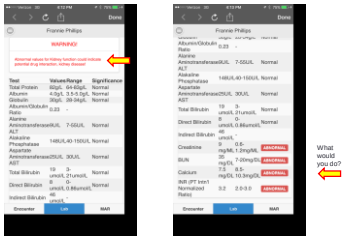
- http://ilab.engr.utk.edu/hits/tberg/frannie

App store QR Code Reader
MixerBox
QR Code Reader
Scan, Inc.
https://play.google.com/store/apps/details?id=me.scan.android.client&hl=en

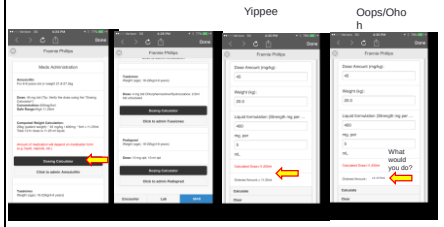
Encounter



LAB



Med Calculation



Things to Remember

- Patient info
- Important information (e.g. new Lab Results)
- Most recent medications given
- Lab results & indications
- Med Orders
- Med Reference
- Handy Dandy Dose Calculator **AND** comparison to Ordered Amount

http://ilab.engr.utk.edu/hits/tberg/frank

Appendix 7: App Worksheet

1. Identify the patient's name, DOB/age and weight?

2. What are the most recent medications, when where they last taken and in what amounts?

3. What is the status of the most recent laboratory results?

4. What medications are ordered?

5. For medication 1, what dose and amount is ordered?

6. What information regarding cautions or alerts is there for the ordered medications?

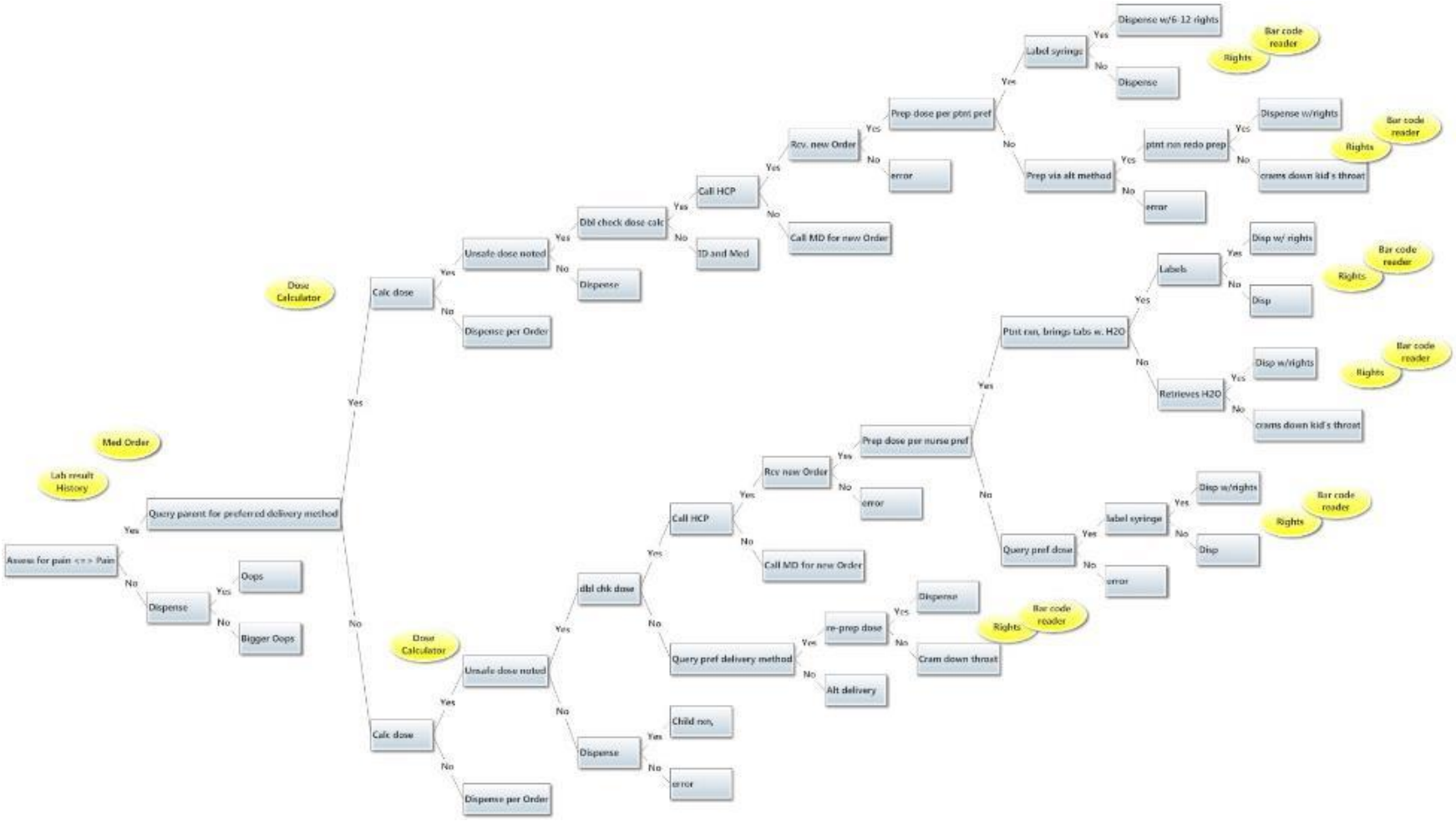
7. For medication 1 provide the dose range, concentration and computed dose range?

8. What is a maximum dose for medication 1?

9. Perform a dose calculation using the dose calculator, how does it compare to the amount ordered in the Calculation Confirmation section?

10. Is there anything notable in the Laboratory Test Results Section?

Appendix 8: Medication Administration Error Decision Tree (Partial)



Appendix 9: Representative drug packaging with similar appearance

Vita

Thomas Berg is originally from Beloit, Wisconsin and presently resides in Knoxville, Tennessee with his wife and daughter along with an assortment of dogs.

Thomas' academic accomplishments include a Bachelor of Science Degree in Biochemical Engineering from the University of Wisconsin-Madison (1979) a Master of Business Administration Degree from the University of Wisconsin-Whitewater (1981) and professional and academic programs at the Massachusetts Institute of Technology in Boston, John Hopkins University in Baltimore, The Wharton School of the University of Pennsylvania. He is currently fulfilling the requirements for a Doctor of Philosophy Degree in Industrial Engineering at the University of Tennessee in Knoxville, Tennessee and is expected to complete the Ph.D. degree in fall of 2018 with a focus on the application of systems engineering principle on minimizing the occurrence of errors.

Over Thomas' professional career he has had the opportunity to hold a wide variety of positions of increasing responsibility. The focus of his career has been related to the development and management of research and development (R&D) programs. His involvement in R&D includes technology transfer, research and business partnerships, development of university research consortia, design and implementation of research programs, and implementation of strategic research initiatives. He currently directs a large multidisciplinary research effort that includes more than 80 individual projects with areas ranging from big data to fundamental materials research, extending from laboratory to pilot scale efforts.