APPLYING THE COGNITIVE RELIABILITY AND ERROR ANALYSIS METHOD TO REDUCE CATHETER ASSOCIATED URINARY TRACT INFECTIONS

by

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Abstract

Catheter associated urinary tract infections (CAUTIs) are a source of concern in the healthcare industry because they occur more frequently than other healthcare associated infections and the rates of CAUTI have not improved in recent years. The use of urinary catheters is common among patients; between 15 and 25 percent of all hospital patients will use a urinary catheter at some point during their hospitalization (CDC, 2016). The prevalence of urinary catheters in hospitalized patients and high CAUTI occurrence rates led to the application of human factors engineering to develop a tool to help hospitals reduce CAUTI rates.

Human reliability analysis techniques are methods used by human factors engineers to quantify the probability of human error in a system. A human error during a catheter insertion has the opportunity to introduce bacteria into the patient's system and cause a CAUTI; therefore, human reliability analysis techniques can be applied to catheter insertions to determine the likelihood of a human error. A comparison of three human reliability analysis techniques led to the selection of the Cognitive Reliability and Error Analysis Method (CREAM).

To predict a patient's probability of developing a CAUTI, the human error probability found from CREAM is incorporated with several health factors that affect the patient's risk of developing CAUTI. These health factors include gender, duration, diabetes, and a patient's use of antibiotics, and were incorporated with the probability of human error using fuzzy logic. Membership functions were developed for each of the health factors and the probability of human error, and the centroid defuzzification method is used to find a crisp value for the probability of a patient developing CAUTI. Hospitals that implement this tool can choose risk levels for CAUTI that places the patient into one of three zones: green, yellow, or red. The

placement into the zones depends on the probability of developing a CAUTI. The tool also provides specific best practice interventions for each of the zones.

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List of Acronyms

ATHEANA .... A Technique for Human Error Analysis

CAUTI .... Catheter Associated Urinary Tract Infection

CDC .... Centers for Disease Control

CPC .... Common Performance Condition

CREAM .... Cognitive Reliability and Error Analysis Method

EFC .... Error Forcing Context

EPC .... Error Producing Condition

HAI .... Healthcare Associated Infection

HEART .... Human Error Assessment and Reduction Technique

HFE .... Human Failure Event

HRA .... Human Reliability Analysis

PIF .... Performance Influencing Factor

PRA .... Probabilistic Risk Assessment

PSF .... Performance Shaping Factor

UA .... Unsafe Action

Chapter 1 - Introduction

Healthcare associated infections (HAIs) are a prevalent issue in the United States. Every day approximately one in twenty-five patients in the United States has an infection that was contracted while the patient was at the hospital (CDC, 2015). Examples of common HAIs include central line-associated bloodstream infections (CLASBI), surgical site infections (SSI), and catheter associated urinary tract infections (CAUTI). The rates of CLASBI and SSI decreased between 2009 and 2013; however, there was a six percent increase in the rates of CAUTI between the same years (CDC, 2015). This research focuses on incorporating human reliability analysis techniques and health factors that contribute to CAUTI to develop a tool to reduce the rates of CAUTI in the United States.

1.1 Human Reliability Analysis Techniques

HRA techniques are tools that quantify the probability of human error in a system in which humans are performing a task. Many HRA methods were developed by engineers and psychologists to gain an understanding of the complexity of human behavior (Konstandinidou, Nivolianitou, Kiranoudis, & Markatos, 2006). In addition to quantifying the probability of human error, some HRA techniques provide a clear method to identify the main factors that contribute to the probability of error. Once these factors are identified, actions are taken to eliminate or reduce the factors contributing to an elevated probability of human error.

The early stages of HRA techniques, first generation HRA techniques, are based on the idea that humans have inherent deficiencies that cause natural failures much like “mechanical, structural, and electrical components do” (Marseguerra, Zio, & Librizzi, 2007). First generation HRA techniques assign human error probabilities to the operators of specific types of tasks. The probabilities assigned to the task are based on extensive research of human failure events across multiple industries. Performance Shaping Factors (PSFs) or Performance Influencing Factors (PIFs) detail the environmental conditions in which the task is performed (Marseguerra, Zio, & Librizzi, 2007). However recent research shows that environmental conditions affect the reliability of an operator more than the task itself (Marseguerra, Zio, & Librizzi, 2007). First generation HRA techniques do not account for the environmental conditions of the task, and therefore do not accurately represent human failure events. This led to human factors experts creating second generation HRA techniques.

Second generation HRA techniques were created to overcome the deficiencies of the first generation techniques by modeling the relationship between the contextual conditions of the task and probability of human error (Marseguerra, Zio, & Librizzi, 2007). Second generation techniques focus on the environmental conditions of the operator while performing a task, and they provide qualitative and quantitative approaches for evaluating the probability of human error. Changes can be made to the context and environment of an operation, and second generation techniques provide a way to identify the factors that affect the reliability of the operator.

1.2 Catheter Associated Urinary Tract Infections

CAUTIs are an issue of concern in the United States because they occur frequently, and the rates of CAUTI are not improving. According to the CDC (2016), urinary tract infections occur more often than any other HAI in the United States. Urinary tract infections are defined as an "infection involving any part of the urinary system, including urethra, bladder, ureters, and kidney" (CDC, 2016). A CAUTI is a urinary tract infection that is caused by the placement of a urinary catheter, which is a "tube inserted into the bladder to drain urine" (CDC, 2016). The

CDC (2016) also reports that 75 percent of urinary tract infections acquired in a hospital setting are associated with a urinary catheter.

The CDC (2016) reports several reasons why a patient may require a urinary catheter, and they are listed next.

- Patient is unable to urinate independently
- Measurement of urine produced is required
- During and/or after some surgeries
- During some tests of the kidneys and bladder

Due to the prevalence of these reasons that require a urinary catheter, between 15 and 25 percent of all hospital patients in the United States will receive a urinary catheter at some point during their hospitalization (CDC, 2016). CAUTIs are caused by bacteria entering the urinary tract either during catheter insertion or while the catheter remains in the bladder. The bacteria that may cause an infection can come from outside the body if proper care is not taken upon catheter insertion or from bacteria that already exists in the intestines that would not normally cause an infection without the presence of a urinary catheter. CAUTIs are identified through a significant amount of bacteria found in a patient's urine and/or the following patient symptoms provided by the CDC (2016):

- Burning or pain in lower abdomen
- Fever
- Bloody urine
- Burning during urination
- Increase in frequency of urination after catheter removal

Methods for preventing CAUTIs vary between hospitals; however, best practices have been suggested by the CDC and other professionals in medical journals. The CDC (2016) suggests the following to prevent CAUTIs:

- Insert catheters only when necessary
- Remove catheters as soon as possible
- Catheter insertion should only be performed by trained persons a using sterile technique
- External catheters should be used for men when possible
- Consider using intermittent urethral catheterization when possible
- Perform proper handwashing techniques before and after inserting or cleaning catheter

Despite the recommendation of these techniques, CAUTI rates have not been significantly reduced in the United States. The most recent HAI progress report from the CDC (2016) found that there was no overall change in CAUTI between 2009 and 2014. The previous year there was a six percent increase in the rates of CAUTI (CDC, 2015).

1.3 Explanation of Chapters

This thesis addresses the opportunity to apply HRA techniques in the healthcare industry, specifically to reduce CAUTIs. It incorporates human factors engineering and medical knowledge to produce a tool capable of predicting a patient's risk of developing a CAUTI. The next chapter is a literature review of HRA techniques. It provides a detailed description of three HRA techniques and examples of their implementation. An example of their implementation in the healthcare industry is provided if such an example was available.

Chapter 3 is a comparison of the three selected HRA techniques for their use in the CAUTI reduction tool. Each technique was analyzed against three criteria: applicability catheter insertion, quantification methods, and availability of data required. Through this analysis the

CREAM method was selected as the HRA method to use in the CAUTI reduction tool because it is applicable to catheter insertions and has well-defined quantification methods that make it useful in a real-time application.

Chapter 4 provides the analysis and modeling behind the CAUTI reduction tool. Many sources were synthesized to acquire the health factors that affect the probability of a patient contracting CAUTI. These factors include gender, duration, diabetes, and if the patient is on antibiotics. These health factors were incorporated with the selected HRA technique, CREAM, using fuzzy logic to create a model that predicts a patient's probability of acquiring CAUTI once a catheter has been placed. Sensitivity analysis was performed on hypothetical patient cases to ensure that the model produced consistent, logical results. The first model based using a fuzzy rule based system did not produce sufficient results for the hypothetical patient cases; therefore, another model was developed using fuzzy associative memory tables. This model produced results that were consistent with the literature review of the health factors and their effect on a patient's risk of developing a CAUTI.

Chapter 5 contains a description of the CAUTI reduction tool, conclusions, and recommendations for future work. It is recommended that experts be consulted to gather information for the fuzzy associative memory tables to strengthen the fuzzy model. The CAUTI reduction tool should be implemented in a hospital unit to test its validity and effectiveness. Patient information about whether or not they developed a CAUTI should be compared to the results of the tool, and adjustments made if necessary.

Chapter 2 - Literature Review of HRA Techniques

Bell and Holroyd (2009) identified 72 HRA techniques and reviewed 35 techniques in detail in their paper, “Review of human reliability assessment methods”. 17 of these methods were recommended for use in industries with humans operating in high risk environments. I reviewed eight HRA methods, and researched three in detail because they are supported by journal articles of their successful implementation in multiple industries.

2.1 Human Error Assessment and Reduction Technique

HEART is a first generation HRA technique, and it was developed in 1985 by J.C. Williams to use in the nuclear industry. However, HEART was designed in a way that makes it applicable across multiple industries and it has since been applied in the medical, nuclear, and aviation industries. According to Chadwick and Fallon (2012), HEART is a “quick, easily-understood, systematic, repeatable, and responsive” HRA tool. HEART provides a structural system for identifying potential sources of human error and assigns nominal probabilities to these human errors. HEART also evaluates the impact of PSFs on the system being analyzed (Williams, 1985).

Williams (1985) described 38 EPCs that may affect operator performance. Each EPC is also assigned a “maximum predicted nominal amount by which unreliability might change from going to good conditions to bad” (Williams, 1985, p. 4). The EPC probabilities were calculated from data gathered from power generation, aviation, and fire safety industries (Chadwick & Fallon, 2012). The first six EPCs which have the highest unreliability probability are in Table 2-1 next, and a complete list of the 38 EPCs and assigned nominal probabilities is in Appendix A following this report.

Table 2-1. EPCs and associated nominal unreliability

Source: Adapted from (Williams, 1985)

No.	Error Producing Condition	Maximum predicted nominal amount by which unreliability might change from going to good conditions to bad
1.	Unfamiliarity with a situation which is potentially important but which only occurs infrequently or which is novel	x17
2.	A shortage of time available for error detection and correction	x11
3.	A low signal-noise ratio	x10
4.	A means of suppressing or over-riding information or features which is too easily accessible	x9
5.	No means of conveying spatial and functional information to operators in a form which they can readily assimilate	x8
6.	A mismatch between an operator's model of the world and that imagined by a designer	x8

HEART is a simple, versatile, and straightforward HRA technique that has been implemented across a wide variety of industries. According to Castiglia and Giardina, HEART is applicable for "human error evaluations in various safety studies relevant to complex systems" (2013).

2.2 Cognitive Reliability and Error Analysis Method

CREAM was developed by Erik Hollnagel in 1998. There are examples of the implementation of CREAM in the healthcare industry, marine engineering, and the rail industry. CREAM is characterized by the focus of the method on the contextual factors of the task on human performance and the ability to use the method retrospectively and prospectively (He, Wang, Shen, & Huang, 2008). CREAM can be used as a retrospective tool to analyze past human failure events and as a prospective tool to quantify the probability of human error.

2.2.1 Retrospective Analysis

The retrospective analysis of CREAM reviews past events to reveal the cognitive reasons that a human failure event occurred. The retrospective method outlined by Hollnagel (1998) is comprised of nine phenotypes, and three genotype categories. Phenotypes are actions caused by a set of genotypes. The phenotypes, genotype categories, and examples of specific genotypes are listed in Table 2-2.

Table 2-2. CREAM retrospective analysis components

Source: Adapted from (Phillips & Sagberg, 2014)

Phenotypes (actions)	Genotype (causes) categories
1. Timing 2. Duration 3. Force 4. Distance 5. Speed 6. Direction 7. Wrong Object 8. Sequence 9. Quality/Volume	1. Human factors - cognitive functions - temporary human functions - permanent human functions 2. Technical/Environmental factors - equipment - procedures - interface 3. Organizational factors - communication - organization - training - working conditions

The retrospective analysis begins by selecting a phenotype to describe the incorrect action of the operator. Next the genotypes defined by Hollnagel (1998) as reasonable causes for the selected phenotype are consulted and the best cause of the phenotype is selected. The selected genotype may also have possible antecedents that led to its occurrence. The genotype search continues until there are no genotypes that describe the current consequent. This search process generates a “chain of antecedents (genotypes) leading to the precipitating action (phenotype)” (Phillips & Sagberg, 2014, p. 94).

2.2.2 Prospective Analysis

The prospective analysis of CREAM is a method that assigns quantitative probabilities to identify high risk systems. This information is used to implement solutions to mitigate the high risk situation. Human performance reliability is split into the following four control modes: strategic, tactical, opportunistic, and scrambled. The control modes describe the level of control the operator has over the task. The control modes, as described by Fujita and Hollnagel (2004), are listed and described in Table 2-3. Each control mode is assigned a range of the probability of human failure. The scrambled control mode has the highest probability of human error, and the strategic control mode has the lowest (Marseguerra, Zio, & Librizzi, 2007). The control modes provide the user with a general idea of the level of reliability the operator has over the task; however, the probability of human error assigned to a task depends on the levels of the CPCs which are described in Table 2-3.

Table 2-3. Control mode descriptions and reliability intervals

Source: Adapted from (Fujita & Hollnagel, 2004)

Control Mode	Description	Reliability Interval
Strategic	Operator has little control over the situation and chooses the next action at random	$0.00005 < p < 0.01$
Tactical	Operator follows a known procedure or rule	$0.001 < p < 0.1$
Opportunistic	Operator chooses actions inefficiently	$0.01 < p < 0.5$
Scrambled	Actions are chosen after careful consideration of functional dependencies between task steps and the interaction between multiple goals	$0.1 < p < 1.0$

There are nine CPCs identified by CREAM, and each one describes a specific contextual area. Linguistic terms describe the CPCs and identify whether the CPCs improve, reduce, or maintain the performance of the task (Marseguerra, Zio, & Librizzi, 2006). An analyst decides which linguistic term best describes each CPC for the task. Table 2-4 lists the nine CPCs and the linguistic terms that describe each one.

Table 2-4. Description of CPCs and associated linguistic terms

Source: Adapted from (Ung, 2015)

No.	CPC	CPC Levels
1.	Adequacy of organization	Deficient, Inefficient, Efficient, Very Efficient
2.	Working conditions	Incompatible, Compatible, Advantageous
3.	Adequacy of man machine interface and support	Inappropriate, Tolerable, Adequate, Supportive
4.	Availability of procedures/plans	Inappropriate, Acceptable, Appropriate
5.	Number of simultaneous goals	More than actual capacity, Matching current capacity, Fewer than actual capacity
6.	Available time	Continuously inadequate, Temporarily inadequate, Adequate
7.	Time of day	Night, Day
8.	Adequacy of training and experience	Inadequate, Adequate with limited experience, Adequate with high experience
9.	Crew collaboration quality	Deficient, Inefficient, Efficient, Very Efficient

Once the linguistic terms are selected, they are used in a quantification method to assign a value to the probability of human error. There are several methods that allow the analyst to accomplish this task. A simplified method to quantify the human failure probability is described by He, Wang, Shen, and Huang (2008). Several journal articles provide a fuzzy modeling approach to quantify human error. Ung (2015) developed a method that allows human error probability to be quantified for tasks that have little historical data. The analyst should choose a quantification technique that fits the task and the amount of data available concerning the task.

2.3 A Technique for Human Error Analysis

ATHEANA was developed by the U.S. Nuclear Regulatory Commission to improve the evaluation of human behavior in relation to accidents that occur in the nuclear industry (Forester, et al., 2004). ATHEANA has a retrospective and prospective analysis; therefore it is used to identify the cause of previous human failure events as well as quantifying the likelihood that a human failure will occur.

There are several characteristics of ATHEANA that are common to both the retrospective and prospective analyses. The common characteristics include HFEs, UAs, EFCs, and PSFs. HFEs are the effects an operator's action has on the surrounding system, and UAs are the specific actions an operator takes that lead to an HFE. An unsafe action does not always lead to a HFE, but it does increase the likelihood of one occurring (Barriere, et al., 2000). EFCs are the conditions that set up the situation for UAs and possibly EFCs to occur. Finally, PSFs describe the conditions in which the task is being performed and the operator is working. There are 16 PSFs described by Barriere et al. (2000), and they are listed in Table 2-5 along with the organizational factors of each PSF.

Table 2-5. Classification of PSFs in ATHEANA

Source: Adapted from (Alvarenga, Frutuoso e Melo, and Fonseca, 2014)

Performance Shaping Factors	Characteristics and Factors
1. Quality of training/experience	Organizational factors: Possible failure in quality assurance. Important: within that factor is another factor, the latent factor, which hides the problem.
2. Quality of procedures/administrative controls	Organizational factors: Possible failure in quality assurance. Important: within that factor is another factor, the latent factor, which hides the problem.
3. Availability and clarity of instrumentation	Man-Machine interface design features

4. Time available and time required to complete the act including the impact of concurrent activities	Cognitive characteristics
5. Complexity of the required diagnosis and response	Cognitive characteristics
6. Workload/time pressure/stress	Cognitive characteristics
7. Crew dynamics and characteristics (e.g., degree of independence among individuals, operator biases/ rules)	Group interaction factors
8. Use of status checks, level of aggressiveness in implementing the procedures	Group interaction factors
9. Available staffing/resources	Organizational factors: Possible failure in quality assurance. Important: within that factor is another factor, the latent factor, which hides the problem.
10. Ergonomic quality of the human-system interface	Design ergonomics factors
11. Environmental factors	Design ergonomics factors
12. Accessibility and operability of the equipment to be manipulated	Design ergonomics factors
13. The need for special tools (e.g., keys, ladder, hoses, clothing)	Design ergonomics factors
14. Communications (strategy and coordination) and whether one can be easily heard	Design ergonomics factors or group interaction factors
15. Special fitness needs	Cognitive characteristics
16. Accident sequence diversions/deviations (e.g., extraneous alarms, outside discussions)	Special characteristics

2.3.1 Retrospective Analysis

The retrospective analysis of ATHEANA was created to identify the cause of human failure events so changes can be made to prevent them from occurring again. The ATHEANA retrospective technique is broad enough to be applied to industries other than the nuclear industry, for which it was initially created (Barriere, et al., 2000). There are four simple steps to the retrospective analysis, described by Barriere, et al. (2000), and they are listed next.

1. Identify the undesired event.
2. Identify the functional failures, the HFEs, and the UAs

3. Identify the causes of the UAs, including plant conditions and PSFs
4. Document the results

2.3.2 Prospective Analysis

The goal of the prospective analysis is to quantify the probability that a human failure event will occur in the situation being analyzed. In the prospective analysis HFEs are modeled in a PRA and represent a "failure of function, system, or component as a result of unsafe human actions" (Barriere, et al., 2000). The HFEs are classified as either errors of commission or errors of omission. Errors of commission represent an operator's incorrect response to an event, and errors of omission represent an operator's failure to respond to an event when a response was necessary. The ten steps given by Barriere et al. (2000) for the prospective analysis are listed next.

1. Define and interpret the issue
2. Define the scope of the analysis
3. Describe the base case scenario
4. Define HFE(s) and/or UAs
5. Identify potential vulnerabilities in the operators' knowledge base
6. Search for deviations from the base case scenario
7. Identify and evaluate complicating factors and links to PSFs
8. Evaluate the potential for recovery
9. Quantify the HFE probability
10. Incorporate the HFE into the PRA

The ATHEANA prospective analysis provides the user with specific plant conditions and environmental factors that have the potential to create an environment that will lead to an operator making an unsafe action. ATHEANA provides the option to quantify the probability of human error and takes into account the organizational factors affecting the situation (Alvarenga, Frutuoso e Melo, & Fonseca, 2014).

2.4 Examples of HRA Technique Implementation

Most HRA techniques were originally designed for use in the nuclear industry; however, a limited number of examples exist in which the technique was implemented in the healthcare industry. This section provides examples of the implementation of each HRA technique including an example from the healthcare industry, if one exists.

2.4.1 HEART

HEART was implemented in the healthcare industry by Chadwick and Fallon (2011) to analyze a data entry task in a radiotherapy system. The data entry task involved nurses manually interpreting patient blood results and entering the data into an electronic medical record system. Nurses that performed this data entry task made up the task evaluation committee instead of relying on a human factor expert. The nurses on the committee selected the nominal human unreliability category, the EPCs, and the assessed proportion of effect for each EPC. The researchers acted as facilitators of the group discussion and performed the necessary calculations. The nurses selected the general nominal human unreliability category described by Williams (1985). They also selected the following EPCs from Williams (1985):

- A shortage of time available for error detection and correction
- No obvious means of reversing an unintended action Poor/ambiguous system feedback
- Little or no independent checking or testing of output
- Task pacing caused by the intervention of others

The researchers made recommendations to improve this task based on the information about the EPCs that the nurses provided, and they concluded that nurses should be provided a space to perform this task without the opportunity for interruptions (Chadwick & Fallon, 2011).

Chadwick and Fallon (2011) also stated that HEART was simple and easy for the nurses to understand.

HEART has been used to identify major EPCs for medical devices in intensive care units (ICU) (Drews, Musters, & Samore, 2007). The following eight EPCs were identified that relate to devices used in an ICU:

1. Unfamiliarity with a situation
2. Time pressure in error detection
3. Low signal-to-noise ratio
4. Mismatch between an operator's mental model and that imagined by the device designer
5. Impoverished information quality
6. Ambiguity in performance standards
7. Disruption in normal work-sleep cycles
8. Unreliable instrumentation

Drews, Musters, & Samore (2008) performed a study that used a questionnaire that was answered by 25 nurses that worked in an ICU. The questionnaire resulted in the following EPCs as being ranked of high importance: low signal to noise ratio, unreliable instrumentation, operator-designer mismatch, and shortage of time (Drews, Musters, & Samore, 2007). Individual ANOVA analyses were performed on each of the eight EPCs with device criticality (high, moderate, and low) as a factor to the analysis (Drews, Musters, & Samore, 2007). The analysis resulted in the determination that as a device becomes less critical, the unfamiliarity with the device becomes less of a factor. It was also determined that the shortage of time should have a "significantly greater negative impact on the risk of errors when nurses are using highly critical devices compared with devices that are moderate or low in criticality" (Drews, Musters, & Samore, 2007). This study is yet another example of the use of nurses to perform an HRA instead of relying solely on an expert in the field, although it is suggested that independent observers still validate the results gathered from the nurses.

An example in a journal article utilized the HEART method to determine the probability of human error in the pre and post maintenance for condensate pumps (Noroozi, Khan, MacKinnon, Amyotte, & Deacon, 2014). The authors began by describing each scenario and the characteristics of the workers performing the activities. The main activities were further broken into sub-activities in order to further identify areas for human error. A human error probability (HEP) calculation was performed for each sub-activity. A generic task and the associated nominal unreliability were identified for the sub-activities from the list provided in the HEART methodology by Williams. Next the EPCs and the maximum predicted nominal amounts were selected, based on the scenario (Noroozi, Khan, MacKinnon, Amyotte, & Deacon, 2014). When an EPC was selected, a proportionate weight factor was applied to the calculation. Through their analysis, Noroozi, Khan, MacKinnon, Amyotte, and Deacon (2014), found that poor information quality was the "most important factor contributing to errors" (p.135). The HEPs for all of the sub-activities were listed, and next the tasks with high probability for error and high consequences (injury and death) were determined using a risk matrix. Two particular activities were chosen that had ranked high in both HEP and consequences and were both due to a shortage of time to complete the activity and operator unfamiliarity with the procedure. These activities were further researched to determine remedial measures that could reduce the probability of a human error (Noroozi, Khan, MacKinnon, Amyotte, & Deacon, 2014).

2.4.2 CREAM

Deeter (2012) used CREAM retrospectively to analyze medical errors that had previously been analyzed using Root Cause Analysis (RCA). The retrospective CREAM analysis was performed on 58 cases that had been analyzed originally using RCA. These events all occurred at the same hospital within a six year time period. According to Deeter (2012), the frequency of events caused by human error did not decrease and the same type of events occurred more than once even with the use of the RCA technique. The reoccurrence of events suggests that the RCA analysis did not successfully identify the cause of the event or that the cause may not have been successfully managed by the hospital staff (Deeter, 2012). By comparing the results from the RCA analysis to the results of the CREAM method, Deeter (2012) found that the RCA technique may not be capable of identifying all of the factors that cause a human error in the medical field. The CREAM technique considered the context of the errors, and several CPCs were identified as reducing the reliability of performance. The majority of errors were caused by organization factors (communication, training, working conditions, etc.) issues. The CREAM analysis of the 58 cases resulted in 80 error modes, 80% of which were identified as Action in Wrong Place and Action at Wrong Time (Deeter, 2012). Deeter (2012) suggested that if CREAM was used in conjunction with RCA, it might be possible to "provide healthcare workers with more insight into why the events occurred in an effort to reduce the risk of them happening again in the future" (p. 36). Deeter made the following recommendations for further use of the CREAM method in the healthcare industry

- Include all staff levels in the analysis
- Attempt to reduce the feeling of authority between upper management and other participants
- Examine recurrent events as one instead of separate events

These recommendations could prove useful in further analysis of human reliability errors in the healthcare industry.

CREAM was implemented by Phillips and Sagberg (2014) in the rail industry to analyze hazardous signal approach incidents. The study aimed to test the ability of CREAM to expose the "limitations in the system of human and organizational factors" surrounding signal approach incidents (Phillips & Sagberg, 2014, p. 97). The researchers surveyed 115 train drivers to gather information about train signal approach incidents that the drivers had personally been involved with. Next they used CREAM based interview questions to get in-depth information from 16 train drivers about the train signal approach incidents they experienced. The researchers concluded that three common antecedent chains led to all 16 hazardous signal approach events (Phillips & Sagberg, 2014). CREAM was successfully implemented in the rail industry, and Phillips and Sagberg (2014) suggested that CREAM be further developed for use in this industry.

2.4.3 ATHEANA

ATHEANA was used retrospectively by Barriere, et al. (2000) to analyze the response to the failure of a pressurizer spray valve in a pressurized water reactor nuclear power plant. This situation deviated from normal plant conditions because the spray valve did not give a correct reading. The researchers created a timeline of the events following the failure of the spray valve, and they used this timeline to identify three UAs of the operators of the plant. Next the researchers described the plant conditions and corresponding PSFs for each UA. Two PSFs that the researchers identified for all three of the UAs were training and supervision (Barriere, et al., 2000). This example did not provide a recommendation for plant improvements, but the plant management can use the information about the PSFs to make improvements on the training of personnel and supervisors.

Chapter 3 - HRA Technique Comparison

To select the best HRA technique to apply in the healthcare industry and reduce CAUTI a comparison between the methods is required. Chapter 3 compares the methods against the following criteria: applicability catheter insertion, quantification methods, and availability of data required.

3.1 Applicability to Catheter Insertions

HRA techniques are not created equal in their ability to be applied across industries and tasks. This section analyzes each HRA technique, and its ability to be applied to the task of inserting a catheter. This is an important step in the comparison process because techniques that are not well-suited to describe the environmental factors of a catheter insertion will not be useful in the CAUTI reduction tool.

3.1.1 HEART

HEART was developed specifically to apply across multiple industries, and it has previously been applied in the healthcare industry (Bell & Holroyd, 2009). The framework for HEART includes 38 EPCs that encompass a wide range of situational conditions. Not all of the EPCs apply to a catheter insertion; however, the EPCs that do not apply are simply excluded in the final human error probability calculation. Each EPC is evaluated for the task being analyzed, and an analyst decides if the EPC applies to the task. Table 3-1 provides a list of potential applicable EPCs to a catheter insertion. HEART is applicable in the healthcare industry, but its framework is limited in its ability to describe all aspects of the environmental factors that affect human factor incidents in a catheter insertion.

Table 3-1. Applicable EPCs to Catheter Insertion

Source: Adapted from (Williams, 1985)

No.	Error Producing Condition	Maximum predicted nominal amount by which unreliability might change from going to good conditions to bad
1.	A shortage of time available for error detection and correction	x11
2.	No obvious means of reversing an unintended action	x8
3.	Ambiguity in the required performance standards	x5
4.	Operator inexperience (e.g. a newly- qualified tradesman, but not an "expert")	x3
5.	A conflict between immediate and long-term objectives	x2.5
6.	No diversity of information input for veracity checks	x2.5
7.	A mismatch between the educational achievement level of an individual and the requirements of the task	x2
8.	Little opportunity to exercise mind and body outside the immediate confines of a job	x1.8
9.	A need for absolute judgments which are beyond the capabilities or experience of an operator	x1.6
10.	Unclear allocation of function responsibility	x1.6
11.	Little or no intrinsic meaning in a task	x1.4
12.	High-level emotional stress	x1.3
13.	Evidence of ill-health amongst operatives, especially fever	x1.2
14.	Low workforce morale	x1.2
15.	Inconsistency of meaning of displays and procedures	x1.2
16.	A poor or hostile environment (below 75% of health or life-threatening severity)	x1.15
17.	Prolonged inactivity or highly repetitious cycling of low mental workload tasks	x1.1 for first half hour x1.05 for each hour thereafter
18.	Disruption of normal work-sleep cycles	x1.1
19.	Task pacing caused by the intervention of others	x1.06
20.	Additional team members over and above those necessary to perform task normally and satisfactorily	x1.03 per additional man
21.	Age of personnel performing perceptual tasks	x1.02

3.1.2 CREAM

CREAM is a versatile HRA method because the contextual factors that describe the task are generalized and it includes a retrospective and prospective analysis description. According to

Bell and Holroyd (2009), CREAM is a suitable HRA method for many different industry sectors because the framework is generic. The CPCs that describe the contextual factors of a task are listed in Table 3-2, and I have provided a single example for each CPC that is relevant to catheter insertions. For example, CPC No. 8, adequacy of training and experience, applies to the level of training and experience the nurse has in inserting catheters. This is not a comprehensive list of all the factors applicable to a catheter insertion, simply an example illustrating the applicability of each CPC to catheter insertions.

Table 3-2. Applicability of CPCs to Catheter Insertions

Source: Adapted from (Ung, 2015)

No.	CPC	Application to Catheter Insertion
1.	Adequacy of organization	Nurse participation in hospital affairs
2.	Working conditions	Distractions to nurse from patient or patient family members
3.	Adequacy of man machine interface and support	Nurse participation in design of catheter insertion kits
4.	Availability of procedures/plans	Standard operating procedures written and available for catheter insertion
5.	Number of simultaneous goals	Number of patients nurse is caring for concurrently
6.	Available time	Adequacy of nurse staffing levels
7.	Time of day	Level of nurse adjustment to the time of day of the shift
8.	Adequacy of training and experience	Level of training/experience the nurse has in inserting a catheter
9.	Crew collaboration quality	Communication quality between nurses and physicians or nurse managers

3.1.3 ATHEANA

ATHEANA was developed specifically for the nuclear industry, but the search process for EFCs, UAs, and PSFs is general enough for use in other industries (Bell & Holroyd, 2009). Table 3-3 lists the PSFs that have potential to describe a catheter insertion and an example of how the PSF relates catheter insertions. Table 3-3 is not a complete list of PSFs related to catheter insertions; it is simply a way to illustrate the applicability of ATHEANA to catheter insertions. For example, if the nurse is caring for more than their usual allotted number of patients, this will impact PSF number four. If the nurse is pressured to complete a catheter insertion quickly due to other activities that require their attention, they are more likely to make an UA such as forgetting to wash their hands or not wearing the proper sanitary equipment. These UAs have the potential to lead to the introduction of bacteria into the patient's system and cause a CAUTI.

Table 3-3. Applicability of PSFs to Catheter Insertions

Source: Adapted from (Alvarenga, Frutuoso e Melo, and Fonseca, 2014)

Performance Shaping Factors	Application to Catheter Insertion
1. Quality of training/experience	Level of training/experience the nurse has with catheter insertions
2. Quality of procedures/administrative controls	Standard operating procedures written and available for catheter insertion
3. Availability and clarity of instrumentation	Availability and clarity of catheter tool kit
4. Time available and time required to complete the act including the impact of concurrent activities	Adequate time allotted to perform catheter insertion
5. Complexity of the required diagnosis and response	Complexity of decision to insert catheter
6. Workload/time pressure/stress	Pressure from supervisors or other nurses to complete task
7. Crew dynamics and characteristics (e.g., degree of independence among individuals, operator biases/ rules)	Level of effectiveness of shift transition in regards to catheter awareness
9. Available staffing/resources	Nurse to patient ratio
10. Ergonomic quality of the human-system interface	Ergonomic quality of catheter insertion tool kit
11. Environmental factors	Noise level, distractions from patient or patient family members
13. The need for special tools (e.g., keys, ladder, hoses, clothing)	Need for gloves, catheter insertion kit, etc.
14. Communications (strategy and	Communication quality nurse and

coordination) and whether one can be easily heard	physician or nurse manager

3.2 Quantification Methods

One of the main features of HRA techniques is quantifying the probability of human error. A different quantification method exists for each HRA technique, and they are discussed in detail next.

3.2.1 HEART

The quantification process for HEART is described by Williams (1985), and involves three steps which are described next. The process is simple, but requires a great deal of input from a human factors expert or an expert in the field which the analysis is being performed.

Step 1: Identify EPCs

An analyst decides if any of the 38 EPCs listed in Williams (1985) exist, and if they do exist the analyst places the task into one of the following categories:

- Impaired system knowledge
- Response time shortage
- Poor/ambiguous system feedback

A complete list of the EPCs and their associate nominal unreliability is located in Appendix A.

Step 2: Identify nominal unreliability of the task

An analyst consults a list of nine generic tasks and their descriptions given by Williams (1985) and chooses the task that best matches the task being analyzed. Each task was assigned a nominal range of human unreliability by Williams (1985). The first three task descriptions with the highest nominal range of human unreliability is provided next in Table3-4, and a complete list of the nine tasks is located in Appendix A.

Table 3-4. Generic task descriptions and associated human unreliability

Source: Adapted from (Williams, 1985)

Generic Task	Proposed Nominal Human Unreliability	5^{th}-95^{th} Percentile Bound
Totally unfamiliar , performed at speed with no real idea of likely consequences	0.55	0.35-0.97
Shift or restore system to a new or original state on a single attempt without supervision or procedures	0.26	0.14-0.42
Complex task requiring high level of comprehension and skill	0.16	0.12-0.28

Step 3: Calculate effect of the EPCs

An analyst, team of analysts, or a human factors expert decides the proportion that each EPC might exist in the system under analysis. Next the basic task unreliability, found in Step 2, is multiplied by the proportions of EPCs. The result of this calculation provides the effect that the EPCs have on the system.

Step 4: Calculate the nominal likelihood of failure

To reach the assessed nominal likelihood of failure, the nominal human unreliability found in step two is multiplied by the assessed proportion of affect found in step three. The probability of failure gives the analyst a reference point for the risk of a system failure due to human error.

3.2.2 CREAM

There are a wide variety of quantification methods for CREAM. One of the most commonly used methods is based on the assessment of the CPCs and whether each improves or reduces the reliability of the operator. The other method discussed in this section is using fuzzy analysis to quantify the probability of human error. Both methods were validated and implemented by the respective authors.

Simplified Quantification Method

He et al. (2007) developed a simplified quantification method to determine the probability of human error using CREAM. The CPCs are used to identify if they either reduce or improve the environment of the operator, which is done through the initial event analysis. The context influence index (CII), is equal to the number of the reduced CPCs minus the number of improved CPCs. The context influence index identifies the control mode the human is operating within. The relations between the CII and the control mode are represented in Table 3-5.

Table 3-5. Relation between CII and control mode

Context Influence Index	Control Mode
-7 to -4	Strategic
-3 to 1	Tactic
2 to 5	Opportunistic
6 to 9	Scrambled

The authors found the value for the initial cognitive failure probability CFP_0, to be equal to 0.0056. This value is based on the minimum and maximum value of CII, and is used in the final formula for the overall cognitive failure probability of the event. This formula can be found in Figure 3-1 where β represents CII, the calculated context influence index (He et al., 2007).

$$CFP = 0.0056 * 10^{0.25*\beta}$$

Figure 3-1.Cognitive failure probability formula for CREAM analysis

This method was tested by the authors and was compared to other second generation human reliability analysis methods. The authors found that this quantification technique of CREAM produces “reasonable results” (He et al. 2007, p. 306). The use of common performance conditions allows for the context of the environment to be a factor when determining the cognitive failure probability.

Fuzzy Analysis Quantification Method

Another CREAM quantification method has been introduced that allows industries with little or no data concerning human failure statistics to implement the CREAM method. This methodology utilizes fuzzy logic, weighted CPC values, and takes into account the relationship between the CPCs and COCOM. The model has been validated by performing a retrospective analysis of an oil tanker example.

The proposed method starts by determining the number of input variables, which are the CPCs. “CPCs are described by a set of pre-defined linguistic descriptors to provide a concise description of how human performance is affected by the context” (Ung, 2015, p. 145). An analyst chooses the number of linguistic terms which leads to the construction of membership functions. According to Ung (2015), several different membership functions are available for fuzzy modeling, but an appropriate membership function should be selected by using the data and information available in relation to the event being analyzed.

Fuzzy logic is used to appropriately quantify the linguistic terms of the CPCs. A fuzzy rule base has two parts, an antecedent and a consequent. The antecedent is comprised of the fuzzy set describing the CPCs, and the consequent of the fuzzy rule can denote the four control modes (Ung, 2015). This method allows for each of the inputs (CPCs) to be weighted according to the influence on the situation being analyzed. The next step according to Ung is to synthesize the consequents of each fuzzy rule by applying the Weighted Membership method. Finally, the fuzzy conclusions can be turned into crisp values by applying one of several defuzzification methods. Ung recommends using the Center of Area (COA) method because it is relatively accurate compared to other methods. The COA method finds the “center of area of the combined membership functions” (Ung, 2015, p. 147). The crisp values are then used to calculate the human failure probability of the task (Ung, 2015). The method proposed by Ung was validated with two axioms, and was used to find the human failure probability of an oil tanker. The author, Ung (2015), also commented on the potential to apply this method to other industries besides the maritime industry.

3.2.3 ATHEANA

The quantification process for ATHEANA involves three steps: determining the probability of the EFCs, the probability of the UA, and the probability of not recovering from the UA (Barriere, et al., 2000). This requires a detailed analysis of the plant and its operators.

EFCs consist of plans conditions and PSFs, and both contribute to the probability of an EFC occurring. Analysts gather plant specific information such as failure probabilities for equipment and instrumentation and the unavailability of equipment. The probabilities are determined through statistical analysis, engineering calculations, or expert opinion (Barriere, et al., 2000). Plant operators should be consulted about the probability of PSFs, and analysts decide whether the conditions of the plant make the PSFs more likely.

The likelihood of UAs are determined by the plant conditions and EFCs. The following three situations describe the likelihood of an UA: the EFC is so strong that an unsafe action is almost certain, the EFC is so weak that there is no increased likelihood of an unsafe action, and situations that fall in between these two extremes (Barriere, et al., 2000). The experience and expertise of operators makes their opinion preferable to determining the probability of UAs, however there are other methods to do so. Barriere et al. (2000) proposed using the PSFs from HEART to determine the probability of UAs (2000).

There is no formula for quantifying the probability of not recovering from the UA. This process requires the analyst to use judgment based on their knowledge of the previous steps in the quantification process. The analyst should take into account items that may prevent the UA from causing a failure event. Examples of these items include “alarms or other indicators, other crew members questioning the on-going response, and potential for consequential changes in the plant leading to new alarms” (Barriere, et al., 2000).

3.3 Availability of Data Required to Perform Analysis

The quantification methods for each of the HRA techniques require different data inputs to reach a probability of human error. This section discusses the data requirements and availability for each HRA method.

3.3.1 HEART

HEART requires a detailed analysis of a task to gather information about the EPCs that affect performance of the task operator. There are 38 EPC categories described by Williams (1985), and each is assigned a number by which unreliability might change. The nominal assignments are based on research of human factor incidents conducted in several different industries. A list of the 38 EPCs and the nominal probabilities is located in Appendix A. Unique probabilities can be created for the EPCs by using historical data gathered from past incidents caused by human error; this would tailor the HEART method to the healthcare industry.

An issue with using the HEART method in regards to catheter insertions is that it is difficult, if not impossible, to trace cases of CAUTI caused by human error. Even if a hospital has a well- organized system for tracking human factor incidents, it is unlikely that any specific incidents regarding CAUTI will be available because it is impossible to determine if the bacteria that caused the infection was introduced by a human error or already in the patient’s system.

Since historical data is most likely unavailable or not relevant to catheter insertions, data about each new catheter insertion could be obtained and analyzed. However, the HEART method was not designed to provide human error probability calculations in real-time because the method relies on expert opinion to determine the EPCs that affected the situation.

3.3.2 CREAM

The first input required for the prospective analysis of CREAM is a detailed analysis of the task and the task environment to determine CPC levels (Bedford, Bayley, & Revie, 2013). An expert or a group of experts in the healthcare industry can provide this analysis or nurses can provide this information through a survey. A benefit to gathering the information about CPC levels from a survey of nurses is the removal of a single expert's opinion. There is also value in gathering information about the task environment from the nurses that work in the environment on a daily basis. Phillips and Sagberg (2014) surveyed train operators to gather information for the implementation of CREAM to improve rail safety, and gathered enough information to complete their analysis.

Many hospitals already implement work environment surveys of the nurses, and this information could be used as a starting point for determining CPC levels at that particular hospital. If the surveys are administered yearly, the new work environment information could be updated easily in the CAUTI reduction tool. CREAM also has quantification methods that allow for the CPC levels to be updated in real-time. The simplified quantification method proposed by He et al., (2007) could allow for the nurse that performed the catheter insertion to select the levels of CPCs from that specific catheter insertion. This information would be used to calculate the probability of human error specifically for that patient's catheter insertion.

The second data requirement for the implementation of CREAM is the decision about the weight of each CPC on the final human failure probability. The weight of each CPC is usually assigned by an expert in the field of the task or a human factors expert. The weighting of the CPCs for a catheter insertion could be determined by a team of healthcare professionals familiar with catheter insertions.

3.3.3 ATHEANA

The first requirement to perform the prospective ATHEANA analysis is a detailed description of the task. Experts use this description to evaluate and assign probabilities to UAs, EFCs, and HFEs. These decisions are the inputs to a probabilistic risk assessment (PRA) which provides a probability of human error for the task being analyzed. ATHEANA relies heavily on an expert's opinion; therefore, Forester et al. (2004) created a method to implement ATHEANA that incorporates viewpoints from "trainers, operations staff, and human reliability analysis experts". This group approach alleviates the need to rely completely on a single expert's opinion. The approach modeled by Forester et al. (2004) also generates information about the probability of UAs and EFCs. These probabilities can be used in a PRA to quantify the probability that a human failure event will occur. The data for the ATHEANA quantification method is acquired through expert opinion, and is not suited for a real-time application.

3.4 Summary of HRA Techniques

After comparing HEART, CREAM, and ATHEANA within applicability to catheter insertions, quantification methods, and data requirements, I recommend using CREAM as the HRA method in the CAUTI reduction tool. HEART is a first generation method, and therefore does not represent contextual and environmental factors well within the model. As second generation techniques, CREAM and ATHEANA are better equipped to represent these important aspects of the probability of error in human performance. Both CREAM and ATHEANA have the potential to be successfully applied in the CAUTI reduction tool; however, CREAM has well-defined quantification methods that are able to be applied in real-time. ATHEANA does not have a well-defined quantification method, and it relies heavily on expert opinion. These factors led to my recommendation of the CREAM method for the CAUTI reduction tool. Key results from the research and comparison of the three HRA techniques are summarized in Table 3-6.

Table 3-6. Summary of HRA Technique Comparison

	CREAM	ATHEANA	HEART
Applicability to Catheter Insertions	CPCs describe catheter insertions well.	PSFs describe catheter insertions well.	EPCs are limited in their ability to describe catheter insertions.
Quantification Methods	Well-defined quantification methods exist.	Quantification methods are not well-defined.	A simple quantification method exists.
Availability of Data Required	Work environment surveys for nurses already exist and are implemented at some hospitals. These surveys along with real-time information gathered from nurses would provide necessary data.	A group of healthcare professionals familiar with catheter insertions would be required to gather necessary data.	Healthcare records tracking human failure events in regards to CAUTI are unavailable; therefore, expert opinion is required.

Chapter 4 – CAUTI Reduction Tool Modeling

The development of the CAUTI reduction tool required researching health factors that affect the likelihood of developing a CAUTI, building membership functions and a rule base for the fuzzy analysis of the probability of developing CAUTI, and developing a program in R to perform the fuzzy analysis. These steps are discussed in detail in this chapter.

4.1 Health Factors

A literature review was performed to identify the health factors that affect a patient's risk of developing CAUTI. Most papers used in this analysis were health studies that recorded patient data and whether or not the patient developed a CAUTI after a catheter insertion. This information was then used to develop an odds ratio or relative risk of a patient with the specific health factor for developing a CAUTI. The four health factors that were cited most often in medical research and found to affect the likelihood of developing a CAUTI were gender, duration of catheterization, systemic antibiotic, and diabetes (Platt, Polk, Murdock, & Rosner, 1986), (Maki & Tambyah, 2001), and (Graves, et al., 2007). These four health factors are discussed next.

4.1.1 Gender

Gender was the most commonly referenced factor said to affect the risk of developing a CAUTI. The literature review of health factors resulted in eight different papers that all concluded that females have a higher risk of developing a CAUTI than males; however, these separate studies provide differing results for the increase in risk for females over males. A complete list of the papers referencing gender as a factor affecting the risk of developing a CAUTI is located in Appendix B.

A comprehensive study of health factors to determine each factor's effect on the risk of developing a CAUTI was performed by Platt, Polk, Murdock, and Rosner (1986). The data for this study was collected from 2,223 adult patients over the span of almost two years. A patient's demographic information was collected the day after a catheter was inserted, and urine samples were obtained daily for culture. Stepwise logistic regression was used to analyze the data and determine the factors that affected the outcome of developing a CAUTI. The study and statistical analysis concluded that the odds ratio for females developing a CAUTI over males is 2.5 (Platt, Polk, Murdock, & Rosner, 1986). Females have a shorter urethra than males which is likely the cause for the increased risk of females developing a CAUTI. According to Platt, Polk, Murdock, and Rosner (1986), "the increased risk among women was probably a consequence of easier access of the perineal flora to the bladder along the outside of the catheter" (p. 979).

Results for the odds ratio or relative risk of developing a CAUTI were similar, but different depending on the study. Table 4-1 is a compilation of the results for odds ratio or relative risk of gender, depending on how the results were reported in the given paper.

Table 4-1. Risk Levels for Female Gender

Study Citation	Odds Ratio for Females	Relative Risk for Females
(Platt, Polk, Murdock, & Rosner, 1986)	2.5	
(Johnson, Roberts, Olsen, Moyer, & Stamm, 1990)		2.0
(Maki &Tambyah, 2001)		2.5 - 3.7
(Crouzet, et al., 2007)	2.54-2.96 (after 4 days)	
(Graves, et al., 2007)	2.27	

4.1.2 Duration of Catheterization

The next major health factor identified as affecting the risk of developing a CAUTI is the duration of catheterization. The likelihood of microbes entering the bladder around the catheter increases the longer the catheter is in place (Platt, Polk, Murdock, & Rosner, 1986). The literature review of health factors resulted in six different papers that all concluded that the longer the catheter is in place the risk of the patient developing a CAUTI increases; however, the number of days that increases the risk and how much the risk increases is dissimilar between the papers. A complete list of the papers referencing duration of catheterization as a factor affecting the risk of developing a CAUTI is located in Appendix B.

The study conducted by Platt, Polk, Murdock, and Rosner (1986) divided the duration into four sections: one day, two to three days, four to five days, and six days and greater. The odds ratio was given for the one day category: 22.4 and the four to five day category: 2.3 (Platt, Polk, Murdock, & Rosner, 1986). The odds ratio is higher for the one day category because it is comparing the odds of developing a urinary catheter infection after having a catheter for one day versus not having a catheter at all. Table 4-2 is a compilation of the results for odds ratio or relative risk of duration of catheterization, depending on how the results were reported in the given paper.

Table 4-2. Risk Levels for Duration of Catheterization

Study Citation	Odds Ratio	Relative Risk
(Platt, Polk, Murdock, & Rosner, 1986)	22.4 (1 day) 2.3 (4-5 days)	
(Johnson, Roberts, Olsen, Moyer, & Stamm, 1990)		2.1 (7 days)
(Maki &Tambyah, 2001)		2.5 - 3.7 (6 days)
(Crouzet, et al., 2007)	2.54-2.96 (after 4 days)	
(Graves, et al., 2007)	5.28 (4-5 days)	

4.1.3 Systemic Antibiotic

The next health factor identified as affecting the risk of developing a CAUTI is the use of systemic antibiotics, which affect a patient’s entire system. The literature review of health factors resulted in six different papers that all concluded that the use of systemic antibiotics reduces the risk of a patient developing a CAUTI. A complete list of the papers referencing use of systemic antibiotic as a factor affecting the risk of developing a CAUTI is located in Appendix B. The patient could be administered a systemic antibiotic for another infection, and this would affect the risk of developing a CAUTI. Platt, Polk, Murdock, and Rosner (1986) analyzed the odds ratio between patients that were administered an antibiotic the week before a catheter insertion and patients that did not receive an antibiotic. They concluded that the patients that did receive an antibiotic had an odds ratio of 0.9 compared to those that did not receive an antibiotic (Platt, Polk, Murdock, & Rosner, 1986). Table 4-3 is a compilation of the results for odds ratio or relative risk for systemic antibiotic, depending on how the results were reported in the given paper.

Table 4-3. Risk Levels for Systemic Antibiotic

Study Citation	Odds Ratio - Antibiotic used	Relative Risk - Antibiotic used
(Platt, Polk, Murdock, & Rosner, 1986)	0.9	
(Johnson, Roberts, Olsen, Moyer, & Stamm, 1990)		0.3
(Maki &Tambyah, 2001)		0.1 - 0.4
(Crouzet, et al., 2007)	0.12 – 0.52 (after 4 days)	

4.1.4 Diabetes

The final health factor identified as affecting the risk of developing CAUTI is if a patient has been diagnosed with diabetes. It is unclear why this increases a patient’s risk of developing a CAUTI, but the literature review of health factors resulted in three different papers that all concluded that if a patient has diabetes this increases the risk of a patient developing a CAUTI. A complete list of the papers referencing diabetes as a factor affecting the risk of developing a CAUTI is located in Appendix B. This study conducted by Platt, Polk, Murdock, and Rosner (1986) found that a patient with diabetes had an odds ratio of 2.3 compared to a patient without diabetes. This result was surprising for the authors because there was no previous research that showed firm evidence of patients with diabetes being at an increased risk of developing a CAUTI (Platt, Polk, Murdock, & Rosner, 1986). A more recent study found that diabetes did increase the risk of developing a CAUTI, but it was not statistically significant (Graves, et al., 2007). Although there is some discrepancy about whether diabetes is a significant risk factor in developing a CAUTI, it was included in the final model because the article by Maki and Tambyah (2001) consolidated four prospective studies and concluded that diabetes increases a patient's risk for developing a CAUTI. Table 4-4 is a compilation of the results for odds ratio or relative risk of diabetes, depending on how the results were reported in the given paper.

Table 4-4. Risk Levels for Diabetes

Study Citation	Odds Ratio - Patient has diabetes	Relative Risk - Patient has diabetes
(Platt, Polk, Murdock, & Rosner, 1986)	2.3	
(Maki &Tambyah, 2001)		2.2 - 2.3
(Graves, et al., 2007)	Not statistically significant	

4.2 Fuzzy Logic Analysis

Fuzzy logic is based on the idea that there is a level of uncertainty in assigning entities to specific sets. The development of fuzzy logic began when Zadeh introduced fuzzy sets in 1965. Until Zadeh's groundbreaking paper, probability theory dominated the realm of evaluating uncertainty (Ross, 2010). According to Ross (2010), fuzzy logic is applicable to complex systems in which "analytic functions or numerical relations do not exist" or the relationship between the causes and effects of a system are not understood (p. 7). Uncertainty exists in the interaction between the aforementioned health factors as well as the environmental factors during the catheter insertion. Therefore, I decided to use fuzzy logic to incorporate the health factors and the CPC factors from the HRA technique, CREAM, to predict the probability of a patient developing CAUTI in the CAUTI reduction tool.

The following sections outline the steps involved in developing the rule base fuzzy system for analyzing a patient's probability of developing CAUTI. The first step was to develop membership functions for each of the health factors and the environmental factors. Next the rule base system was developed, and finally a fuzzy model was developed in R using the 'sets' package developed by Meyer and Hornik (2009) to quickly analyze different patient cases.

4.2.1 Membership Functions

Membership functions contain all of the information that describes a fuzzy set. Membership functions are often graphed on a Cartesian coordinate system, but only in the I and II quadrants because the values for the y-axis of the graph are only between zero and one. The height of a membership function describes the degree of membership; full membership in a fuzzy set is a height of one. A crossover point between two membership functions is the point where membership is 0.5 for each set (Ross, 2010). This section describes the membership functions for each of the factors in the fuzzy model for predicting a patient's probability of developing a CAUTI: gender, duration, systemic antibiotic, diabetes, and environmental factors.

4.2.1.1 Gender

Gender, in a medical sense, is not a fuzzy set; a patient is either male or female. Crisp sets can still be modeled in a fuzzy system, and this was required to incorporate gender into the fuzzy model. There is no crossover point between the male and female sets because the variables were considered as discrete variables. The membership function for gender is shown in Figure 4-1.

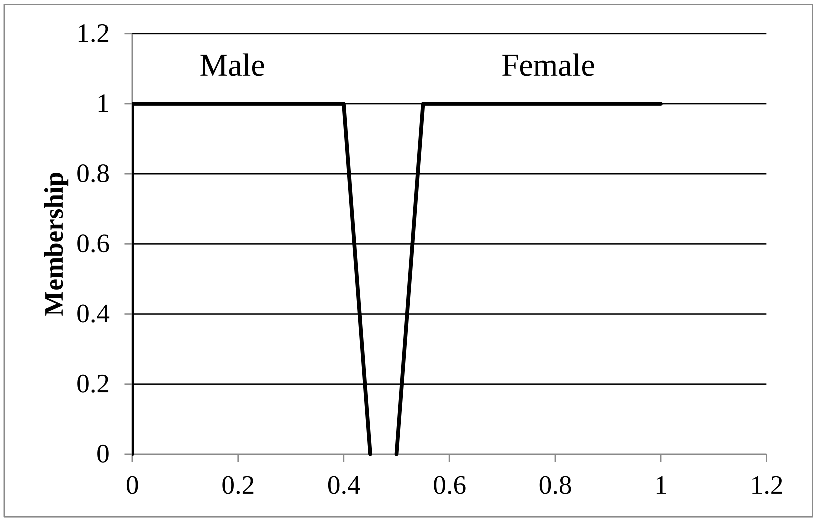

Figure 4-1.Gender Membership Function

The male set is on the lower end of the x-axis because males have a lower risk of developing a CAUTI than females, as was discovered in the review of the literature surrounding health factors contributing to CAUTI. According to Maki and Tambyah (2001), females have a relative risk of 2.5-3.7 as compared to males. While this risk factor cannot be directly converted into a probability of developing a CAUTI, it was useful in developing the membership function that places females at a higher probability level than males. In the fuzzy model, this will give more weight for a male to have a lower probability of CAUTI, and a female to have a higher probability of CAUTI. The boundaries of the sets are not exactly vertical because of a programming issue in the sets package in R (Meyer & Hornik, 2009).

4.2.1.2 Duration

The number of days a patient has a catheter is a crisp number; however, whether the number of days is a short, average, or long time to have a catheter in place can be developed as fuzzy sets. The literature surrounding the effect of duration on the risk of developing a CAUTI varied in its reporting of number of days; however, a one area that several of the studies reviewed was days four and five of catheterization. The odds ratio for days four and five ranged between 2.3 and 5.8 (refer to Table 4-2, page 34). Other studies reviewed the risk after six or seven days; Crouzet, et al. (2007) reported that throughout their observation the number of CAUTIs peaked on day six and recommended removing unnecessary catheters on day four. The information about increased risk and duration of catheterization was used to develop the membership function for duration which is split into three sets describing the length of duration: short, average, and long. Figure 4-2 depicts the membership function for duration of catheterization.

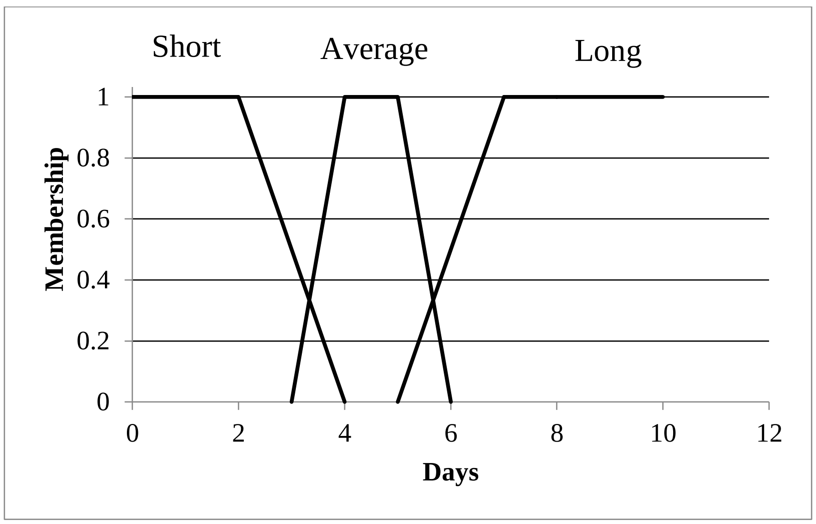

Figure 4-2. Duration Membership Function

The set for 'short' number of days ranges between zero and four, but days one and two are fully in the short membership function. Days four and five belong fully to the 'average' range because many of the studies reported an increased risk after these days. It was less clear which set day six belonged to; therefore, it is belongs to both the 'average' and 'long' sets. Although Crouzet, et al. (2007) saw a peak in the number of CAUTIs on day six, a CAUTI can still develop after day six. Day seven begins the full membership in the 'long' category.

4.2.1.3 Systemic Antibiotic

Whether a patient is receiving a systemic antibiotic or not is another example of crisp sets that can be modeled as such and incorporated into the fuzzy model. The membership function for systemic antibiotic is set up the same way as the gender membership function because they are both crisp sets with binary variables. Figure 4-3 depicts the membership function for systemic antibiotic. ‘Yes’ represents a patient that is receiving an systemic antibiotic, and ‘no’ represents a patient that is not receiving a systemic antibiotic.

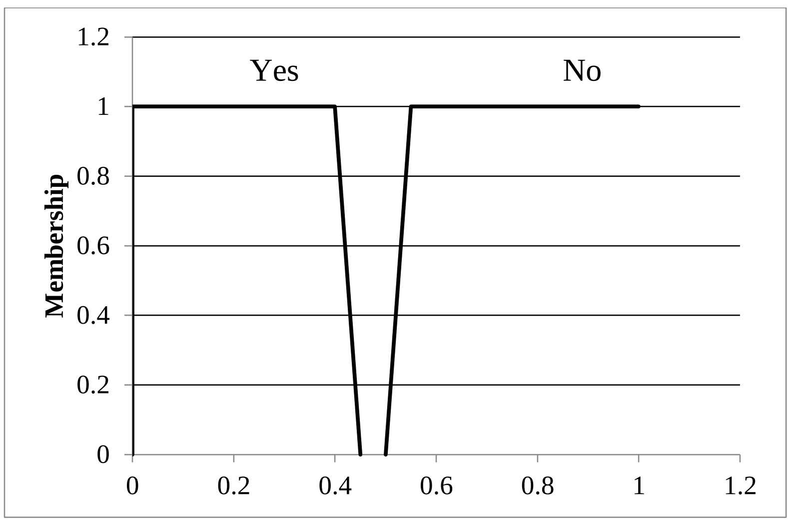

Figure 4-3. Systemic Antibiotic Membership Function

The set for a patient that is receiving a systemic antibiotic is on the lower end of the graph because such patients have a lower risk of developing a CAUTI than patients that are not receiving an antibiotic. According to Maki and Tambyah (2001), the relative risk for patients receiving an antibiotic compared to those that are not is between 0.1 and 0.4. In the fuzzy model, this will give more weight for a patient receiving a systemic antibiotic to have a lower probability of CAUTI.

4.2.1.4 Diabetes

According to Platt, Polk, Murdock, and Rosner (1986), patients with diabetes have an odds ratio of 2.3 compared to patients without diabetes. Two sets for diabetes were developed: a patient with diabetes and a patient without diabetes. It seems as though diabetes would be another crisp set, but the membership function developed for diabetes overlaps. This is allows for the incorporation of the patients that have never been tested for diabetes, but may have some form of the disease. Liebman reported that about 28% of adults in the U.S. have diabetes, but do not know it (2014). Figure 4-4 depicts the membership function for diabetes.

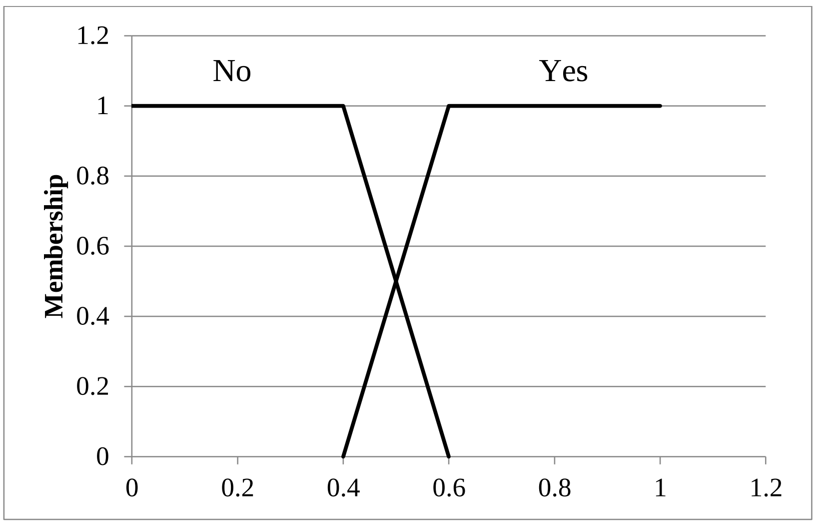

Figure 4-4. Diabetes Membership Function

The set on the left of the graph, labeled ‘no’ represents patients that have been tested for diabetes and were not diagnosed with the disease. The set on the right of the graph labeled ‘yes’ represents patients that have been tested for diabetes and were diagnosed with the disease. In the fuzzy model, this will give more weight for a patient who does not have diabetes to have a lower probability of CAUTI than a patient that was diagnosed with diabetes.

4.2.1.5 Environmental Factors

The environmental factors membership function is based on the methodology from the HRA technique, CREAM. Several journal articles used fuzzy logic to develop a membership function for the four control modes: scrambled, opportunistic, tactic, and strategic. The membership function for the CAUTI reduction tool is based on the membership function that Ung (2015) developed which uses only triangular functions for the control modes, and can easily be modeled in the R 'sets' (Meyer & Hornik, 2009) program. I used the shape that Ung (2015) developed and transformed the values to fit between zero and one to put it in terms of probability to match the other health factors, not including duration. The membership function for environmental factors is given in Figure 4-5.

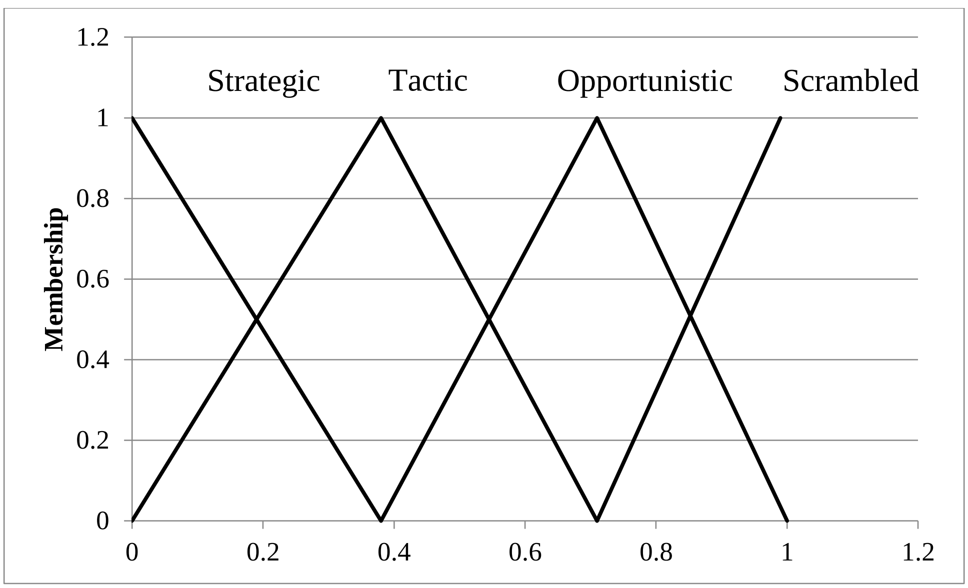

Figure 4-5. Environmental Factors Membership Function

The scrambled control mode is the highest risk category for a nurse to operating within, and the tactic control mode is the lowest risk category. A detailed description of the control modes can be found in Table 2-3 (page 9). The scrambled control mode is further to the right of the graph; therefore, this will give a patient that had a catheter inserted in poor environmental conditions a higher probability of developing a CAUTI. In the scrambled control mode the nurse would be at a higher risk for making a mistake like forgetting to wash their hands and introducing bacteria into the patient's system. A patient that had a catheter inserted in the best environmental conditions will have a lower probability of developing a CAUTI because the nurse would be less likely to make a mistake that leads to bacteria infecting the patient.

4.2.2 Fuzzy Rule Base System

Fuzzy rule based systems are a way to incorporate human knowledge into an analysis system. The most common fuzzy rule base system is the IF-THEN rule base system, illustrated in Figure 4-6.

IF premise (antecedent), THEN conclusion (consequent)

Figure 4-6. IF-THEN Rule Base System

The antecedent in the IF-THEN rule base system represents portion of the information that if it is known as a fact to the analyst then the consequent can be inferred from this information (Ross, 2010). For example, if the analyst knows for a fact that it is sunny outside and there is high humidity (antecedent), then the analyst can infer that it will feel hot outside (consequent). The IF-THEN rule base system was used as the basis for predicting a patient's probability of developing a CAUTI in the CAUTI reduction tool because it is capable of capturing the information known about each individual factor and relating it to the risk of developing a CAUTI.

The information about the interaction between health factors and a patient's probability of developing a CAUTI is limited because studies adjust their results to compensate for confounding between factors. It is also difficult to track the interaction between all of the different health factors and the effects on the risk of a patient developing a CAUTI. Therefore the assumption was made to treat the factors as independent in the fuzzy rule base. An expert could provide additional information about the interaction between the factors, but this leaves the judgement of the interaction up to one or a few individuals.

The rule base system is shown in Table 4-5. The antecedents are the linguistic terms in the table, and the risk level represents the antecedent. The table should be read as follows: if gender is male then risk is low. The risk levels were assigned based on knowledge of increased or decreased risk from the literature review of the health factors.

Table 4-5. Fuzzy Rule Base System

Factor	Linguistic Term	Risk Level
Gender	Male	Low
Gender	Female	Medium
Duration	Short	Low
Duration	Average	Medium
Duration	Long	High
Systemic Antibiotic	Yes	Low
Systemic Antibiotic	No	Medium
Diabetes	No	Low
Diabetes	Yes	Medium
Environmental Factors	Strategic	Low
Environmental Factors	Tactic	Low
Environmental Factors	Opportunistic	Medium
Environmental Factors	Scrambled	High

4.2.3 Fuzzy Model Developed in R Software

R is a free statistical software program that allows for open source participation. A fuzzy sets package was developed by Meyer and Hornik (2009) that allows for the analysis of fuzzy rule base systems. The sets package was used to develop a model for analyzing the health and environmental factors that affect the probability of developing CAUTI to predict the probability that a patient will develop CAUTI. This section provides information about the development of the fuzzy model.

The fuzzy model is split into three main sections in the R sets package: development of the fuzzy variables, development of the rules, and the defuzzification of the variables. The development of the fuzzy variables is simply setting up the membership functions defined in section 4.2.1 and developing a membership function for the output variable. The development of the rules involves setting up the rules that were defined in section 4.2.2. Finally, defuzzification is performed by calling one of the pre-defined defuzzification methods in the R sets package which include the smallest of max, mean of max, largest of max, and centroid methods.

The output of the fuzzy model is the probability of the patient developing a CAUTI, and three linguistic terms describe this variable in the fuzzy model: low, medium, and high. The membership function for the output variable can be determined by the hospital implementing the CAUTI reduction tool based on their preferences for nurse action based on the patient's probability of developing a CAUTI. I developed a basic membership function for the output variable, and it is shown in Figure 4-7. A patient is fully in the low probability range from 0 to 0.2, fully in the medium range from 0.4 to 0.6, and in fully in the high range from 0.8 to 1.

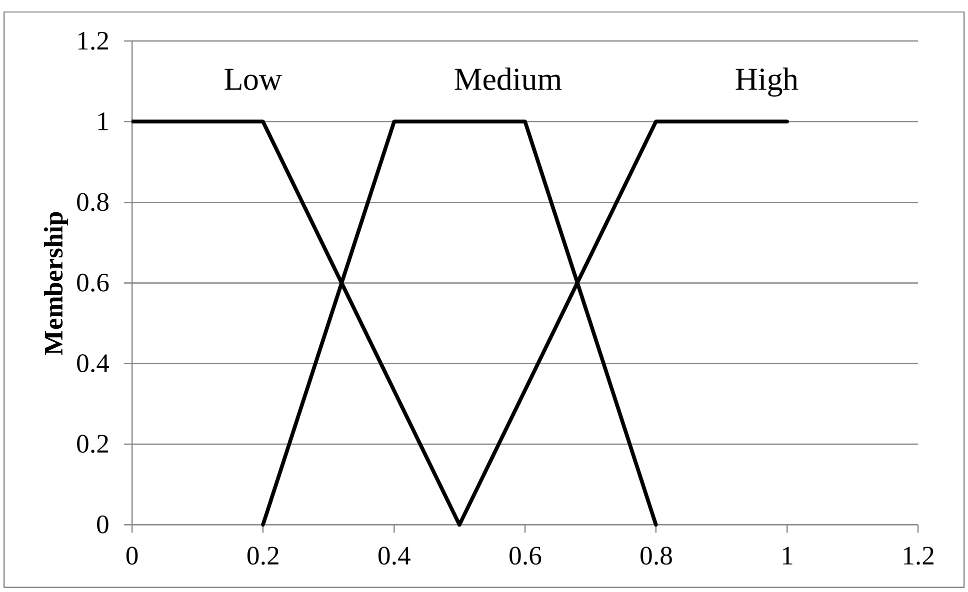

Figure 4-7. Probability of CAUTI Membership Function

The final step in the fuzzy model is the defuzzification process, and there are four defuzzification methods available in the R sets package. The four methods of defuzzification are smallest of max, mean of max, largest of max, and centroid. The defuzzification method for a fuzzy model should be based on the specific fuzzy model and the desired results. According to the R sets package description, the smallest of max returns the minimum of the set elements with maximal membership degree. The mean of max returns the mean of the set elements with maximal membership degree, and the largest of max return the largest of the set elements with maximal membership degree (Meyer & Hornik, 2009). The centroid method is a popular defuzzification method, and it returns the arithmetic mean of the set elements (Meyer & Hornik, 2009).

Twenty different cases were tested in the initial fuzzy model and the results were found using each of the defuzzification methods. The smallest of max method gave the most optimistic results for the probability of developing a CAUTI because it returns the smallest value of the output membership function that is created through the inference of the rule base system. This is not the best defuzzification method for this fuzzy model because hospitals would want to be alerted that a patient is at a higher risk of developing a CAUTI sooner than this method would place the patient in a higher probability level. The largest of max method gave the most pessimistic results because it returns the largest value of the set elements with maximal membership degree. This method would place patients in a high probability level very early in their catheterization, and would result in hospitals being alerted that many patients are at a high risk. Both the smallest of max and largest of max methods were not as sensitive to changes in hypothetical patient cases, and therefore did not describe the different health and environmental factors very well.

The mean of max membership function gave results that were in-between the smallest of max and largest of max methods. This would place a more reasonable number of patients in low and high probability levels, but the results were not as sensitive to changes in the input variables as the centroid method. The centroid method produced results that were in the mid-range between optimism and pessimism and it was the most sensitive method to changes in the input variables. Therefore the centroid method was selected as the defuzzification method to implement in the CAUTI prediction fuzzy model.

4.3 Fuzzy Rule Base Model Results

The first fuzzy model that was tested was set up with the membership functions described in section 4.2.1 and the fuzzy rule base described in section 4.2.2. Random data was generated in excel for the following input variables: environmental conditions, systemic antibiotic, and diabetes to create twenty different hypothetical patient cases. Each of the twenty patient cases was run for the male gender and female gender from one day to ten days. This allowed for the comparison of the same health factor cases between males and females to validate that the female gender had a higher probability of CAUTI than the male gender. It also allowed the same hypothetical patient case to be tracked from day one to day ten to verify that the probability of CAUTI increased as the duration of catheterization increased. Figure 4-8 depicts the results of the twenty hypothetical patient cases for males, and Figure 4-9 shows the results for the same twenty hypothetical cases for females. The raw data for these results is given in Appendix C.

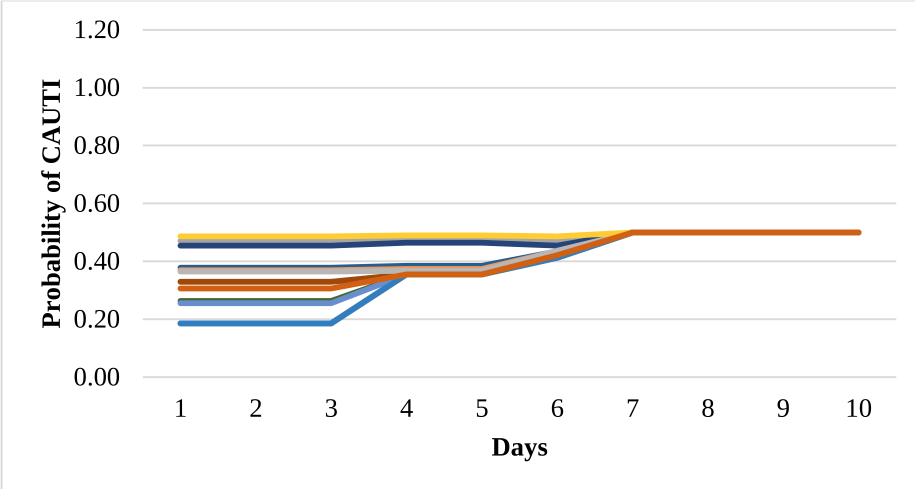

Figure 4-8. Results of Hypothetical Cases for Males

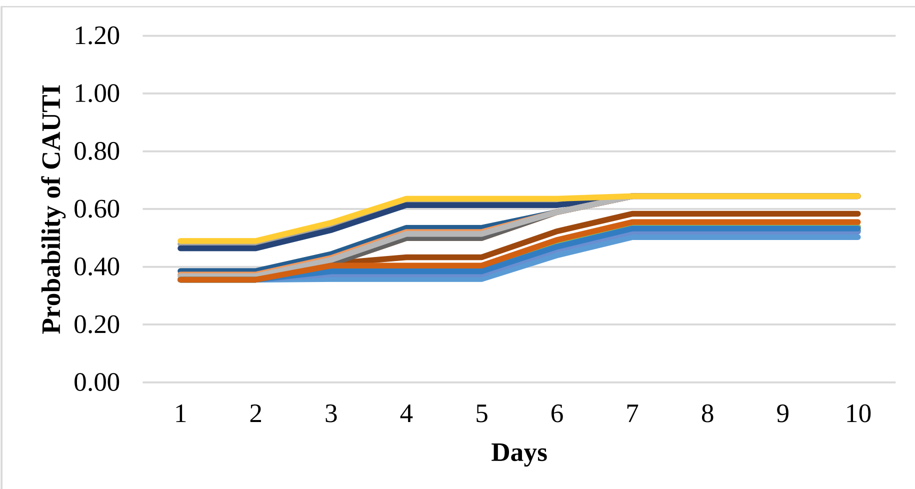

Figure 4-9. Results of Hypothetical Cases for Females

The probability of developing a CAUTI ranged between approximately 20 percent and 50 percent for males, and approximately 36 percent and 64 percent for females. This is because females were placed in the ‘medium’ risk category and males were placed in the ‘low’ risk category in the fuzzy model. The probability of developing a CAUTI increased after days three and five for both the male and female cases. Once the duration reached day seven the probability of developing a CAUTI remained the same for both the male and female cases. These results are consistent with the duration of catheterization membership function. The ‘long’ category for duration of catheterization fully includes days seven through ten in the set, and therefore the results are the same for that range of days.

It is more difficult to draw conclusions about the model’s sensitivity to the other input variables: diabetes, use of a systemic antibiotic, and environmental factors. However, by analyzing the raw data conclusions can be drawn that cases with environmental factors in the scrambled and opportunistic control modes had higher probability of CAUTI results than cases in the tactic and strategic control modes. Patient cases that had not received an antibiotic and had been diagnosed with diabetes had higher probability of CAUTI results than patients that were receiving an antibiotic and did not have diabetes. These results are consistent with the literature review of the health factors.

The major failing of this model is that the probability of developing a CAUTI never goes above 50 percent for males. This result does not provide the necessary sensitivity to track a patient’s probability in an actual healthcare setting because all of the male patients would reach the same probability level after day six. Due to the shortcomings of this model, incremental changes were made and the results were calculated and recorded to determine if the change improved upon the original model.

4.3.1 Model Improvement Process

There are many areas in the fuzzy rule base system that could be altered; the two areas I focused on changing incrementally included the risk membership function and the rule base system. The membership functions for the input variables were based upon the literature review of the input variable; therefore, I did not consider altering them. A single change was made to the model at a time, and the results for the worst hypothetical male patient case were calculated using the new model and the R sets program. The worst hypothetical patient case for males was tested first because if any case would go above the 50 percent probability level for males, it would have been the worst case.

The risk membership function was altered by changing the values for the trapezoidal function, changing the shape for the 'medium' risk variable to a triangular function, and changing all of the shapes to a triangular function. Figure 4-10 depicts one of the triangular membership functions for risk that was tested. None of these changes resulted in the worst hypothetical case for a male patient to go above 50 percent probability. The results were capped at 50 percent like the original model shown in Figure 4-8 (page 48).

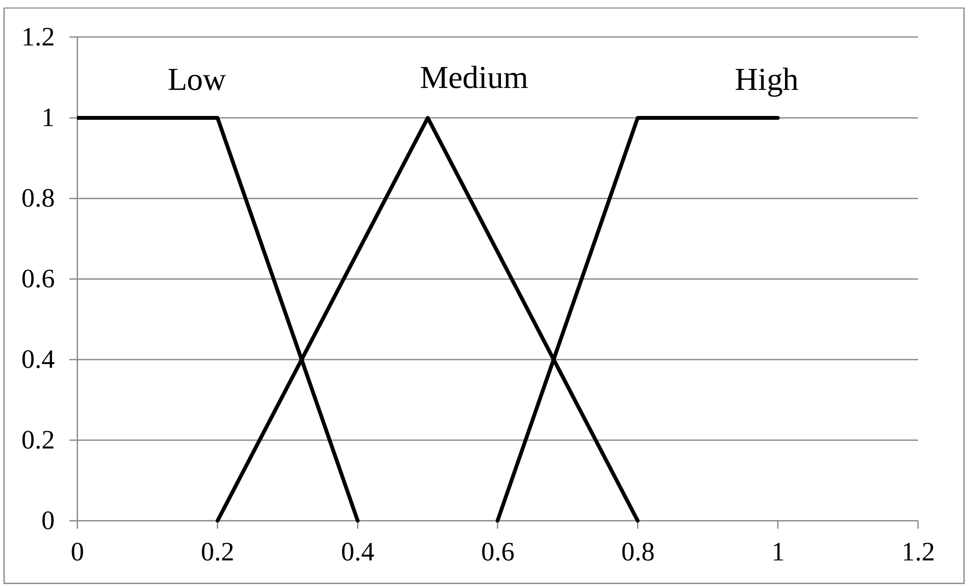

Figure 4-10. Triangular Risk Membership Function

Next, the rule base system was altered by adding rules with an interaction between the variables. The male input variable was assigned a risk of 'low' in the original rule base system; therefore, it was possible that this causing the probability of a male developing CAUTI to peak at 50 percent. Rules that better defined the probability of CAUTI for males were developed using the information from Platt, Polk, Murdock, and Rosner (1986) that duration "is the most important predictor of infection" (p.979). Although males have a lower risk of developing a CAUTI than females they are still at a high risk of infection when the duration is long.

One trial of the rule base system added the following rules to the existing independent rules defined in Table 4-5 (page 44): If duration is long and gender is male, risk is high. If gender is male and environment is scrambled and duration is average, risk is high. The worst hypothetical male patient case was tested with these additional rules and the result did not change; the probability of developing a CAUTI peaked at 50 percent for the male gender.

Another trial of the rule base system changed the existing rule base system so the risk level for females was set to 'high' and the risk level for males was set to 'medium'. The best and worst hypothetical patient cases were tested for both males and females. The worst case for males did go above 50 percent probability on day three, but the best case for females returned a value of 50 percent probability for days one through ten. This result was not desirable either because it reduced the sensitivity of the female cases to changes in the other health factors and the environmental factor.

None of the eighteen trials of the original fuzzy rule base system produced consistent results for both males and females that did not either cap the male probability at 50 percent or set a lower limit of 50 percent for females. After this analysis another fuzzy technique was implemented to attempt to produce more consistent, logical results. The discussion of this technique is in the following section, 4.4.

4.4 Fuzzy Associative Memories Model

The fuzzy associative memories model is a compact form of representing fuzzy rule based systems. According to Ross (2010), the total number of possible rules that govern a fuzzy system is much greater than the number of rules that are necessary to model the system. A fuzzy associative memory table maps the relationship between the input variables and the output variable. Not all fuzzy relations are necessary for the model; the known relations are sufficient.

The five input variables for the CAUTI probability fuzzy system described in Section 4.2.1 were split into crisp variables and fuzzy variables. The crisp variables include gender, diabetes, and use of systemic antibiotic; the fuzzy variables include duration and environmental conditions. The three crisp variables generate eight cases of homogenous conditions which are listed in Table 4-6. Each of these eight cases has its own fuzzy associative memory table that compares the relationship between duration and environmental factors for the specific case of homogenous conditions.

Table 4-6. Crisp Variable Combinations

Case	Gender	Patient has diabetes	Patient is on an antibiotic
1	Male	Yes	Yes
2	Male	No	Yes
3	Male	Yes	No
4	Male	No	No
5	Female	Yes	Yes
6	Female	No	Yes
7	Female	Yes	No
8	Female	No	No

Normally the information about the relationship between the fuzzy variables and the output variable would be gathered from an expert or team of experts. Due to limitations an expert's opinion was not available; therefore, the relationships were based on my knowledge of the effects of duration on the likelihood of developing a CAUTI and the risks associated with poor healthcare environments. Table 4-7 shows the relationship between duration and environmental factors for the worst combination of crisp variables for a female, case seven in Table 4-6. The terms in the matrix describe the output variable, risk level. The missing terms represent the unknown relationships between duration and control mode.

Table 4-7. Fuzzy Associative Memory Table for Patient Case 7

Duration/Environment	Scrambled	Opportunistic	Tactic	Strategic
Short	Medium	Medium		Medium
Average	High		Medium	Medium
Long	High		High	High

The R sets package (Meyer & Hornik, 2009) is capable of analyzing these systems, but each case must be analyzed separately because they all have unique rule base systems. There are only two input variables for the model: duration and environmental conditions. The same membership functions for duration and environmental factors were used in this model as were described in section 4.2.1. The membership function for the output variable, risk, is the same as was described in section 4.2.3. The rules for the fuzzy system are based on the fuzzy associative memory table developed for the specific case. An example of a rule in the rule base system for case seven would be: If duration is short and environment is scrambled, risk is medium.

The model testing phase began with testing the different defuzzification methods in the R sets package (Meyer & Hornik, 2009). The defuzzification testing was performed using the worst female case, Case 7 in Table 4-6. The largest of max method was not sensitive to the changes in the environmental conditions; it returned a probability of one for days seven through ten for all of the cases tested. This is an undesirable result because we cannot say with certainty that all patients will develop a CAUTI after a catheter is in place six days. The mean of max method was also tested, and it was more sensitive to changes in the environmental conditions than the largest of max method. However, it returned inconsistent results for the duration. In some cases the probability for developing a CAUTI would be higher on days four and five than it would be on days six and seven. Finally, the centroid method was tested. This was the most sensitive method to changes in environmental conditions and it provided more consistent results for duration than the mean of max method. Therefore, the centroid method was chosen as the defuzzification method for the fuzzy associative memories model.

The model was tested for validity using the best and worst case for males and females. The best case for males is Case 2, and the worst case for males is Case 3 from Table 4-6. The best case for females is Case 6, and the worst case for females is Case 7 from Table 4-6. The fuzzy associative memory tables were required for all four of these patient cases to test the model. The following tables (4-8, 4-9, and 4-10) describe the relationship between duration and environmental factors for each of the previously mentioned cases. The fuzzy associative memory table is already depicted in Table 4-7 for Case 7.

Table 4-8. Fuzzy Associative Memory Table for Patient Case 2

Duration/Environment	Scrambled	Opportunistic	Tactic	Strategic
Short	Medium	Low		Low
Average	Medium	Medium		Low
Long	High		Medium	Medium

Table 4-9. Fuzzy Associative Memory Table for Patient Case 3

Duration/Environment	Scrambled	Opportunistic	Tactic	Strategic
Short	Medium		Low	Low
Average	High	Medium		Low
Long	High	High		Medium

Table 4-10. Fuzzy Associative Memory Table for Patient Case 6

Duration/Environment	Scrambled	Opportunistic	Tactic	Strategic
Short	Medium	Medium		Low
Average	High		Medium	Low
Long	High		High	Medium

4.5 Fuzzy Associative Memories Model Results

The fuzzy associative memories model was tested for the best and worst cases for both the female and male gender. Each patient case was tested at different environmental conditions for a range of ten days. The results were recorded and charts for each patient case were created to easily compare the results between cases. The raw data for the results of this section is included in Appendix D. This section provides an analysis of the results of the fuzzy associative memories model for the four patient cases.

The first case tested was the worst case for females. The probability of CAUTI did not go below 0.5 for any combination of the environmental conditions and duration tested. This is most likely because none of the rules in the system for this case were set to 'low' risk; all of the relationships between duration and the environmental conditions were either 'medium' or 'high'. Figure 4-11 shows the probability of a Case 7 patient developing a CAUTI at differing environmental conditions ranging from one to ten days of catheterization. The legend on the right of the graph describes the input for environmental conditions.

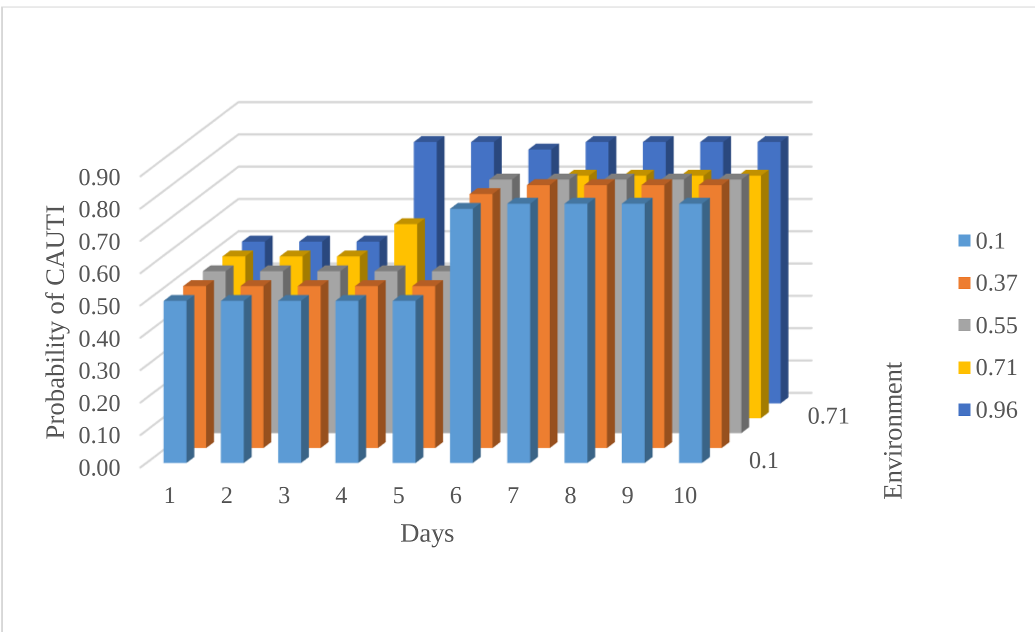

Figure 4-11. Probability of CAUTI for Case 7 Patients

The next patient case tested was the best case for female patients, Case 6. The probability of developing a CAUTI did go below 0.5 for better environmental conditions and lower days of catheterization. This result is consistent with the fuzzy associative memory table for Case 6 which has a 'low' result for the strategic control mode and short and average days of catheterization. There are a few inconsistent points with this example. When the input for environmental control mode was 0.96 and 0.55 the probability peaked at a lower number of days than the final probability at day seven. This only occurred in two of the six cases tested and the general trend of the data is still logical; therefore, I considered the results acceptable. Figure 4-12 shows the probability of a Case 6 patient developing a CAUTI at differing environmental conditions ranging from one to ten days of catheterization. The legend on the right of the graph describes the input for environmental conditions.

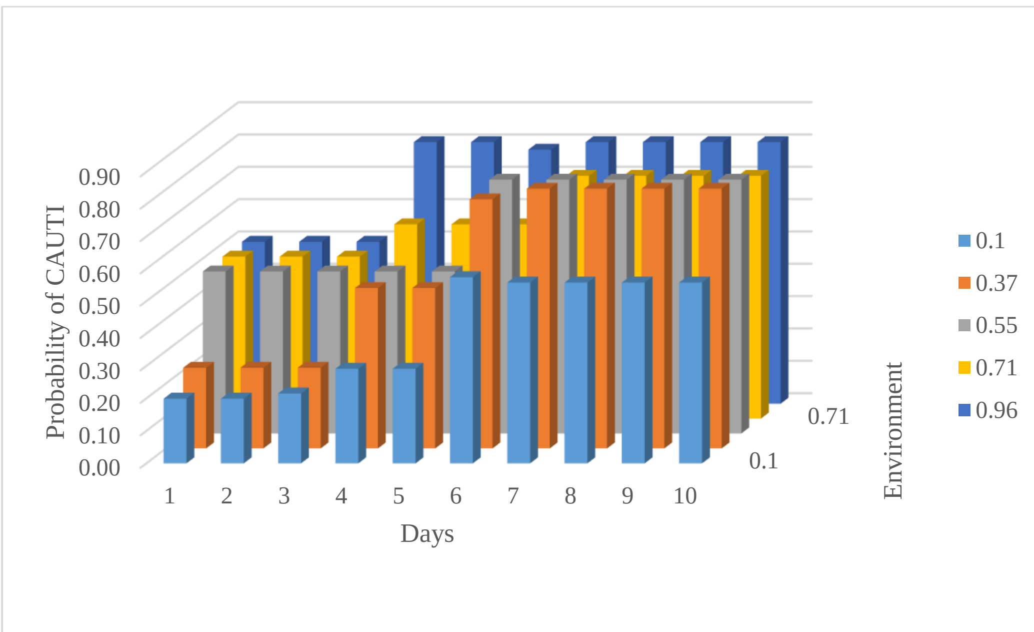

Figure 4-12. Probability of CAUTI for Case 6 Patients

The next patient case tested was the worst case for male patients, Case 3. The probability of a patient developing CAUTI ranged from 0.2 to 0.8. This result is consistent with the fuzzy associative memory table for Case 3 which has a 'low' result for shorter duration and better environmental conditions. There are two inconsistent results for this set of data. When the input for environmental control mode was 0.96 and 0.55 the probability peaked at a lower number of days than the final probability at day seven. However, the general trend of these environmental conditions is consistent so I considered the results acceptable. Figure 4-13 shows the probability of a Case 3 patient developing a CAUTI at differing environmental conditions ranging from one to ten days of catheterization. The legend on the right of the graph describes the input for environmental conditions.

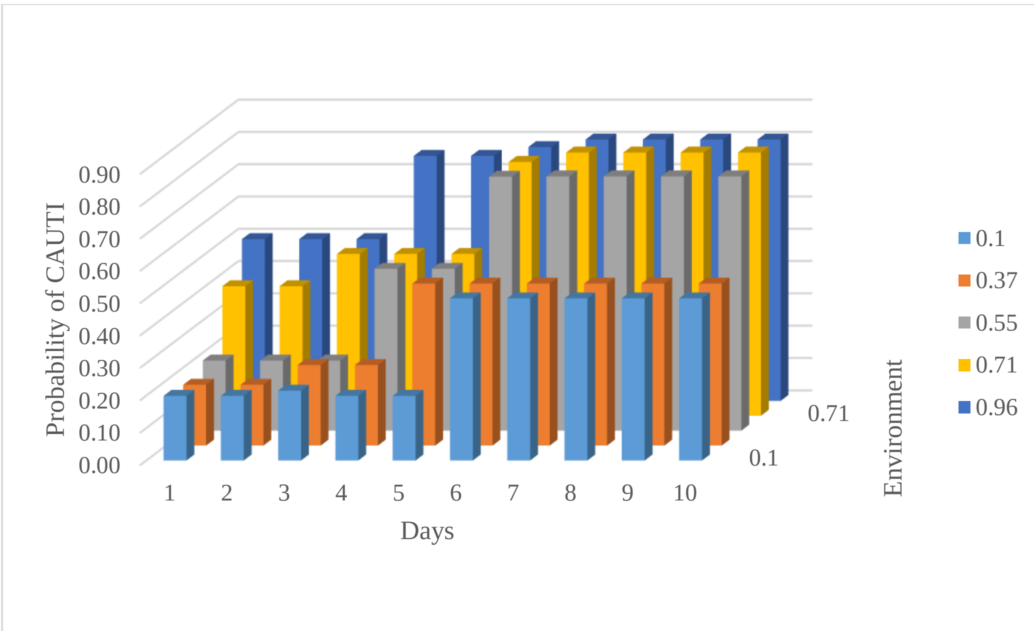

Figure 4-13. Probability of CAUTI for Case 3 Patients

The final case tested was the best case for male patients, Case 2. The probability of a patient developing a CAUTI ranged from about 0.18 to 0.8. This result is consistent with the fuzzy associative memory table developed for Case 2 which ranges from ‘low’ to ‘high’ depending upon the interaction between duration and environmental conditions. Figure 4-14 shows the probability of a Case 2 patient developing a CAUTI at differing environmental conditions ranging from one to ten days of catheterization. The legend on the right of the graph describes the input for environmental conditions. Overall the results of the test for Case 2 patients are consistent. Higher levels of environmental conditions produce higher levels of probability than lower levels of environmental conditions. The length of duration also increases the probability of the patient developing a CAUTI.

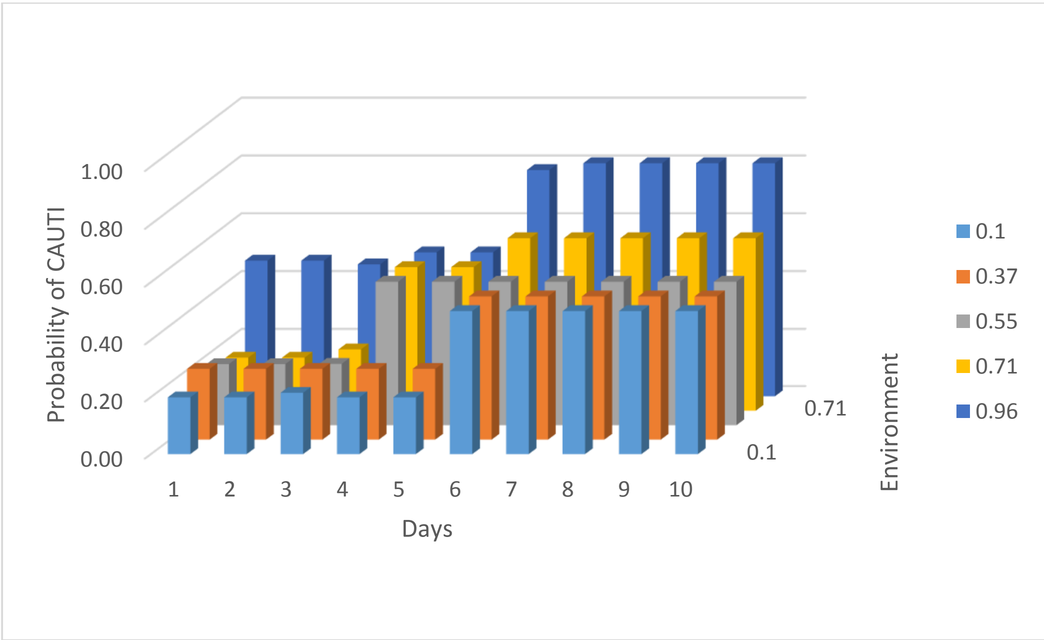

Figure 4-14. Probability of CAUTI for Case 2 Patients

The results from each patient case were also compared to each other to ensure that the results were consistent with the findings from the literature review about the effect health factors on the likelihood of a developing a CAUTI. Overall the probabilities from worst female case were higher than the probabilities from the best female case. The probability never went below 0.5 for the worst female case, but for the best female case the better environmental conditions produced a probability of 0.2, which is lower than 0.5. This is a logical result because the fuzzy associative memory tables were developed so that the best female case was at a lower risk level than the worse female case for the best environmental conditions and a lower number of days. Both the best and worst case for females reaches about the same level of probability for the higher number of days. This also matches how the fuzzy associative memory tables were developed; the best and worst cases have ‘high’ risk levels when the duration is long and the environmental conditions are poor.

Overall the probabilities from worst male case were higher than the probabilities from the best male case. The ranges of probabilities were about the same for both the best and worst case, but the best case had fewer instances of the probability reaching the high level around 0.8. When the environmental conditions were higher the results for the best and worst case were similar because the fuzzy associative memory tables for both cases had ‘high’ values for a long duration and poor environmental conditions. The results were also consistent for better environmental conditions and shorter days because the best male case had lower levels of probability than the worst male case.

The cases were also compared across gender because according to the research about health factors, males have a lower level of risk for developing a CAUTI than females. The results of this model are consistent with this conclusion. Comparing the best case for males and females, there are more cases that result in a high probability for females than males. Two cases with poor environmental conditions produce similar results for both the male and female best cases. This is aligned with the fuzzy associative memory tables; both males and females are at a ‘high’ risk level for poor environmental conditions and a long duration of catheterization.

Finally the worst female and male cases were compared. Overall, the female cases had a higher probability of CAUTI than the male cases. This is apparent when the number of days is shorter. The female cases never go below a 0.5 probability, but the male cases drop down to a probability of 0.2. However, when the number of days is longer and the environmental conditions are poor, the probability of CAUTI for the worst male case reaches a higher level than the worst case for females. The highest discrepancy between the worst male and female case occurred when the environmental input was 0.71, which is in the scrambled category of environmental factors. The worst male case returned a probability of 0.81 when the duration was long, and the worst female case returned a probability of only 0.75.

The discrepancy between the worst female and male cases was due to the difference in each case's fuzzy associative memory table. The fuzzy associative memory table for the worst female case went through several iterations of changes to produce more consistent results. The fuzzy associative memory table for the worst female case was missing rules for the opportunistic category whereas the worst male case was missing rules for the tactic category. The first iteration of changes included updating the fuzzy associative memory table for the worst female case to exclude the same rules as the worst male case. This produced results that solved the issue of the male cases having a higher probability of CAUTI than the female cases when the environmental conditions were poor and the duration was long. However, the worst female case still did not allow the probability of CAUTI to drop below 0.5 when the environmental conditions were good and the duration was short. This led to the next iteration of changes to the fuzzy associative memory table for the worst female case; the rule when the environment is strategic and the duration is short was changed to 'low'. The new fuzzy associative memory table for the worst female case, Case 7, is shown in Table 4-11.

Table 4-11. Updated Fuzzy Associative Memory Table for Patient Case 7

Duration/Environment	Scrambled	Opportunistic	Tactic	Strategic
Short	Medium	Medium		Low
Average	High		Medium	Medium
Long	High	High		High

The same cases were tested for the updated fuzzy associative memory table for the worst female case, and probability of infection for females increased in the cases with a higher environmental factor input. For example, when the environmental input was 0.71 and the duration was long, the worst male case returned a probability of 0.81; the worst female case also returned a probability of 0.81. These results are more consistent with the literature about health factors affecting CAUTI. When the duration was short and the environmental conditions were in the strategic category this model returned results below 0.5, and the results did not drop below those of the worst male case. These results fit with the knowledge gained from the literature review of the health factors affecting CAUTI. Appendix E includes the data comparing the worst male case to the updated worst female case. Figure 4-15 shows the probability of a Case 7 patient developing a CAUTI at differing environmental conditions ranging from one to ten days of catheterization. These results include the changes made to the fuzzy associative memory table shown in Table 4-11. The legend on the right of the graph describes the input for environmental conditions.

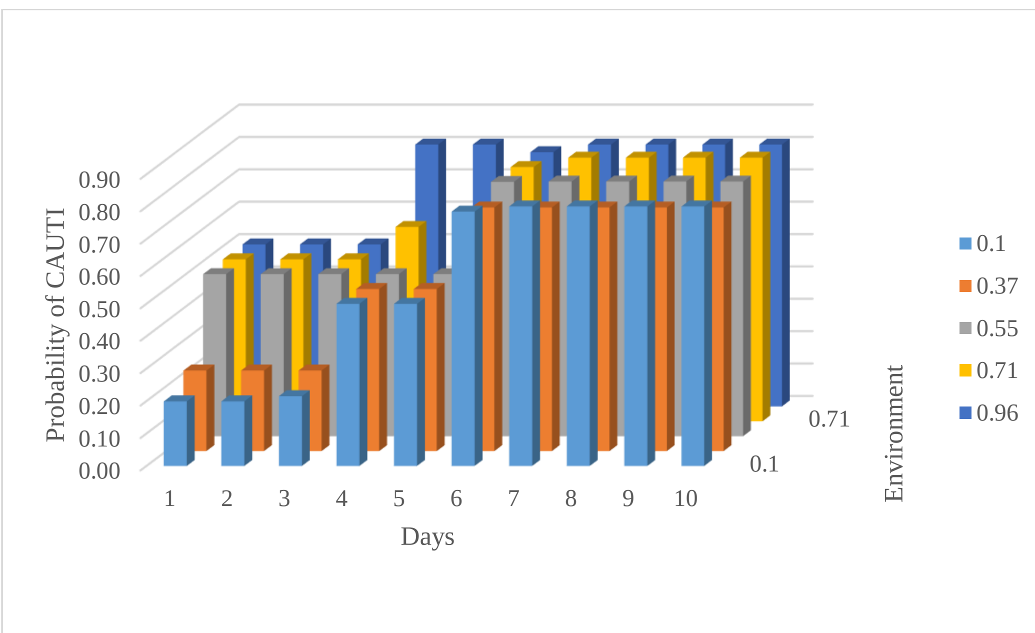

Figure 4-15. Updated Probability of CAUTI for Case 7 Patients

Each of the four patient cases was tested for the same levels of environmental conditions from one to ten days. The results were compared between the best and worst case for each gender to validate that the patient with better health conditions was at a lower level for developing a CAUTI. The results for both genders were compared for the best and worst cases to validate that the probability of developing a CAUTI were higher for females than males. After testing the best and worst patient cases for both males and females, it can be concluded that the fuzzy associative memories model produces consistent results aligned with the literature review of health factors.

Chapter 5 - Conclusion

HAIs are a significant problem in the United States healthcare industry. Although there has been improvement in the rates of some HAIs, the rates of CAUTIs are not improving even with increased attention on the issue. The goal of this research was to incorporate human reliability analysis techniques with health factors that contribute to CAUTI and create a tool to predict the probability of the patient developing a CAUTI.

HRA techniques have been applied in the healthcare industry, but never incorporated with human health factors to predict a patient's probability of developing an infection. Three HRA techniques were researched and compared to determine that CREAM is the most applicable in a healthcare setting and has the best quantification methods for producing a probability of human error during a catheter insertion. Extensive research was performed on health factors contributing to CAUTI. The four factors determined to have the most effect on a patient developing CAUTI include gender, duration, diabetes, and the use of systemic antibiotics.

The environmental factors and the health factors contributing to CAUTI were first modeled using fuzzy logic and a rule based system. The environmental factors included in the fuzzy model are derived from the HRA technique, CREAM. The CPCs from CREAM are analyzed for their effect on the likelihood of the nurse making an error, and a control mode is selected from this analysis. Throughout analysis of hypothetical patient cases it was determined that the rule based system was unfit for successfully predicting the probability of CAUTI for both male and female patients. Another model was built using a fuzzy associative memory system. The fuzzy associative memory model produced more consistent and logical results for the patient cases that were tested. The final deliverable of this report is a tool that predicts a patient's probability of CAUTI using the fuzzy associative model. It can be implemented in a hospital allowing nurses to track a patient's probability of developing a CAUTI. The CAUTI reduction tool is described in detail next.

5.1 CAUTI Reduction Tool

The CAUTI reduction tool is a chart that tracks the probability of a patient developing a CAUTI on each day of catheterization. The chart places the patient in a low, medium, or high risk level of developing a CAUTI. Specific actions are suggested for nurses to take when the patient is in each of the risk levels. The information required to run this tool is the environmental conditions of the hospital during the catheter insertion and the patient's health history. This section outlines the data and steps necessary to implement the CAUTI reduction tool.

The information about the environmental conditions of the hospital can be gathered several ways. Many hospitals implement yearly nurse climate surveys that relate to the CPCs in the chosen HRA technique, CREAM. Examples of CPCs that could be defined by a yearly climate survey include adequacy of organization, crew collaboration quality, and working conditions. The other CPCs relate more closely to each specific catheter insertion. A complete list of CPCs, as defined in the CREAM method, is given in Table 2-4 on page 10 of this report. It must be decided whether each CPC improves, reduces, or has no effect on the reliability of the nurse while performing the catheter insertion. A simple tool in Microsoft Excel takes this information and calculates the control mode of the operator using the simplified quantification method described in section 3.2.2. Figure 5-1 is a snapshot of the environmental analysis tool. The user simply selects whether each CPC reduces, improves, or has no effect on the reliability of the operator. Figure 5-1 shows two examples of environmental conditions and the resulting control mode. Case 1 has very poor environmental conditions in all of the categories; therefore, the calculated control mode is scrambled. Case 2 has very good environmental conditions in most categories; therefore, the calculated control mode is strategic.

	A	B	C
1	**CPC**	**Effect Case 1**	**Effect Case 2**
2	Adequacy of Organization	Reduces	Improves
3	Working Conditions	Reduces	Improves
4	Adequacy of MMI & OS	Reduces	Improves
5	Availability of P&P	Reduces	Improves
6	Number of Simultaneous Goals	Reduces	Improves
7	Available Time	Reduces	Improves
8	Time of Day	Reduces	Reduces
9	Adequacy of T&E	Reduces	Improves
10	Crew Collaboration Quality	Reduces	Improves
11			
12	Total Reduced	9	1
13	Total Improved	0	8
14	Reduced - Improved	9	-7
15		0.99583647	9.9584E-05
16	Control Mode	Scrambled	Strategic

Figure 5-1. Environmental Analysis Tool

The next step is to collect the patient's health factors and place them into one of the eight homogenous cases outlined in Table 4-6 on page 52. These health factors determine which fuzzy associative memory table to use in the fuzzy analysis. Next, the fuzzy associative memory model is run using the R sets package (Meyer & Hornik, 2009). The output from this model is the probability of the patient developing a CAUTI on day one through ten of catheter duration. These probabilities can be used to generate a chart for nurses to track the patient's risk of CAUTI. Lower levels of probability are shown in the green zone, medium levels are shown in the yellow zone, and high levels of probability are shown in the red zone. Each hospital implementing this tool can choose their own levels for the risk zones based on their individual preferences. In the Figure 5-2, the green zone ranges from 0 to 0.45, the yellow zone ranges from 0.45 to 0.62, and the red zone ranges from 0.62 to 1.

For example, Figure 5-2 depicts the probability chart for the best case for a female patient (patient does not have diabetes and is on an antibiotic) when the environmental conditions were in the opportunistic control mode. Although this patient has the best combination of health factors for a female, their probability level begins in the yellow zone. This is because the opportunistic environmental control mode raises the initial probability of a CAUTI.

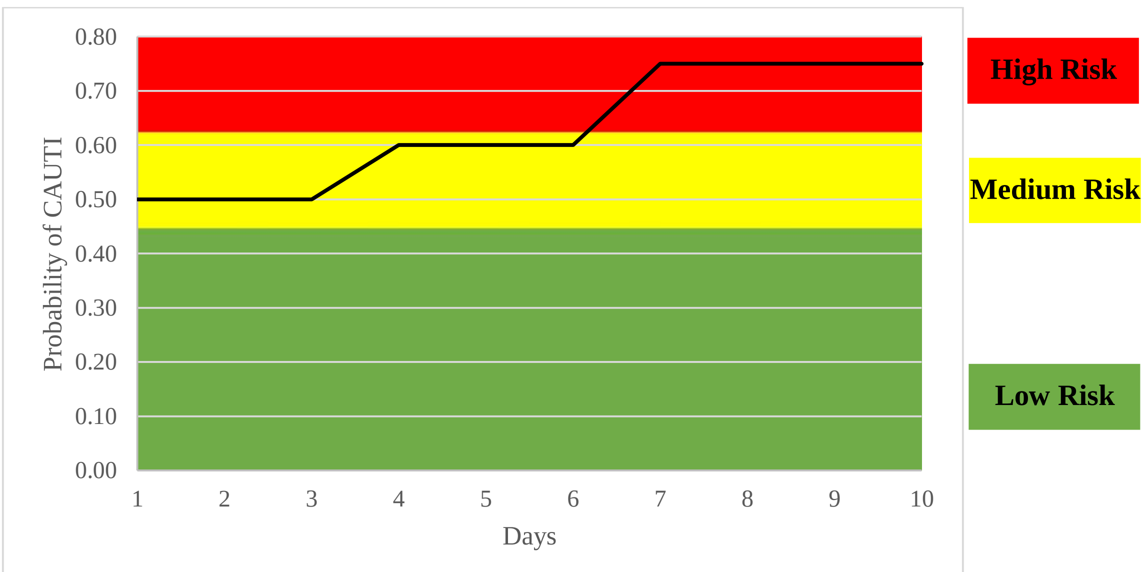

Figure 5-2. Probability of CAUTI for Best Female Patient Case

The probability chart for CAUTI will help nurses visually recognize when patients are at an increased likelihood of developing a CAUTI. To reduce the rates of CAUTI, actions must be implemented to prevent patients with a high probability of developing CAUTI from actually developing an infection. Once the nurses identify which risk category the patient falls within, they can consult the information in Table 5-1 that has specific actions that should be taken at each risk level. The actions range from basic hygiene reminders to considering using a different type of catheter for patients with a higher risk level. This list is not exhaustive because each individual hospital will be responsible for deciding which actions to take at each risk level.

Table 5-1. Nurse Actions and Associated Risk Level

Probability of CAUTI	Action
Low Risk	Unobstructed flow maintained at all times.
Low Risk	Action to remove or continue with catheter is documented every 24 hr. and communicated to nurse on every shift.
Low Risk	Hand hygiene performed for patient contact.
Low Risk	Meatal hygiene performed with soap and water only, every shift.
Low Risk	Catheter maintenance is performed regularly and documented.
Low Risk	Educate the patient and family about catheters and CAUTI.
Medium Risk	Drainage bag emptied using clean container.
Medium Risk	Make sure the seal that connects the catheter to drainage bag is intact.
Medium Risk	Catheter secured/stat lock is in place.
Medium Risk	Consider using a different type of catheter
High Risk	Consider removing catheter.

5.2 Areas of Future Research

Further development of this work can be done in two main ways. First, an expert's opinion on the interaction between the duration and environmental factors could be obtained for the fuzzy associative model. To avoid the bias of one individual, a group of experts could be analyzed and their input combined to produce results for the interaction of environmental factors and duration. Doctors and nurses could be consulted as experts in the health industry. It may also be beneficial to consult an expert in human factors engineering to assess the impact the environmental conditions have on the system. This would strengthen the results produced from the fuzzy associative model, and therefore the CAUTI reduction tool.

Another area of research would be implementing the CAUTI reduction tool in a real hospital setting. Whether or not the patient develops a CAUTI should be recorded for patients being tracked with the CAUTI reduction tool. This information can be used to determine the validity of the tool. The rates of CAUTI in the hospital should be gathered before and after the implementation of the tool to assess the impact the tool had on reducing the rates of CAUTI.

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Appendix A - EPCs in HEART

Table A-1. Complete List of EPCs in HEART

No.	Error Producing Condition	Maximum predicted nominal amount by which unreliability might change from going to good conditions to bad
1.	Unfamiliarity with a situation which is potentially important but which only occurs infrequently or which is novel	x17
2.	A shortage of time available for error detection and correction	x11
3.	A low signal-noise ratio	x10
4.	A means of suppressing or over-riding information or features which is too easily accessible	x9
5.	No means of conveying spatial and functional information to operators in a form which they can readily assimilate	x8
6.	A mismatch between an operator's model of the world and that imagined by a designer	x8
7.	No obvious means of reversing an unintended action	x8
8.	A channel capacity overload, particularly one caused by simultaneous presentation of non-redundant information	x6
9.	A need to unlearn a technique and apply one which requires the application of an opposing philosophy	x6
10.	The need to transfer specific knowledge from task to task without loss	x5.5
11.	Ambiguity in the required performance standards	x5
12.	A mismatch between perceived and real risk	x4
13.	Poor, ambiguous, or ill-matched system feedback	x4
14.	No clear direct and timely confirmation of an intended action from the portion of the system over which control is to be exerted	x4
15.	Operator inexperience (e.g. a newly- qualified tradesman, but not an "expert")	x3
16.	An impoverished quality of information conveyed by procedures and person/ person interaction	x3
17.	Little or no independent checking or testing of output	x3
18.	A conflict between immediate and long-term objectives	x2.5
19.	No diversity of information input for veracity checks	x2.5
20.	A mismatch between the educational achievement level of an individual and the requirements of the task	x2
21.	An incentive to use other more dangerous procedures	x2

22.	Little opportunity to exercise mind and body outside the immediate confines of a job	x1.8
23.	Unreliable instrumentation (enough that it is noticed)	x1.6
24.	A need for absolute judgments which are beyond the capabilities or experience of an operator	x1.6
25.	Unclear allocation of function responsibility	x1.6
26.	No obvious way to keep track of progress during an activity	x1.4
27.	A danger that finite physical capabilities will be exceeded	x1.4
28.	Little or no intrinsic meaning in a task	x1.4
29.	High-level emotional stress	x1.3
30.	Evidence of ill-health amongst operatives, especially fever	x1.2
31.	Low workforce morale	x1.2
32.	Inconsistency of meaning of displays and procedures	x1.2
33.	A poor or hostile environment (below 75% of health or life-threatening severity)	x1.15
34.	Prolonged inactivity or highly repetitious cycling of low mental workload tasks	x1.1 for first half hour x1.05 for each hour thereafter
35.	Disruption of normal work-sleep cycles	x1.1
36.	Task pacing caused by the intervention of others	x1.06
37.	Additional team members over and above those necessary to perform task normally and satisfactorily	x1.03 per additional man
38.	Age of personnel performing perceptual tasks	x1.02

Appendix B - CAUTI Health Factors References

Table B-1. CAUTI Health Factors References

Health Factor	References
Gender	(Platt, Polk, Murdock, & Rosner, 1986) (Maki &Tambyah, 2001) (Graves, et al., 2007) (How-to Guide: Prevent Catheter-Associated Urinary Tract Infections, 2011) (Johnson, Roberts, Olsen, Moyer, & Stamm, 1990) (Riley, Classen, Stevens, & Burke, 1995) (Crouzet, et al., 2007) (Tambyah & Oon, 2012)
Duration of catheterization	(Platt, Polk, Murdock, & Rosner, 1986) (Maki &Tambyah, 2001) (Graves, et al., 2007) (Riley, Classen, Stevens, & Burke, 1995) (Crouzet, et al., 2007) (Tambyah & Oon, 2012)
Systemic antibiotic	(Platt, Polk, Murdock, & Rosner, 1986) (How-to Guide: Prevent Catheter-Associated Urinary Tract Infections, 2011) (Johnson, Roberts, Olsen, Moyer, & Stamm, 1990) (Riley, Classen, Stevens, & Burke, 1995) (Crouzet, et al., 2007) (Tambyah & Oon, 2012)
Diabetes	(Platt, Polk, Murdock, & Rosner, 1986) (Maki &Tambyah, 2001) (Graves, et al., 2007)

Appendix C - Fuzzy Rule Base Model Results

Table C-1. Fuzzy Rule Base Model Results

Case	Duration	Patient has diabetes	Patient is receiving antibiotic	Environmental control mode	Female Probability	Male Probability
1	1	no	no	0.37	0.36	0.19
1	2	no	no	0.37	0.36	0.19
1	3	no	no	0.37	0.36	0.19
1	4	no	no	0.37	0.36	0.36
1	5	no	no	0.37	0.36	0.36
1	6	no	no	0.37	0.44	0.41
1	7	no	no	0.37	0.50	0.50
1	8	no	no	0.37	0.50	0.50
1	9	no	no	0.37	0.50	0.50
1	10	no	no	0.37	0.50	0.50
2	1	no	no	0.83	0.36	0.19
2	2	no	no	0.83	0.36	0.19
2	3	no	no	0.83	0.41	0.19
2	4	no	no	0.83	0.50	0.36
2	5	no	no	0.83	0.50	0.36
2	6	no	no	0.83	0.59	0.41
2	7	no	no	0.83	0.64	0.50
2	8	no	no	0.83	0.64	0.50
2	9	no	no	0.83	0.64	0.50
2	10	no	no	0.83	0.64	0.50
3	1	no	no	0.93	0.48	0.47
3	2	no	no	0.93	0.48	0.47
3	3	no	no	0.93	0.54	0.47
3	4	no	no	0.93	0.63	0.48
3	5	no	no	0.93	0.63	0.48
3	6	no	no	0.93	0.63	0.47
3	7	no	no	0.93	0.64	0.50
3	8	no	no	0.93	0.64	0.50
3	9	no	no	0.93	0.64	0.50
3	10	no	no	0.93	0.64	0.50
4	1	yes	yes	0.59	0.36	0.33
4	2	yes	yes	0.59	0.36	0.33
4	3	yes	yes	0.59	0.41	0.33
4	4	yes	yes	0.59	0.43	0.36
4	5	yes	yes	0.59	0.43	0.36
4	6	yes	yes	0.59	0.52	0.43
4	7	yes	yes	0.59	0.58	0.50

4	8	yes	yes	0.59	0.58	0.50
4	9	yes	yes	0.59	0.58	0.50
4	10	yes	yes	0.59	0.58	0.50
5	1	no	no	0.48	0.36	0.28
5	2	no	no	0.48	0.36	0.28
5	3	no	no	0.48	0.38	0.28
5	4	no	no	0.48	0.38	0.36
5	5	no	no	0.48	0.38	0.36
5	6	no	no	0.48	0.47	0.42
5	7	no	no	0.48	0.53	0.50
5	8	no	no	0.48	0.53	0.50
5	9	no	no	0.48	0.53	0.50
5	10	no	no	0.48	0.53	0.50
6	1	no	no	0.10	0.36	0.19
6	2	no	no	0.10	0.36	0.19
6	3	no	no	0.10	0.38	0.19
6	4	no	no	0.10	0.38	0.36
6	5	no	no	0.10	0.38	0.36
6	6	no	no	0.10	0.46	0.41
6	7	no	no	0.10	0.53	0.50
6	8	no	no	0.10	0.53	0.50
6	9	no	no	0.10	0.53	0.50
6	10	no	no	0.10	0.53	0.50
7	1	no	yes	0.76	0.39	0.38
7	2	no	no	0.76	0.39	0.38
7	3	no	no	0.76	0.44	0.38
7	4	no	no	0.76	0.53	0.39
7	5	no	no	0.76	0.53	0.39
7	6	no	no	0.76	0.59	0.43
7	7	no	no	0.76	0.64	0.50
7	8	no	no	0.76	0.64	0.50
7	9	no	no	0.76	0.64	0.50
7	10	no	no	0.76	0.64	0.50
8	1	yes	yes	0.59	0.36	0.33
8	2	yes	yes	0.59	0.36	0.33
8	3	yes	yes	0.59	0.41	0.33
8	4	yes	yes	0.59	0.43	0.36
8	5	yes	yes	0.59	0.43	0.36
8	6	yes	yes	0.59	0.52	0.43
8	7	yes	yes	0.59	0.58	0.50
8	8	yes	yes	0.59	0.58	0.50
8	9	yes	yes	0.59	0.58	0.50
8	10	yes	yes	0.59	0.58	0.50

9	1	yes	yes	0.35	0.36	0.19
9	2	yes	yes	0.35	0.36	0.19
9	3	yes	yes	0.35	0.41	0.19
9	4	yes	yes	0.35	0.50	0.36
9	5	yes	yes	0.35	0.50	0.36
9	6	yes	yes	0.35	0.59	0.41
9	7	yes	yes	0.35	0.64	0.50
9	8	yes	yes	0.35	0.64	0.50
9	9	yes	yes	0.35	0.64	0.50
9	10	yes	yes	0.35	0.64	0.50
10	1	no	no	0.25	0.36	0.19
10	2	no	no	0.25	0.36	0.19
10	3	no	no	0.25	0.39	0.19
10	4	no	no	0.25	0.39	0.36
10	5	no	no	0.25	0.39	0.36
10	6	no	no	0.25	0.48	0.41
10	7	no	no	0.25	0.54	0.50
10	8	no	no	0.25	0.54	0.50
10	9	no	no	0.25	0.54	0.50
10	10	no	no	0.25	0.54	0.50
11	1	no	yes	0.90	0.46	0.45
11	2	no	yes	0.90	0.46	0.45
11	3	no	yes	0.90	0.53	0.45
11	4	no	yes	0.90	0.61	0.46
11	5	no	yes	0.90	0.61	0.46
11	6	no	yes	0.90	0.61	0.45
11	7	no	yes	0.90	0.64	0.50
11	8	no	yes	0.90	0.64	0.50
11	9	no	yes	0.90	0.64	0.50
11	10	no	yes	0.90	0.64	0.50
12	1	yes	yes	0.46	0.36	0.26
12	2	yes	yes	0.46	0.36	0.26
12	3	yes	yes	0.46	0.38	0.26
12	4	yes	yes	0.46	0.38	0.36
12	5	yes	yes	0.46	0.38	0.36
12	6	yes	yes	0.46	0.46	0.41
12	7	yes	yes	0.46	0.53	0.50
12	8	yes	yes	0.46	0.53	0.50
12	9	yes	yes	0.46	0.53	0.50
12	10	yes	yes	0.46	0.53	0.50
13	1	no	yes	0.10	0.36	0.19
13	2	no	yes	0.10	0.36	0.19
13	3	no	yes	0.10	0.38	0.19

13	4	no	yes	0.10	0.38	0.36
13	5	no	yes	0.10	0.38	0.36
13	6	no	yes	0.10	0.46	0.41
13	7	no	yes	0.10	0.53	0.50
13	8	no	yes	0.10	0.53	0.50
13	9	no	yes	0.10	0.53	0.50
13	10	no	yes	0.10	0.53	0.50
14	1	yes	no	0.74	0.37	0.37
14	2	yes	no	0.74	0.37	0.37
14	3	yes	no	0.74	0.43	0.37
14	4	yes	no	0.74	0.52	0.37
14	5	yes	no	0.74	0.52	0.37
14	6	yes	no	0.74	0.59	0.44
14	7	yes	no	0.74	0.64	0.50
14	8	yes	no	0.74	0.64	0.50
14	9	yes	no	0.74	0.64	0.50
14	10	yes	no	0.74	0.64	0.50
15	1	no	no	0.73	0.37	0.36
15	2	no	no	0.73	0.37	0.36
15	3	no	no	0.73	0.42	0.36
15	4	no	no	0.73	0.51	0.37
15	5	no	no	0.73	0.51	0.37
15	6	no	no	0.73	0.59	0.44
15	7	no	no	0.73	0.64	0.50
15	8	no	no	0.73	0.64	0.50
15	9	no	no	0.73	0.64	0.50
15	10	no	no	0.73	0.64	0.50
16	1	yes	no	0.96	0.49	0.49
16	2	yes	no	0.96	0.49	0.49
16	3	yes	no	0.96	0.55	0.49
16	4	yes	no	0.96	0.64	0.49
16	5	yes	no	0.96	0.64	0.49
16	6	yes	no	0.96	0.64	0.49
16	7	yes	no	0.96	0.64	0.50
16	8	yes	no	0.96	0.64	0.50
16	9	yes	no	0.96	0.64	0.50
16	10	yes	no	0.96	0.64	0.50
17	1	yes	yes	0.45	0.36	0.26
17	2	yes	yes	0.45	0.36	0.26
17	3	yes	yes	0.45	0.37	0.26
17	4	yes	yes	0.45	0.37	0.36
17	5	yes	yes	0.45	0.37	0.36
17	6	yes	yes	0.45	0.46	0.41

17	7	yes	yes	0.45	0.52	0.50
17	8	yes	yes	0.45	0.52	0.50
17	9	yes	yes	0.45	0.52	0.50
17	10	yes	yes	0.45	0.52	0.50
18	1	no	yes	0.25	0.36	0.19
18	2	no	yes	0.25	0.36	0.19
18	3	no	yes	0.25	0.39	0.19
18	4	no	yes	0.25	0.39	0.36
18	5	no	yes	0.25	0.39	0.36
18	6	no	yes	0.25	0.48	0.41
18	7	no	yes	0.25	0.54	0.50
18	8	no	yes	0.25	0.54	0.50
18	9	no	yes	0.25	0.54	0.50
18	10	no	yes	0.25	0.54	0.50
19	1	no	no	0.12	0.36	0.19
19	2	no	no	0.12	0.36	0.19
19	3	no	no	0.12	0.38	0.19
19	4	no	no	0.12	0.38	0.36
19	5	no	no	0.12	0.38	0.36
19	6	no	no	0.12	0.47	0.41
19	7	no	no	0.12	0.53	0.50
19	8	no	no	0.12	0.53	0.50
19	9	no	no	0.12	0.53	0.50
19	10	no	no	0.12	0.53	0.50
20	1	no	no	0.53	0.36	0.31
20	2	no	no	0.53	0.36	0.31
20	3	no	no	0.53	0.40	0.31
20	4	no	no	0.53	0.40	0.36
20	5	no	no	0.53	0.40	0.36
20	6	no	no	0.53	0.49	0.42
20	7	no	no	0.53	0.56	0.50
20	8	no	no	0.53	0.56	0.50
20	9	no	no	0.53	0.56	0.50
20	10	no	no	0.53	0.56	0.50

Appendix D - Fuzzy Associative Memories Model Results

Table D-1. Fuzzy Associative Memory Model Results

Duration	Environment	Case 7, Worst Female	Case 6, Best Female	Case 3, Worst Male	Case 2, Best Male
1	0.1	0.50	0.20	0.20	0.20
2	0.1	0.50	0.20	0.20	0.20
3	0.1	0.50	0.21	0.21	0.21
4	0.1	0.50	0.29	0.20	0.20
5	0.1	0.50	0.29	0.20	0.20
6	0.1	0.79	0.57	0.50	0.50
7	0.1	0.80	0.56	0.50	0.50
8	0.1	0.80	0.56	0.50	0.50
9	0.1	0.80	0.56	0.50	0.50
10	0.1	0.80	0.56	0.50	0.50
1	0.37	0.50	0.25	0.19	0.25
2	0.37	0.50	0.25	0.19	0.25
3	0.37	0.50	0.25	0.25	0.25
4	0.37	0.50	0.49	0.25	0.25
5	0.37	0.50	0.49	0.50	0.25
6	0.37	0.79	0.77	0.50	0.50
7	0.37	0.81	0.80	0.50	0.50
8	0.37	0.81	0.80	0.50	0.50
9	0.37	0.81	0.80	0.50	0.50
10	0.37	0.81	0.80	0.50	0.50
1	0.73	0.50	0.50	0.50	0.22
2	0.73	0.50	0.50	0.50	0.22
3	0.73	0.50	0.50	0.50	0.25
4	0.73	0.76	0.76	0.51	0.50
5	0.73	0.76	0.76	0.51	0.50
6	0.73	0.76	0.76	0.79	0.76
7	0.73	0.76	0.76	0.81	0.76
8	0.73	0.76	0.76	0.81	0.76
9	0.73	0.76	0.76	0.81	0.76
10	0.73	0.76	0.76	0.81	0.76
1	0.96	0.50	0.50	0.50	0.47
2	0.96	0.50	0.50	0.50	0.47
3	0.96	0.50	0.50	0.50	0.46
4	0.96	0.81	0.81	0.76	0.50
5	0.96	0.81	0.81	0.76	0.50
6	0.96	0.79	0.79	0.79	0.79
7	0.96	0.81	0.81	0.81	0.81

8	0.96	0.81	0.81	0.81	0.81
9	0.96	0.81	0.81	0.81	0.81
10	0.96	0.81	0.81	0.81	0.81
1	0.55	0.50	0.50	0.22	0.21
2	0.55	0.50	0.50	0.22	0.21
3	0.55	0.50	0.50	0.22	0.21
4	0.55	0.50	0.50	0.5	0.50
5	0.55	0.50	0.50	0.5	0.50
6	0.55	0.78	0.78	0.79	0.50
7	0.55	0.78	0.78	0.79	0.50
8	0.55	0.78	0.78	0.79	0.50
9	0.55	0.78	0.78	0.79	0.50
10	0.55	0.78	0.78	0.79	0.50
1	0.71	0.50	0.50	0.4	0.19
2	0.71	0.50	0.50	0.4	0.19
3	0.71	0.50	0.50	0.5	0.21
4	0.71	0.60	0.60	0.5	0.50
5	0.71	0.60	0.60	0.5	0.50
6	0.71	0.60	0.60	0.79	0.60
7	0.71	0.75	0.75	0.81	0.60
8	0.71	0.75	0.75	0.81	0.60
9	0.71	0.75	0.75	0.81	0.60
10	0.71	0.75	0.75	0.81	0.60
1	0.8	0.50	0.50	0.5	0.31
2	0.8	0.50	0.50	0.5	0.31
3	0.8	0.50	0.50	0.5	0.34
4	0.8	0.77	0.77	0.57	0.5
5	0.8	0.77	0.77	0.57	0.5
6	0.8	0.77	0.77	0.79	0.77
7	0.8	0.77	0.77	0.80	0.77
8	0.8	0.77	0.77	0.80	0.77
9	0.8	0.77	0.77	0.80	0.77
10	0.8	0.77	0.77	0.80	0.77
1	0.6	0.50	0.50	0.23	0.20
2	0.6	0.50	0.50	0.23	0.20
3	0.6	0.50	0.50	0.23	0.21
4	0.6	0.50	0.50	0.5	0.5
5	0.6	0.50	0.50	0.5	0.5
6	0.6	0.77	0.77	0.79	0.5
7	0.6	0.77	0.77	0.80	0.5
8	0.6	0.77	0.77	0.80	0.5
9	0.6	0.77	0.77	0.80	0.5
10	0.6	0.77	0.77	0.80	0.5

Appendix E - Comparison Data for Worst Female Male Cases

Table E-1. Comparison Data for Worst Female and Worst Male Cases

Duration	Environment	Case 3, Worst Male	Case 7, Worst Female
1	0.1	0.20	0.20
2	0.1	0.20	0.20
3	0.1	0.21	0.21
4	0.1	0.20	0.5
5	0.1	0.20	0.5
6	0.1	0.50	0.79
7	0.1	0.50	0.80
8	0.1	0.50	0.80
9	0.1	0.50	0.80
10	0.1	0.50	0.80
1	0.37	0.19	0.25
2	0.37	0.19	0.25
3	0.37	0.25	0.25
4	0.37	0.25	0.5
5	0.37	0.50	0.5
6	0.37	0.50	0.75
7	0.37	0.50	0.75
8	0.37	0.50	0.75
9	0.37	0.50	0.75
10	0.37	0.50	0.75
1	0.73	0.50	0.50
2	0.73	0.50	0.50
3	0.73	0.50	0.50
4	0.73	0.51	0.76
5	0.73	0.51	0.76
6	0.73	0.79	0.79
7	0.73	0.81	0.81
8	0.73	0.81	0.81
9	0.73	0.81	0.81
10	0.73	0.81	0.81
1	0.96	0.50	0.50
2	0.96	0.50	0.50
3	0.96	0.50	0.50
4	0.96	0.76	0.81
5	0.96	0.76	0.81
6	0.96	0.79	0.79
7	0.96	0.81	0.81

8	0.96	0.81	0.81
9	0.96	0.81	0.81
10	0.96	0.81	0.81
1	0.55	0.22	0.50
2	0.55	0.22	0.50
3	0.55	0.22	0.50
4	0.55	0.5	0.50
5	0.55	0.5	0.50
6	0.55	0.79	0.79
7	0.55	0.79	0.79
8	0.55	0.79	0.79
9	0.55	0.79	0.79
10	0.55	0.79	0.79
1	0.71	0.4	0.5
2	0.71	0.4	0.5
3	0.71	0.5	0.5
4	0.71	0.5	0.6
5	0.71	0.5	0.6
6	0.71	0.79	0.79
7	0.71	0.81	0.81
8	0.71	0.81	0.81
9	0.71	0.81	0.81
10	0.71	0.81	0.81
1	0.8	0.5	0.50
2	0.8	0.5	0.50
3	0.8	0.5	0.50
4	0.8	0.57	0.77
5	0.8	0.57	0.77
6	0.8	0.79	0.79
7	0.8	0.80	0.80
8	0.8	0.80	0.80
9	0.8	0.80	0.80
10	0.8	0.80	0.80
1	0.6	0.23	0.50
2	0.6	0.23	0.50
3	0.6	0.23	0.50
4	0.6	0.5	0.50
5	0.6	0.5	0.50
6	0.6	0.79	0.79
7	0.6	0.80	0.80
8	0.6	0.80	0.80
9	0.6	0.80	0.80
10	0.6	0.80	0.80