Winter 2014

Naval Aviation Squadron Risk Analysis Predictive Bayesian Network Modeling Using Maintenance Climate Assessment Survey Results

Harry Michael Robinson
Old Dominion University

NAVAL AVIATION SQUADRON RISK ANALYSIS PREDICTIVE BAYESIAN NETWORK MODELING USING MAINTENANCE CLIMATE ASSESSMENT SURVEY RESULTS

by

Harry Michael Robinson
B.S. May 1982, Pennsylvania State University
M.S. December 1992, University of Tennessee

A Dissertation Submitted to the Faculty of
Old Dominion University in Partial Fulfillment of the
Requirements for the Degree of

DOCTOR OF PHILOSOPLY

MODELING AND SIMULATION

OLD DOMINION UNIVERSITY
December 2014

Approved by:

John A. Sokolowski (Director)

Ivan K. Ash (Member)

Anthony P. Ciavarelli (Member)

C. Ariel Pinto (Member)

Robert R. Safford (Member)

ABSTRACT

NAVAL AVIATION SQUADRON RISK ANALYSIS PREDICTIVE BAYESIAN NETWORK MODELING USING MAINTENANCE CLIMATE ASSESSMENT SURVEY RESULTS

Harry Michael Robinson
Old Dominion University, 2014
Director: Dr. John A. Sokolowski

Associated risks in flying have resulted in injury or death to aircrew and passengers, and damage or destruction of the aircraft and its surroundings. Although the Naval Aviation's flight mishap rate declined over the past 60 years, the proportion of human error causal factors has stayed relatively constant at about 80%. Efforts to reduce human errors have focused attention on understanding the aircrew and maintenance actions occurring in complex systems.

One such tool has been the Naval Aviation squadrons' regular participation in survey questionnaires deigned to measure respondent ratings related to personal judgments or perceptions of organizational climate for meeting the extent to which a particular squadron achieved the High Reliability Organization (HRO) criteria of achieving safe and reliable operations and maintenance practices while working in hazardous environments. Specifically, the Maintenance Climate Assessment Survey (MCAS) is completed by squadron maintainers to enable leadership to assess their unit's aggregated responses against those from other squadrons.

Bayesian Network Modeling and Simulation provides a potential methodology to represent the relationships of MCAS results and mishap occurrences that can be used to derive and calculate probabilities of incurring a future mishap. Model development and simulation analysis was conducted to research a causal relationship

through quantitative analysis of conditional probabilities based upon observed evidence of previously occurred mishaps. This application would enable Navy and Marine Corps aviation squadron leadership to identify organizational safety risks, apply focused proactive measures to mitigate related hazards characterized by the MCAS results, and reduce organizational susceptibility to future aircraft mishaps.

This dissertation is dedicated to my family, especially Anne and Andrew, for their support and understanding. I am grateful to my father, Captain "Fast Eddie" Robinson, U.S. Naval Reserve, who introduced me to Naval Aviation and my mother, Deborah Lowenthal Robinson who pinned on my wings of gold.

The research conducted and detailed here within is for the men and women who ardently serve in the United States Navy and Marine Corps. Their determination and spirit is the bedrock of Naval Aviation which enables the capability to Fly, Fight, and Lead.

ACKNOWLEDGEMENTS

There are many individuals whom have guided me and supported the successful completion of this dissertation. I extend my sincere gratitude to my committee members for their counsel, advice, and patience on my research and editing of this manuscript. I am very appreciative for the advocacy and mentoring provided by my dissertation director, Dr. Sokolowski. My attendance at his dissertation defense in 2003 as the first doctoral candidate in Modeling and Simulation at Old Dominion University served to be very inspiring. A temporary duty assignment to the Aviation Safety Officer course at the Naval Postgraduate School in 1993 led to my introduction to Dr. Tony Ciavarelli. His instruction in Aviation Psychology served as a firm footing for this research, and his continued support was critical.

John Scott, the Data Management and Services Division Head, U.S. Naval Safety Center, was absolutely essential for providing the double blinded data set for the Maintenance Climate Assessment Surveys and Aviation Mishap Summary Reports. Without his effort, accomplished above his normal duties, this research could not have been conducted. I am also appreciative to Rear Admiral George Mayer and Commander Michael Scavone from the Naval Safety Center for their support of this endeavor.

I need to publicly recognize the counsel and advice received from both Missy Cummings, Ph.D., of Duke University and former Navy F/A-18 fighter pilot as well as Paul Weigand, PhD from the University of Central Florida, Institute of Simulation and Technology. Their suggestions, instructions, and encouragement were critical in starting this effort and bringing it to conclusion.

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1. INTRODUCTION

1.1. PURPOSE

The main objective for pursuit of this research effort was to accurately model the impact of naval aviation squadron maintenance on mishap occurrence. The purpose of the developed model(s) would serve as an effective predictive tool for leadership to enable conduct of proactive risk management that would reduce likelihood for sustaining an aviation related mishap.

1.2. BACKGROUND

From its inception, flying has been accompanied by inherent, unique, and sometimes unforgiving risks. The exposure to these associated hazards results in injury or death to aircrew and passengers, and damage or destruction of the aircraft and its surroundings. In the effort to improve aviation safety, post-crash inspections continue to be conducted to identify specific material and mechanical failure modes. Initially, attention was directed towards improving aircraft material defects. The iterative engineering process of developing and manufacturing better aircraft based upon lessons learned from previous material and component failures led to significant reductions in aviation mishap rates. Continued post-mishap analysis demonstrates that there has been a decrease in material failures as contributing causal factors; however, human error is still a leading cause of numerous aircraft accidents. [Nagel, 1998]

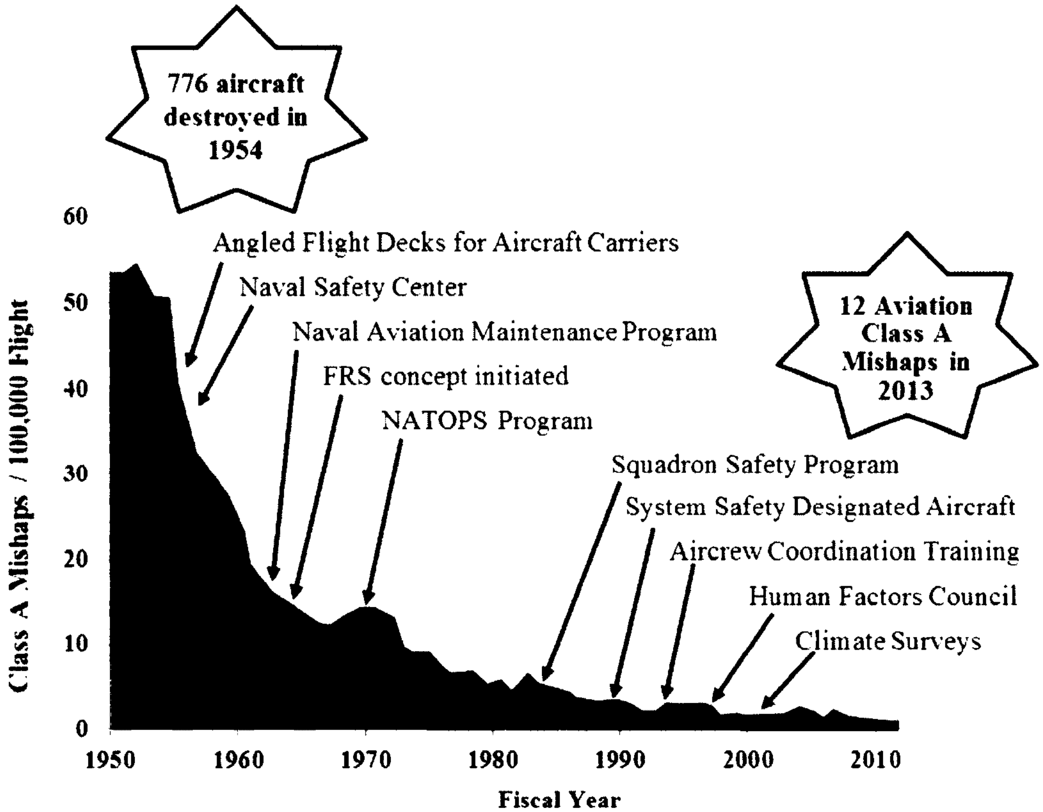
Two approaches have been directed to mitigate the effects of human error. First, application of Human Factors engineering and ergonomics enhanced the interfaces between the human operator and individual component system. Second, Human Factors programs were implemented to define and enforce acceptable standards in maintenance proficiency, aircrew skills, and safety in the effort to further reduce the risks associated with aviation. These programs served to train key personnel within the aviation field to improve their capabilities, knowledge, and imperviousness to committing errant actions. Aircraft mishap investigations continue to focus on human error. "Indeed, estimates in the literature indicate that somewhere between 70 and 80 percent of all aviation accidents can be attributed, at least in part, to human error." [Wiegmann & Shappell, 2003, p. 2] As shown in Table 1 below, during Fiscal Years 2011 and 2012, U.S. Navy and Marine Corps Aviation Characterization Factors, human factors error contributed to 61% of sustained Class A mishaps. [Naval Safety Center, 2013]

Table 1. U.S. Navy and Marine Corps Aviation Characterization Factors Leading up to Class A Mishaps for Fiscal Years 2011 and 2012 [Naval Safety Center, 2013]

Characterization Factor	2011	2012	Total
Maintenance Failure only	1	1	2
Material Failure only	5	3	8
Aircrew Related Human Factors Error only	6	7	13
Maintenance / Material Failure Leading to Aircrew Related Human Factors Error	4	3	7
Undetermined	0	0	1
Total	16	15	31

Since 1950, Naval Aviation has employed several intervention strategies to reduce the occurrences of aircraft mishaps. A standard measurement to evaluate aviation safety performance uses the number of aviation mishap events per 100,000 flight hours. Naval Aviation classifies mishaps under three different severity classifications and three mishap categories. Class A mishaps are the most severe and are described by the result in which the "total damage cost is $1,000,000 or more and/or aircraft destroyed and/or fatal injury and or permanent disability." [OPNAVINST 3750.6R, 2003, Appendix 3C] On October 6, 2009, the Class A cost threshold was revised to $2,000,000 total damage. Mishap severity categories range from Class A through Class C depending upon the cost of damage and amount of personnel injury sustained. A complete description of mishap type and severity can be found in Appendix A.

Figure 1 shows a clear reduction in the Class A mishap rate from 1950 through 1980. However in recent years, the slope of the incidence rate has leveled out at approximately 2 per 100,000 flight hours through application of various additional engineering and administrative control measures.



Note:

- NAMP-Naval Aviation Maintenance Program. Established 3 tiered maintenance system, organizational level at squadron, intermediate level, and depot level.
- FRS-Fleet Replacement Squadron designed to train aviators in their specific aircraft after earning wings in the training command and prior to fleet squadron assignment.
- NATOPS-Naval Air Training and Operating Procedures Standardization. A program consisting of general and specific instructions that provide guidance and constraints for all naval aircraft and associated activities.

Figure 1. U.S. Naval Aviation Accident Rate and Intervention Strategies [U.S. Naval Safety Center, Aviation Statistics]

Former Secretary of Defense Donald Rumsfeld stated that "World-class organizations do not tolerate preventable accidents…I challenge all of you to reduce the number of mishaps and accident rates by at least 50% in the next two years. These goals are achievable, and will directly increase our operational readiness." [Rumsfeld, 2003] The data presented in table 2 indicate that Naval Aviation has not met the Secretary's goals.

Table 2. Navy and Marine Corps Class A Mishap Rates For Fiscal Years 2000-2013 per 100,000 Flight Hours [Source: U.S. Naval Safety Center]

Fiscal Year (FY)	Flight Hours	Mishaps	Mishap Rate
FY00	1,460,003	29	1.99
FY01	1,479,915	19	1.28
FY02	1,577,217	36	2.28
FY03	1,516,049	37	2.44
FY04	1,360,632	30	2.20
FY05	1,229,555	22	1.79
FY06	1,218,498	20	1.64
FY07	1,260,083	16	1.27
FY08	1,243,350	21	1.69
FY09	1,225,297	15	1.22
FY10	1,175,929	11	0.94
FY11	1,244,903	16	1.29
FY12	1,175,830	15	1.28
FY13	1,084,016	12	1.11
FY00-13	18,251,277	299	1.64

Although the Naval Aviation's flight mishap rate declined over the past 60 years, the proportion of human error causal factors has stayed relatively constant at about 80% [Naval Safety Center, 2010]. Efforts to reduce human errors have focused attention on understanding the aircrew and maintenance actions occurring in complex systems. In 1996, a Human Factors Quality Management Board was tasked to analyze and recommend processes, programs, and systems that would improve human performance with the purpose of reducing the aviation mishap rate. The board's recommendations included Naval Aviation squadrons' regular participation in survey questionnaires. These were designed to assess the operational and maintenance practices from a safety perspective as a tool for leadership to proactively employ the command's influence on the chain of events that may lead to an aircraft mishap. The Command Safety Assessment (CSA) surveys are taken by squadron aircrew and Maintenance Climate Assessment Survey (MCAS) are completed by squadron maintainers. Leadership may view anonymous results and compare their unit's aggregated responses against those from other squadrons.

The Aviation CSA questionnaire was first used in 1996 to survey Navy and Marine Corps aviation units to measure respondent ratings related to personal judgments or perceptions of command climate for meeting the High Reliability Organization (HRO) criteria of achieving safe and reliable operations and maintenance practices while working in hazardous environments. HROs two key characteristics were defined by Roberts as capability to proactively manage organizational complexity and tightly coupled operations. [Roberts, 1990b] These characteristics were further refined into the Model of Organizational Safety Effectiveness (MOSE) that is based upon the framework by Roberts [1990a, 1990b] and Libuser [1994]. The MOSE conceptual model consists of:

1. Process Auditing. Continuing analysis for hazard identification and establishment of corrective measures.
2. Reward System and Safety Culture. Use of rewards and discipline to achieve and maintain desired safe behavior.
3. Quality Assurance. Policies and procedures that promote and reinforce high quality of work performance.

4. Risk Management. Processes to accurately perceive risk, identify hazards, and implement control measures.
5. Command and Control. Consists of unit climate, effectiveness of leadership, policies, and management processes.

Subsequent to refinement and statistical validation, the 57 item CSA was conducted through secure internet-based evaluations that provide unit commanders feedback regarding their command climate, safety culture, workload, resource availability, estimated success of certain safety intervention programs, and other associated factors related to managing safe flight operations. [Ciavarelli, 2001] Aircrew respondents provide their assessments using a quantitative Likert-type, five-point rating scale (i.e., Strongly Disagree, Disagree, Neutral, Agree, or Strongly Agree). "These responses are given numeric values of 1, 2, 3, 4, and 5 respectively. For all but one of the survey's Likert items, a positive response to the Likert item implies that the respondent takes a view that his/her squadron is addressing that issue in a safe manner." [Schimpf, 2004b, p. 3]

The CSA was augmented by the 43 question Maintenance Climate Assessment Survey (MCAS) to determine the significance of a unit's maintenance effort in achieving safe flight operations. The MCAS is utilized to provide a maintenance centralized focus to measure an organization's ability to safely conduct operations in terms of leadership, culture, policies, standards, procedures, and practices. [Figlock, 2004] It is one of 14 climate assessment surveys used within the Department of Defense that provides individual response anonymity, organizational confidentiality, and restricted access to the results. A study conducted at the Naval Postgraduate School determined the MCAS survey adequately assesses a maintenance technician's perception of safety climate and that there is a positive correlation between the human errors in squadron mishaps and their corresponding survey results. [Adamshick, 2007]

Although research studies have been conducted to evaluate correlation of survey results to mishap occurrence, these have not resulted in providing a suitable metric that would support use of the survey results as a predictive tool to accurately assess the risk of a squadron incurring a future mishap. Over the last 10 years, the Navy-Marine Corps Class A - Aviation Mishap Rate has not significantly decreased despite leadership directives to do so. This research effort was undertaken to study the potential of a new methodology to achieve improved aviation safety by using MCAS response data as input for Bayesian Network Modeling to predict a squadron's likelihood to incur a future mishap.

1.3. PROBLEM STATEMENT

Decreases in naval aviation mishap occurrence rates and percentage of mishap causal errors related to human errors have plateaued in recent years. Although squadron CSA and MCAS participation has been conducted, related intervention programs implemented, and research efforts executed to analyze correlation between survey results and subsequent mishap occurrences, no definitive tool has been demonstrated to serve as a predictive model for risk analysis. As currently implemented, CSA and MCAS results comparisons to similar organizations do not adequately support squadron leadership / supervisors planning and execution of risk management to prevent the potential occurrence of an aviation mishap. Accurate predictive modeling would provide squadron leadership with better understanding and situational awareness to deploy proactive risk mitigation to reduce incurring future mishaps.

1.4. THESIS STATEMENT

The Maintenance Climate Assessment Survey provides the means for Naval Aviation squadron leadership to obtain a measurement produced from internal organizational personnel. Although this metric tool may be used to compare results to other organizations flying similar Type/Model/Series aircraft, it has limited ability to serve as a predictive instrument for incurring a future mishap. Bayesian Network Modeling and Simulation provides a potential methodology that might be used to represent the relationships of MCAS results and mishap occurrences that can be used to derive and calculate probabilities of incurring a future mishap. Model development and simulation analysis will support defining causal relationships through quantitative analysis of conditional probabilities based upon observed evidence of previously occurred mishaps. This application would enable Navy and Marine Corps aviation squadron leadership to identify organizational safety risks, apply focused proactive measures to mitigate related hazards characterized by the MCAS results, and reduce organizational susceptibility to future aircraft mishaps

1.5. RESEARCH QUESTIONS AND HYPOTHESES

The dissertation research was conducted to address the follow questions and corresponding hypotheses.

1.5.1. RESEARCH QUESTION 1

Does Bayesian Network Modeling provide a better predictor for future mishap occurrence than the MCAS frequency observation reference study of observed probabilities?

$H1_A$: Use of Bayesian Network Modeling to represent the relationship between organizational MCAS results and mishap occurrence will provide improved methodology compared to MCAS frequency observed reference study analysis to predict occurrence of future mishaps.

$H1_0$: Use of Bayesian Network Modeling to represent the relationship between organizational MCAS results and mishap occurrence will not provide improved methodology compared to MCAS frequency observation reference study analysis to predict occurrence of future mishaps.

1.5.2. RESEARCH QUESTION 2

Do any of the individual MOSE components serve as a better indicator for future mishap occurrence using Bayesian Network Modeling?

$H2_A$: Use of Bayesian Network Modeling with specific individual component MCAS results will provide improved methodology compared to aggregated MCAS results to predict occurrence of future mishaps.

$H2_0$: Use of Bayesian Network Modeling with specific component MCAS results will not provide improved methodology compared to aggregated MCAS results to predict occurrence of future mishaps.

1.6. RESEARCH EXPECTATIONS

The expected outcome and goal from this research was to derive an accurate computational Bayesian Network Model that:

1. Characterizes the causal relationships between MCAS results and aircraft mishap occurrence within a Naval Aviation squadron;
2. Enables model execution and analysis for both individual specific MOSE components and aggregated-averaged data;
3. Represents a Naval Aviation squadron's defined relationship between maintenance safety climate and conduct of safe flight operations.

Research questions focused on the adequacy of the computation model to accomplish the three above listed goals.

1.7. ASSUMPTIONS

Assumptions for this dissertation were made as they were required for model development, execution, and analysis. Initial general assumptions which shaped the overall effort include:

- ASSUMPTION 1. Design and implementation of a computational Bayesian Network Model using MCAS derived inputs does not substantially change the intent of the original framework. MCAS was implemented to capture maintenance related items within the MOSE framework.

- ASSUMPTION 2. Use of a computational model to accurately produce conditional probability predictions that reflect causal network relationships between MCAS results and mishap occurrences continues to provide the means to accurately represent MOSE components.
- ASSUMPTION 3. Averaging aggregated organizational response scores of MCAS questions does not alter the accuracy of survey results.
- ASSUMPTION 4: Changes in an organization's safety climate reflected by MCAS results occur at a linear rate for the time period between implementation of successive safety surveys

1.8. SCOPE AND LIMITATIONS

This dissertation focuses upon establishing conceptual and computational Bayesian Network Models that reflect causal relationships between an organization's MCAS results and mishap occurrences. Data analysis was limited to information that was made available by the Naval Safety Center. Due to availability of furnished data, the scope of this research was limited to Naval and Marine Corps squadrons that flew aircraft that deployed onboard aircraft carriers. Mishap narrative and causal factor identification resulted from defined procedures for conduct of Aviation Mishap Boards for producing reports and were vetted via respective chains of command for ultimate concurrence and/or rejection of findings. Other internal and external aspects were not examined or modeled in this study.

1.9. MOTIVATION

The value of this research is to create a computational model that enables squadron leadership to identify defensive gaps in their organizations and to quantify associated risks. Ideally, subsequent to obtaining results from an MCAS survey, squadron leadership could compare the data to previous survey results and actual mishap occurrence and use the models developed from this research to proactively identify risks for future mishap occurrence. Model result would enable directed application of proactive risk management to mitigate potential mishap likelihood and / or severity. The ability to develop, test, and evaluate the desired model for application in Naval Aviation is supported by existing data and metrics.

Due to the tasking of military aircraft and service members for use in armed conflict or supporting missions, military aviation represents a significant investment in financial and human capital. The Fiscal Year (FY) 2014 budget submission for the Naval Aviation Enterprise included \$17.9 Million in Aircraft Procurement and \$8.6 Million in Operations and Maintenance. [Kelly, 2013]

Personnel, air vehicle, and weapons system attrition may be expected in combat as a result of engagements against an armed enemy. However, loss of or degradation to either military aircraft or related service members as the consequence of human error during maintenance evolutions adversely affects combat readiness and impairs the nation's capability to achieve its strategic, operational, and tactical goals. Analysis by the Naval Safety Center indicates that losses due to human error are greater than those sustained from direct enemy action in the Global War on Terrorism.

During most recent participation in prolonged combat operations through the first 11 months of FY 2006, Naval Aviation sustained 25 Class-A mishaps consisting of 21 aircrew deaths and 17 aircraft destroyed compared against the combat loss of a single AH-1W helicopter and 2 aircrew. "The vast majority of our aviation losses are not because of engagements with enemy forces. Our losses overwhelmingly are due to mishaps." [Mayer, 2006, p. 2]

1.10. RESEARCH CONTRIBUTION

The contributions provided by this dissertation research include:

- Providing Naval Aviation squadron leadership with a tool to enable timely identification of risks related to their maintenance safety climate and use of proactive measures to reduce occurrence of future mishaps.
- In addition to Naval Aviation, this application of Bayesian Network Modeling was designed to be of utility to other military and commercial aviation activities. This research was undertaken to provide a foundation that might be adapted for use by industries striving to achieve (near) error free processes for highly reliable and safe operation under hazardous conditions.
- Narrowing the research field for utility of questionnaire surveys for measuring impacts of an organization's safety climate.

1.11. RESEARCH APPROACH AND ORGANIZATION

The research presents a formal simulation architecture that focuses on a Bayesian Network Model of risk and probabilities using the MCAS / MOSE framework as a supporting element. The derived computational model's purpose is to accurately represent the associated risks resulting from a squadron's maintenance safety climate in supporting the operational demands for providing aircrew with mission capable aircraft. Model input was derived through decomposition of the MCAS by specific individual MOSE components. Validation of the model's credibility was accomplished using statistical comparison against Aviation Mishap Board investigation reports.

This dissertation consists of the chapters detailing the following sub-divisions:

1. Introduction
2. Literature Review
3. Methodology
4. Results
5. Interpretation, Conclusions, and Recommendations.

2. LITERATURE REVIEW

2.1. DEFINITION OF TERMS

Safety is a desirable characteristic of a squadron's culture; however, safety in itself is not the ultimate priority. If it were, no risks of any degree would be undertaken. "Risk is inherent in everything that the Navy does. Managing risk requires an in-depth understanding of the issues and trade-offs associated with key decisions." [Mullen, 2006, p. 21] Mission accomplishment is of primary efficacy to a military organization. Safety is a critical trait in obtaining and executing combat proficiency to successfully achieve assigned tasking. Some degree of risk is inherent to aviation, and safety allows for effective management of risk. These terms are further defined below:

- Safety. The result of preservation of human lives and material resources through conduct of hazard detection, hazard elimination, and awareness enhancement of all concerned individuals. [OPNAVINST 3750.7R, 2003] As such, safety does not include the absence of incurring a material failure or personal injury simply as a matter of insufficient exposure length. Safety applied to military aviation positively influences mission accomplishment. Losses or injuries sustained directly from combat or sabotage are not considered representative aspects of a unit's safety posture. Reason defined safety as a dynamic non-event. A stable and reliable outcome is due to the application of constant change rather than continuous repetition. To achieve stability, a change in one system must be compensated for by changes in other parameters. [Reason, 1997, p. 37]

- Hazard. Any real or potential risk that can cause personal injury, property damage, mission degradation, or damage to environment. The severity of a hazard is an assessment of the expected consequence, defined by degree of injury, occupational illness, loss, or damage that could occur from exposure to a hazard.
- Risk. The chance of adverse outcome or bad consequences; such as injury, illness, or loss. Risk level is expressed as a function of both hazard probability and severity. [OPNAVINST 3500.39, 2004]

2.1.1. ORGANIZATIONAL SAFETY, SAFETY CULTURE, AND SAFETY CLIMATE

As a means of planning and performing operations related to and required for flight, safety is a critical feature in obtaining and executing combat proficiency to successfully achieve assigned tasking. However, in response to operational stress, safety requirements such as wearing protective equipment, reviewing checklists, and inspections by quality assurance representatives are often seen by front line operators as impediments to achieving short-term goals associated with flight operations. Whether at a local or global level, safety then may be considered an emergent behavior that is not completely captured by the behavior of individual organizational divisions or personnel. Safety is emergent in that it characterizes collective behavior that may be understood through study of the components in the context of the whole organization in which global emergent properties are formed from interdependent parts. [Bar-Yam, 1997] Achievement of safety requires the coordination of the entire organization at each hierarchical level. The conflicting requirements for safety and combat readiness can lead to unpredictability and non-ergodicity.

An aviation squadron's organization is detailed in numerous instructions as to components, functions, and interrelationships. These are rational systems with formal structures and hierarchical organization. As such, a squadron exists in a positivistic reality where objective analysis and degrees of causal linkage may be determined. However, applying analytic reduction to a squadron's organization does not reduce it to independent subsystems. Decomposition results in non-linear interactions and feedback channels, which often produces different behavior when examined individually or as part of the whole system. As an organization, the functions of an aviation squadron are easily bounded, reducible, frequently irreversible, and often contain multiple feedback loops, numerous people and process interactions, and non-linear procedures.

Both safety culture and safety climate are used to describe attributes of an organization to achieve its goals and accomplish its vision while reducing susceptibility to personnel injuries or equipment damage. Safety culture delineates an enduring trait that is reflective of the fundamental values, norms, assumption and expectation that to some extent exist within the group's societal culture. [O'Connor, et. al., 2011b] The culture is passed on to successive generations within the organization. It serves to mold individual behaviors by systematic use of rewards, status expectations, power, authority, inclusion/exclusion of group boundaries, and underlying concepts for managing behavioral deviations. Organizational culture is strongly influenced by its operational / associative structure and leadership/subordinate relationships. [Ciavarelli, 2007]

An organization's safety climate represents a significant component of a High Reliability Organization. Safety climate is the surfaced manifestation of culture and refers to the shared perception organizational personnel that their leaders and personnel are: genuinely committed to safety of operations; have taken appropriate steps to implement and communicate safety standards, processes, and procedures; and ensure adherence. [Goodrum, 1999] Their leaders are genuinely committed to safety of operations, take appropriate measure to communicate safety principles, and ensure adherence to safety standards and procures. [Ciavarelli, 2007] An organization's safety climate is considered to be a more visible manifestation of the culture at a particular moment in time. It is generally accepted that am organization's safety climate at a specific point in time can be measured through use of survey questionnaires. [O'Connor et al, 2011b]

Metrics of components that comprise an organization's safety climate are considered to have utility as both lead and lag indicators.

> "Safety climate introduces the notion that the likelihood of accidents occurring can be predicted on a basis of certain organizational factors. These organizational factors can be used as leading indicators to identify, in advance, the strengths and weaknesses of an organization that influence the likelihood of accidents occurring. Once weaknesses are identified, remedial actions can be taken." [O'Connor et al., 2011a, pp. 27-28]

2.1.2. RISK MANAGEMENT

Accident prevention initiatives are the primary means Naval Aviation has to reduce personnel losses and material costs associated with mishaps. [Schmorrow, 1998] The purpose of this research is to provide a tool to conduct risk management enabling proactive measures to be taken to prevent aviation mishaps. Risk management is a process used to mitigate the undesirable effects of an event that may cause damage or loss to personnel or equipment. Figure 2, below, depicts a structure for implementing risk management as a continuous and iterative cycle.

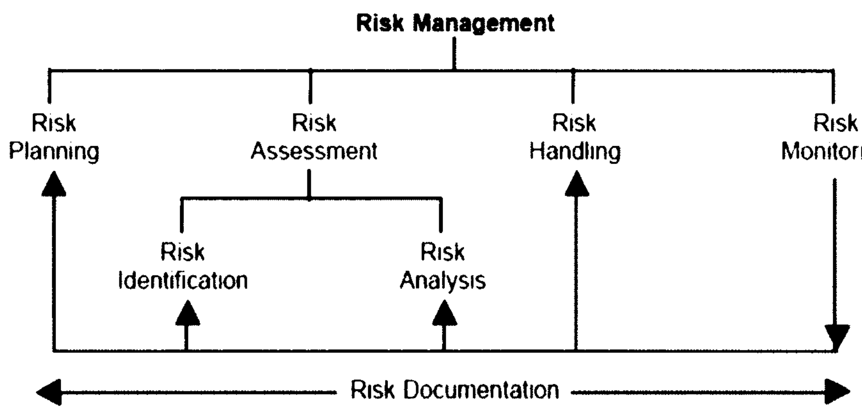


Figure 2. Risk Management Structure [Bahnmaier, 2003, p. 6]

Steps include:

- Risk Assessment. Identification of critical events and analysis to determine their impact. Risks are rated or prioritized based upon their respective probability of occurrence, severity of associated consequences, and relationship to other risks.
- Risk Planning. Conducted in response to continual risk assessments to determine impact of change in associated risks. This process defines and documents the strategy to assign adequate resources to mitigate risks enabling mission accomplishment.

- Risk Handling. Identifies, evaluates, selects, and implements mitigation options to bound risk at an acceptable level given governing constraints and objectives.
- Risk Monitoring. Tracking and appraisal of the success of employed risk handling techniques through use of performance evaluation metrics. It provides a feedback channel for the management cycle.
- Risk Documentation. Data gathering and maintenance to support assessment, handling, planning, and monitoring.

Conduct of aircraft maintenance provides the opportunity for inducing human error. To ensure aircraft are ready for tasking, they require both scheduled upkeep to accomplish routine periodic servicing as well as unscheduled maintenance to correct discrepancies that impede proper system operation. [Commander, Naval Air Forces Instruction (CNAFINST) 4790.2 Change 1, 2006] Aircraft maintenance includes troubleshooting to determine the exact source of a fault, component removal and replacement, repair of defective items, preventive measures that decrease potential failures during flight, and servicing of consumable items that are designed for wear. Quality assurance inspections are conducted on all maintenance actions to ensure the effort was correctly performed. Considerable maintenance efforts are expended for each flight, and maintenance man-hours per flight hours in the range of 10-40 are common for the current inventory of fleet aircraft. As such, each maintenance action provides an opportunity for human error to adversely impact an organization's defense against a mishap.

Design and use of a computational model that may be accurately used to calculate risks resulting from maintenance error would allow applicable squadron personnel to maximize use of Operational Risk Management (ORM). All naval activities are required to apply the ORM process in planning, training, and execution to optimize their operational capability and readiness. [OPNAVINST 3500.39B, 2004, p. 2] This is accomplished through the five-step process of:

1. Hazard Identification
2. Hazard Assessment
3. Risk Decisions
4. Control Implementation
5. Supervision

The goal of this dissertation was to provide a tool for the predictive risk assessment of a squadron's maintenance organization to successfully accomplish its mission of providing and launching aircraft ready for tasking. The intent for the model output is to furnish squadron leadership accurate information to subsequently reach proper risk decisions, implement adequate controls, and provide required supervision to reduce aviation mishaps.

2.2. INFLUENTIAL WORK

This section details key published works that led to crafting the problem and thesis statements and provided direction for this research.

2.2.1. HIGH RELIABILITY ORGANIZATIONS

Roberts [1990b] investigated organizations that had achieved near error free operations for considerable periods of time. An interdisciplinary research team selected three "high reliability" organizations (HROs) that maintained safe and reliable operations under hazardous conditions. HROs consistently conduct operations on the order of tens of thousands of opportunities for experiencing a mishap without experiencing a catastrophic consequence due to human error. [Roberts, 1990b] Operational procedures were examined at Pacific Gas and Electric Company (operator of the Diablo Canyon nuclear power plant and Western U.S. electrical services power grid), Federal Aviation Administration (FAA) Air Traffic Control Centers, and U.S. Navy aircraft carriers. [Roberts, 1990a]

Roberts identified two groups of key traits in common among the three organizational examples to explain their respective successes. First, they were capable of managing complexity through reaction to unexpected sequences of events. On-going training that presented several possible emergency situations prepared essential personnel to face actual crises. The HROs countered the effects of losses by providing for redundancy of essential personnel and equipment. Each establishment used advanced technology requiring high degrees of specialized understanding and interdependence requiring high degrees of generalized understanding. Each of the three entities assigned exceptional responsibility and accountability to low-level employees. The study revealed the HRO personnel understood and managed the potential for the interaction of systems that supported incompatible functions, took advantage of both direct and indirect sources of information, and educated their staffs concerning the complexities resulting from human-machine interfaces to minimize baffling interactions.

Second, the HROs were characterized for management controls of tightly coupled, mechanistic, and brittle (in an engineering sense) operations. Due to execution of time dependent processes, specific functions were decomposed to achieve dispersed redundancy. Flexibility resulted from the coordination of component actions. The HROs defined one way to reach a goal and accepted minimal deviation in performance.

Weick and Sutcliffe [2007] expanded upon the concept of HROs through a social psychology approach to studying the effect of cognitive dissonance on performance. Introducing the themes of collective mindfulness and collective enactment, they described the impact of people on the behaviors of others.
Weick and Sutcliffe identified that HROs contain distinctive structures and their actions are a result of mindful organizing for the unexpected as well as the expected through anticipation and containment.

Anticipation includes both application of early warning mechanisms and control of undesirable events. Components for anticipation include:

- Preoccupation with failure through sensitivity to early signs of failure
- Reluctance to simplify by further investigating to determine and analyze causes
- Sensitivity to operations in understanding dynamic and non-linear organizational inter-relationships.

For unanticipated consequences that occur, containment serves to limit damage and exposure. Elements of containment are:

- Commitment to resilience by maintaining operational functionality during high demand events by absorbing strain and preserving functionality during adversity; maintaining ability to regain functionality after untoward events; and learning / applying lessons from previous events.
- Deference to expertise regardless of organizational hierarchy.

2.2.2. NORMAL ACCIDENT THEORY

Perrow developed the Normal Accident Theory (NAT) after examination of the incident at the Three Mile Island Nuclear Power Plant in 1979. He proposed that two related characteristics, complex interactions between system components and tight coupling, made certain technologically advanced systems susceptible to unavoidable accidents. He contrasted the two theories stating that HRO "believes that if only we try harder we will have virtually accident-free systems even if their inter-relationships and feedback represent complexity (i.e., difficult to quantify)and tightly coupled, while NAT believes that no matter how hard we try we will still have accidents because of intrinsic characteristics of complex/coupled systems." [Perrow, 1999, p. 369] Perrow acknowledged that the four HRO fundamentals are sufficient for linear, looser coupled systems, but trying harder would not prevent a systems accident. He found fault with attempts to make safety the first priority, and he elicited reasons for organizations not achieving increased learning. Perrow characterized NAT and HRO disparities concerning systems prone to multiple errors resulting in unanticipated interactions that defeat the constraints of safety systems. He identified the following characteristics that determine the scope of inevitable failures: operating scale experience, experience with critical processes, information errors, close proximity of "elites" to the system, organizational control over personnel, and organizational density within the system environment.

2.2.3. COMMAND SAFETY CLIMATE SURVEYS

A common method to obtain data that provides measurement of an organization's safety climate is through use of survey questionnaires. This analysis of this information has been used over the past two decades to demonstrate relationships across many safety climate components and mishap occurrence rates in a variety of high-risk industries. [O'Connor et al., 2011a] Naval Aviation uses several surveys for defining organizational safety climate. Climate assessment surveys are used as a measurement of an organization's capability to safely conduct operations in terms of leadership, culture, policies, standards, procedures, and practices. [Figlock, 2004] These include those administered at the squadron level, Fleet Readiness Centers (previously referred to as Aircraft Intermediate Maintenance Departments and Aviation Depots), higher headquarters, support personnel, and contractors. Surveys provide for respondent anonymity, organizational confidentiality (due to limited access to survey results), World Wide Web implementation, and comparative analysis to prior results and like squadron flying similar aircraft. Quantitative data are generated by: demographic questions (e.g., rank, years of experience, service, status, parent command, and location); closed-ended questions and Likert-scale responses;

and qualitative data are supplied through open-ended questions and free text responses to describe unit specific issues.

The squadron level surveys are the Command Safety Assessment and Maintenance Climate Assessment Survey. In 2004, Vice Admiral Zortman, Commander, U.S. Naval Air Forces ordered mandatory compliance for all aviation squadrons to complete assessment surveys semiannually and within 30 days following a change of command. [Buttrey, 2010] The CSA provides aircrew interpretation of key organizational issues that relate to a command's influence on the organizational safety climate factors that may lead to an aircraft mishap. It was developed using the HRO framework for entities that operate in high-risk environments, but have fewer failures than would be predicted. Similarly, the MCAS was designed as a diagnostic tool to capture the maintainers' perspective of risk management and safety climate. The MCAS was developed two years after the CSA and added a sixth component to the MOSE conceptual model, Command and Functional Relationships (C/FR). C/FR consists of the internal organizational communications paths for timely distribution of information to support safe job accomplishment, coordination, and execution of aircraft maintenance.

Schimpf used both squadron CSA and MCAS data for statistical comparison against actual mishap occurrence. He used MathCAD software to develop a mathematical model to predict the frequency of squadrons experiencing 0, 1, 2, 3, or 4 mishaps within 12 months post survey and a provide a means to relate the safety climate survey score to a quantitative measure of mishap likelihood. [Schimpf, 2004b]

Schimpf's research project for the School of Aviation Safety, Naval Postgraduate School at Monterey, California had the primary goal of quantitatively defining a squadron's probability of incurring a mishap based upon survey results. "Toward this aim, a MathCAD model was implemented to simulate the mishap probability process. This simulation generated an equation that predicts the frequency of squadrons experiencing zero, one, two, three, or four mishaps within 12 months post survey and also provides a means to relate survey score to a quantitative measure of mishap likelihood." [Schimpf, 2004b, p. 20] The research showed quantitative and descriptive statistical relationships between survey results and squadron safety performance using the following assumptions:

- Gaussian distribution of survey results.
- Numbers of mishap events within a fixed period are the result of a Poisson process.
- Future mishap probability increases in an exponential manner corresponding to the average survey score (i.e., increased risk resulting from lower average score, and vice versa).

Schimpf developed a mathematical model using a Gaussian score distribution with each datum contained within distribution generating a Poisson distribution of mishaps proportional to the probability. The Poisson distribution was modified by exponential variation of average risk (denoted as "α" in the Poisson equation) dependent on survey score.

$$P_{Mishap}(n,x) = P_{Gaussian}(x)P_{Poisson}(n,\alpha(x)) \text{ where} \qquad \text{(EQ 1)}$$

$$P_{Gaussian}(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \qquad \text{(EQ 2)}$$

$$P_{Poisson}(n,\alpha) = \frac{\alpha^n e^{-\alpha}}{n!} \qquad n = 0, 1, 2, \ldots \qquad \text{(EQ 3)}$$

where n is the number of mishaps that have occurred in the last 12 months since the MCAS

$$\alpha = \alpha(x) = \alpha_o e^{-\beta_o \frac{(x-\mu)}{\sigma}} \qquad \text{(EQ 4)}$$

[Schimpf, 2004b, p. 21]

In a follow on study, Schimpf and Figlock averaged all 43 MCAS survey items to derive a metric of overall safety climate which was compared to individual unit performance. The analysis was based on the sample of 17,228 completed MCASs from 168 Naval Aviation squadrons (65% Navy and 35% Marine Corps). Mishap data were provided by the U.S. Naval Safety Center for the period from August 10, 2000 through April 1, 2004. This study was conducted to explore the potential relationship between safety climate score and occurrences of mishaps. As shown in Figure 3, there were substantial differences in incurred mishap occurrence among the safety climate quartiles. The aviation units in the lowest quartile (interval 2.90-3.59) had nearly twice the number of accidents (94 versus 49) in the 24 month time frame. [Ciavarelli, 2007]

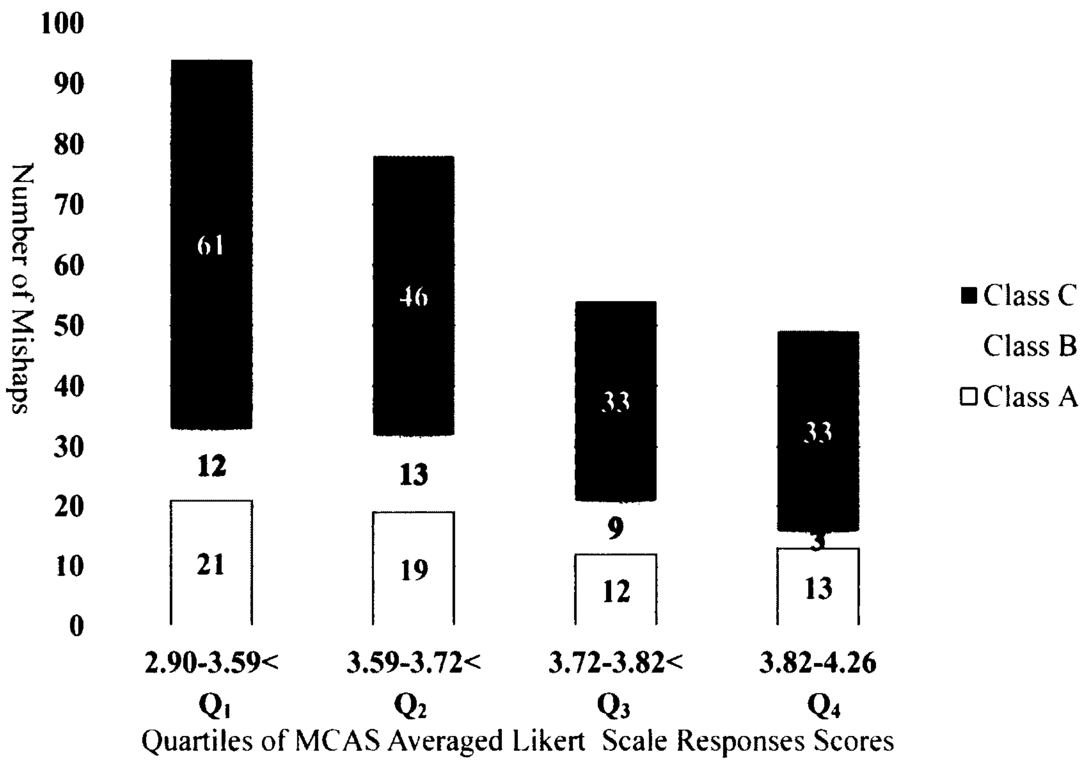


Figure 3. MCAS Survey versus Mishaps Within 24 Months After Survey
[Ciavarelli, 2007, Schimpf and Figlock, 2006]

Conditional probabilities of future mishap occurrence within 24 months after survey based upon the frequency events for quartile distribution shown in Figure 3, above, were computed. The equation for conditional probability used was:

Conditional Probability (Q_i) = frequency / total occurrence, such that:

$$\sum_{i=1}^{4} \text{Conditional Probability } (Q_i) = 1 \qquad \text{(EQ 5)}$$

The conditional probability data are depicted in Table 3 below:

Table 3. Conditional Probability of Future Mishap Occurrence within 24 Months after Survey Dependent upon MCAS Quartile Results

Quartile/ Class Mishap Category	Q_1	Q_2	Q_3	Q_4
Alpha	0.3231	0.2923	0.1846	0.2000
Bravo	0.3243	0.3514	0.2432	0.0811
Charlie	0.3987	0.1699	0.2157	0.2157
Total A, B, and C	0.3686	0.2275	0.2118	0.1922

2.2.4. HUMAN ERROR

Human error has resulted in numerous well-known catastrophes resulting in significant loss of life and equipment destruction. Some recent examples include the Tenerife runway collision in 1977 [Weick, 1990], Three Mile Island in 1979 [Bowen, 1983], Bhopal methyl isocyanate release in 1984 [Fischer, 1996], Challenger destruction [Rogers, 1986], Chernobyl tragedy of 1988 [World Nuclear Association, 2006] , and Columbia mishap in 2003. [Columbia Accident Investigation Report, 2003] Effects of industrial growth, technology, and automation have significantly increased the inherent consequences of mishaps due to human error.

In his seminal work, Human Error, Reason asserted "that the relatively limited number of ways in which errors actually manifest themselves are inextricably bound up with the 'computational primitives' by which stored knowledge structures are selected and retrieved in response to current situational demands." [Reason, 1990a, p. 1] He defined the nature of error, reviews influential studies on human error, and presented a Generic Error Modeling System which categorized three basic error types: skill-based slips and lapses; rule-based mistakes; and knowledge-based mistakes. He addressed the human input to mishaps occurring in fields of high-risk, complex technologies, and he distinguished between active and latent errors. Active errors are committed by personnel who implement controls that have immediate impact on system operation. Latent errors most commonly reside within higher organizational levels and "may lie dormant for a long time, only making their presence felt when they combine with other 'resident pathogens' and local triggering events to breach the system's defenses." [Reason, 1990a, p. xi] The author stated that latent errors pose a greater threat to technologically advanced systems than active failures and are much harder to recognize. He defined dynamics of accident causation with the trajectory of an accident opportunity having to penetrate several defensive layers. These layers served as a defense-in-depth representing the complex inter-relationships between latent failures and a variety of local triggers. As shown in Figure 4, Reason characterized the chances of an opportunity trajectory finding aligned holes in successive defensive layers at any one time as very small. This research effort was undertaken to develop models that would represent multiple characteristics that comprise a naval aviation squadron's defenses against mishap occurrence.

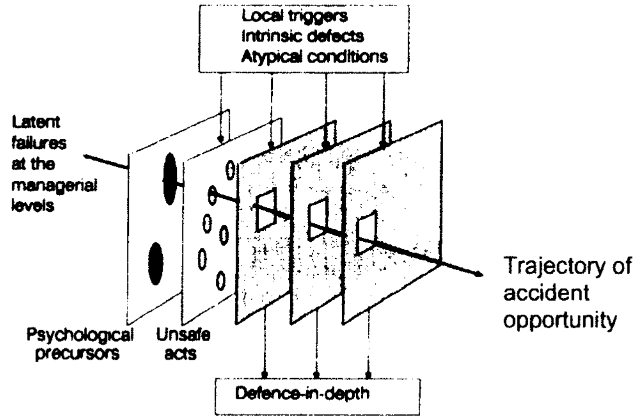


Figure 4. Dynamics of Accident Causation [Reason, 1990a, p. 208]

Investigation data for mishaps provided by the Naval Safety Center identified that human error or failure causal factors were identified for 91% of 244 Class A, 76% of 207 Class B, and 54% of 606 Class C mishaps which occurred between October 1999 and August 2009. [O'Connor et al., 2011a]

2.2.5. HUMAN FACTORS ANALYSIS AND CLASSIFICATION SYSTEM

Wiegmann and Shappell in 2000, adapted Reason's theory to produce a model of accident causation. They depicted latent and active failures as producing "holes" within layers categorized as Unsafe Acts, Preconditions for Unsafe Acts, Unsafe Supervision, and Organizational Influences. Depending upon the alignment of the "holes" or gaps in each layer, the failures may provide the opportunity for a single vector of causal elements to pass unimpeded and result in a mishap. This model, shown in Figure 5, represents a mishap as the result of aligned failures or absence of defenses in each layer. "It is well established that mishaps are rarely attributed to a single cause, or in most instances even a single individual. Rather, mishaps are the end result of a myriad of latent failures or conditions that precede active failures." [Office of the Chief of Naval Operations Instruction (OPNAVINST) 3750.6R, 2003, O-1]

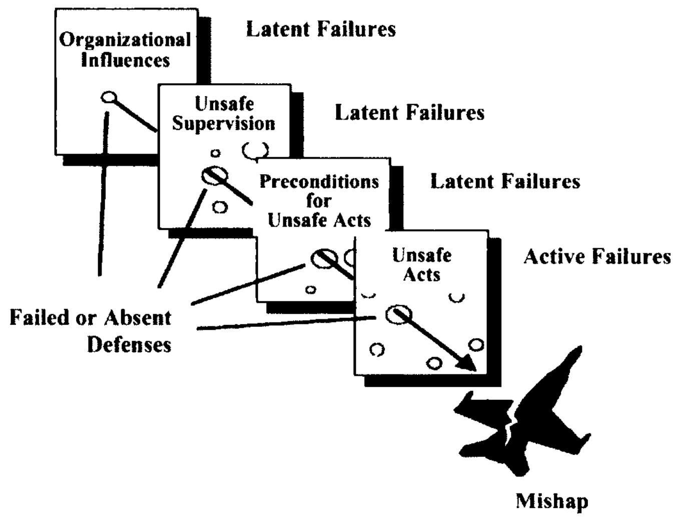


Figure 5. Swiss Cheese Model of Accident Causation
[Shappell & Wiegmann, 2000, p. 4]

Through decomposition of the four layers into their respective causal elements, Wiegmann and Shappell developed the Human Factors Analysis Classification System (HFACS) shown in Figure 6, as an accident investigation and analysis tool [Wiegmann & Shappell, 2003] Each layer is comprised of categories which represent specific causes for failed or absent defenses against mishaps. Human errors that are the consequence of aircrew, maintenance personnel, and supervisors represent three prevalent categories in aviation. [Fry, 2000] HFACS is used throughout the Department of Defense and many different government agencies for post-mishap investigation and analysis of human error.

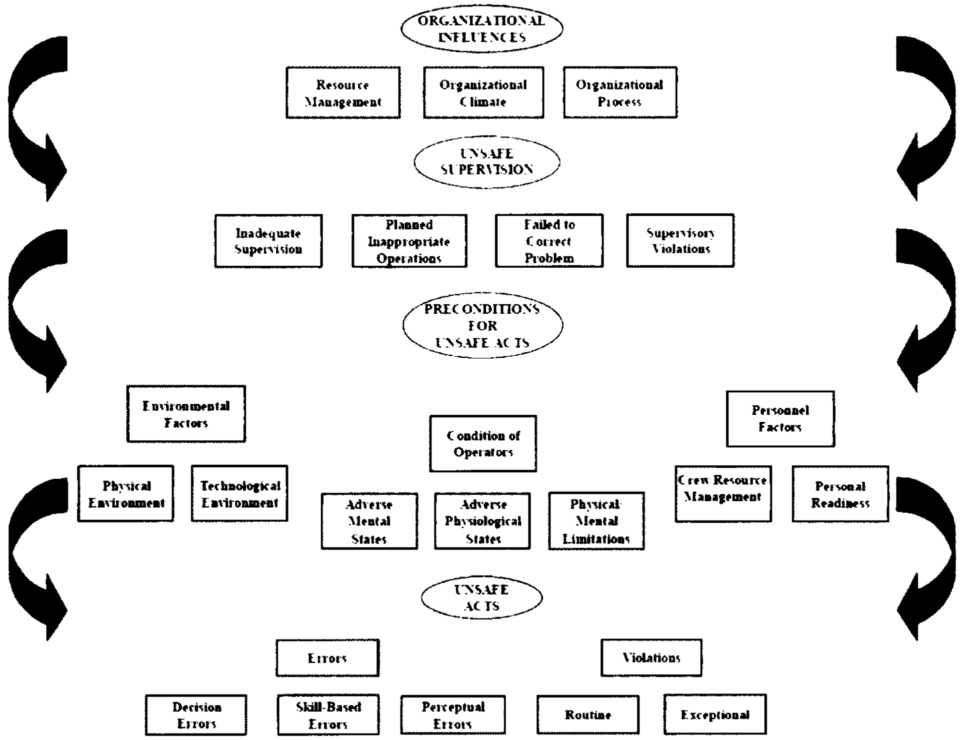


Figure 6. Human Factors Analysis and Classification System
[Shappell and Wiegmann, 2000]

Wiegmann and Shappell [2003] developed HFACS to provide aviation mishap investigators with the required tools to analyze the causal effects of human error. The development of HFACS was an iterative process of verification and improvement. HFACS categorization and decomposition were empirically derived and refined through the analysis of the causal factor data listed in numerous mishap investigations.

Supplementary extensions of the HFACS have been developed to focus specifically upon a common subset of related human factors errors that may present causal factors for a mishap. The Maintenance Extension is a subset of the HFACS domain that provides a unique perspective for analyzing the impact of individual malpractices and organizational / supervisory failures in triggering an aviation-related casualty or loss. The HFACS-ME uses a three-tiered order of effects perspective to precisely characterize a lapse in the respective defensive layers found within an aviation unit's maintenance department. A breakdown of contributing mishap causal factors, organized by first, second, and third order tiers is listed below in Table 4.

Table 4. HFACS-ME Taxonomy [OPNAVINST 3750.6R, 2003, O-16]

First Order	Second Order	Third Order
Management Conditions	Organizational	Inadequate Processes Inadequate Documentation Inadequate Design Inadequate Resources
	Supervisory	Inadequate Supervision Inappropriate Operations Uncorrected Problem Supervisory Misconduct
Maintainer Conditions	Medical	Adverse Mental State Adverse Physical State Unsafe Limitation
	Crew Coordination	Inadequate Communication Inadequate Assertiveness Inadequate Adaptability/Flexibility
	Readiness	Inadequate Training/Preparation Inadequate Certification/Qualification Personnel Readiness Infringement
Working Conditions	Environment	Inadequate Lighting/Light Unsafe Weather/Exposure Unsafe Environmental Hazards
	Equipment	Damaged/Unserviced Unavailable/Inappropriate Dated/Uncertified
	Workspace	Confining Obstructed Inaccessible
Maintainer Acts	Error	Attention/Memory Knowledge/Rule Skill/Technique Judgment/Decision
	Violation	Routine Infraction Exceptional Fragrant

The HFACS-ME framework provides an effective methodology for classifying mishap causal factors resulting from maintenance errors. Its capability mirrors that of the overall system with full applicability in scope from near miss to major damage and significant personnel loss. A study of aircraft mishap information contained within the Maintenance Error Information Management System (MEIMS) database analyzed the third order effects (found in Table 4) for correlation. Of 1,016 aviation mishaps that occurred between 1996 and 2001 in which maintenance issues were attributed as causal factors, 4,235 associated third-order factors were identified. As shown in Figure 7, there is a non-uniform distribution of causal factors with the highest frequencies falling under the first-order classifications of unsafe management conditions and unsafe maintainer acts.

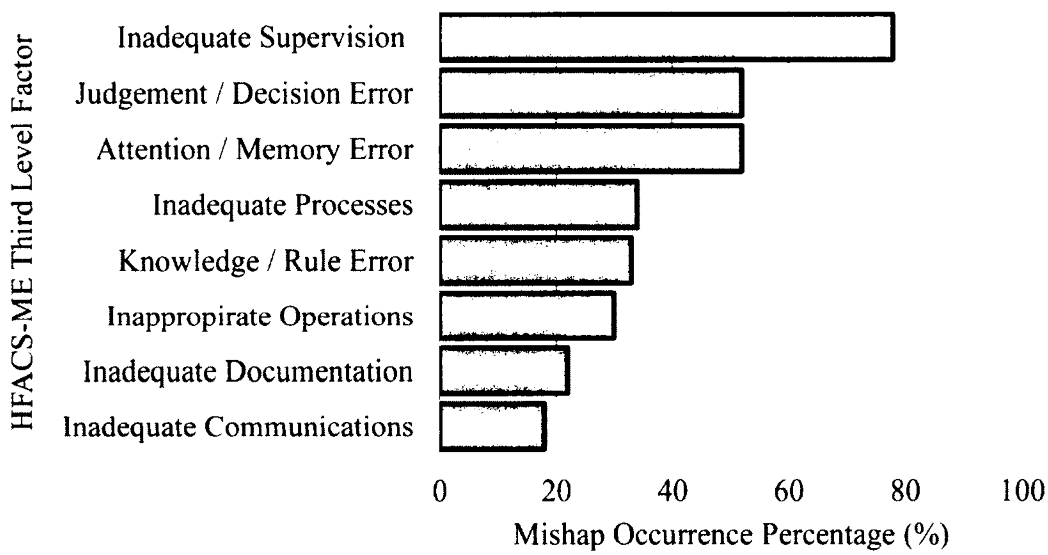


Figure 7. Mishap Occurrence Percentage for Selected HFACS-ME Third-Order Factors (n=1,016) [Source, Krulak, 2004, p. 431]

"It is apparent from the graphical frequency data that the different HFACS-ME factors are associated in dissimilar ways in aviation mishaps. In the simplest form, some factors are far more likely to be seen in a mishap than others. These differences are important because an understanding of which factors cause the most mishaps may improve the focus of safety programs, and direct scarce resource to where the largest safety impact can be made." [Krulak, 2004, p. 431]

Schmorrow conducted a study of 470 Naval Aviation Maintenance Related Mishaps (MRMs) that occurred from Fiscal Years 1990 through 1997. Analysis included coding the mishap data causal factors from the Naval Safety Center using the HFACS-ME to account for the scope of error types. Determination was made using the second order error types. Results are shown in Table 5.

Table 5. Frequency of Error Type by Accident Type and Class
[Schmorrow, 1998, p. 64]

	Organizational / Unforseen	Supervisory / Squadron	Environment	Equipment	Workspace	Medical	Personal Readiness	Crew-Resource Managemnt	Error	Violation
FM	68	80	0	4	0	0	0	13	126	52
FRM	8	17	0	0	0	1	1	2	27	9
AGM	75	185	6	16	2	22	2	63	217	121
Class A	30	42	0	2	0	2	1	10	47	25
Class B	25	41	1	3	0	3	0	6	44	21
Class C	96	199	5	5	2	18	2	62	279	136
Total	151	282	6	20	2	23	3	78	370	182

FM-Flight Mishap FRM-Flight Related Mishap AGM –Aircraft Ground Mishap

The study revealed that over 95% of the identified human error causal factors were attributed to five error types (listed in descending order): Error, Supervisory / Squadron, Violation, Organizational / Unforeseen, and Crew Resource Management. [Schmorrow, 1998, p. 64]

2.3. RESEARCH CONTEXT

Supplementary literature that supports the conduct of this research for Modeling and Simulation domain for framework, theory, and formalisms used in conceptual and computational model development efforts included:

- Law, A. & Kelton W., Simulation Modeling and Analysis. This text book offered many state-of-the art areas within the field of Modeling & Simulation including software, validation and verification, input modeling, processes, statistical design, and analysis.
- Zeigler, B., Praehofer, H., & Kim, T., Theory of Modeling and Simulation: Integrating Discrete Event and Continuous Complex Dynamic Systems. This manual introduced formalisms, and specifications that define applicable components and extensions. Approaches to frameworks, system morphisms, verification and validation, design methodology, and system entity structures are presented.

2.4. USE OF SURVEY RESULTS TO ASSESS ORGANIZATIONAL SAFETY

Organizational surveys completed by workforce personnel provide a means to obtain both quantitative and qualitative data regarding perceptions of the unit's characteristics. Quantitative results are provided through use of questionnaires that use a scaled answering mechanism. Qualitative data are normally obtained through use of open ended questions enabling the respondent to provide less-constrained details on their individual opinions. Surveys provide a broad-based appeal that impart an implied sense of legitimacy, compare favorably with other methods to gain meaningful data in ease of use and base effectiveness. They may be used to explore and understand employee opinions and attitudes, assess behaviors and attributes in employee day-to-day work experiences, obtain baseline measures for benchmarking change, and drive organizational change and development. [Church and Waclaswki, 1998]

Application of survey questionnaires are used develop and define organizational safety climate metrics. Guldenmund [2000] stated, "Organizational climate is commonly conceived of as a distinct configuration with limited dimensionality surveyed through self-administered questionnaires. Such measures are, up to a certain point, objective and semi-quantitative. Organizational culture is often determined phenomenologically, i.e. through observations and interviews, through trial-and-error, mutual comparison and the like. Such measures are regarded as qualitative and thus difficult to quantify." [p. 221] Safety climate survey questionnaires enable statistical comparisons among different variables and components as well as means to quantify changes that occur between successive occurrences of the survey being taken [O'Connor et al., 2011b] Command climate assessment surveys serve to provide senior leadership with an instantaneous metric to evaluate their safety climate at the time of administration. The assessment survey's goal is to provide useful information that enables advanced identification of issues that may increase risk and mishap occurrence. Ideally, the early ascertained, lead indicators allow leadership the opportunity to employ proactive risk mitigation efforts to rectify those situations before a mishap occurs. [Buttrey, 2010] Safety surveys have wide applications not only in Naval Aviation, but also are used in evaluation of clinical healthcare delivery, industry. A relationship was suggested from safety survey results demonstrating that employee perceptions of the safety systems are related to management's commitment to safety and related to sustained injury rates. [O'Toole, 2002]

The Maintenance Climate Assessment Survey contained 43 questions that were answered via computer entered radio button selection as shown in Figure 8.

○ Strongly Disagree	○ Disagree	○ Neutral	○ Agree	○ Strongly Agree	○ N/A ○ Don't Know

Figure 8. Maintenance Climate Assessment Survey Response Options
Source: Aviation Climate Assessment Survey System

This represented a bi-directional rating Likert scale quantitative five point range as shown below

1 = Strongly Disagree
2 = Disagree
3 = Neutral
4 = Agree
5 = Strongly Agree
No points were assigned for responses of either N/A or Don't Know

Additional details regarding use of Likert Scales can be found in section B.1 of Appendix B.

2.5. DISCRETE EVENT SIMULATION MODELING TECHNIQUES

A wide range of techniques are available for computational modeling. Simulations of models possessing continuous states and times are traditionally represented using differential equation systems. [Ziegler et al., 2000] Simulation using discrete event models involves representing a system's evolution over time through state variables that (are considered to) change instantaneously at separate points in time. Events are the term used to define the point in time when an instantaneous occurrence may change the system's state. [Law and Kelton, 2000] Discrete event simulations may reflect either a standardized, incremental time-advance feature (i.e., simulation clock) in which state variable metrics are provided or use non-uniform time increments that reflect state variable metrics that occur at a point in time concurrent with a significant event affecting a state variable component. Discrete event formalisms use a stepwise mode of execution to define a model's state at a particular point in time and how the respective state's change in the future, and environmental influences. [Ziegler et al., 2000]

This section reviews five discrete event simulation techniques and lists advantages and disadvantages for their use for predictive risk analysis modeling based upon MCAS survey results:

2.5.1. BAYESIAN NETWORK MODEL

Bayesian Network Models (BNMs) rest on the application of Bayes Theorem: If A and B are events with $P(B)>0$, then

$$P(A \mid B) = \frac{P(B \mid A)\, P(A)}{P(B)} \qquad \text{(EQ 6)}$$

[Jackman, 2009, p. 9] They are discrete event models of domains with inherent uncertainty. BNMs are represented by graphical structures that consist of nodes and arcs. The nodes correspond to random state variables and arcs represent the direct probabilistic relationships between the connected variables. These probabilistic relationships are quantified through use of probability distributions which are usually a conditional probability table associated to the nodes. [Bayesia, 2001, p. vi]

The goal for use of BNMs is to produce statistics that update conditional probabilities in light of observed evidence. This supports a quantitative method to evaluate the model's subjective sense, i.e., probability as a degree of belief. BNMs allow for calculation of all the possible combinations of causal connections between nodes relating only neighboring nodes. Bayesian networks contain a built-in independence assumption. [Charniak, 1991] Components of Bayesian Networks include:

- A set of variable and a set of directed edges between variables
- Each variable has a finite set of mutual exclusive states.
- The variables together with the directed edges form a Directed Acyclic Graph.
- To each variable A with parents $B_1, \ldots, B_n$ there is attached a conditional probability table $P(A \mid B_1, \ldots, B_n)$. [Jensen, 1996, p. 18]

BNMs may be used for determining model causality where understanding of what's occurring is incomplete. With Directed Acyclic Graphs containing prior probabilities of all root nodes and conditional probabilities of all non-root nodes given all possible combinational of direct predecessors, the conditional probabilities of network nodes are calculated given the values of observed nodes. [Charniak, 1991] An example of a BNM is show in Figure 9

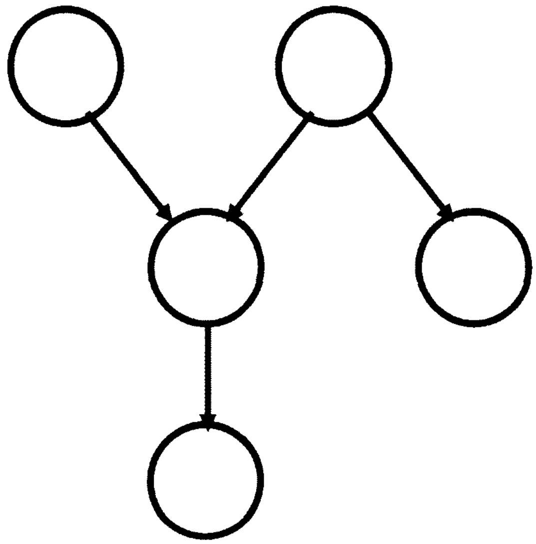


Figure 9. Example of a Bayesian Network Model

Advantages for use of BNMs include capability to:

- Readily accommodate a variety of knowledge sources and data types including incomplete data sets.
- Allow one to learn about causal relationships by transparent representations between system variables
- Support use observed knowledge to determine the validity of the acyclic graph represented in the BNM.
- Facilitate use of prior knowledge. Causal networks represent prior knowledge whereas the weight of the directed edges can be updated in a posterior manner based on new data.

- Perform relatively straightforward construction of prior knowledge through use of "causal" edges between any two factors that are believed to be correlated.
- Provide an efficient method for preventing the over fitting of data.

Some disadvantages for use of BNMs are:

- There is no universally accepted method for constructing a network from data.
- Potential difficulty for experts to agree on model structure.
- Limit to the spatial and temporal scales that can be represented in one BNM.
- Inability to support feedback loops. [McCloskey, 1999; Heckerman, 2006; Landscape Logic, 2009]

2.5.2. HIDDEN MARKOV MODEL

Hidden Markov Models (HMMs) are a subset of Bayesian modeling defined as a statistical model employing doubly stochastic process with an underlying stochastic process that is not directly observable through another set of stochastic processes that produce a sequence of observed results. Transition functions are utilized to represent the dynamics occurring in the unobservable space. This modeling technique is represented by the following characteristics:

- N, the number of states in the model with individual states denoted as

  $S=\{S_1, S_2, \ldots, S_N\}$ and the state at time t as q_t. (EQ 7)

- M, the number of distinct observation symbols per state. Observation symbols match to the model's output. Individual symbols are denoted as

  $V=\{v_1, v_2, \ldots, v_M\}$. (EQ 8)

- Probability distribution of state transition:

  $A=\{a_{ij}\}$ where $a_{ij}=P(q_{t+1} = S_j \mid q_t = S_i)$ for $1 \leq i, j \leq N$. (EQ 9)

- Probability distribution of the observation symbol in state j,

  $B = \{b_j(k)\}$ where $b_j(k) = P[v_k \text{ at } t \mid q_t = S_j]$ for $1 \leq j \leq N$ *and*

  $1 \leq k \leq M$. (EQ 10)

- The initial state distribution for $\pi = \pi_i$ where

  $\pi_i = P[q_1 = S_i]$ (EQ 11)

- Input variable values for N, M, A, B, and π are used by the HMM to produce an observation vector sequence:

  $O = O_1, O_2, \ldots O_T$ (EQ 12)

[Bilmes, 2002; Rabiner and Juang, 1986, p.5; Rabiner, 1989, p. 259]

Given a finite sequence of hidden states, probabilities of all possible transitions are multiplied by probabilities of observed output symbols to determine the overall probability of all output symbols produced in the current path of transitions to that point. Model parameters must be valid probabilities and conform with:

$\sum_j^N a_{ij} = 1, \sum_k^M b_j(k) = 1$ (EQ 13)

$a_{ij} \geq 0, b_j(k) \geq 0$ (EQ 14)

[Boussemart, 2011]

Computational HMMs require the ability to address three issues in:

- Evaluation: Determining the probability that a given sequence is produced by the HMM;

- Decoding: Determining the most probable path of hidden states, given a sequence of observable symbols; and
- Learning: How to adjust the model parameters for A, B, and π to maximize the likelihood that the HMM could produce the observed string of symbols.

HMMs are used for automatic word, speech, and hand gesture pattern recognitions, and health state modeling. [Bilmes, 2002; Rabiner and Juang, 1986; Rabiner, 1989, Kadous, 1995]. A depiction of an HMM is shown in Figure 10 below.

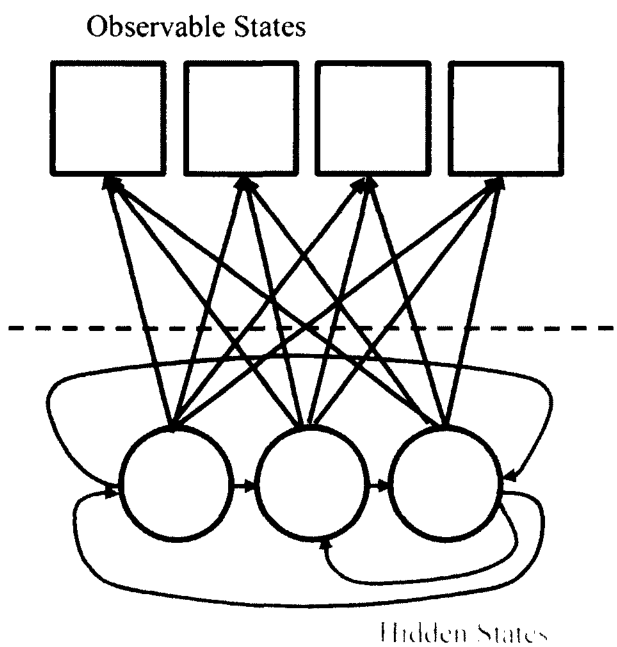


Figure 10. Example of a Hidden Markov Model

Advantages of use of HMMs include the capability to:

- Provide a solid statistical foundation for modeling
- Use efficient learning algorithms

- Develop flexible and general models to represent sequencing properties
- Incorporate prior knowledge into the model's architecture through initializing close to something believed to be correct
- Support use prior knowledge to constrain the training process
- Combine individual HMMs into larger HMMs

HMM utility presents the following disadvantages:

- They contain a large number of unstructured parameters
- Accurate modeling requires large amounts of data
- Conditional independence properties are inaccurate if there are too few hidden states, or if there are inaccuracies in the observation distributions
- They make very large assumptions about the data through the Markovian assumption that emission and transition probabilities depend only on the current state. [Kadous, 1995; Bilmer, 2002; Salifu, 2003; Zoltan and Zoltan, 2006]

2.5.3. NAÏVE BAYESIAN MODEL

Naïve Bayesian Models (NBMs) are the simplest form of a Bayesian network, in which this technique "naively" assumes that all attributes are independent given the value of the class variable. [Zhang, 2004] By making this assumption, the probability distribution may be efficiently represented as the product of many simpler distributions:

$$P(A_1, A_2, \dots, A_n, C) = P(C) \prod_{i=1}^{n} P(X_i \mid C) \qquad \text{(EQ 15)}$$

As a special case of a Bayesian network, Naïve Bayes attribute variables $A_1....A_n$ over and cluster variable C, in which the parent of each A_i is C and C has no parents. The efficiency gains over general Bayesian networks come from using this restricted structure. [Lowe, 2005, p. 4] An NBM schematic is depicted in Figure 11.

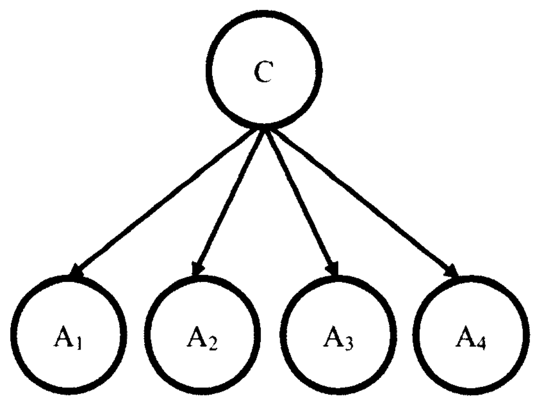


Figure 11. Naïve Bayesian Network

NBMs use a generative based approach in which a conceptual framework combines prior knowledge and observed data. It functions as a basic - conditional probabilistic classification algorithm through application of Bayes' Theorem by making strong (naive) assumptions about the independence of observed characteristic variables. Probabilities are calculated by dividing the percentage of pairwise occurrences where both conditions occur simultaneously by the percentage of singleton occurrences where only the prior event occurs. NBMs use the assumption that all the predictors are conditionally independent of the each other. [Oracle, 2005; de Kok and Brouwer, 2010]

NBM advantages include:

- Fast, simple, easy to implement, and affords highly scalable building and scoring
- It is one of the most efficient and effective inductive learning algorithms for machine learning and data mining that provides competitive performance in classification. [Zhang, 2004]
- Good results obtained in many cases with strong applications for use as a text classifier for anti-spam e-mail filtering [Schneider, 2003]

NBM disadvantages include:

- A loss of accuracy may be induced due to the assumption of class conditional independence
- Often, dependencies exist among attribute variables
- Model results often demonstrate produced conditional probabilities that over fit to observed non-coherent data (i.e., noise in the data)
- Naïve Bayesian assumes that events that don't occur in the data are deemed to have impossible probabilities.

2.5.4. ARTIFICIAL NEURAL NETWORK MODEL

Artificial Neural Network Models (ANNMs) are a form of Artificial Intelligence (AI) that use a network of nodes and highly interconnected synapses to represent modeled processes. They are widely recognized to have begun by McCulloch-Pitts regarding the representation of functioning of neurons in the 1940s through development of a computational modeled binary decision machine that applied weights to input activations, summed the products, and produced output activations. ANNM structure is largely distributed in parallel as opposed to sequential processing found in other forms of AI. This non-linearity affords flexibility, the means to learn to acquire knowledge by adaptation of internal parameters applied to previous examples and generalize. ANNMs are considered to be totally connected when all the outputs from a level connect with all the nodes in the following level. They are partially connected if some of the links in the network are not facilitated [Russell, 1991; Alvarez, 2006; Leverington, 2009; Boussemart, 2011]. A graphical representation of a totally connected ANNM is shown in Figure 12.

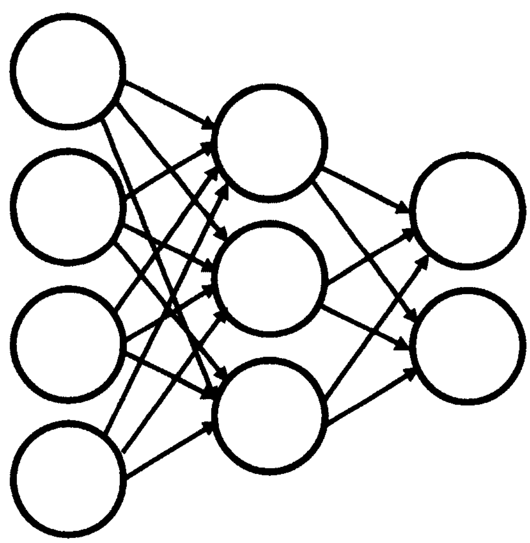


Figure 12. Artificial Neural Network Model

Applications for ANNMs cover many different fields of engineering and science including speech synthesis, pattern recognition, diagnostic problems, medical illnesses, robotic control and computer vision. [Russell, 1991]

The advantages for use of ANNMs include the capabilities to:

- Perform tasks that cannot be done through a linear program
- Continue operations when a node fails by its parallel nature
- Learn without the need to be reprogrammed
- Implicitly detect complex nonlinear relationships between independent and dependent variables
- Detect all possible interactions between predictor variables.

Disadvantage in using ANNMs include the

- The weighting is usually not interpretable. This leads to inability to provide explanatory power captured in the intermediate process. It is key to understand that ANNMs are "black box" operations and have limited ability to explicitly identify possible causal relationships
- Requirement for training to operate.
- Necessity of high processing time for large neural networks.
- Susceptibility to over fitting
- Need to resolve methodological issues in model development due to its empirical nature. [Tu, 1996; NeuroAI, 2007, Boussemart, 2011]

2.5.5. SUPPORT VECTOR MACHINE MODEL

Support Vector Machine Models (SVMMs) use supervised learning algorithms to conduct binary and multi-class discriminatory classification by taking training data as input to produce an optimal hyper-plane that categorizes new examples. This output represents the largest minimum distance between training examples by achieving the widest margin across the training data. The original SVMM was invented in 1963 by Vladimir N. Vapnik and it denotes a modern outgrowth of ANMMs that support highly accurate modeling. This technique uses linear models to implement nonlinear class boundaries by transforming input space using a nonlinear mapping into a new space. A linear model constructed in the new space may be used to represent a nonlinear decision boundary in the original space. SVMMs may apply a sigmoid kernel function to transform low dimensional training samples to higher dimensional solutions (for linear separability problem) and use Quadratic Programming (QP) to find the best classifier boundary hyper-plane. [Boswell, 2002; Zhang, 2011; Pedregosa et al., 2011; Tomuro, 2011; DTREG, 2013] A depiction of a SVMM is displayed in Figure 13.

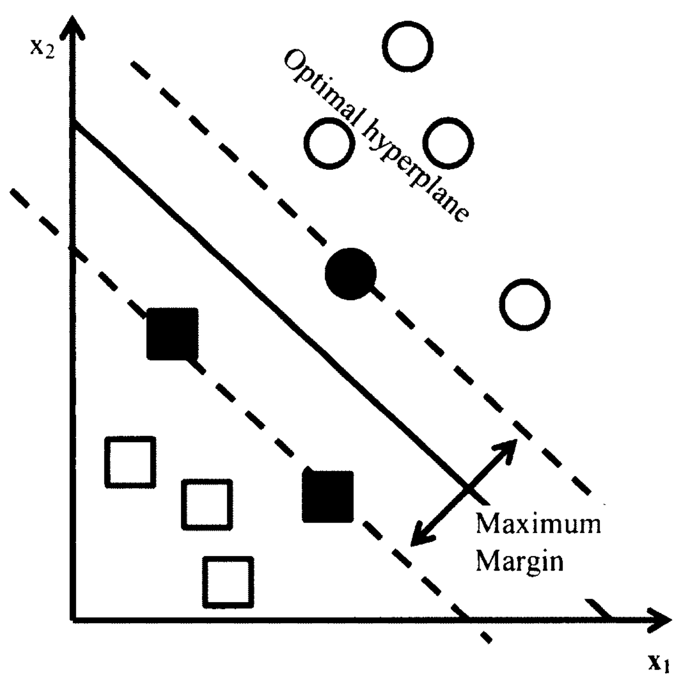


Figure 13. Support Vector Machine Model Classification

SVMMs have been applied to crowd monitoring systems, intrusion detection, distracted driving classification, insolvency analysis, predicting common diseases, decision tree predicative modeling, and image classification. [Auria and Moro, 2008; We, 2010; Boussemart, 2011]

The advantages of SVMMs are:

- They deliver a unique optimal solution in comparison to ANNMs which have multiple solutions associated with local minima
- Effectiveness in high dimensional spaces
- Production of very accurate classifiers with generally high prediction accuracy
- They are less susceptible to over fitting
- Ability to provide a good out-of-sample generalization. By choosing an appropriate generalization grade, SVMMs can be robust, despite cases in which the training sample has some bias.

The disadvantages of SVMMs include:

- Requirement for long training time and difficulty in understanding the learned function of weights.
- If the number of features is much greater than the number of samples, the method is likely to give poor performances.
- SVMMs do not directly provide probability estimates
- They require extensive computations and therefore run slow comparatively. [Auria and Moro, 2008; Yu, W, et. al, 2010; Pedregosa et al., 2011; Tomuro, 2011; Zhang, 2011]

3. METHODOLOGY

3.1. DESCRIPTION

This dissertation was pursued to conduct research and development of an accurate Discrete Event Model for predictive risk analysis of mishap occurrence based upon input derived from Maintenance Climate Assessment Survey responses and corresponding organizational mishap report summaries. It involved the following research components:

- Real World Applicability: Basic Research attempting to clarify underlying processes.
- Purpose: Causal-Comparative Study. Determination if there was an association or relationship between variables derived from event sequences and conditions that had already occurred. This was conducted to attempt to determine the reason for the observed results and differences.
- Goal: Descriptive Survey. Measurement of attitudes obtained by asking the same set of questions to a large number of individuals. In this case the personnel who were assigned and / or conduct maintenance within a Naval Aviation squadron.
- Perspective: Historical. Research that was based upon previous events.

[Fraenkel, Wallen, and Hyun, 2012]

3.2. APPROACH

Research consisted of evaluation of instrumentation for provided, available, quantitative data, definition of key variables, and selection of Bayesian Network Modeling as the discrete event modeling framework followed by, development of applicable conceptual models, and construction / implementation of computational models. Actual squadron MCAS response data were aggregated for each organization (i.e., aviation squadron) and cross matched against corresponding aviation mishap report summaries as system input to ascertain model performance and determine conditional probabilities distributions for mishap occurrence. The research supporting model development was conducted in an iterative process. Verification and validation was performed throughout the developmental research to confirm computational model correctness and to enable assessment of the dissertation problem statement and research questions.

3.3. NAVAL AVIATION ORGANIZATIONAL CONSTRUCT AND PROCESSES

A preliminary analysis of a Naval Aviation squadron as an organization was conducted to include decomposition, review of instructions, and definition of processes. The results are contained within Appendix C.

3.4. EVALUATION OF INSTRUMENTATION FOR PROVIDING DATA

3.4.1. DATA SOURCES

Initial data for this research effort were requested in 2005 from the U.S. Navy. Data requests included MCAS results, maintenance statistics, and mishap investigation report results. This information was necessary to define a methodology that the data would support, conduct of further model development, and refinement from the conceptual phase to a computational model that could be executed and analyzed.

USN and USMC aviation squadrons conduct periodic surveys by maintainers and aircrew to assess safety issues within their command. Since results are not releasable outside of the command, sanitized data were requested that did not provide identification of specific squadrons. In order to validate model results, additional data were requested that would provide mishap report summaries that included:

- The summary of mishap events
- The causal factors identified by the mishap investigation board and approved upon review by the chain of command.

It was necessary that the mishap summaries could be associated with the respective squadrons' MCAS results from a recent previous survey.

After numerous unsuccessful attempts to obtain requested information, the Naval Safety Center (NSC) in Norfolk, Virginia was approached in 2008 as a repository of both MCAS data and mishap reports. NSC functions to support the Naval Safety Program by providing guidance and direction, safety data and program services, and the marketing of safety. NSC's mission is to provide safety assistance and advice to senior Navy and Marine Corps leadership in order to enhance the services' warfighting capability, preserve resources, and improve combat readiness by preventing mishaps and saving lives. [Naval Safety Center, 2010]

The NSC Safety Data Manager offered to sanitize both MCAS results and matching mishap reports and coordinated to release the double blind data. This was vetted by the CNAF Judge Advocate General and approved by Safety Officer contingent upon certification by the Safety Data Manager that all the provided information was sanitized. An updated list of detailed data requirements was requested from NSC. This is categorized below:

Communication with the Dissertation Faculty Advisor and NSC Safety Data Manager was undertaken to determine an acceptable number of mishap report summaries to be used to achieve statistical significance. From Fiscal Year 2000 through 2009 there had been 2,300 surveys from 369 commands and the Navy/Marine Corps had experienced 1,696 Class A-C mishaps from 384 commands. A summary of mishaps sorted by classification (A, B, C) and year is provided in Table 6.

Table 6. Naval Aviation Mishaps Class A-C for Fiscal Years 2000-2009 [Scott, 2009]

Fiscal Year	Class A	Class B	Class C	Total
2000	32	21	115	168
2001	21	16	114	151
2002	39	32	106	177
2003	40	29	138	207
2004	34	35	133	202
2005	26	28	131	185
2006	24	37	125	186
2007	19	39	118	176
2008	24	40	102	166
2009	8	21	49	78
Total	267	298	1,131	1,696

The Safety Data Manager requested that this research data inquiry be limited in scope by defining the following characteristics required: timeframe, severity, and/or airframe. In coordination with the Dissertation Faculty Advisor, the decision was made to limit the request for mishap summary reports to squadrons that incurred only Class A mishaps and to receive a minimum number of 50 mishap summary reports that could be matched against corresponding MCAS results. Additional clarification was provided to limit mishap results to those squadrons that comprised aircraft carrier air wings, since they incurred similar types of operations and tempos. The Type/Model/Series included:

- E-2C
- EA-6B
- F-14
- C-2A
- F/A-18
- S-3B
- SH-60
- HH-60

The Safety Data Manager and Customer Support Division Head at the Naval Safety Center took the MCAS data and removed identification containing each squadron's name (i.e., VAW-XXX) and replaced it with a unique 3 digit numeric code to designate the specific squadron. This 3 digit code was matched against the mishap summary reports for Class A mishap incidents which occurred in corresponding squadrons. The squadron names in the mishap report summaries were replaced with the respective 3 digit code aligned to the squadron. The MCAS data were provided in a tabular spreadsheet and the mishap summary report was furnished in text format.

3.4.1.1. MCAS RESULTS DATA

The MCAS results were provided by the Naval Safety Center in tabular spreadsheet format for 2,300 aggregated sets of survey data. 2,114 of the unit survey results came from U.S. Navy and Marine Corps squadrons taking the survey, and 186 survey results were derived from organizations representing Aircraft Intermediate Maintenance Departments, Fleet Repair Centers, Naval and Marine Corps Air Stations, Marine Air Logistics Squadrons, Research Developmental Test and Evaluation outfits, and other entities. Each set of results for a specific unit was assigned a unique 3 digit identification code which served to blind the true identity of unit. Each set of aggregated survey data included information contained within Table 7.

Table 7. MCAS Results Raw Data Terminology

Data	Description
First Appear Serial	Using the 3 digit squadron identification code, this indicated the first time within this total data presentation that a single particular unit participated by taking the MCAS
Squadron Appear Serial	Using the 3 digit squadron identification code to provide a single set of MCAS results from a participating unit
Number of Respondents	Total number of individuals who participated in the survey. This value ranged from a minimum of 10 to a maximum of 742. The mean number of respondents for the 2,300 sets of survey data was 118 with a standard deviation of 73.76
Community	Represented the type of squadron or unit. (e.g., VAQ, VAW, etc.)
Squadron Service	Either U.S. Navy or U.S. Marine Corps
First Survey Date	The time and date the first respondent submitted a survey
Mean Survey Date	Represented a computation of the mean time and date that the survey was taken in the window between First Survey Date and Last Survey Date
Last Survey Date	The time and date that the last respondent submitted a completed survey
Mean Likert Score Response to MCAS Question	Represented the computed mean value for the aggregated Likert Scores from the surveys in the Squadron Appear Serial

The text containing the 43 close-ended MCAS questions and quantitative Likert Scale values per response option are contained in Appendix D.

The mean time of survey results covered the span from August 23, 2000 through January 6, 2009. The breakdown of surveys by the communities that compose a Carrier Air Wings is provided in Table 8.

Table 8. Survey Breakdown by Community and Aircraft

Community	Primary Mission	Aircraft	Surveys
HS/HSC	Helicopter ASW/Combat	SH-60F and HH-60H	159
VAQ	Tactical Electronic Warfare	EA-6B	138
VAW	Airborne Early Warning	E-2C	106
VF	Fighter	F-14B and F-14D	30
VFA	Strike Fighter	F/A-18A, F/A-18C, F/A-18D, F/A-18E, and F/A-18F	421
VRC	Logistics	C-2A	18
VS	Sea Control	S-3B	57
		Total	930

3.4.1.2. AVIATION MISHAP SUMMARY RESULTS

The Naval Safety Center provided a written summary of the Class A mishaps that had occurred in Navy squadrons that comprised Carrier Air Wings for the period from October, 1, 2002 through July 20, 2009. Aviation mishap investigations were conducted in accordance with the Naval Aviation Safety Program Instruction (OPNAVINST 3750.6 series). Per instruction, a mishap investigation panel was convened by the Commanding Officer of the reporting unit that was the custodian for the aircraft or aircrew involved. (For mishaps involving multiple squadrons, the senior Commanding Officer appointed the board members from involved units.) Upon completion of the investigation and analysis, the mishap investigation report was reviewed by the Commanding Officer and was routed up through the chain-of-command hierarchy. Each sequential reviewing authority is empowered to make changes to board determinations and recommendations. The final approved version was archived at the Naval Safety Center. The summary provided as data for this research was taken from the final mishap investigation reports and contained the information provided in Table 9.

Table 9. Class A Mishap Summary Report Data Terminology

Data	Description
Event Serial Number	5 digit serial number used to uniquely identify the mishap event
Aircraft	Type / Model / Series used to designate aircraft (e.g., E-2C)
Activity Name	Corresponded to Squadron Appear Serial in Table 16. The unique 3-digit number used to indicate a single set of MCAS results from a participating unit
Event Date	Date of mishap occurrence
Event Summary	Included the following information: • Description of incident, equipment damage/loss, and personnel injury/loss • Narrative summary of mishap • List of causal factors attributed to: o Aircrew / Personnel o Material o Supervisory o Facilities o Maintenance

The mishap summary data included 57 separate mishap events that involved 67 aircraft and their aircrew.

3.4.2. CONSIDERATIONS FOR USE OF LIKERT SCALE DATA

The MCAS was composed of 43 questions which evaluate six separate areas. The number of questions per area is depicted in Table 10.

Table 10. Distribution of MOSE Areas within MCAS

MOSE Question Area	Number of respective questions	Percentage of total questions
Process Auditing	6	14.0 %
Reward System and Safety Culture	8	18.6 %
Quality Assurance	6	14.0 %
Risk Management	9	20.9 %
Command & Control	8	18.6 %
Communication/Functional Relationships	6	14.0 %

Through use of multiple questions, the MCAS reduces measurement errors inherent with single item questions that tend to be less valid, less accurate, and less reliable than their multiple item equivalents. [Nunnally and Bernstein, 1994] Details concerning Likert Scale as metric data is contained in Appendix B, Section B.2.

In order to evaluate the utility of Likert Scale derived data, two characteristics of the test / survey were evaluated: Reliability and Construct Validity. "Scales, as measuring instruments, are evaluated primarily on the basis of two criteria: reliability or the proportion of scale score variance that is not error variance, and validity, or the proportion of scale score variance that accurately represents the construction or the proportion of criterion variance that is predicted by the scale." [Dawis, 1997, p. 486] "Measurement errors are induced from the measurement instrument's systemic biasing or random error. Validity references the degree of bias in the measurement instrument while reliability is a reference to the random error introduced by the measurement instrument. Validity and reliability are independent of each other. Validity is often thought of as the 'accuracy' of the scale while reliability is its 'precision.' Scales that lack validity have systematic biases to them, while those that lack reliability have large random errors associated with their measurement." [DeCoster, 2005, p. 7]

In December 2012, a study was published on the conduct of construct validity testing for the MCAS [Brittingham, 2012] investigating the relationship between Naval Aviation Mishaps and Squadron Maintenance Safety. This research examined the construct of the squadron maintenance safety climate survey and its possible relationship to aviation mishaps. The raw data employed included MCAS responses from 126,058 maintainers between August 2000 and August 2005 and included the same data responses in this dissertation research during that same timeframe.

The author surmised that MCAS content validity, along with factor analysis, should yield six distinct categories, corresponding to the six components of the Model of Organizational Safety Effectiveness (MOSE) including Process Auditing, Reward System and Safety Culture, Quality Assurance, Risk Management, Command and Control, and Communications / Functional Relationships. The research conclusions were:

- Through data analysis, specifically, factor analysis, the MCAS was found to be an inadequate tool with questionable validity for gauging maintenance safety climate.
- It has one main factor on which every MCAS question loads.
- With one main factor, the MCAS is not providing the results in content areas as originally planned.
- The analysis of the data clearly shows that with only one factor, versus six which would correspond to the six MOSE categories, the MCAS is not measuring what it was intended to measure.

3.4.3. MCAS RELIABILITY

Reliability is a quantitative assessment used to describe the consistency of (repeated) measurements derived from a test. Additional information on reliability is contained within Section B.3 of Appendix B.

Computed Cronbach Alpha Coefficients for reliability of each of the six MOSE components across all the aircraft Type / Model / Series groups are shown below in Table 11.

Table 11. Computed Cronbach Alpha Values for MOSE components of Respective T/M/S Communities

Type / Model / Series Community	PA	RS/SC	QA	RM	C2	C/FR	Average	Standard Deviation
HS	0.944	0.936	0.848	0.898	0.956	0.935	0.920	0.040
VAQ	0.939	0.919	0.925	0.878	0.948	0.914	0.921	0.024
VAW	0.942	0.921	0.941	0.899	0.960	0.940	0.934	0.021
VF	0.938	0.924	0.900	0.904	0.956	0.915	0.923	0.021
VFA -1 Seat	0.944	0.933	0.928	0.897	0.960	0.942	0.934	0.021
VFA -2 Seat	0.966	0.947	0.943	0.914	0.971	0.951	0.949	0.020
VS	0.973	0.967	0.968	0.905	0.981	0.969	0.972	0.006

The above table indicates strong reliability for all 6 components for each of the squadrons that comprise a carrier air wing.

3.5. DEFINITION OF KEY VARIABLES

3.5.1. SQUADRON MAINTENANCE DISCRETE EVENT MODEL COMPONENTS

The purpose of this research's Bayesian Network Modeling was to accurately represent the conduct of squadron maintenance as an event-based entity in order to clarify knowledge of the system and comprehend the relationship to safety and human error. Boundaries for the Bayesian Network Modeling were defined by selecting an initial list of model components. Components are entities that were supportable by the available data and necessary to properly represent system behavior in accordance with the model's purpose. Components within the defined boundary were classified as either endogenous or exogenous. Endogenous components contain variables involved in providing direct and observable impact to the system. Exogenous elements classify components whose values were not directly affected by the system. [Albin, 1997, p. 10] Excluded components were listed to assure the constructed model was appropriate for the purpose of this research. The initial boundary layer was defined to include elements within the sphere of direct influence by the aviation squadron organization. Endogenous and Exogenous elements are listed in Table 12. A brief description of each component is provided below:

Table 12. Initial Maintenance Discrete Event Model Components

ENDOGENOUS	EXOGENOUS	EXCLUDED
• Previous MCAS Results • Current MCAS Results • Future MCAS Results • Inter-Period MCAS Quartile Transition • Inter-Period Mishap Occurrence • Future Mishap Occurrence	• Previous Organizational Climate • Current Organizational Climate	• Maintenance Required • Maintenance Conducted • Aircraft Flight Operations • Collateral Damage • Preventative Maintenance • Operational demand • Assigned Personnel • Assigned Aircraft • Available Parts Inventory • Quality Assurance Inspections

3.5.2. ENDOGENOUS COMPONENTS

- Current MCAS Results. This describes the results of responses from the most recent iteration of MCAS that had been conducted within the organization.
  - Likert scale value responses for each of the 43 close-ended questions were averaged across all participant responses.
  - Where appropriate, all 43 MCAS responses were aggregated by equal weighted averaging to provide a single Likert scale value.
  - Additionally, questions which composed specific MOSE areas (i.e., Process Auditing, Reward System, Quality Control, Risk Management, Command and Control, and Communications / Functional Relationships) were aggregated by equal weight averaging to provide single Likert scale values.
  - Since Question #21 was written with negative connotation (i.e., evaluation of a condition that adversely affected safety), in order for all responses to be aligned, the inverse of the value was obtained by subtracting the response value from 6 (e.g., response of strongly disagree = 1; 6 - response value; 6 - 1=5; becomes strongly agree).
  - When results of multiple units were obtained, quartiles for the distribution were defined. An organization's aggregated and averaged Likert scale value were assigned a quartile ranking as depicted below in Table 13.

Table 13. MCAS Result Quartile Distribution

Quartile	Description
Q_1	Lowest Likert scale values, $0 \le x < 25\%$
Q_2	$25\% \le x < 50\%$
Q_3	$50\% \le x < 75\%$
Q_4	Highest Likert scale values, $75\% \le x \le 100\%$

- Previous MCAS Results. This describes the results of responses from the MCAS administered immediately prior to the Current MCAS Results. Its numerical value was derived similarly to the means used for Current MCAS Results using corresponding Likert Scale values and quartiles as defined in Table 13, above. The time increment between Previous and Current MCAS Results was not constant and varied considerably among the organizations.
- Future MCAS Results. This describes the results of responses from the MCAS administered immediately subsequent to the Current MCAS Results. Its numerical value was derived similarly to the means used for Current MCAS Results using corresponding Likert Scale values and quartiles as defined in Table 13, above. The time increment between Previous and Current MCAS Results was not constant and varied considerably among the organizations.
- Inter-Period MCAS Transition. This component represents the change in corresponding quartile assignment based upon aggregated and averaged Likert scale values derived from two immediate iterations for administering the MCAS (i.e., the delta in quartile obtained between Previous and Current MCAS Results). This was calculated by:
    - Inter-Period MCAS Transition =

      Current MCAS Results – Previous MCAS Results (EQ 16)
    - The value of the transition could be calculated by the numerical difference in the whole number change in quartiles (i.e., range of -3, -2, -1, 0, 1, 2, 3)
- Inter-Period Mishap Occurrence This element is used to describe whether or not an Aviation Flight Mishap occurred during the time inter-period between

successive administrations of the Past and Current MCAS and associated responses. The range of responses was binary, either YES or NO.

- Future Mishap Occurrence. This factor describes whether or not an Aviation Flight Mishap occurs during the time inter-period between success delivery of the Current and Future MCAS and respective responses. The range of responses was binary, either YES or NO.

3.5.3. EXOGENOUS COMPONENTS

- Current Organizational Climate. Although not directly observable or measurable, this element was defined to represent the capability of the Current MCAS Results to accurately represent an organization's existing climate with respect to operational safety within the context of the MOSE foundation. This definition enabled application of HMMs which contained hidden states (safety climate), observations (MCAS) results, and probabilities of observation and transition occurrences.
- Previous Organizational Climate. Similar to Current Organizational Climate, this component described the adequacy of the Past MCAS Results to accurately represent the organization's operational safety climate during the time period between administration of the Past and Current MCASs.

3.5.4. EXCLUDED COMPONENTS

Endogenous and exogenous components listed above were supportable by the sufficiency and scope of the data provided by the U.S. Naval Safety Center for this research effort. Within this section, excluded components are listed which are within a sphere of influence that could impact MCAS Results and Mishap occurrence; however, insufficient data were provided to enable their definition or development.

- Maintenance Required. A measure of the work effort necessary to facilitate attainment of operational aircraft. This includes required pre- and post-flight servicing and inspections, preventative maintenance, and the correction of known discrepancies that are sufficiently severe as to prevent aircraft from being characterized as safe for flight.
- Maintenance Performed. This is an overarching classification of the types of maintenance performed by the squadron comprised of inspections, servicing, handling, on-equipment corrective and preventive maintenance, incorporation of technical directives, and record keeping and reports preparation.
- Aircraft Flight Operations. Actual flights in which the aircraft are launched and the assigned mission is successfully completed.
- Collateral Damage. Impairment to linked system elements which are caused by component breakdown, incorrect operation, or failure and result in creation of new Aircraft Discrepancies. Collateral damage may also be caused from incorrectly performed maintenance.
- Preventative Maintenance is a subset of maintenance performed, and it describes the effort which is conducted to maintain the aircraft in adequate material condition to accomplish assigned missions. Preventative maintenance is a proactive effort undertaken to mitigate creation of Aircraft Discrepancies and related component failures.

- Operational Demand. Operational demand. A measure of the demand placed upon the squadron thorough assignment of respective missions. Operational demand is composed of two inputs: tasking and employment scheduling.
    - Tasking. The number of flight sorties required to be flown in order to fulfill training or currency requirements from the squadron's operations department or those missions assigned from superior commands.
    - Employment scheduling. For operational squadrons that deploy, Naval aviation has adopted the Fleet Response Plan based on a notional 27-month Inter-Deployment Readiness Cycle (IDRC) which includes 6 months for aircraft maintenance, followed by 6 months for training, and a 15 month employment window. During the employment window the squadron is expected to sustain a high degree of readiness which may include forward deployed operations. A depiction of the IDRC is shown in Figure 14. The IDRC driven employment schedule is the critical driver for squadron receipt of operational funding, personnel, aircraft and associative weapons systems (e.g., laser designators, forward looking infra-red pods, etc.) inventory, required readiness levels, and operational demand.

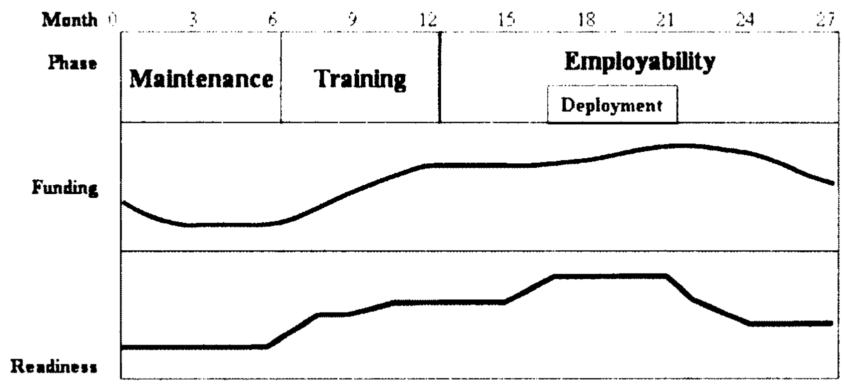


Figure 14. Inter-Deployment Readiness Cycle
[CNAF Training and Readiness Review Conference, 2003]

- Assigned Personnel. Sufficient manpower is required to be assigned to the squadron in order to accomplish assigned missions. Personnel are ordered into the squadron to fill billets listed in the authorized manpower documents, and they are rotated out when their tours of duty are complete.
- Assigned Aircraft. Represents the number of aircraft assigned to the organization that are maintained and tasked to meet Operational Demand.
- Available Parts Inventory. Very few replacement parts are assigned directly to the squadron inventory. These replacement spare items are normally limited to consumable components or bit / piece parts such as hardware (nuts, bolts, etc.) or other items that routinely require removal and replacement due to wear. Primarily specific replacement components are maintained in a ready-for-issue status by respective supply departments located at either naval air station or shipboard from which the squadron is operating. A lack of parts availability may be mitigated through cannibalization of parts from other aircraft. This results in additional maintenance performed to remove the needed component from one airframe and

the subsequent effort to replace it when the needed spare part becomes available through the supply system.

- Quality Assurance Inspections. Inspections of conducted maintenance that ensures quality workmanship. Quality Assurance (QA) is fundamentally employed to prevent the occurrence of defects. The concept embraces all events from the start of the maintenance operation to its completion and is the responsibility of all maintenance personnel. [CNAFINST 4790.2 Vol. 1, 2005, p. 14-2.] Highly skilled representatives are assigned to the QA division to inspect maintenance work for conformance to technical requirements and to audit work centers for evaluation of plans, policies, procedures, products, directives, and records.

3.6. SELECTION OF BAYESIAN NETWORK MODELING AS THE DISCRETE EVENT MODELING FRAMEWORK

Prior to conceptual model development, the five unique discrete modeling techniques described in Section 2.7 were comparatively evaluated for utility for this research application. Primary considerations were utility for execution based upon data set provided by the U.S. Naval Safety Center, ability to accurately represent and determine model causality relationships between respective, successive MCAS results and mishap occurrence; wherewithal to generate probability distributions for statistical comparison; flexibility to enable generation and execution of a set of models with minor modifications in causal relationships; and minimum impact of inherent disadvantages associated with the modeling technique for this research effort. A presentation of the comparison evaluation is summarized in Table 14.

Table 14. Comparative Evaluation Analysis of Utility for Discrete Event Modeling Techniques

Technique / Characteristic	Represent and Determine Model Causality	Generation of Probability Distributions for Statistical Comparison	Flexibility for Minor Modifications	Minimum Impact of Inherent Disadvantage
Bayesian Network Model (BNM)	✔	✔	✔	✔
Hidden Markov Model (HMM)	✔	✔	✔	✘
Naïve Bayesian Model (NBM)	✘	✔	✘	✘
Artificial Neural Network Model (ANNM)	✘	✘	✔	✘
Support Vector Machine Model (SVMM)	✘	✘	✔	✘

3.6.1. MODEL CAUSALITY

The BNM and HMM techniques contained the requisite capabilities to support detailed representation of model causality of specific nodes contained within the models. BNMs support use for determining model causality where there is an incomplete understanding of all occurring events and enable learning about the causal relationships between system variables. Although BNMs provide for causality representation, the naïve assumption of a single parent and cluster of same generation child nodes inhibits defining multiple parent-child relationships for multiple sequels and branching. ANNM use of neural nets in a similar fashion as a "black box" does not afford sufficient explanatory power regarding the underlying relationships to represent or determine causal relationships. ANNMs have limited ability to explicitly identify possible causal relationships. SVMs possess limited capability to represent the dynamics of underlying processes and causalities. [Boussemart, 2011, p. 334]

3.6.2. GENERATION OF PROBABILITY DISTRIBUTIONS FOR STATISTICAL COMPARISON

BNMs are built upon direct probabilistic relationships between the connected variables that are quantified through use of probability distributions As a subset of BNMs, HMMs also provide a solid statistical foundation for modeling. NBM definition for efficient generation of a probability distribution represented as the product of many simpler distributions provides sufficient capability for statistical comparison of model probability outputs. ANNMs and SNNMs are discriminative in that they may generate conditional probability distributions but do not allow generation of samples from the joint distribution. Discriminative modeling techniques contain limitations in their predictive power due to their reliance on conditional probabilities. [Boussemart, 2011, p 29] Additionally, a disadvantage of SVMMs includes that this technique does not directly provide probability estimates.

3.6.3. FLEXIBILITY FOR MINOR MODIFICATIONS

BNM use of Directed Acyclic Graphs containing causal linkages and observed probabilities are easily adaptable to support minor changes to defined relationships between state variables. Likewise, HMMs may be used to develop flexible and general models to represent sequencing properties and may be constructed to combine individual HMMs into larger HMMs. Since NBM uses only one parent and one level of child nodes, this technique was adjudicated not to have sufficient flexibility to support minor modifications to modeling causal relationships between the state variables. Both ANNM and SVM techniques were evaluated to have sufficient utility to incorporate minor adjustments in conceptual and computational development and modification.

3.6.4. MINIMUM IMPACT OF INHERENT DISADVANTAGES

Disadvantages of BNM technique include lack of a universally accepted method for constructing a network from data and potential difficulty for experts to agree on model structure. Neither of these was considered significant adverse to this research effort. HMM disadvantages of necessity to obtain large amounts of data for accurate modeling and potential for generating inaccurate conditional independence properties if there are too few hidden states or inaccuracies in the observation distributions were considered to present the potential for substantial challenges due to limited data provided by the U.S. Naval Safety Center. NBM's inherent disadvantage of the potential for a loss of accuracy induced due to the assumption of class conditional independence where often there exists dependencies among attribute variables was evaluated to be an unwanted characteristic for selection. The manner in which ANNMs store knowledge as weights between nodes and the limitations in interpretation of the weights result in "black box" appraisal of the results. These inherent disadvantages of ANNM were assessed to be undesirable. SVMs require supervised learning and a priori labeled data. They are suitable for use with categorical data but do not possess similar capabilities for temporal data.

3.6.5. SUMMARY OF DISCRETE EVENT MODELING COMPARISON

Based upon the information presented above and as depicted in Table 14, BNM technique was selected as the best fit for this research effort. In contrast, all the other techniques contained a documented limitation that impaired their uses for this purpose.

3.7. CONCEPTUAL MODEL DEVELOPMENT

Subsequent to selection of BNMs as the best methodology for this research effort, Bayesian Network conceptual models were initially constructed to accurately represent the causal relationship between the endogenous and exogenous components listed in Table 12, above. Arcs were incorporated to detail the direct probabilistic relationships between the connected variables. Inherent in the conceptual design, Bayesian Network modeling was the goal to produce statistical output data that would update conditional probabilities in light of observed evidence. Per Section 2.7 above, the BNM conceptual models included the following attributes:

- A set of variable and a set of directed edges (i.e., arcs) between variables
- Each variable has a finite set of mutual exclusive states.
- The variables together with the directed edges form a Directed Acyclic Graph.
- To each variable A with parents $B_1, \ldots, B_n$ there is attached a conditional probability table $P(A \mid B_1, \ldots, B_n)$.

Review of the inherent disadvantages for application of BNMs (lack of universally accepted method for model construction, potential disagreement on model structure by subject matter experts, limitation on spatial / temporal scale representations, and inability to support feedback loops) was determined to have little-to-no relevant impact on this research effort. Evidentiary data for the respective probability distributions would be derived from the actual squadron / unit MCAS results and corresponding mishap summary reports.

3.7.1. SYSTEM FORMALISM

The BNM foundation resulted in use of a classical Discrete Event System Specification (DEVS) to specify and describe the notation required to relate input and model state derivatives for model development. The classical DEVS framework enabled representation of the BNM for depicting and evaluating causal relationships between the selected components. The DEVS structure is defined as:

$DEVS = (X, Y, S, \delta_{ext}, \delta_{int}, \lambda, ta)$ where (EQ 17)

X is the set of inputs
Y is the set of outputs
S is the set of *sequential* states
$\delta_{ext:}\ Q \times X \rightarrow S$ is the *external state transition function*
$\delta_{int}: S \rightarrow S$ is the *internal state transition function*
$Q = \{(s\ ,\ e) \mid s \in S, 0 = e = ta(s)\}$ is the *total state* set (EQ 18)
e is the *time elapsed* since last transition
$\lambda: S \rightarrow Y$ is the output function
$ta: S \rightarrow R^{+}_{0,\infty}$ is the set positive reals with 0 and ∞
[Zeigler, et. al, 2000, p. 75-6, Joslyn, 1996]

Application of the DEVS formalism to the BNM defined variables and causal relationships resulted in the following classifications:

- Input Set *X*:
  - Previous MCAS Results
  - Current MCAS Results
  - Future MCAS Results
  - Inter-period MCAS Transition
  - Inter-period Mishap Occurrence
  - Future Mishap Occurrence
- Output Set *Y*:
  - Probability distributions for MCAS Result set variables when Inter-Period / Future Mishap Occurrence values are set exclusively to Yes or No
- Sequential States *S*: ○ Quartile (1 through 4 dependent upon MCAS Results)
- Time advance function *ta*: non uniform nor constant time period between iterations of completing successive MCAS surveys

3.7.2. BAYESIAN NETWORK APPLICATION

Conceptual modeling processes were undertaken to leverage a key features of BNM that is they provide a suitable method for decomposing a probability distribution into a set of local distributions. Although the component nodes would contain quantitative data, the arcs defining causal relationships would represent qualitative aspects for the model. The separation of the qualitative representation of the influences between variables from the numeric quantification of the strengths of the influences presented a significant advantage for knowledge engineering. BNM conceptual development supported first focusing on the specific qualitative structure of the domain followed by quantifying the influences. This was employed to ensure a complete specification of the joint-probability distribution. (Haddawy, 1999)

Table 15 contains a list of component variables, respective abbreviations, and description of the appropriate ranges of data. Depictions and overall narrative of the BNM conceptual models are provided below.

Table 15. Component Abbreviations and Data Ranges

Abbreviation	Component Variable	Data Range
PMR	Previous MCAS Results	Quartile 1 through 4
CMR	Current MCAS Results	Quartile 1 through 4
FMR	Future MCAS Result	Quartile 1 through 4
IMT	Inter-period MCAS Transition	Lower: $Q_i \rightarrow Q_j$ where $i > j$ Neutral: $Q_i \rightarrow Q_j$ where $i=j$ Higher: $Q_i \rightarrow Q_j$ where $i < j$
IMO	Inter-period Mishap Occurrence	Yes, No
FMO	Future Mishap Occurrence	Yes, No

3.7.3. BAYESIAN NETWORK CONCEPTUAL MODEL NUMBER 1

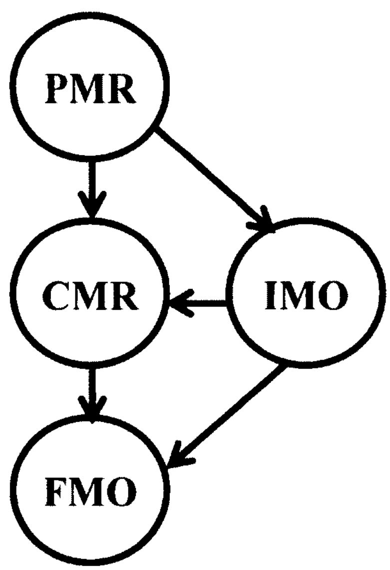


Figure15. Bayesian Network Conceptual Model #1

As depicted in Figure 15, this model is based on the following qualitative description of the causal relationships between selected components:

- Previous MCAS results have an impact on both current MCAS results and whether an inter-period mishap occurred
- Inter-period mishap occurrence (Yes/No) impacts current MCAS results and future mishap occurrence
- Current MCAS results impacts future mishap occurrence.

3.7.4. BAYESIAN NETWORK CONCEPTUAL MODEL NUMBER 2

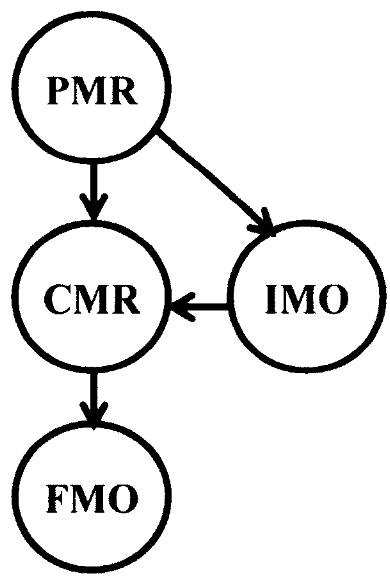


Figure 16. Bayesian Network Conceptual Model #2

This model shown in Figure 16 is similar to Model #1 above; however, it removes the direct influence of the inter-period mishap occurrence on the future mishap occurrence.

3.7.5. BAYESIAN NETWORK CONCEPTUAL MODEL NUMBER 3

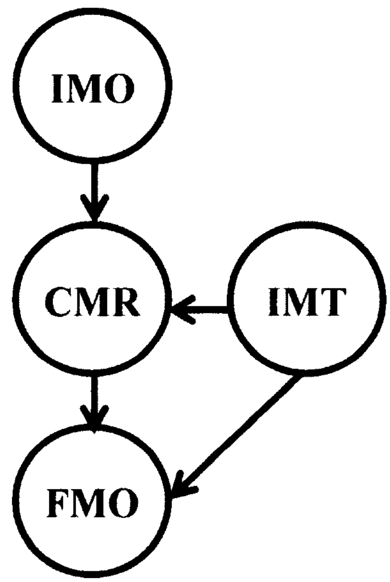


Figure 17. Bayesian Network Conceptual Model #3

This model displayed in Figure 17 is based on the following qualitative description of the causal relationships between selected components:

- Previous Inter-period Mishap Occurrence (Yes / No) has an impact on Current MCAS Results
- Inter-period MCAS result quartile transition impacts current MCAS results and future mishap occurrence
- Current MCAS Results impacts Future Mishap Occurrence.

3.7.6. BAYESIAN NETWORK CONCEPTUAL MODEL NUMBER 4

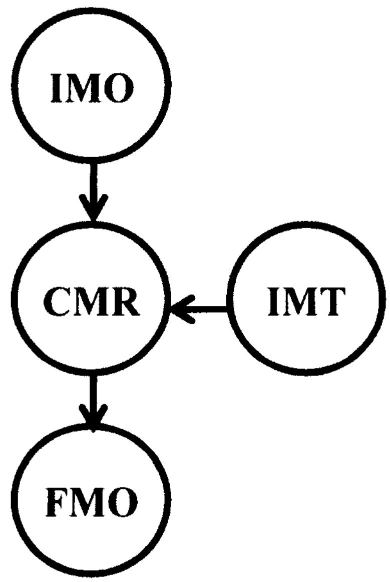


Figure18. Bayesian Network Conceptual Model #4

Figure 18 presents a model is similar to Model #3 above; however, it removes the direct influence of the inter-period MCAS results quartile transition on the future mishap occurrence.

3.7.7. BAYESIAN NETWORK CONCEPTUAL MODEL NUMBER 5

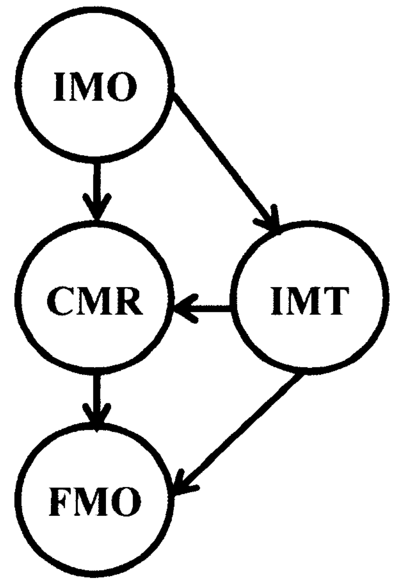


Figure 19. Bayesian Network Conceptual Model #5

This model as shown in Figure 19 is similar to Model #3 above; however it adds the causal impact of inter-period mishap occurrence on inter-period MCAS results quartile transition.

3.8. COMPUTATIONAL MODEL DEVELOPMENT, CONSTRUCTION, AND IMPLEMENTATION

This process adapted the conceptual model using software to construct an executable program that provided a simulated abstraction of the Bayesian Network models. As the conceptual model was a first-step transformation of the real world system, the computational model expressed a second-step transformation into an operational entity that was represented by a software coded and a computer recognizable version of the conceptual model. Key features in a computational model included both composability and interoperability. "Composability is concerned with how to create different models that are semantically consistent. Interoperability is focused on the software used to support communication and synchronization at runtime." [Godding, Sarjoughian, and Kempf, 2004, p. 232] The computation model was designed to allow for study of the causal relationships between model components of the represented Bayesian Network Model through generation of probability distributions to match model output.

GeNIe software version 2.0.4535.0 was built on June 1, 2012 by Decision Systems Laboratory (DSL), University of Pittsburgh was selected for programming the computational model. GeNIe (acronym taken from Graphical Network Interface) was designed to provide a developmental environment for building graphical decision-theoretic models [DSL, 2010]. It is implemented in Visual C++ and interfaces with the Structural Modeling, Inference, and Learning Engine (SMILE) software also developed by DSL. SMILE operates and independent library of C++ classes for reasoning in graphical probabilistic models, such as Bayesian networks and influence diagrams and using them for probabilistic reasoning and decision making under uncertainty. [DSL, 2007]

The Conceptual Bayesian Network Models #1-5 as shown in Figures 15 through 19 were refined subsequent to definition of the necessary causal relationships. Models were executed using actual MCAS results and mishap summary report data. Bayesian Network Computational Models were implemented within the GeNIe software programs based upon the following node variables and equations. Input values were provided from actual MCAS results and corresponding inter-period / future mishap occurrence. Output probabilities were derived through model execution by setting conditions of respective nodes.

3.8.1. BAYESIAN NETWORK COMPUTATIONAL MODEL NUMBER 1

BNM Computational Model #1 node variables and model equations are depicted below in Tables 16 through 19.

Table 16. BNM Computational Model #1 Prior MCAS Result Quartile Probabilities

PMR Quartile	Probability *
PMR Q_1	P (PMR Q_1) ≈ 0.25
PMR Q_2	P (PMR Q_2) ≈ 0.25
PMR Q_3	P (PMR Q_3) ≈ 0.25
PMR Q_4	P (PMR Q_4) ≈ 0.25

Note: * - n = the total number of observations.
Where n / 4 is equal to an integer, all P (PMR Qi) = 0.25.

$$\sum_{i=1}^{4} P\ (\text{PMR}\ Q_i) = 1 \qquad \text{(EQ 19)}$$

Table 17. BNM Computational Model #1 Conditional Probabilities of Inter-Period Occurrence Mishap Given Prior MCAS Result Quartile

PMR Quartile / IMO	PMR Q_1	PMR Q_2	PMR Q_3	PMR Q_4
YES	P (YES | PMR Q_1)	P (YES | PMR Q_2)	P (YES | PMR Q_3)	P (YES | PMR Q_4)
NO	P (NO | PMR Q_1)	P (NO | PMR Q_2)	P (NO | PMR Q_3)	P (NO | PMR Q_4)

For i= 1 to 4,

$$P\ (\text{IMO} = \text{YES} \mid \text{PMR}\ Q_i) + P\ (\text{IMO} = \text{NO} \mid \text{PMR}\ Q_i) = 1 \qquad \text{(EQ 20)}$$

Table 18. BNM Computational Model #1 Conditional Probabilities of Current MCAS Results Quartile Given Inter-period Mishap Occurrence Given Prior MCAS Result Quartile

PMR	PMR Q_1		PMR Q_2		PMR Q_3		PMR Q_4	
IMO	YES	NO	YES	NO	YES	NO	YES	NO
CMR Q_1	$P\,(\text{CMR } Q_1 \mid \text{IMO} = \text{YES} \mid \text{PMR } Q_1)$	$P\,(\text{CMR } Q_1 \mid \text{IMO} = \text{NO} \mid \text{PMR } Q_1)$	$P\,(\text{CMR } Q_1 \mid \text{IMO} = \text{YES} \mid \text{PMR } Q_2)$	$P\,(\text{CMR } Q_1 \mid \text{IMO} = \text{NO} \mid \text{PMR } Q_2)$	$P\,(\text{CMR } Q_1 \mid \text{IMO} = \text{YES} \mid \text{PMR } Q_3)$	$P\,(\text{CMR } Q_1 \mid \text{IMO} = \text{NO} \mid \text{PMR } Q_3)$	$P\,(\text{CMR } Q_1 \mid \text{IMO} = \text{YES} \mid \text{PMR } Q_4)$	$P\,(\text{CMR } Q_1 \mid \text{IMO} = \text{NO} \mid \text{PMR } Q_4)$
CMR Q2	$P\,(\text{CMR } Q_2 \mid \text{IMO} = \text{YES} \mid \text{PMR } Q_1)$	$P\,(\text{CMR } Q_2 \mid \text{IMO} = \text{NO} \mid \text{PMR } Q_1)$	$P\,(\text{CMR } Q_2 \mid \text{IMO} = \text{YES} \mid \text{PMR } Q_2)$	$P\,(\text{CMR } Q_2 \mid \text{IMO} = \text{NO} \mid \text{PMR } Q_2)$	$P\,(\text{CMR } Q_2 \mid \text{IMO} = \text{YES} \mid \text{PMR } Q_3)$	$P\,(\text{CMR } Q_2 \mid \text{IMO} = \text{NO} \mid \text{PMR } Q_3)$	$P\,(\text{CMR } Q_2 \mid \text{IMO} = \text{YES} \mid \text{PMR } Q_4)$	$P\,(\text{CMR } Q_2 \mid \text{IMO} = \text{NO} \mid \text{PMR } Q_4)$
CMR Q3	$P\,(\text{CMR } Q_3 \mid \text{IMO} = \text{YES} \mid \text{PMR } Q_1)$	$P\,(\text{CMR } Q_3 \mid \text{IMO} = \text{NO} \mid \text{PMR } Q_1)$	$P\,(\text{CMR } Q_3 \mid \text{IMO} = \text{YES} \mid \text{PMR } Q_2)$	$P\,(\text{CMR } Q_3 \mid \text{IMO} = \text{NO} \mid \text{PMR } Q_2)$	$P\,(\text{CMR } Q_3 \mid \text{IMO} = \text{YES} \mid \text{PMR } Q_3)$	$P\,(\text{CMR } Q_3 \mid \text{IMO} = \text{NO} \mid \text{PMR } Q_3)$	$P\,(\text{CMR } Q_3 \mid \text{IMO} = \text{YES} \mid \text{PMR } Q_4)$	$P\,(\text{CMR } Q_3 \mid \text{IMO} = \text{NO} \mid \text{PMR } Q_4)$
CMR Q4	$P\,(\text{CMR } Q_4 \mid \text{IMO} = \text{YES} \mid \text{PMR } Q_1)$	$P\,(\text{CMR } Q_4 \mid \text{IMO} = \text{NO} \mid \text{PMR } Q_1)$	$P\,(\text{CMR } Q_4 \mid \text{IMO} = \text{YES} \mid \text{PMR } Q_2)$	$P\,(\text{CMR } Q_4 \mid \text{IMO} = \text{NO} \mid \text{PMR } Q_2)$	$P\,(\text{CMR } Q_4 \mid \text{IMO} = \text{YES} \mid \text{PMR } Q_3)$	$P\,(\text{CMR } Q_4 \mid \text{IMO} = \text{NO} \mid \text{PMR } Q_3)$	$P\,(\text{CMR } Q_4 \mid \text{IMO} = \text{YES} \mid \text{PMR } Q_4)$	$P\,(\text{CMR } Q_4 \mid \text{IMO} = \text{NO} \mid \text{PMR } Q_4)$

For i= 1 to 4, and IMO= YES or NO,

$$\sum_{j=1}^{4} P\left(\text{CMR } Q_j \mid \text{IMO} \mid \text{PMR } Q_i\right) = 1 \qquad \text{(EQ 21)}$$

Table 19. BNM Computational Model #1 Conditional Probabilities of Future Mishap Occurrence Given Current MCAS Results Quartile Given Inter-period Mishap Occurrence

IMO	YES				NO			
CMR	CMR Q_1	CMR Q_2	CMR Q_3	CMR Q_4	CMR Q_1	CMR Q_2	CMR Q_3	CMR Q_4
FMO = YES	*P* (FMO = YES | CMR Q_1 | IMO = YES)	*P* (FMO = YES | CMR Q_2 | IMO = YES)	*P* (FMO = YES | CMR Q_3 | IMO = YES)	*P* (FMO = YES | CMR Q_4 | IMO = YES)	*P* (FMO = YES | CMR Q_1 | IMO = NO)	*P* (FMO = YES | CMR Q_2 | IMO = NO)	*P* (FMO = YES | CMR Q_3 | IMO = NO)	*P* (FMO = YES | CMR Q_4 | IMO = NO)
FMO = NO	*P* (FMO = NO | CMR Q_1 | IMO = YES)	*P* (FMO = NO | CMR Q_2 | IMO = YES)	*P* (FMO = NO | CMR Q_3 | IMO = YES)	*P* (FMO = NO | CMR Q_4 | IMO = YES)	*P* (FMO = NO | CMR Q_1 | IMO = NO)	*P* (FMO = NO | CMR Q_2 | IMO = NO)	*P* (FMO = NO | CMR Q_3 | IMO = NO)	*P* (FMO = NO | CMR Q_4 | IMO = NO)

For IMO = YES or NO and i = 1 to 4,

$$\sum_{FMO=YES}^{NO} P\ (\text{FMO} \mid \text{CMR } Q_i \mid \text{IMO}) = 1 \qquad \text{(EQ 22)}$$

3.8.2. BAYESIAN NETWORK COMPUTATIONAL MODEL NUMBER 2

BNM Computational Model #2 node variables and model equations are depicted below in Tables 20 through 23.

Table 20. BNM Computational Model #2 Prior MCAS Result Quartile Probabilities

PMR Quartile	Probability *
PMR Q_1	P (PMR Q_1) ≈ 0.25
PMR Q_2	P (PMR Q_2) ≈ 0.25
PMR Q_3	P (PMR Q_3) ≈ 0.25
PMR Q_4	P (PMR Q_4) ≈ 0.25

Note: * - n = the total number of observations.
Where n / 4 is equal to an integer, all P (PMR Q_i) = 0.25.

$$\sum_{i=1}^{4} P\ (\text{PMR } Q_i) = 1 \qquad \text{(EQ 23)}$$

Table 21. BNM Computational Model #2 Conditional Probabilities of Inter-Period Mishap Occurrence Given Prior MCAS Result Quartile

PMR Quartile / IMO	PMR Q_1	PMR Q_2	PMR Q_3	PMR Q_4
YES	P (YES | PMR Q_1)	P (YES | PMR Q_2)	P (YES | PMR Q_3)	P (YES | PMR Q_4)
NO	P (NO | PMR Q_1)	P (NO | PMR Q_2)	P (NO | PMR Q_3)	P (NO | PMR Q_4)

For i= 1 to 4,

$$P\ (\text{IMO} = \text{YES} \mid \text{PMR } Q_i) + P\ (\text{IMO} = \text{NO} \mid \text{PMR } Q_i) = 1 \qquad \text{(EQ 24)}$$

Table 22. BNM Computational Model #2 Conditional Probabilities of Current MCAS Results Quartile Given Inter-period Mishap Occurrence Given Prior MCAS Result Quartile

PMR	PMR Q_1		PMR Q_2		PMR Q_3		PMR Q_4	
IMO	YES	NO	YES	NO	YES	NO	YES	NO
CMR Q_1	P (CMR $Q_1 \mid$ IMO = YES $\mid$ PMR Q_1)	P (CMR $Q_1 \mid$ IMO = NO $\mid$ PMR Q_1)	P (CMR $Q_1 \mid$ IMO = YES $\mid$ PMR Q_2)	P (CMR $Q_1 \mid$ IMO = NO $\mid$ PMR Q_2)	P (CMR $Q_1 \mid$ IMO = YES $\mid$ PMR Q_3)	P (CMR $Q_1 \mid$ IMO = NO $\mid$ PMR Q_3)	P (CMR $Q_1 \mid$ IMO = YES $\mid$ PMR Q_4)	P (CMR $Q_1 \mid$ IMO = NO $\mid$ PMR Q_4)
CMR Q2	P (CMR $Q_2 \mid$ IMO = YES $\mid$ PMR Q_1)	P (CMR $Q_2 \mid$ IMO = NO $\mid$ PMR Q_1)	P (CMR $Q_2 \mid$ IMO = YES $\mid$ PMR Q_2)	P (CMR $Q_2 \mid$ IMO = NO $\mid$ PMR Q_2)	P (CMR $Q_2 \mid$ IMO = YES $\mid$ PMR Q_3)	P (CMR $Q_2 \mid$ IMO = NO $\mid$ PMR Q_3)	P (CMR $Q_2 \mid$ IMO = YES $\mid$ PMR Q_4)	P (CMR $Q_2 \mid$ IMO = NO $\mid$ PMR Q_4)
CMR Q3	P (CMR $Q_3 \mid$ IMO = YES $\mid$ PMR Q_1)	P (CMR $Q_3 \mid$ IMO = NO $\mid$ PMR Q_1)	P (CMR $Q_3 \mid$ IMO = YES $\mid$ PMR Q_2)	P (CMR $Q_3 \mid$ IMO = NO $\mid$ PMR Q_2)	P (CMR $Q_3 \mid$ IMO = YES $\mid$ PMR Q_3)	P (CMR $Q_3 \mid$ IMO = NO $\mid$ PMR Q_3)	P (CMR $Q_3 \mid$ IMO = YES $\mid$ PMR Q_4)	P (CMR $Q_3 \mid$ IMO = NO $\mid$ PMR Q_4)
CMR Q4	P (CMR $Q_4 \mid$ IMO = YES $\mid$ PMR Q_1)	P (CMR $Q_4 \mid$ IMO = NO $\mid$ PMR Q_1)	P (CMR $Q_4 \mid$ IMO = YES $\mid$ PMR Q_2)	P (CMR $Q_4 \mid$ IMO = NO $\mid$ PMR Q_2)	P (CMR $Q_4 \mid$ IMO = YES $\mid$ PMR Q_3)	P (CMR $Q_4 \mid$ IMO = NO $\mid$ PMR Q_3)	P (CMR $Q_4 \mid$ IMO = YES $\mid$ PMR Q_4)	P (CMR $Q_4 \mid$ IMO = NO $\mid$ PMR Q_4)

For i= 1 to 4, and IMO= YES or NO,

$$\sum_{j=1}^{4} P\left(\mathrm{CMR\ Q_j}\ \middle|\ \mathrm{IMO} \mid \mathrm{PMR\ Q_i}\right) = 1 \qquad \text{(EQ 25)}$$

Table 23. BNM Computational Model #2 Conditional Probabilities of Future Mishap Occurrence Given Current MCAS Result Quartile

CMR Quartile / FMO	CMR Q_1	CMR Q_2	CMR Q_3	CMR Q_4
YES	P (YES | CMR Q_1)	P (YES | CMR Q_2)	P (YES | CMR Q_3)	P (YES | CMR Q_4)
NO	P (NO | CMR Q_1)	P (NO | CMR Q_2)	P (NO | CMR Q_3)	P (NO | CMR Q_4)

For i= 1 to 4,

$$P\,(\text{FMO} = \text{YES} \mid \text{PMR } Q_i) + P\,(\text{FMO} = \text{NO} \mid \text{PMR } Q_i) = 1 \qquad \text{(EQ 26)}$$

3.8.3. BAYESIAN NETWORK COMPUTATIONAL MODEL NUMBER 3

BNM Computational Model #3 node variables and model equations are depicted below in Tables 24 through 27.

Table 24. BNM Computational Model #3 Inter-period Mishap Occurrence

Inter-period Mishap Occurrence	Probability
IMO = YES	P (IMT = YES)
IMO = NO	P (IMT = NO)

$$P\,(\text{IMT} = \text{YES}) + P\,(\text{IMT} = \text{NO}) = 1 \qquad \text{(EQ 27)}$$

Table 25. BNM Computational Model #3 Inter-period MCAS Transition

Inter-period MCAS Transition	Probability
IMT = HIGHER	P (IMT = HIGHER)
IMT = NEUTRAL	P (IMT = NEUTRAL)
IMT = LOWER	P (IMT = LOWER)

$$P\,(\text{IMT} = \text{HIGHER}) + P\,(\text{IMT} = \text{NEUTRAL}) + P\,(\text{IMT} = \text{LOWER}) = 1 \qquad \text{(EQ 28)}$$

Table 26. BNM Computational Model #3 Current MCAS Results Given Inter-period MCAS Transition Given Inter-period Mishap Occurrence

IMO	YES			NO		
IMT	HIGHER	NEUTRAL	LOWER	HIGHER	NEUTRAL	LOWER
CMR Q_1	P (CMR Q_1 | IMT = HIGHER | IMO = YES)	P (CMR Q_1 | IMT = NEUTRAL | IMO = YES)	P (CMR Q_1 | IMT = LOWER | IMO = YES)	P (CMR Q_1 | IMT = HIGHER | IMO = NO)	P (CMR Q_1 | IMT = NEUTRAL | IMO = NO)	P (CMR Q_1 | IMT = LOWER | IMO = NO)
CMR Q_2	P (CMR Q_2 | IMT = HIGHER | IMO = YES)	P (CMR Q_2 | IMT = NEUTRAL | IMO = YES)	P (CMR Q_2 | IMT = LOWER | IMO = YES)	P (CMR Q_2 | IMT = HIGHER | IMO = NO)	P (CMR Q_2 | IMT = NEUTRAL | IMO = NO)	P (CMR Q_2 | IMT = LOWER | IMO = NO)
CMR Q_3	P (CMR Q_3 | IMT = HIGHER | IMO = YES)	P (CMR Q_3 | IMT = NEUTRAL | IMO = YES)	P (CMR Q_3 | IMT = LOWER | IMO = YES)	P (CMR Q_3 | IMT = HIGHER | IMO = NO)	P (CMR Q_3 | IMT = NEUTRAL | IMO = NO)	P (CMR Q_3 | IMT = LOWER | IMO = NO)
CMR Q_4	P (CMR Q_4 | IMT = HIGHER | IMO = YES)	P (CMR Q_4 | IMT = NEUTRAL | IMO = YES)	P (CMR Q_4 | IMT = LOWER | IMO = YES)	P (CMR Q_4 | IMT = HIGHER | IMO = NO)	P (CMR Q_4 | IMT = NEUTRAL | IMO = NO)	P (CMR Q_4 | IMT = LOWER | IMO = NO)

For IMT = HIGHER, NEUTRAL OR LOWER, and IMO= YES or NO,

$$\sum_{i=1}^{4} P\text{ (CMR } Q_i \mid \text{IMT} \mid \text{IMO}) = 1 \qquad \text{(EQ 29)}$$

Table 27. BNM Computational Model #3 Current MCAS Results Given Inter-period MCAS Transition Given Inter-period Mishap Occurrence

CMR	CMR Q_1			CMR Q_2			CMR Q_3			CMR Q_4		
IMT #	H	c	L	H	N	L	H	N	L	H	N	L
FMO = YES	*1	*2	*3	*4	*5	*6	*7	*8	*9	*10	*11	*12
FMO = NO	*13	*14	*15	*16	*17	*18	*19	*20	*21	*22	*23	*24

Notes: #: H=HIGHER, N=NEUTRAL, L = LOWER

* 1: P (FMO = YES | IMT = HIGHER | CMR Q_1)
* 2: P (FMO = YES | IMT = NEUTRAL | CMR Q_1)
* 3: P (FMO = YES | IMT = LOWER | CMR Q_1)
* 4: P (FMO = YES | IMT = HIGHER | CMR Q_2)
* 5: P (FMO = YES | IMT = NEUTRAL | CMR Q_2)
* 6: P (FMO = YES | IMT = LOWER | CMR Q_2)
* 7: P (FMO = YES | IMT = HIGHER | CMR Q_3)
* 8: P (FMO = YES | IMT = NEUTRAL | CMR Q3)
* 9: P (FMO = YES | IMT = LOWER | CMR Q_3)
*10: P (FMO = YES | IMT = HIGHER | CMR Q_4)
*11: P (FMO = YES | IMT = NEUTRAL | CMR Q_4)
*12: P (FMO = YES | IMT = LOWER | CMR Q_4)
*13: P (FMO = NO | IMT = HIGHER | CMR Q_1)
*14: P (FMO = NO | IMT = NEUTRAL | CMR Q_1)
*15: P (FMO = NO | IMT = LOWER | CMR Q_1)
*16: P (FMO = NO | IMT = HIGHER | CMR Q_2)
*17: P (FMO = NO | IMT = NEUTRAL | CMR Q_2)
*18: P (FMO = NO | IMT = LOWER | CMR Q_2)
*19: P (FMO = NO | IMT = HIGHER | CMR Q_3)
*20: P (FMO = NO | IMT = NEUTRAL | CMR Q_3)
*21: P (FMO = NO | IMT = LOWER | CMR Q_3)
*22: P (FMO = NO | IMT = HIGHER | CMR Q_4)
*23: P (FMO = NO | IMT = NEUTRAL | CMR Q_4)
*24: P (FMO = NO | IMT = LOWER | CMR Q_4)

For IMT = HIGHER, NEUTRAL, or LOWER and i= 1 to 4,

$$\sum_{FMO=YES}^{NO} P\ (\text{FMO} \mid \text{IMT} \mid \text{CMR } Q_i) = 1 \qquad \text{(EQ 30)}$$

3.8.4. BAYESIAN NETWORK COMPUTATIONAL MODEL NUMBER 4

BNM Computational Model #4 node variables and model equations are depicted below in Tables 28 through 31.

Table 28. BNM Computational Model #4 Inter-period Mishap Occurrence

Inter-period Mishap Occurrence	Probability
IMO = YES	P (IMT = YES)
IMO = NO	P (IMT = NO)

P (IMT = YES) + P (IMT = NO) = 1 (EQ 31)

Table 29. BNM Computational Model #4 Inter-period MCAS Transition

Inter-period MCAS Transition	Probability
IMT = HIGHER	P (IMT = HIGHER)
IMT = NEUTRAL	P (IMT = NEUTRAL)
IMT = LOWER	P (IMT = LOWER)

P (IMT = HIGHER) + P (IMT = NEUTRAL) +
P (IMT = LOWER) = 1 (EQ 32)

Table 30. BNM Computational Model #4 Current MCAS Results Given Inter-period MCAS Transition Given Inter-period Mishap Occurrence

IMO	YES			NO		
IMT	HIGHER	NEUTRAL	LOWER	HIGHER	NEUTRAL	LOWER
CMR Q_1	P (CMR Q_1 | IMT = HIGHER | IMO = YES)	P (CMR Q_1 | IMT = NEUTRAL | IMO = YES)	P (CMR Q_1 | IMT = LOWER | IMO = YES)	P (CMR Q_1 | IMT = HIGHER | IMO = NO)	P (CMR Q_1 | IMT = NEUTRAL | IMO = NO)	P (CMR Q_1 | IMT = LOWER | IMO = NO)
CMR Q_2	P (CMR Q_2 | IMT = HIGHER | IMO = YES)	P (CMR Q_2 | IMT = NEUTRAL | IMO = YES)	P (CMR Q_2 | IMT = LOWER | IMO = YES)	P (CMR Q_2 | IMT = HIGHER | IMO = NO)	P (CMR Q_2 | IMT = NEUTRAL | IMO = NO)	P (CMR Q_2 | IMT = LOWER | IMO = NO)
CMR Q_3	P (CMR Q_3 | IMT = HIGHER | IMO = YES)	P (CMR Q_3 | IMT = NEUTRAL | IMO = YES)	P (CMR Q_3 | IMT = LOWER | IMO = YES)	P (CMR Q_3 | IMT = HIGHER | IMO = NO)	P (CMR Q_3 | IMT = NEUTRAL | IMO = NO)	P (CMR Q_3 | IMT = LOWER | IMO = NO)
CMR Q_4	P (CMR Q_4 | IMT = HIGHER | IMO = YES)	P (CMR Q_4 | IMT = NEUTRAL | IMO = YES)	P (CMR Q_4 | IMT = LOWER | IMO = YES)	P (CMR Q_4 | IMT = HIGHER | IMO = NO)	P (CMR Q_4 | IMT = NEUTRAL | IMO = NO)	P (CMR Q_4 | IMT = LOWER | IMO = NO)

For IMT = HIGHER, NEUTRAL, or LOWER, and IMO= YES or NO,

$$\sum_{i=1}^{4} P\ (\text{CMR}\ \ Q_i\ \mid \text{IMT} \mid \text{IMO}) = 1 \qquad \text{(EQ 33)}$$

Table 31. BNM Computational Model #4 Future Mishap Occurrence Given Current MCAS Results

CMR	CMR Q_1	CMR Q_2	CMR Q_3	CMR Q_4
FMO = YES	P (FMO = YES) | CMR Q_1)	P (FMO = YES) | CMR Q_2)	P (FMO = YES) | CMR Q_3)	P (FMO = YES) | CMR Q_4)
FMO = NO	P (FMO = NO) | CMR Q_1)	P (FMO = NO) | CMR Q_2)	P (FMO = NO) | CMR Q_3)	P (FMO = NO) | CMR Q_4)

For i= 1 to 4,

$$\sum_{FMO=YES}^{NO} P\ (\text{FMO} \mid \text{CMR}\ Q_i) = 1 \qquad \text{(EQ 34)}$$

3.8.5. BAYESIAN NETWORK COMPUTATIONAL MODEL NUMBER 5

BNM Computational Model #5 node variables and model equations are depicted below in Tables 32 through 35.

Table 32. BNM Computational Model #5 Inter-period Mishap Occurrence

Inter-period Mishap Occurrence	Probability
IMO = YES	P (IMT = YES)
IMO = NO	P (IMT = NO)

P (IMT = YES) + P (IMT = NO) = 1 (EQ 35)

Table 33. BNM Computational Model #5 Inter-period MCAS Transition Given Inter-period Mishap Occurrence

Inter-period Mishap Transition	IMO = YES	IMO = NO
IMT = HIGHER	P (IMT = HIGHER | IMO = YES)	P (IMT = HIGHER | IMO = NO)
IMT = NEUTRAL	P (IMT = NEUTRAL | IMO = YES)	P (IMT = NEUTRAL | IMO = NO)
IMT = LOWER	P (IMT = LOWER | IMO = YES)	P (IMT = LOWER | IMO = NO)

For IMO = YES or NO
P (IMT = HIGHER | IMO) + P (IMT = NEUTRAL | IMO) +
P (IMT = LOWER | IMO)= 1 (EQ 36)

Table 34. BNM Computational Model #5 Current MCAS Results Given Inter-period MCAS Transition Given Inter-period Mishap Occurrence

IMO	YES			NO		
IMT	HIGHER	NEUTRAL	LOWER	HIGHER	NEUTRAL	LOWER
CMR Q_1	P (CMR Q_1 | IMT = HIGHER | IMO = YES)	P (CMR Q_1 | IMT = NEUTRAL | IMO = YES)	P (CMR Q_1 | IMT = LOWER | IMO = YES)	P (CMR Q_1 | IMT = HIGHER | IMO = NO)	P (CMR Q_1 | IMT = NEUTRAL | IMO = NO)	P (CMR Q_1 | IMT = LOWER | IMO = NO)
CMR Q_2	P (CMR Q_2 | IMT = HIGHER | IMO = YES)	P (CMR Q_2 | IMT = NEUTRAL | IMO = YES)	P (CMR Q_2 | IMT = LOWER | IMO = YES)	P (CMR Q_2 | IMT = HIGHER | IMO = NO)	P (CMR Q_2 | IMT = NEUTRAL | IMO = NO)	P (CMR Q_2 | IMT = LOWER | IMO = NO)
CMR Q_3	P (CMR Q_3 | IMT = HIGHER | IMO = YES)	P (CMR Q_3 | IMT = NEUTRAL | IMO = YES)	P (CMR Q_3 | IMT = LOWER | IMO = YES)	P (CMR Q_3 | IMT = HIGHER | IMO = NO)	P (CMR Q_3 | IMT = NEUTRAL | IMO = NO)	P (CMR Q_3 | IMT = LOWER | IMO = NO)
CMR Q_4	P (CMR Q_4 | IMT = HIGHER | IMO = YES)	P (CMR Q_4 | IMT = NEUTRAL | IMO = YES)	P (CMR Q_4 | IMT = LOWER | IMO = YES)	P (CMR Q_4 | IMT = HIGHER | IMO = NO)	P (CMR Q_4 | IMT = NEUTRAL | IMO = NO)	P (CMR Q_4 | IMT = LOWER | IMO = NO)

For IMT = HIGHER, NEUTRAL, or LOWER and IMO= YES or NO,

$$\sum_{i=1}^{4} P\,(\text{CMR } Q_i \mid \text{IMT} \mid \text{IMO}) = 1$$

(EQ 37)

Table 35. BNM Computational Model #5 Future Mishap Occurrence Given Inter-period MCAS Transition Given Current MCAS Results

CMR	CMR Q_1			CMR Q_2			CMR Q_3			CMR Q_4		
IMT #	H	N	L	H	N	L	H	N	L	H	N	L
FMO = YES	*1	*2	*3	*4	*5	*6	*7	*8	*9	*10	*11	*12
FMO = NO	*13	*14	*15	*16	*17	*18	*19	*20	*21	*22	*23	*24

Note: #: H=HIGHER, N=NEUTRAL, L=LOWER

* 1: P (FMO = YES | IMT = HIGHER | CMR Q_1)
* 2: P (FMO = YES | IMT = NEUTRAL | CMR Q_1)
* 3: P (FMO = YES | IMT = LOWER | CMR Q_1)
* 4: P (FMO = YES | IMT = HIGHER | CMR Q_2)
* 5: P (FMO = YES | IMT = NEUTRAL | CMR Q_2)
* 6: P (FMO = YES | IMT = LOWER | CMR Q_2)
* 7: P (FMO = YES | IMT = HIGHER | CMR Q_3)
* 8: P (FMO = YES | IMT = NEUTRAL | CMR Q3)
* 9: P (FMO = YES | IMT = LOWER | CMR Q_3)
*10: P (FMO = YES | IMT = HIGHER | CMR Q_4)
*11: P (FMO = YES | IMT = NEUTRAL | CMR Q_4)
*12: P (FMO = YES | IMT = LOWER | CMR Q_4)
*13: P (FMO = NO | IMT = HIGHER | CMR Q_1)
*14: P (FMO = NO | IMT = NEUTRAL | CMR Q_1)
*15: P (FMO = NO | IMT = LOWER | CMR Q_1)
*16: P (FMO = NO | IMT = HIGHER | CMR Q_2)
*17: P (FMO = NO | IMT = NEUTRAL | CMR Q_2)
*18: P (FMO = NO | IMT = LOWER | CMR Q_2)
*19: P (FMO = NO | IMT = HIGHER | CMR Q_3)
*20: P (FMO = NO | IMT = NEUTRAL | CMR Q_3)
*21: P (FMO = NO | IMT = LOWER | CMR Q_3)
*22: P (FMO = NO | IMT = HIGHER | CMR Q_4)
*23: P (FMO = NO | IMT = NEUTRAL | CMR Q_4)
*24: P (FMO = NO | IMT = LOWER | CMR Q_4)

For IMT = HIGHER, NEUTRAL, or LOWER and i= 1 to 4,

$$\sum_{FMO=YES}^{NO} P\text{ (FMO | IMT | CMR Q}_i) = 1 \tag{EQ 38}$$

3.9. EVALUATION METHODOLOGIES

In order for the derived computational Bayesian Network Models outputs to be of utility in serving as a predictive tool for naval aviation squadron leadership to measure likelihood of incurring a future mishap, the models' performance would indicate higher probabilities of future mishap occurrences for worse MCAS result performance. Worse MCAS result performance is considered to be those with lower quartiles of compared, averaged Likert Scale response values. This translates to either lower quartile or transition from previous to current MCAS that decremented to a lower quartile. Ideally the probability density distribution would show that the probability of a future mishap occurring is greater for the MCAS results of the lower quartiles. Mathematically this is expressed as

$$P_{\mathrm{FMO}}\,(Q_1) > P_{\mathrm{FMO}}\,(Q_2) > P_{\mathrm{FMO}}\,(Q_3) > P_{\mathrm{FMO}}\,(Q_4), \text{ where } \sum_{i=1}^{4} P_{FMO}\,(Q_i) = 1 \qquad \text{(EQ 39)}$$

This is pictorial displayed in Figure 20 below.

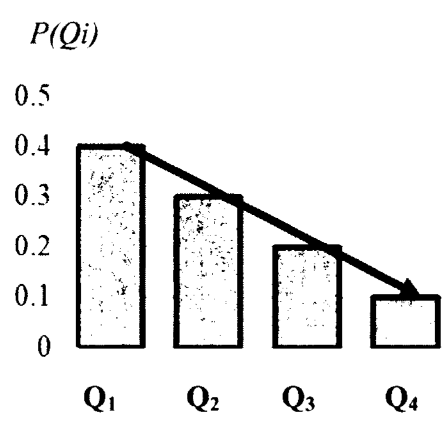


Figure 20. Ideal Probability of Mishap Occurrences Given MCAS Quartile Results

3.9.1. SKEWNESS

The statistical attributes in Figure 20 demonstrate a unimodal distribution and asymmetry with higher number of occurrences in the lower quartiles (Q_1 and Q_2) vice those occurring in the upper quartiles (Q_3 and Q_4). This is right skewness, i.e., the asymmetric distribution of the quartiles with the decreasing "tail" to the right side of the chart. Although it is common for right skewness that the mode occurs at a lesser value than the median which occurs at a lesser value than the mean, it is not unusual for right tailed asymmetry in discrete distributions to violate this rule of thumb [Von Hippel, 2005]. Addition details concerning Skewness may be found in Section B.3 of Appendix B.

The equations denoted as B and E from Table 66 in Appendix B, possessed the best average rank values. These two equations were both used for the evaluation of the BNM model outputs with Equation B designated as Skewness$_1$ and Equation E designated as Skewness$_2$ as shown below in Table 36. This ensured that at least one of the skewness tests did not result in a non-parametric value of zero.

Table 36. Skewness Equations

Designation	Equation
Skewness$_1$	$\frac{\max - median}{median - min}$
Skewness$_2$	$\frac{\frac{1}{2}\,(min + max)}{median}$

Using $Skewness_1$ and $Skewness_2$ Equations B and E, the potential characteristics of skewness ranges for the distribution of the quartile probabilities are:

- Right Tailed $0 < x < 1$ (EQ 40)
- Symmetric $x = 1$ (EQ 41)
- Left Tailed $x > 1$ (EQ 42)

To summarize the desired attributes for a BNM to serve as a meaningful predictive tool to measure likelihood of incurring a future mishap, the model's discrete output of probability density distribution attributes include:

- Unimodal distribution
- Q_1 is the mode
- Right tailed asymmetry
- $P_{FMO}(Q_1) > P_{FMO}(Q_2) > P_{FMO}(Q_3) > P_{FMO}(Q_4)$, where $\sum_{i=1}^{4} P_{FMO}(Q_i) = 1$ (EQ 43)

Additionally, to serve as predictive tool to measure likelihood of *not* incurring a future mishap, the model's output of discrete probability density distribution attributes include:

- Unimodal distribution
- Q_4 is the mode
- Left tailed asymmetry
- $P_{FMO}(Q_1) < P_{FMO}(Q_2) < P_{FMO}(Q_3) < P_{FMO}(Q_4)$, where $\sum_{i=1}^{4} P_{FMO}(Q_i) = 1$ (EQ 44)

3.9.2. SLOPE

Slope was the metric used to serve as a quantitative comparative means to evaluate performance of probability density functions that were unimodal and aligned in Skewness. The larger absolute value of derived slope was considered to be of a higher utility for serving as a predictive tool. The equations for calculating slope values were:

- Slope = $P(Q_4) - P(Q_1) / 4$ for comparison of quartile probabilities of occurrence (EQ 45)
- Slope = P (Higher) – P (Lower) / 3 for comparison of quartile transition probabilities of occurrence. (EQ 46)

4. RESULTS

4.1. DATA PREPARATION

4.1.1. MCAS DATA PREPARATION

The 2,300 aggregated sets of survey data were culled to retain only those from organizations that were components of aircraft carrier air wings. Data from the remaining 930 MCAS results were organized in a Microsoft Excel ® tabular spreadsheet to present survey results categorized by Type / Model / Series (T/M/S) aircraft, squadron / organizational unit (as denoted by squadron serial number), and in successive chronological order based upon Mean Survey Date. This sorting demonstrated that there were 136 distinct units that participated in the MCAS. Likert value responses were averaged across the span of 43 aggregated questions, and subsequently across each of the six MOSE functional component areas shown in Table 37 below.

Table 37. MOSE Functional Components of the MCAS

MOSE Functional Component Area	Question Numbers
Process Auditing (PA)	1 - 6
Reward System and Safety Culture (RS / SC)	7 - 14
Quality Assurance (QA)	15 - 20
Risk Management (RM)	21 - 29
Command and Control (C2)	30 - 37
Communication / Functional Relationships (C / FR)	38 - 43

The Likert value for Question 21 was inverted on the 1-5 scale to account for its negative connotation. Embedded software functionality within Excel was used to determine MCAS results quartile boundaries and assign result placement in the quartile continuum of Q_1, Q_2, Q_3, and Q_4 with Q_1 containing the lowest score values and Q_4 containing the highest score values.

4.1.2. AVIATION MISHAP SUMMARY DATA PREPARATION

Select data from the Class A - Aviation Safety Mishap Summary Reports were organized in corresponding Microsoft Excel ® tabular spreadsheets to arrange results in chronological order of the mishap date. These reports involved a total of 67 aircraft. Additional data included the mishap event serial number, applicable T/M/S, identification of primary causal factors, and brief description of the incident. Mishap Summary data were cross-referenced with the MCAS results spreadsheets, and where applicable and based upon mishap occurrence date, were inserted between MCAS results bounded by the Mean Survey Dates. Cross matching mishap summary data to corresponding MCAS result data was not achieved for nine mishaps. The reasons for these and frequencies of occasions are depicted in Table 38 below.

Table 38. Reasons For Mishap Summary Data Without Corresponding MCAS Survey Results

Reason	Frequency
Unit First Appear Serial Number in Mishap Summary Data corresponds to Fleet Logistics squadron (VR) which does not fly Type / Model / Series aircraft assigned to a Carrier Air Wing (CVW)	1
Unit First Appear Serial Number in Mishap Summary Data that no corresponding organization within the 2,300 provided MCAS response data	1
Mishaps occurred in Research, Test, Development, and Evaluation (RDTE) Squadrons that were not representative of subordinate components of a CVW	2
Date of occurrence contained within the Mishap Summary report was earlier than the corresponding unit's first MCAS response Mean Survey Date	5

Of the remaining individual 58 aircraft mishaps, only 55 had corresponding matches for both Previous and Current MCAS Result Quartiles (PMR Q_i and CMR Q_j).

4.1.3. GENERATION OF INPUT DATA FOR BAYESIAN NETWORK MODELS

Linked worksheets from the MCAS results and Aviation Mishap Summary data supported the process to calculate observational frequencies and percentages necessary to define the node probability distributions for the Bayesian Network computational models described in Section 3.7. Previous and Current MCAS Results (PMRs and CMRs) were provided and represented by respective quartile assignments.

Inter-period MCAS Transitions (IMTs) by quartile were computed by comparing results of two chronologically successive results taken from the same unit and determining the numerical value representing the shift in quartile. (Example: if PMR was in Q_3 and CMR was in Q_1, then IMT = LOWER for a decrement of 2).

Initial chronological MCAS results for each unit were deemed to be "Not Applicable" for IMT.

Inter-period Mishap Occurrence (IMO) value was the binary result (i.e., YES or NO) as to whether a reported mishap summary existed with an incident date between the current and previous MCAS Mean Survey Dates. Similarly, Future Mishap Occurrence (FMO) value was the binary result as to whether a reported mishap summary existed with an incident date immediately after current MCAS results but prior to the next subsequent MCAS Mean Survey Date.

For each applicable listed mishap, the immediately previous and subsequent MCAS responses averaged Likert scale values, quartile placement, and transition values were determined.

4.2. AGGREGATED INPUT DATA FOR REFINED RESEARCH QUESTION 1 BAYESIAN NETWORK MODELS

The BNM input probability distributions for the 930 aggregated MCAS result data (responses to Questions 1 through 43) are contained in Tables 39 through 49 and presented in Figures 21 through 26, below.

Table 39. BNM Computational Models #1 and #2 Prior MCAS Result Quartile Observed Frequencies and Probabilities

PMR Quartile	Quartile Likert Scale Value Lower Bound	Quartile Likert Scale Value Upper Bound	Observed Frequency	Probability
PMR Q_1	3.159	< 3.588	233	0.2505
PMR Q_2	3.588	< 3.692	232	0.2495
PMR Q_3	3.692	< 3.796	232	0.2495
PMR Q_4	3.796	$\leq$ 4.431	233	0.2505
		Total	930	1.0000

Table 40. BNM Computational Model #1 and #2 Observed Frequencies and Conditional Probabilities of Inter-Period Occurrence Mishap Given Prior MCAS Result Quartile

PMR Quartile	PMR Q_1	PMR Q_2	PMR Q_3	PMR Q_4
Observed Frequency	233	232	232	233
Final Unit Quartile Observations	36	37	31	32
IMO = YES	16	16	14	12
IMO = NO	181	179	187	189
Total	197	195	201	201
Probability				
Inter-period Mishap=YES	0.0812	0.0821	0.0697	0.0597
Inter-period Mishap=NO	0.9188	0.9179	0.9303	0.9403
Total	1.0000	1.0000	1.0000	1.0000

Table 41. BNM Computational Model #1 and #2 Observed Frequency and Conditional Probabilities of Current MCAS Results Quartile Given Inter-period Mishap Occurrence Given Prior MCAS Result Quartile

PMR	PMR Q_1		PMR Q_2		PMR Q_3		PMR Q_4	
IMO	YES	NO	YES	NO	YES	NO	YES	NO
Observed Frequency								
CMR Q_1	9	75	7	41	2	34	0	18
CMR Q_2	1	66	3	53	2	40	1	34
CMR Q_3	3	27	1	53	4	63	2	46
CMR Q_4	2	15	4	32	5	51	9	91
Total	15	183	15	179	13	188	12	189
Probability								
CMR Q_1	0.6000	0.4098	0.4667	0.2291	0.1538	0.1809	0.0000	0.0952
CMR Q_2	0.0667	0.3607	0.2000	0.2961	0.1538	0.2128	0.0833	0.1799
CMR Q_3	0.2000	0.1475	0.0667	0.2961	0.3077	0.3351	0.1667	0.2434
CMR Q_4	0.1333	0.0820	0.2666	0.1787	0.3847	0.2712	0.7500	0.4815
Total	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Note: # - There are only 55 individual aircraft mishaps that had corresponding matches with both Previous and Current MCAS Response Quartiles. Three of the 58 had no subsequent MCAS response data after the mishap occurrence date.

Table 42. BNM Computational Model #1 Conditional Probabilities of Future Mishap Occurrence Given Current MCAS Results Quartile Given Inter-period Mishap Occurrence

IMO	YES				NO			
CMR	CMR Q_1	CMR Q_2	CMR Q_3	CMR Q_4	CMR Q_1	CMR Q_2	CMR Q_3	CMR Q_4
Observed Frequency								
FMO = YES	0	1	1	1	18	5	7	15
FMO = NO	18	5	7	15	130	152	157	157
Total	18	6	8	16	148	157	162	172
Probability								
FMO = YES	0.0000	0.1667	0.1250	0.0625	0.1216	0.0318	0.0427	0.0872
FMO = NO	1.0000	0.8333	0.8750	0.9375	0.8784	0.9682	0.9573	0.9128
Total	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

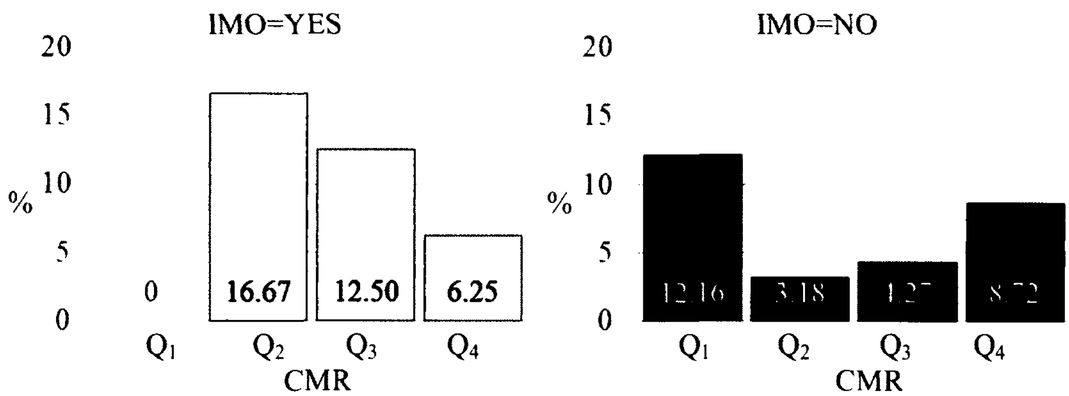


Figure 21. BNM Computational Model #1 Conditional Probabilities of Current MCAS Survey Results by Quartile Preceding Future Mishap Occurrence Given Inter-Period Mishap Occurrence Equals YES or NO

Table 43. BNM Computational Model #2 Observed Frequency and Conditional Probabilities of Future Mishap Occurrence Given Current MCAS Result Quartile

CMR Quartile / FMO	CMR Q_1	CMR Q_2	CMR Q_3	CMR Q_4
Observed Frequency				
YES	18	6	8	16
NO	148	157	164	172
Probability				
YES	0.1084	0.0368	0.0465	0.0851
NO	0.8916	0.9632	0.9535	0.9149
Total	1.0000	1.0000	1.0000	1.0000

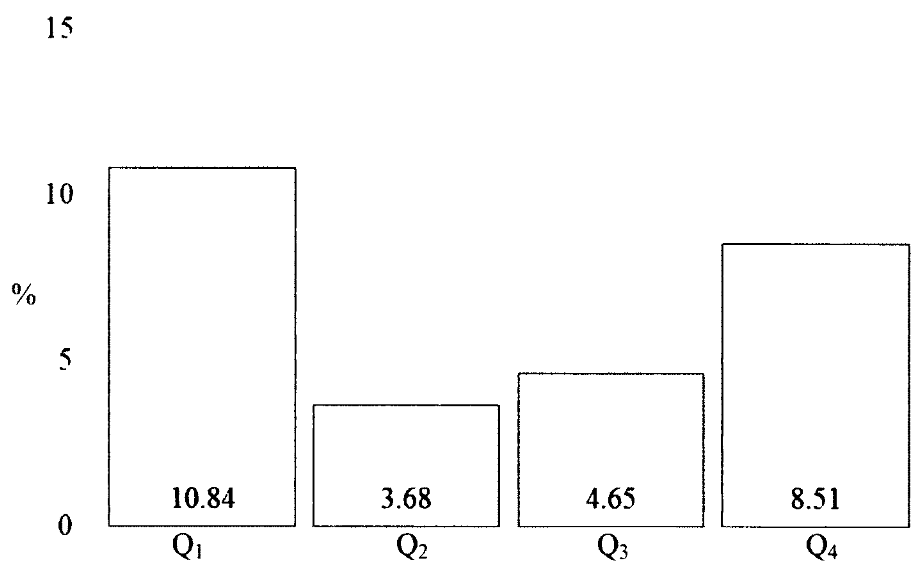


Figure 22. BNM Computational Model #2 Conditional Probabilities of Current MCAS Survey Results by Quartile Preceding Future Mishap Occurrence

Table 44. BNM Computational Model #3, #4, and #5 Inter-period Mishap Occurrence Observed Frequency and Probabilities

Inter-period Mishap Occurrence	Observed Frequency	Probability
IMO = YES	53	0.0661
IMO = NO	749	0.9339
Total	802	1.0000

Table 45. BNM Computational Model #3 and #4 Inter-period MCAS Transition Observed Frequency and Probabilities

Inter-period MCAS Transition	Observed Frequency	Probability
IMT = HIGHER	260	0.3275
IMT = NEUTRAL	307	0.3866
IMT = LOWER	227	0.2859
Total	794	1.0000

Table 46. BNM Computational Model #3, #4, and #5 Current MCAS Results Given Inter-period MCAS Transition Given Inter-period Mishap Occurrence Given Observed Frequency and Probabilities

IMO	YES			NO		
IMT	HIGHER	NEUTRAL	LOWER	HIGHER	NEUTRAL	LOWER
Observed Frequency						
CMR Q_1	0	9	8	0	75	94
CMR Q_2	1	3	3	66	53	74
CMR Q_3	3	2	2	81	65	46
CMR Q_4	8	6	0	101	93	0
Total	12	20	13	248	286	214
Probability						
CMR Q_1	0	0.4500	0.6154	0	0.2622	0.4392
CMR Q_2	0.0833	0.1500	0.2308	0.2661	0.1853	0.3458
CMR Q_3	0.2500	0.1000	0.1538	0.3266	0.2273	0.2150
CMR Q_4	0.6667	0.3000	0	0.4073	0.3252	0
Total	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Table 47. BNM Computational Model #3 and #5 Future Mishap Occurrence Given Inter-period MCAS Transition Given Current MCAS Results Observed Frequency and Probabilities

CMR	CMR Q_1			CMR Q_2		
IMT #	HIGHER	NEUTRAL	LOWER	HIGHER	NEUTRAL	LOWER
Observed Frequency						
FMO = YES	0	4	4	5	1	4
FMO = NO	0	69	78	54	41	62
Total	0	73	82	59	42	66
Probability						
FMO = YES	NA #	0.0548	0.0488	0.0847	0.0238	0.0606
FMO = NO	NA #	0.9452	0.9512	0.9153	0.9762	0.9394
Total	NA #	1.0000	1.0000	1.0000	1.0000	1.0000

CMR	CMR Q_3			CMR Q_4		
IMT #	HIGHER	NEUTRAL	LOWER	HIGHER	NEUTRAL	LOWER
Observed Frequency						
FMO = YES	3	3	2	4	4	0
FMO = NO	70	56	37	92	79	0
Total	73	59	39	96	83	0
Probability						
FMO = YES	0.0411	0.0508	0.0513	0.0417	0.0482	NA *
FMO = NO	0.9589	0.9492	0.9487	0.9583	0.9518	NA *
Total	1.0000	1.0000	1.0000	1.0000	1.0000	NA *

Notes: # - Not Applicable due to inability to transition from a lower quartile than CMR Q_1

* - Not Applicable due to inability to transition from a higher quartile than CMR Q_4

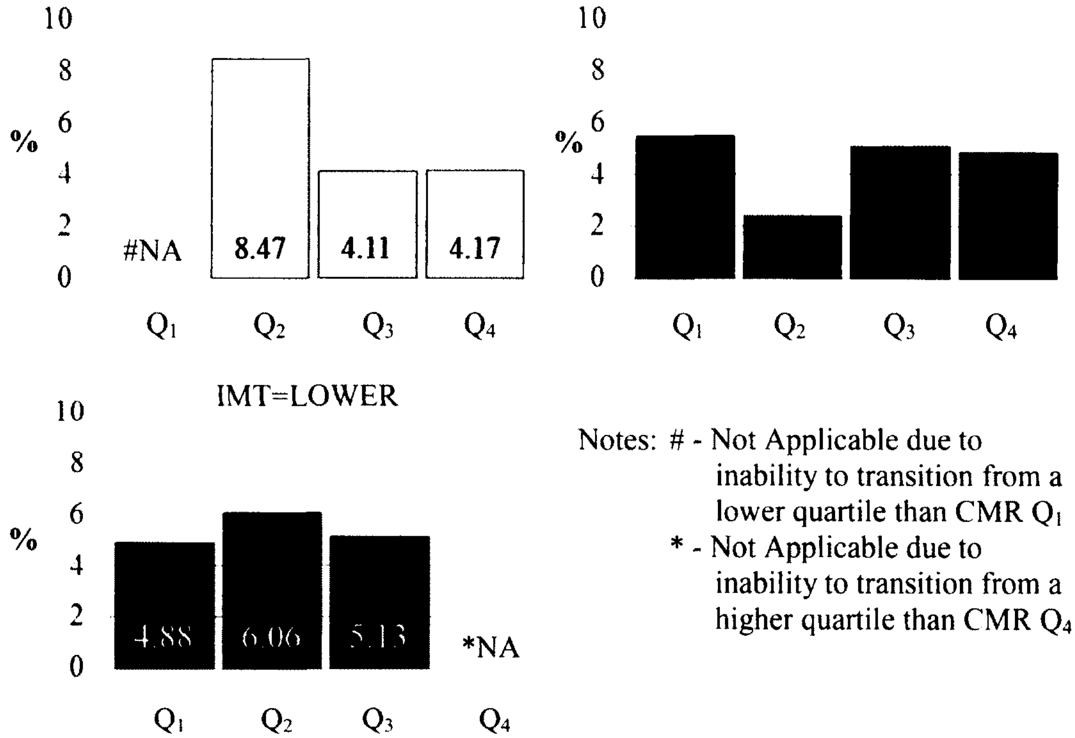


Figure 23. BNM Computational Model #3 Conditional Probabilities of MCAS Survey by Quartile Preceding Future Mishap Occurrence Given Inter-MCAS Transition Equals HIGHER, NEUTRAL, or LOWER

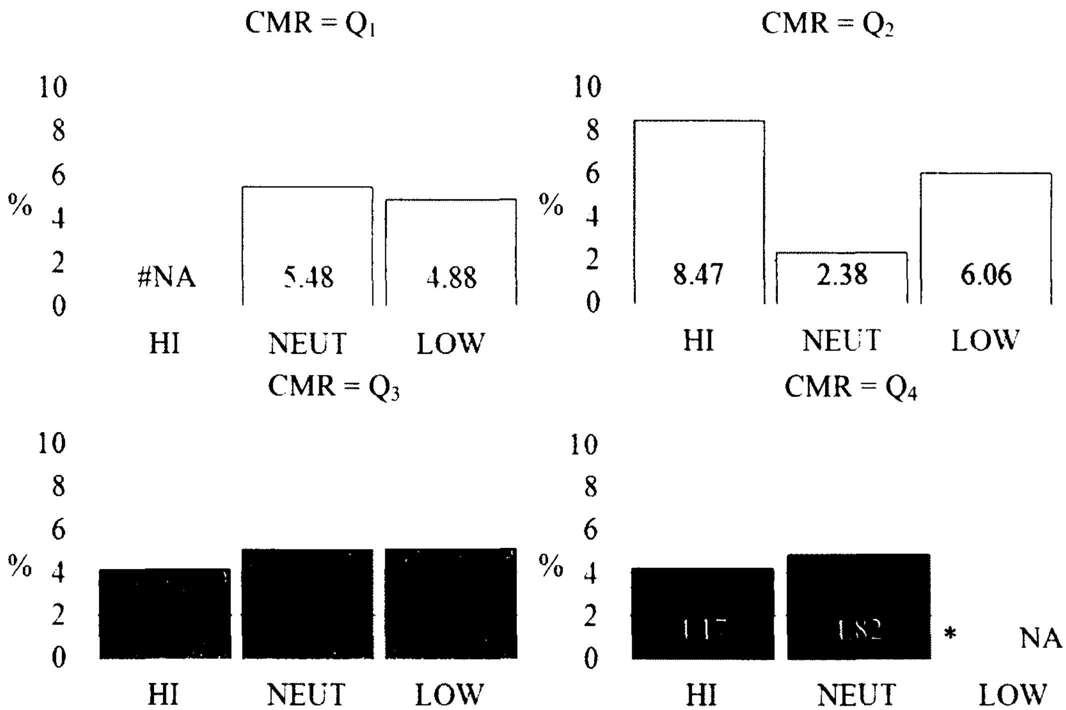


Figure 24. BNM Computational Model #3 Conditional Probabilities of Inter-MCAS Transition Preceding Future Mishap Occurrence Given Current MCAS Results Equal Q_1, Q_2, Q_3, or Q_4

Table 48. BNM Computational Model #4 Future Mishap Occurrence Given Current MCAS Results Observed Frequency and Probabilities

CMR	CMR Q_1	CMR Q_2	CMR Q_3	CMR Q_4
Observed Frequency				
FMO = YES	8	10	8	8
FMO = NO	147	157	163	171
Total	155	167	171	179
Probability				
FMO = YES	0.0516	0.0599	0.0468	0.0447
FMO = NO	0.9484	0.9401	0.9532	0.9553
Total	1.0000	1.0000	1.0000	1.0000

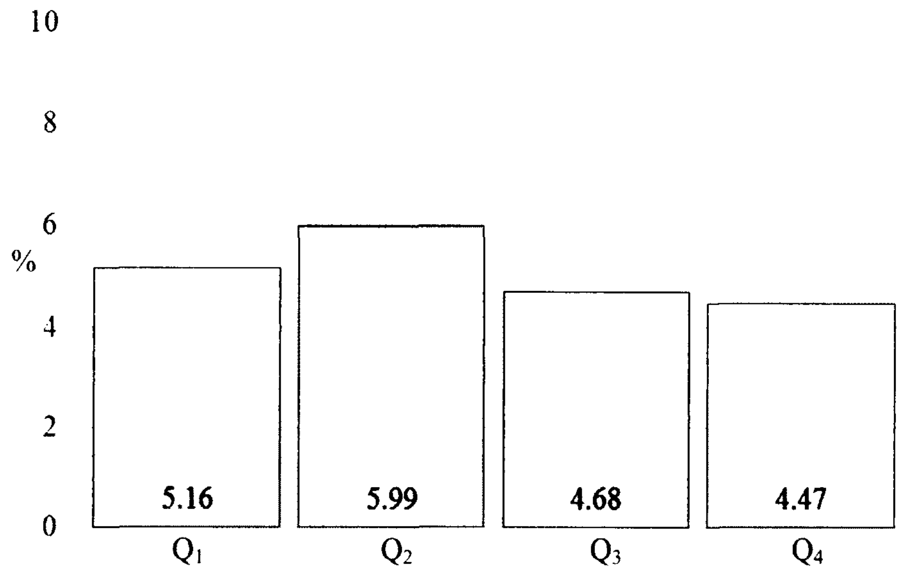


Figure 25. BNM Computational Model #4 Conditional Probabilities of Current MCAS Results Quartiles Preceding Future Mishap Occurrence

Table 49. BNM Computational Model #5 Inter-period MCAS Transition Given Inter-period Mishap Occurrence Observed Frequency and Probability

Inter-period Mishap Transition	IMO = YES	IMO = NO
Observed Frequency		
IMT = HIGHER	12	248
IMT = NEUTRAL	21	286
IMT = LOWER	13	214
Total	46	748
Probability		
IMT = HIGHER	0.2609	0.3316
IMT = NEUTRAL	0.4565	0.3824
IMT = LOWER	0.2826	0.2860
Total	1.0000	1.0000

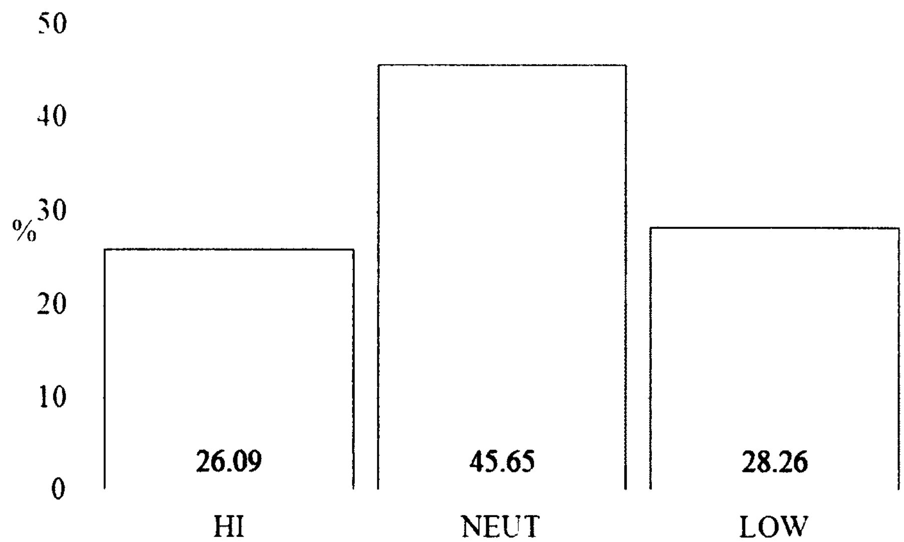


Figure 26. BNM Computational Model #5 Conditional Probabilities of Inter-MCAS Transitions Preceding Future Mishap Occurrence

4.3. DATA RESULTS FOR RESEARCH QUESTION 1 BAYESIAN NETWORK MODELS

The five BNM computational models were executed by setting evidence that either the Future Mishap Occurrence did happen (i.e., P (FMO = YES) = 1) or did not happen (i.e., P (FMO = NO) = 1). This enabled calculation of the nodal probability distribution for each characteristic. The data are contained in Tables 50 through 54 and Figures 27 through 31 below.

Table 50. BNM Computational Model #1 Nodal Probability Distribution

FMO =	YES	NO
PMR Q_1	0.2626	0.2496
PMR Q_2	0.2349	0.2506
PMR Q_3	0.2468	0.2497
PMR Q_4	0.2557	0.2501
CMR Q_1	0.3724	0.2255
CMR Q_2	0.1345	0.2607
CMR Q_3	0.1707	0.2560
CMR Q_4	0.3223	0.2578

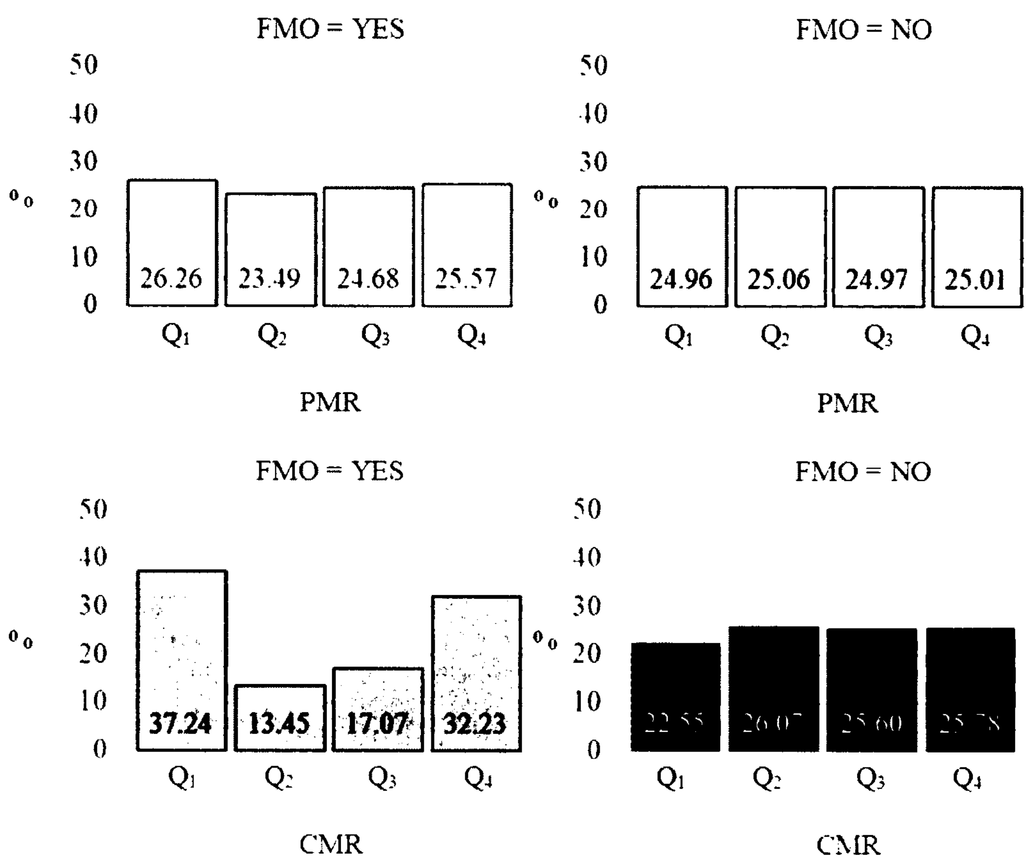


Figure 27. BNM Computational Model #1 Nodal Conditional Probabilities

Table 51. BNM Computational Model #2 Nodal Probability Distribution

FMO =	YES	NO
PMR Q_1	0.2626	0.2496
PMR Q_2	0.2349	0.2506
PMR Q_3	0.2468	0.2497
PMR Q_4	0.2557	0.2501
CMR Q_1	0.3724	0.2255
CMR Q_2	0.1345	0.2607
CMR Q_3	0.1707	0.2560
CMR Q_4	0.3223	0.2578

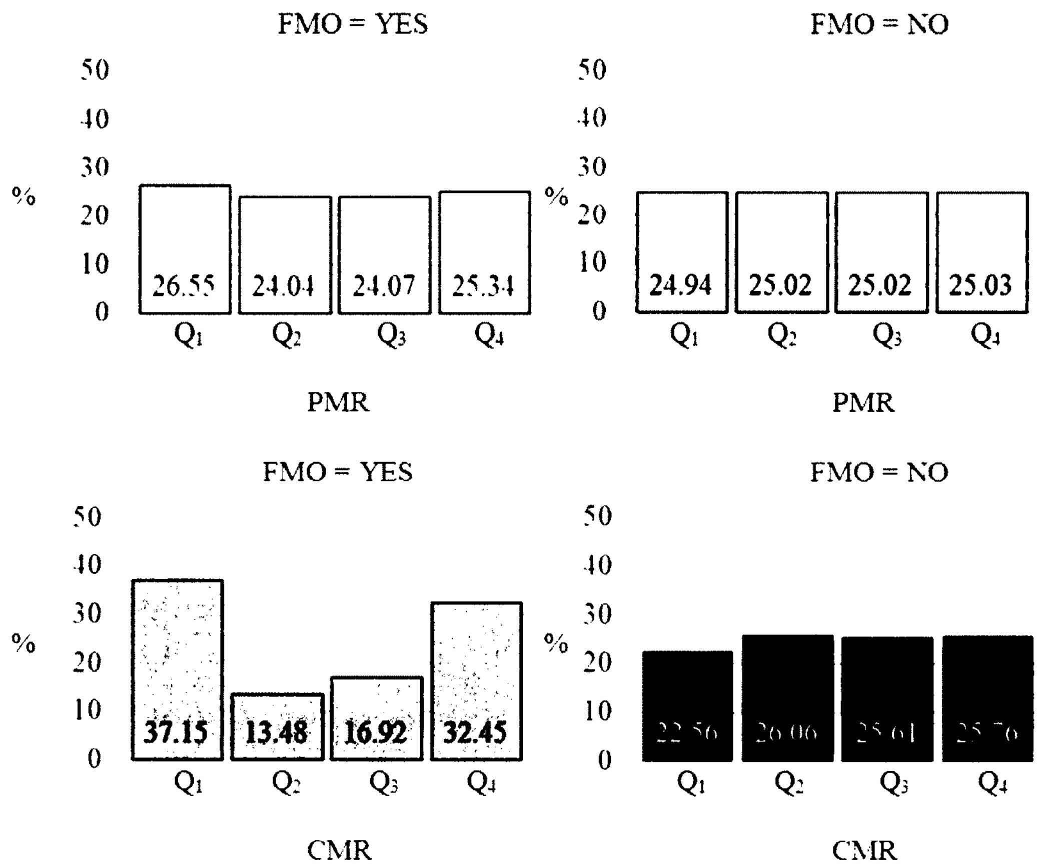


Figure 28. BNM Computational Model #2 Nodal Conditional Probabilities

Table 52. BNM Computational Model #3 Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2410	0.2347
CMR Q_2	0.2904	0.2485
CMR Q_3	0.2333	0.2511
CMR Q_4	0.2354	0.2656
IMT Higher	0.3418	0.3267
IMT Neutral	0.3549	0.3883
IMT Lower	0.3034	0.2850

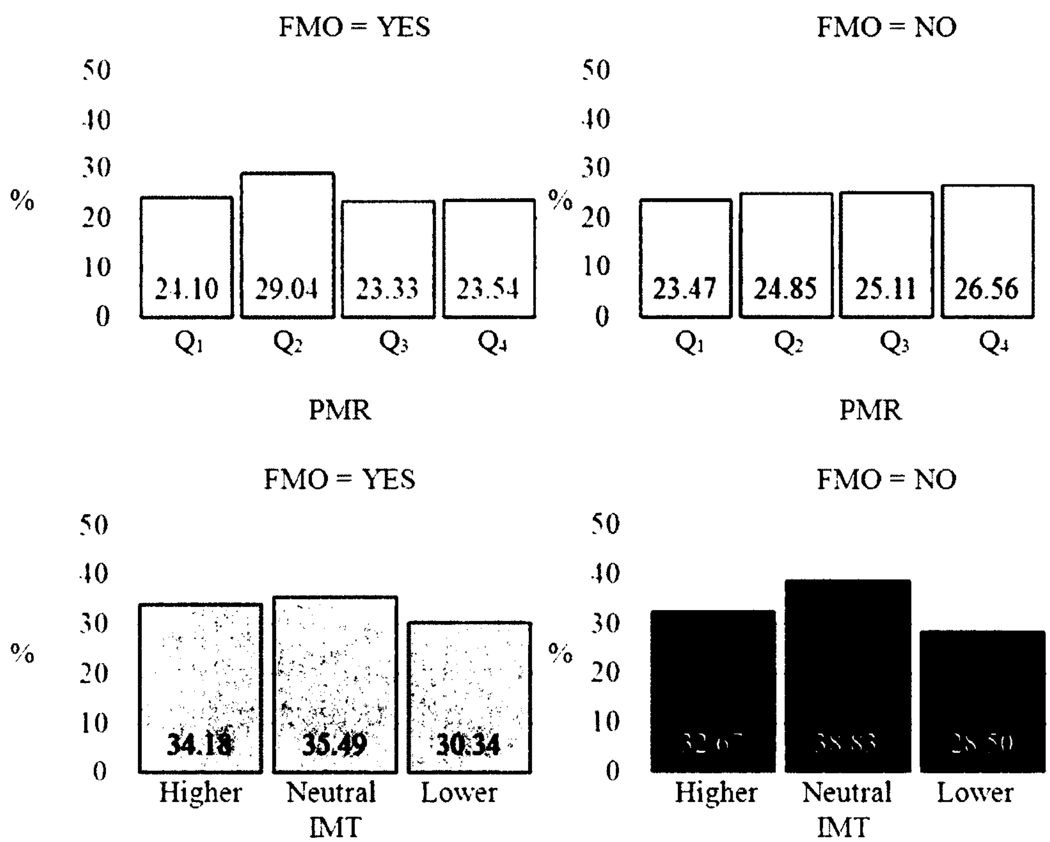


Figure 29. BNM Computational Model #3 Nodal Conditional Probabilities

Table 53. BNM Computational Model #4 Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2394	0.2348
CMR Q_2	0.2963	0.2482
CMR Q_3	0.2312	0.2513
CMR Q_4	0.2330	0.2657
IMT Higher	0.3183	0.3280
IMT Neutral	0.3803	0.3869
IMT Lower	0.3014	0.2851

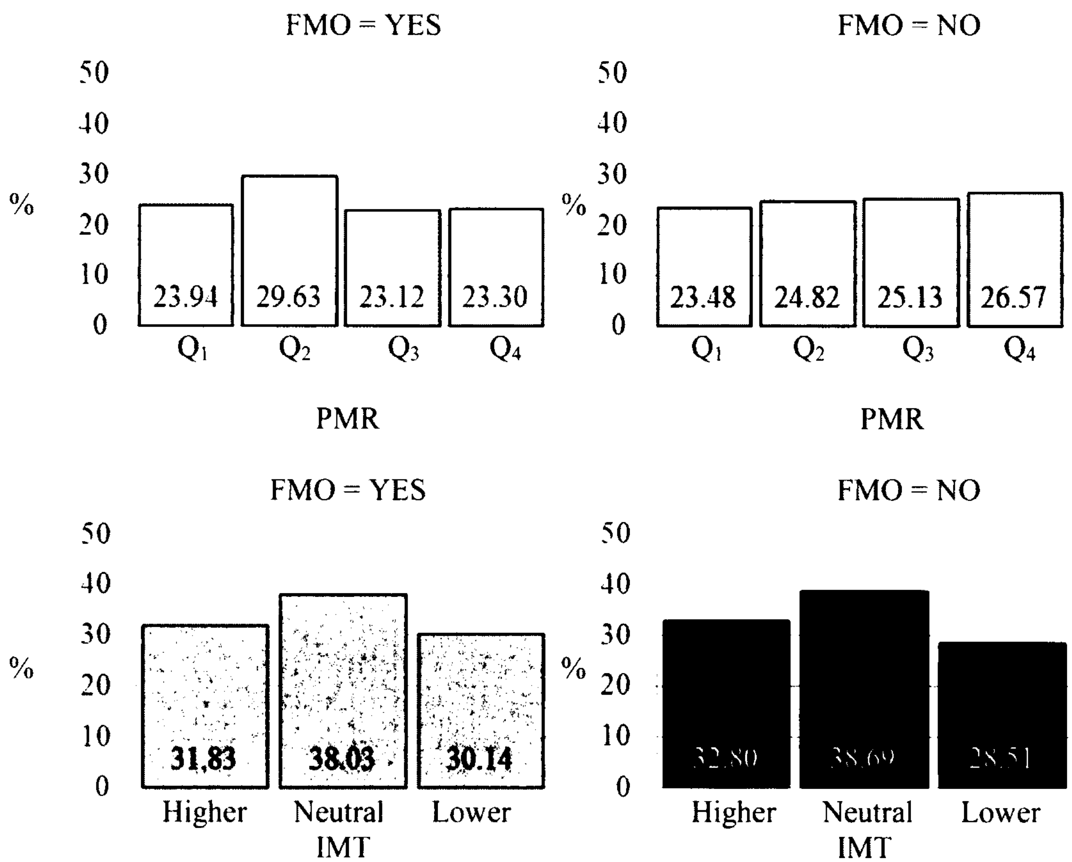


Figure 30. BNM Computational Model #4 Nodal Conditional Probabilities

Table 54. BNM Computational Model #5 Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2419	0.2357
CMR Q_2	0.2912	0.2491
CMR Q_3	0.2328	0.2509
CMR Q_4	0.2341	0.2643
IMT Higher	0.3416	0.3262
IMT Neutral	0.3554	0.3890
IMT Lower	0.3030	0.2849

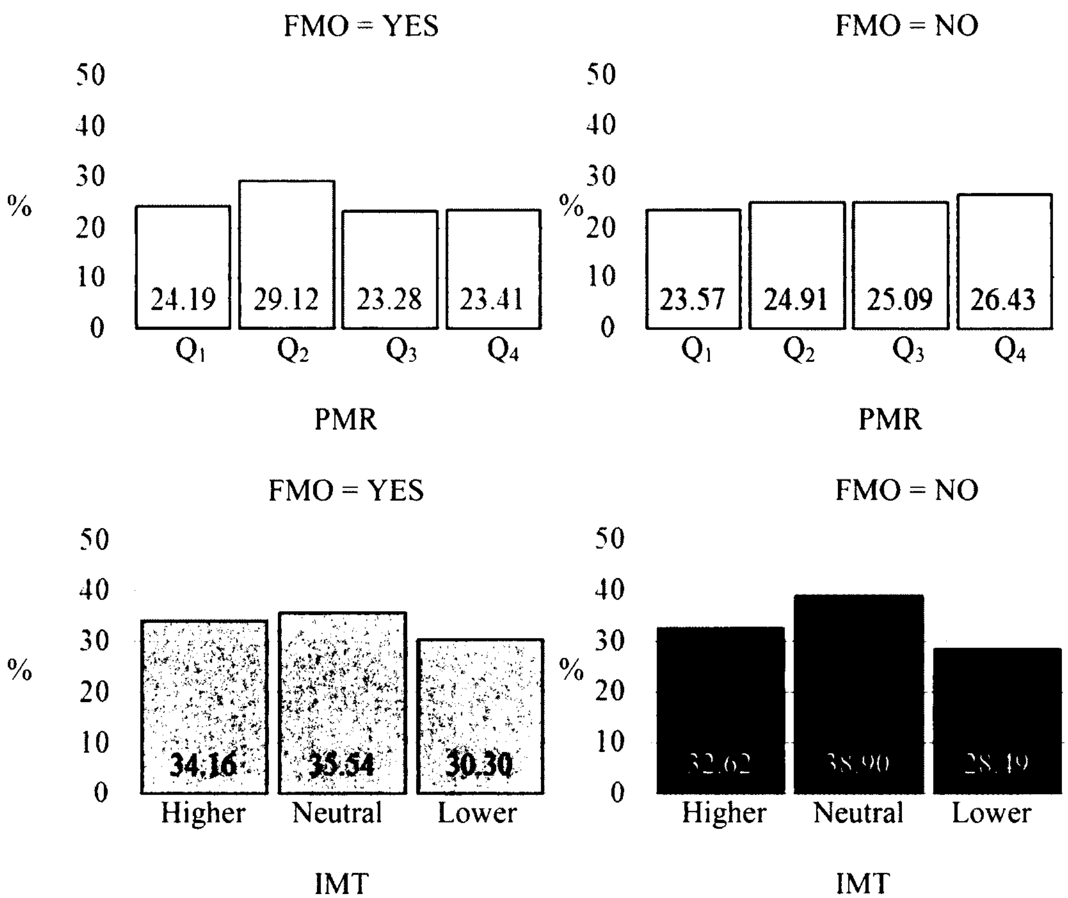


Figure 31. BNM Computational Model #5 Nodal Conditional Probabilities

4.4. DATA RESULTS FOR RESEARCH QUESTION 2 BAYESIAN NETWORK MODELS

The five BNM computational models were executed for each of the six MOSE components by evaluating performance for the specific questions in each category. This was done by setting evidence that either the Future Mishap Occurrence did happen (i.e., P (FMO = YES) = 1 or did not happen (i.e., P (FMO = NO) = 1) enabling calculation of the nodal probability distribution for each characteristic. The data are contained in Appendix E.

5. INTERPRETATION, CONCLUSIONS, AND RECOMMENDATIONS

5.1. PRELIMINARY EVALUATION OF DATA SET

Prior to evaluating the output from the Bayesian Network Models, a preliminary evaluation of the research input data was conducted. The research data provided by the U.S. Naval Safety Center contained information from 930 MCAS results of carrier air wing based squadrons conducted from 2000-2009 and 58 Class A mishap events for which there were corresponding MCAS result data for a survey administered prior to the mishap date. The initial examination compared the 2000-2009 data provided for this research against the April 2004 reference data shown in Figure 3 [Ciavarelli-2007, Schimpf, Figlock-2006] from Section 2.2.3. The aggregated MOSE component Likert Score values from the most recent 2000-2009 MCAS result data distribution (without developed Bayesian Network Modeling execution) in squadrons that had subsequently incurred a Class A mishap prior to the next administration of the MCAS are shown below in Figure 32.

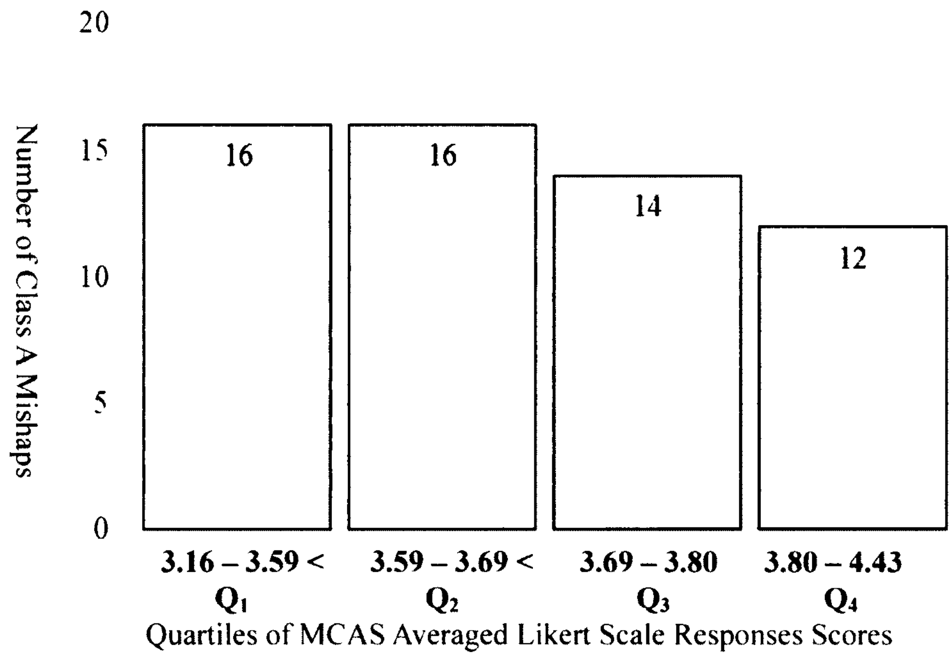


Figure 32. Previous MCAS Results for Subsequent Class A Mishap Occurrences on Data Provided by the U.S. Naval Safety Center

The discrete quartile distributions for occurrence frequency of mishaps and probabilities from the reference study conducted in April 2004 and the data provided for this research covering 2000-2009 are displayed in Tables 55 and 56 below.

Table 55. Mishap Occurrences

Data Set	Mishap Occurrence Frequency of Aggregate Likert Scale Result Quartiles			
	Q_1	Q_2	Q_3	Q_4
April 2004 Study Class A Mishaps	21	19	12	13
April 2004 Study Class A, B & C Mishaps	94	78	54	49
Dissertation Research Data for Class A Mishaps with associated MCAS results from 2000-2009	16	16	14	12

Table 56. Mishap Probabilities

Data Set	Mishap Probability of Aggregate Likert Scale Result Quartiles			
	Q_1	Q_2	Q_3	Q_4
April 2004 Study Class A Mishaps	0.3231	0.2923	0.1846	0.2000
April 2004 Study Class A, B & C Mishaps	0.3418	0.2836	0.1964	0.1782
Dissertation Research Data for Class A Mishaps with associated MCAS results from 2000-2009	0.2759	0.2759	0.2414	0.2069

A Chi Squared Distribution Test for Homogeneity was conducted to compare the data received from the U.S. Naval Safety Center covering 2000-2009 for this research against the study result data from April 2004 by Ciavarelli, Schimpf, and Figlock that is displayed in Figure 3. This was conducted to assess that the U.S. Naval Safety Center provided data set was proportionally representational. The test statistic evaluation was

$$x^2 = \sum_{all\ quartiles} \frac{(Observed-Expected)^2}{Expected} \qquad \text{(EQ 47)}$$

Test metrics used the four quartiles for comparison of the cells resulted in three degrees of freedom (i.e. n = 4 - 1), using a one sided P-value. (DeVeaux et al., 2012). The critical value for 3 degrees of freedom and $\alpha = 0.05$ is

$X^2_{0.05,3} = 11.345$.

- The null hypothesis for this preliminary evaluation was that the data sets had the same distribution of counts.
- The alternate hypothesis was that the distributions were different.

The derived Chi Squared statistic for comparing the U.S. Naval Safety Center provide data against the April 2004 Reference Class A Mishap occurrences yielded X^2 = 1.4799, and the derived Chi Squared statistics for comparing the U.S. Naval Safety Center provide data against the April 2004 Reference Class A, B, and C Mishap occurrences yielded X^2 =1.6174. Neither comparison X^2 exceeded the critical value indicating that there was no significant difference for 3 degrees of freedom and $\alpha = 0.05$. Therefore the null hypothesis was retained serving to demonstrate that the research data from 2000-2009 provided by the U.S. Naval Safety Center was representative in comparison to the April 2004 reference study.

5.2. EVALUATION OF DATA SUPPORTING ANSWER TO RESEARCH QUESTION 1

Research Question 1 queried whether Bayesian Network Modeling provided a better predictor for future mishap occurrence than the probabilities generated from the MCAS frequency observations in the reference study. Comparison of the probability density distributions and their respective attributes for the results from the April 2004, Ciavarelli, Schimpf, and Figlock published study labeled here as "Reference", research data provided from the U.S. Naval Safety Center covering 2000-2009, and output from the Bayesian Network Models #1 through #5 are presented in Tables 57 through 59.

Table 57. Attributes of Probability Density Distributions of MCAS Result Likert Scale Quartiles Followed by Actual Mishap Occurrence

Model	MOSE Charac –teristic	Proba – bility Variable	Depiction	Mode	Skew-ness$_1$	Skew-ness$_2$	Slope
Reference Class A Mishaps	All #	CMR	Unimodal	Q_1	0.6250	0.8125	-0.0308
Reference Class A, B & C Mishaps	All	CMR	Unimodal	Q_1	0.5988	0.7994	-0.0409
U.S. Navy Safety Center Provided, 2000-2009 Research Data Set for Class A Mishaps	All	CMR	Bimodal	Q_1, Q_2	0.8125	0.9063	-0.0172

Note: #- All indicates aggregation of all 6 MOSE components into a single metric value: Process Auditing (PA), Reward Systems / Safety Culture (RS/SC), Quality Assurance (QA), Risk Management (RM), Command and Control (C2), and Communications and Functional Relationships (C/FR)

Table 58. Attributes of Probability Density Distributions of Bayesian Network Model (BNM) Output When Future Mishap Occurrence FMO = YES

Model	MOSE Charac –teristic	Proba – bility Variable	Depiction	Mode *	Skew-ness$_1$	Skew-ness$_2$	Slope
BNM #1	All	PMR	Bimodal	Q_1, Q_4	1.0101	1.0050	-0.1725
		CMR	Bimodal	Q_1, Q_4	0.9728	0.9864	-1.2525
BNM #2	All	PMR	Bimodal	Q_1, Q_4	0.9767	0.9883	-0.3025
		CMR	Bimodal	Q_1, Q_4	0.9751	0.9876	-1.1750
BNM #3	All	CMR	Unimodal	Q_2	0.8818	0.9409	-0.1400
		IMT	Unimodal	Neutral	0.9259	0.9629	-1.2800
BNM #4	All	CMR	Unimodal	Q_2	0.8667	0.9334	-0.1600
		IMT	Unimodal	Neutral	0.9668	0.9834	-0.5633
BNM #5	All	CMR	Unimodal	Q_2	0.8758	0.9379	-0.1950
		IMT	Unimodal	Neutral	0.9257	0.9628	-1.2867

Note: * - For comparison of PMR and CMR probability distributions, the mode was a quartile (i.e., Q_i). For IMT probability distributions, the mode was either Higher, Neutral, or Lower transition of quartiles.

Table 59. Attributes of Probability Density Distributions of BNM Output When FMO = NO

Model	MOSE Charac - teristic	Proba – bility Variable	Depiction	Mode	Skew-ness$_1$	Skew-ness$_2$	Slope
BNM #1	All	PMR	Uniform	None	0.9992	0.9996	0.0125
		CMR	Unimodal	Q_2	1.0568	1.0284	0.8075
BNM #2	All	PMR	Uniform	None	1.0016	1.0008	0.0225
		CMR	Unimodal	Q_2	1.0568	1.0284	0.8000
BNM #3	**All**	**CMR**	**Unimodal**	$\mathbf{Q_4}$	**1.0695**	**1.0348**	**1.0300**
		IMT	Unimodal	Neutral	0.9199	0.9600	-1.3900
BNM #4	**All**	**CMR**	**Unimodal**	$\mathbf{Q_4}$	**1.0704**	**1.0352**	**1.0300**
		IMT	Unimodal	Neutral	0.9177	0.9589	-1.4300
BNM #5	**All**	**CMR**	**Unimodal**	$\mathbf{Q_4}$	**1.0627**	**1.0314**	**0.9533**
		IMT	Unimodal	Neutral	0.9205	0.9602	-1.3767

A review of Table 58 demonstrated that for cases in which future mishaps did occur subsequent to the MCAS result data, that there were no sets of BNM output using either Previous / Current MCAS Result (PMR / CMR) for BNMs #1 and #2, or Current MCAS Results (CMR) /Inter-Period MCAS Transition (IMT) for BNMs #3, #4, or #5 that met the desired attributes of modality, skewness, and slope. Since no BNM outputs met all criteria for desired attributes, no statistical analysis was conducted to evaluate the significance of the models' performance. Therefore the null hypothesis for Research Question 1 listed below could not be rejected.

> **$H1_0$**: Use of Bayesian Network Modeling to represent the relationship between organizational MCAS results and mishap occurrence will not provide improved methodology compared to MCAS frequency observation reference study analysis to predict occurrence of future mishaps

In evaluating the converse utility in table 59 for those cases in which a future mishap did not occur subsequent to the MCAS result data, as shown in the shaded rows, the use of BNMs #3, #4, and #5 output of PMR quartiles met the desired attributes. No reference data were available for MCAS results of squadrons that did not incur an aviation mishap, precluding statistical analysis for comparison to the results of the derived data contained in Table 57, above. Face inspection of the results indicates that there are indications for the BNMs #3, #4, #5 that fourth quartile performance resulted in higher probability of not incurring a future mishap.

5.3. EVALUATION OF DATA SUPPORTING ANSWER TO RESEARCH QUESTION 2

Research Question 2 inquired whether any of the individual MOSE components served as a better indicator than aggregation of all six MOSE components for future mishap occurrence using Bayesian Network Modeling. Comparison of the probability density distributions and their respective attributes for the results from the output from the Bayesian Network Models #1 through #5 broken out by the aggregate and individual MOSE components are presented in Appendix F.

Review of Tables 100 through 101 in Appendix F indicates (as shown in the shaded rows) demonstrates that the desired attributes for modality, skewness, and slope, dependent upon FMO equal to YES or NO, were evident for these select cases. These select cases demonstrating the desired attributes are displayed below in Tables 60 and 61.

Table 60. Attributes of Probability Density Distributions for Specific MOSE Components and Select BNM Outputs When FMO = YES

Model	MOSE Charac –teristic	Proba – bility Variable	Depiction	Mode	Skew-ness$_1$	Skew-ness$_2$	Slope
BNM #1	QA	PMR	Unimodal	Q_1	0.9238	0.9619	-0.7825
BNM #1	RM	PMR	Unimodal	Q_1	0.9026	0.9513	-1.1575
BNM #2	QA	PMR	Unimodal	Q_1	0.9448	0.9724	-0.8050
BNM #2	RM	PMR	Unimodal	Q_1	0.9201	0.9601	-0.9700
BNM #2	C2	PMR	Unimodal	Q_1	0.9596	0.9798	-0.6525

Table 61. Attributes of Probability Density Distributions for Specific MOSE Components and Select BNM Outputs When FMO = NO

Model	MOSE Charac –teristic	Proba – bility Variable	Depiction	Mode	Skew-ness$_1$	Skew-ness$_2$	Slope
BNM #3	All	CMR	Unimodal	Q_4	1.0695	1.0348	1.0300
BNM #3	QA	CMR	Unimodal	Q_4	1.0247	1.0124	0.2233
BNM #3	RM	CMR	Unimodal	Q_4	1.1231	1.0616	1.6433
BNM #4	All	CMR	Unimodal	Q_4	1.0704	1.0352	1.0300
BNM #4	QA	CMR	Unimodal	Q_4	1.0243	1.0121	0.2300
BNM #4	RM	CMR	Unimodal	Q_4	1.1236	1.0618	1.6400
BNM #4	C/FR	CMR	Unimodal	Q_4	1.0454	1.0227	0.7300
BNM #5	All	CMR	Unimodal	Q_4	1.0627	1.0314	0.9533
BNM #5	RM	CMR	Unimodal	Q_4	1.1222	1.0611	1.6233
BNM #5	C/FR	CMR	Unimodal	Q_4	1.0392	1.0196	0.6800

An inspection of the two tables above indicates that there were no specific pairing of MOSE component and BNM demonstrated better desired behavior as a predicting tool when both:

- MCAS result performance was in a lower or the lowest quartile when a future mishap did occur, and
- MCAS result performance was in a higher or the highest quartile when a future mishap did not occur.

A summary of individual examples that contained probability variable quartile distributions that met desired attributes is shown below in Table 62.

Table 62. MOSE component and Corresponding Bayesian Network Model Outputs Demonstrating Desired Probability Distribution

MOSE component	BNM	FMO	Probability Variable Quartile
Aggregate	#3, #4, #5	NO	CMR
QA	#1, #2	YES	PMR
	#3, #4	NO	CMR
RM	#1, #2	YES	PMR
	#3, #4, #5	NO	CMR
C2	#2	YES	PMR
C/FR	#4, #5	NO	CMR

Table 62, above, displays that:

- None of the BNMs using aggregation of the six MOSE components demonstrated all desired traits to serve as a predictive tool for future mishap occurrence (i.e., when FMO = YES). There were 3 instances for BNM #3, #4, and #5 using aggregated MCAS data that displayed suitable traits when future mishap occurrence did not occur (i.e., when FMO = NO).
- There is no single MOSE component that meets desired attributes for serving as a predictive tool for both when future mishap occurrences occur and do not occur. As stated in Section 3.9.1 above, satisfactory model performance would support utility as a predictive tool for both future likelihoods to incur and not incur a future mishap. None of the developed Bayesian Network Models when applied to individual and aggregate MOSE components displayed satisfactory predictive performance for both outcomes in which FMO = YES and FMO = NO.

Since none of the output data from BNMs using input aggregated from all six MOSE components demonstrated acceptable criteria for all probability distribution traits. no statistical analysis was conducted to evaluate the significance of the models' performance when compared to input from individual MOSE component. Therefore the null hypothesis for Research Question 2 listed below could not be rejected.

> **$H2_0$**: Use of Bayesian Network Modeling with specific component MCAS results will not provide improved methodology compared to aggregated MCAS results to predict occurrence of future mishaps.

5.4. ANALYSIS

5.4.1. EVALUATION OF BAYESIAN NETWORK MODELING FOR PREDICTING FUTURE MISHAP OCCURRENCE

In evaluation of data produced from the developed and executed Bayesian Network Models, for Research Questions 1 and 2, the null hypotheses could not be rejected. Examination of the model outputs and their characteristic traits did not support using Bayesian Network Models of sequential MCAS results as a predictive tool to gauge likelihood for incurring or not incurring a future mishap.

For Research Question 1, in comparison of the aggregated MCAS data for all MOSE components to the April 2004 reference study detailed by Ciavarelli in 2007, Schimpf, and Figlock in 2006, none of the Bayesian Network models developed for this research demonstrated improved performance.

For Research Question 2, statistical analysis of Bayesian Network modeling results from specific MOSE component input compared to aggregated input from all 6 MOSE components was not conducted as the models using aggregated data did not demonstrate all required traits for probability distribution. Additional analysis was conducted to determine if any specific MOSE component used in a defined BNM had superior performance than the others.

Consideration was given for utility of statistical analyses to compare results for specific MOSE components and BNM outputs for those cases in which output performance met desired attributes for predicting future mishap occurrence. The one-sided paired *t*-test was selected for use to compare paired differences in slopes from one given specific MOSE component – BNM case listed below in Table 63 against the others.

Table 63. Previous MCAS Result Quartile Probability Distributions for Specific MOSE component – BNMs with FMO = YES

MOSE component	BNM	Q_1	Q_2	Q_3	Q_4	Slope
QA	#1	0.2705	0.2493	0.2410	0.2392	-0.0078
	#2	0.2737	0.2405	0.2443	0.2415	-0.0081
RM	#1	0.2847	0.2409	0.2360	0.2384	-0.0116
	#2	0.2761	0.2447	0.2419	0.2373	-0.0097
C2	#2	0.2715	0.2388	0.2443	0.2454	-0.0065

The null hypothesis for this additional evaluation was that the slopes for the specific MOSE component – BNMs were essentially similar while the alternate hypothesis was that one of the slopes demonstrated significantly better performance than the others. This calculation was accomplished using the statistic for paired *t*- test. (DeVeaux et al., 2012)

$t_{n-1} = {\bar{d} - \Delta_0}/{SE(\bar{d})}$, where: (EQ 48)

$\bar{d}$ =	mean of pairwise differences
S_d =	standard deviation of mean s of pairwise differences
n =	number of pairs
n-1 =	degrees of freedom
$SE(\bar{d}) = {S_d}/{\sqrt{n}}$	standard error for the mean, applied to the differences

(EQ 49)

For this analysis: $n = 4$, Degrees of Freedom was n-1= 3, with $\alpha = 0.05$, the one-sided critical t value for negative slopes was $t_{0.05,3}$ = -2.3534 such that for the derived t value to exceed the critical value, it had to be less than -2.3534. Results of the paired t-test one-sided statistical analysis are shown below in Table 64.

Table 64. Paired t-Test One Sided Analysis of MOSE component – BNM Slopes

Basis Slope	Slope Value	Derived t –Statistic compared to other MOSE component-BNM slopes	Exceeds Critical t value such that it is less than -2.3534
QA-BNM #1	-0.0078	1.0478	NO
QA-BNM #2	-0.0081	0.7765	NO
RM-BNM #1	**-0.0116**	**-5.4475**	**YES**
RM-BNM #2	-0.0097	1.1162	NO
C2- BNM #2	-0.0065	3.1770	NO

As shown in the gray shaded row above, only the MCAS data results using the Risk Management MOSE component for Previous MCAS Results with BNM #1 demonstrated all the desired attributes for probability distribution with a quantifiable slope value that exceeded the one-side, paired t-tests critical value. This enabled rejection of the null hypothesis indicating that for the use of the Risk Management MOSE component as input data for BNM #1, PMR provided significantly improved performance than the other tested BNMs; however its slope value of -0.0116 did not outperform the April 2004 reference study published by Ciavarelli in 2007 and Schimpf and Figlock in 2006 for Class A mishaps (-0.0308) / Class A, B, and C mishaps (-0.0409) or the dissertation research data set (-0.0172) depicted in Table 64 above.

5.4.2. APPLICATION OF BAYESIAN NETWORK MODELING FOR PREDICTING FUTURE MISHAP OCCURENCE

Bayesian Network Models developed for this research did not demonstrate sufficient performance to meet the intended goal of providing squadron leadership with a tool that could be used for predicting future mishap occurrence. The modeling and simulation of Bayesian Networks is a valid methodology for existing data to determine conditional probability, i.e., the probability of an event given that we know some other event has occurred. However the developed and executed models in this research did not add improved quantitative metrics for representing the relationship between sequential MCAS results and future mishap occurrence / non-occurrence. Reasons that may have impacted Bayesian Network Model performance include:

- Data provided by the U.S. Naval Safety Center did not support development of Bayesian Network Models that demonstrated desirable traits for use as a predictive tool.

- Poor construct validity of the MCAS to accurately reflect six distinct categories, corresponding to the six components of the Model of Organizational Safety Effectiveness.
- The state variable nodes and their inter-relationships in the developed conceptual Bayesian Network Models did not capture key elements necessary to produce results that could be used as a predictive tool.
- Use of Likert Scale data did not adequately establish significant state variable nodes for Bayesian Network Model execution that supports predictive tool use. Additional related components to this involve:
    - Quartiles were used to differentiate levels of performance from squadron MCAS performance. This was done to enable direct comparison with the April 2004 reference study published by Ciavarelli in 2007 and Schimpf and Figlock in 2006 . This coarse level of gradation with only four discrete values may not have demonstrated sufficient distinction to enable meaningful model output.
    - Quartile transition was defined as a state variable to reflect direction of movement in quartiles from sequential MCAS results. Characterization of direction of change as Lower ($Q_i \rightarrow Q_j$ where $i > j$) or Higher ($Q_i \rightarrow Q_j$ where $i < j$) may not have demonstrated a sufficient level of fine distinction to enable meaningful model output.

5.4.2.1. REVIEW OF ASSUMPTIONS

Assumptions listed in Section 1.7 were reviewed for potential adverse impact on research results.

- ASSUMPTION 1
    - Statement: Design and implementation of a computational Bayesian Network Model using MCAS derived inputs does not substantially change the intent of the original framework. MCAS was implemented to capture maintenance related items within the MOSE framework.
    - Review: The use of MCAS results as input data for computational execution of Bayesian Network Models should not have imparted any substantial change to the intent of the original MCAS framework nor led to incorrect assessments of squadron maintainers' perspective of organizational risk management and safety climate.
- ASSUMPTION 2
    - Statement: Use of a computational model to accurately produce conditional probability predictions that reflect causal network relationships between MCAS results and mishap occurrences continues to provide the means to accurately represent MOSE components.
    - Review: The reliance of computational Bayesian Network Models to accurately produce conditional probability predictions that reflect causal network relationships between MCAS results and future mishap occurrences should not have introduced means to inaccurately represent MOSE components. Simulation through basic Bayesian Network

Modeling cannot incorporate feedbacks and dynamics. [Albert, 2012] The five discrete models contained in this research had no feedback mechanisms to distort representation of MOSE components.

- ASSUMPTION 3
  - Statement: Averaging aggregated organizational response scores of MCAS questions does not alter the accuracy of survey results.
  - Review: Averaging aggregated organizational responses should not have altered accuracy of MCAS results. Aggregated results were used in computation model execution to derive results which were directly comparable to the April 2004 reference study published by Ciavarelli in 2007 and Schimpf and Figlock in 2006 to evaluate models' performance.

ASSUMPTION 4
  - Statement: Changes in an organization's safety climate reflected by MCAS results occur at a linear rate for the time period between implementation of successive safety surveys
  - Review: Discrete event modeling contains an inherent limitation for reflecting changes in state variables between observation times. Without use of either dynamic modeling techniques or additional observation points within a given time period, the use of only two sequential MCAS results constrains derivation of a linear rate of change for the for the time period between implementation of successive safety surveys.

5.4.2.2. ADDITIONAL FACTORS INFLUENCING EVALUATION OF RESEARCH MODELS' PERFORMANCE

A useful model to serve as a tool for squadron leadership was to demonstrate performance for accurately predicting likelihood for both when future mishap will and will not happen. Although model execution was conducted for both outcomes of FMO = YES and FMO = NO, there were limitations in comparative evaluation against a reference for MCAS results in which a future mishap did not occur.

- The reference study April 2004 published by Ciavarelli in 2007 and Schimpf and Figlock in 2006, contained only data that represented the quartile distributions and frequency of mishap occurrences. No complementary MCAS result data were available for squadrons that did not incur mishaps. Additionally, no breakdown of aggregated MCAS survey results into individual MOSE components were available for the April 2004 reference study.
- Disparities in frequency number of events for when future mishaps did and did not occur were also significant. There were
    - Only 58 instances in which corresponding mishaps occurred and only 55 that had corresponding previous and current MCAS results (PMR and CMR).
    - 736 instances in which there were a matched set of previous and current MCAS results and no future mishap occurrence.
- The data provided contained MCAS administered between the dates of September 7, 2000 and January 6, 2009 and mishap occurrence dates between October 18, 2002 and August 15, 2007. The potential exists that there were additional mishap

occurrences with dates subsequent to that of the last MCAS result and prior to the administration of the next MCAS.

5.5. CONCLUSIONS

This dissertation presented a methodology for developing conceptual and computational Bayesian Network Models to generate conditional probability predictions that would be useful as an improved predictive tool for squadron leadership. The goal behind employment of these methods was to accurately represent the modeling causal network relationships between MCAS results and future mishap occurrences. Through leveraging definition of state variable nodes and their directed path connections, resultant conditional probabilities, this endeavor sought to closely associate successive MCAS survey results with observed mishap occurrence. Comparison of Bayesian Network Model outputs to reference data and simple / tabular presentation of mishap occurrence frequency to quartile placement failed to demonstrate improved performance. As such, this dissertation research effort was unsuccessful in formally establishing and validating the application of the Bayesian Network Modeling methodology in the context for its use for evaluating successive MCAS results as a predictive tool for future mishap occurrence.

5.6. RECOMMENDATIONS

This research addressed an important topic area in striving to develop a computational model that would serve as a predictive tool for squadron leadership to conduct risk analysis, apply risk management, and reduce susceptibility for future mishap occurrence. The costs in manpower and equipment are worthy concerns to assist aviation squadron leadership and our nation with a methodology that will serve to reduce mishap occurrence rates and improve our combat readiness.

Although this research did not produce the desired results, it has served to narrow the field of study in this area while providing avenues for future research that may serve to achieve the goals of this effort. Recommendations for forthcoming scholarly exploration in this field include suggestions regarding data and modeling:

- Data:
    - Coordinate and liaison with U.S. Naval Safety Center for obtaining additional data that would provide for finer levels of detail and / or definition of other critical state variables for expressing causal network relationships. Additional data would support model execution for:
        - Squadrons flying supplementary Type/Model/Series aircraft other than those that comprise a carrier air wing;
        - Inclusion of both Class B and Class C mishaps;
        - Incorporation of aircraft / equipment damage and personnel injuries located in submitted squadron Hazard Reports. These incidents do not meet the minimal criteria set for Class C mishaps; however, they would provide higher observed frequencies than reliance on only Class A mishap data.
    - Conduct further analysis on reference data study by Schimpf and Figlock (as shown in Figure 3) to evaluate results and respective quartile distributions for those squadrons that did not experience a future mishap

occurrence within 24 months after survey. This would support better comparison of modeling results.

  - Collaborate with US Naval Safety Center for potential changes to the MCAS questions that would improve construct validity in supporting unique features of all six MOSE components. This would address the current issue in which every MCAS question loading on one main factor.

- Modeling
  - Perform model execution using single specific questions in each of the 6 MOSE components and perform evaluation to determine if there is a solitary question that may serve as necessary input for the developed computation models to produce an operational predictive tool. Initial consideration should be given to the questions which comprise the Risk Management Characteristic in execution of BNM #1. This case had all the desired traits for probability distributions and best slope value performance.
    - This is aligned to the results of research conducted of MCAS results for U.S. Navy Fleet Logistic Support squadrons. "The two MOSE components of greatest concern as identified by aviation maintenance personnel of the Fleet Logistics Support Wing while participating in the MCAS are Communication/Functional Relationships and Risk Management. The focusing intervention efforts in those two areas should be a priority." [Goodrum, 1999, p. 42]

    - However, since the Cronbach Alpha Coefficient values as shown in Table 11, in Section 3.4.3 are all greater than 0.9 demonstrating excellent reliability, this may not be sufficient to result in improved performance over that of the individual MOSE components.
- Investigate whether the developed computation models demonstrate improved performance for a specific Type / Model / Series (T/M/S) squadron. Potential exists that tighter scope application may have applicability for a specific T/M/S. Within the limitations of the data provided by the U.S. Naval Safety Center, issues with this recommendation involve the disparity in numbers of similar T/M/S squadrons and their associated mishap occurrences / rates.
- Further refine definition of the state variable for Inter-Period MCAS Transition (IMT) of quartiles to account not only for direction of movement (i.e., Higher, Neutral, or Lower), but also quantify the amount of quartile movement. The potential exists that the scalar value for quartile transition (with potential range of (-3, -2, -1, 0, 1, 2, 3) may serve to impart more utility in the results of model execution.
- Try use of other discrete event modeling techniques defined in Section 2.7 such as Hidden Markov Model (HMM) or Naïve Bayesian Model (NBM). Although Artificial Neural Network Model (ANNM), and Support Vector Machine Model (SVMM) methodologies could be used, they possess inherent disadvantages. ANNM "black box" operations may not afford meaningful understanding of causal relationships between state variable

and SVMM contains a limitation for dealing with temporal data relationships and in providing direct probability estimates.

- Investigate and determine applicability of dynamic modeling techniques. This will require additional data to support development of a conceptual and computational dynamic model that uses a Differential Equations System Specification (DESS).

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APPENDIX A. NAVAL AVIATION MISHAP CLASSIFICATION

A.1. MISHAP CATEGORY [OPNAVINST 3750.6S, Paragraph 313, 2014]

- CLASS A MISHAP: A class A mishap is one in which the total cost of damage to Department of Defense (DoD) or non-DoD property, aircraft or Unmanned Aerial Vehicles (UAVs) is $2 million or more, or a naval aircraft is destroyed or missing, or any fatality or permanent total disability of personnel results from the direct involvement of naval aircraft or UAV. A destroyed or missing UAV is not a class A unless the cost is $2 million or more.
- CLASS B MISHAP. A class B mishap is one in which the total cost of damage to DoD or non-DoD property, aircraft or UAVs is $500,000 or more, but less than $2 million, or results in a permanent partial disability, or when three or more personnel are hospitalized for inpatient care (which, for mishap reporting purposes only, does not include just observation or diagnostic care) as a result of a single mishap.
- CLASS C MISHAP. A class C mishap is one in which the total cost of damage to DoD or non-DoD property, aircraft or UAVs is $50,000 or more, but less than $500,000, or a nonfatal injury or illness that results in 1 or more days away from work, not including the day of the injury.
- CLASS D MISHAP. A class D mishap is one in which the total cost of damage to DoD or non-DoD property, aircraft or UAVs is $20,000 or more, but less than $50,000; or a recordable injury (greater than first aid) or illness results not otherwise classified as a class A, B, or C mishap

A.2. MISHAP SUB-CATEGORY [OPNAVINST 3750.6S, Paragraph 314, 2014]

- FLIGHT MISHAP (FM). A flight mishap is where there is intent for flight and reportable damage to a DoD aircraft or UAV or the loss of a DoD manned aircraft. Explosives, chemical agent, or missile incidents that cause damage to an aircraft or UAV with intent for flight are categorized as FMs. Mishaps involving factory new production aircraft until successful completion of the postproduction flight are reported as contractor mishaps.
- FLIGHT RELATED MISHAP (FRM). A mishap where there is intent for flight and no reportable damage to the aircraft or UAV itself, but the mishap involves a fatality, reportable injury, or reportable property damage. A missile that is launched from an aircraft or UAV departs without damaging the aircraft, and is subsequently involved in a mishap is reportable as a guided missile mishap.
- AIR GROUND MISHAP (AGM). A mishap where there is no intent for flight that results in reportable damage to an aircraft or UAV, or death or injury involving an aircraft or UAV. This applies to both on land and on board ship. Damage to an aircraft when it is being handled as a commodity or cargo is not reportable as an aircraft mishap.

APPENDIX B. INSTRUMENT AND MODEL METRICS

B.1 INTRODUCTION

This appendix section contains additional information providing detailed descriptions and background information regarding specific metrics that were used to support quantitative data generation and analysis for this research.

B.2. USE OF LIKERT SCALES

The scale is attributed to Rensis Likert who developed this technique for the evaluation of attitudes. A significant amount of literature exists that describes methodologies for using Likert scale derived data. Likert scales are commonly aligned with use in marketing, business, social science, medicine and educational research as well as the service sector. [Gliem and Gliem, 2003, Göb, et al,, 2007]

> A common feature of marketing research is the attempt to have respondents communicate their feelings, attitudes, opinions, and evaluations in some measureable form. To this end marketing researchers have developed a range of scales. Each of these has unique properties...Some scales are at very best limited in their mathematical properties to the extent that they can only establish an association between variables. Other scales have more extensive mathematical properties, and some, hold out the possibility to establish cause and affect relationships between variables. [Crawford, 1998, p. 3-1.]

A scale is a collection of items that provides a means to measure and quantify characteristics under evaluation. It serves as an instrument that is constructed by researchers in order to obtain quantitative data on variable for which appropriate standardized instruments are not available. [Dawis, 1987]

B.2.1. LEVELS OF MEASUREMENT

Scale scores are categorized by different levels of measurement that are commonly used. Their characteristics are defined below and are presented in hierarchical order (from lowest to highest) of mathematical properties:

- Nominal. A categorical sale consisting of a set of frequency counts. A nominal scale often contains a list of categories to which items may be assigned. Chi-Square testing may be used to support hypothesis tests to determine whether two or more variables are associated and the strength of that relationship. However, it does not support use for establishing cause and effect relationships.
- Ordinal (also known as Rank Ordered). This measurement involves the ranking of characteristics being scaled. Except for the relative order of items, there are no means to quantify or measure the distance between two scale values. For marketing, ordinal number scaling supports determining the order of preference of different brands, but it does not contain information about the interval between any two brands. Ordinal scales enable the same data analysis available from nominal scales. Additionally, positional statistics may be derived which include median, quartile, and percentile. Ordinal scales permit tests for order correlation of ranked data such as Spearman's Ranked Correlation Coefficient and Kendall's Coefficient of Concordance. The use of mean and standard deviation are inappropriate for ordinal data.
- Interval. Also referred to as a cardinal scale, it has equal units of measurement, which allow for interpretation of the interval scale's scores and quantifiable relative distances between them. The scale's zero point is arbitrary and not

necessarily an absolute true zero (e.g., zero degrees on the Fahrenheit temperature scale). Constants may be added or subtracted to an interval scale value without affecting the scale's form; however, this does not apply to multiplication or division. Many common statistical analysis methods may be conducted using interval scale data. Cardinal measure scales express magnitude.

- Ratio. This scale has the same properties of interval scales and includes a fixed origin or zero point. This provides an indication of the absolute distance of any measured object from a true-zero point on the scale. Examples include lengths, time, and weights. Data from ratio measurement scales permit comparison of differences and relative magnitude.

[Crawford, 1998; Brown, 2000; Jamieson, 2004; Göb et al., 2007; Dawis, 1987] Both interval and ratio scales are considered to be continuous scales.

B.2.2. SCALE DESIGN AND FORMAT

Structured verbal scales contain individual items with a stimulus component and matching response section. The stimulus is written as sentence or phrase that describes a particular attribute or event related to a specific object. The stimulus can be drafted to ascribe different levels of exactness or generality. Response choices may vary in the measurement dimension (e.g., agree-disagree, important-unimportant) and the range of associated scale point choices (2, 3, or 5 are most common. The response choices may be weighted or un-weighted, and the formats may one or two sided [Dawis, 1987] The Likert scale contains brief descriptions associated with each category option that are ordered in position with bipolar adjectives at the end point extremes on the scale (i.e., strongly disagree and strongly agree). As a monadic scale, the respondent evaluates only one object or question at a time. The Likert scale is described as

> A set of items, composed of approximately an equal number of favorable and unfavorable statements concerning the attitude toward an object that is given to a group of subjects. They are asked to respond to each statement in terms of their won degree of agreement or disagreement. The specific responses to the items are combined so that individuals with the most favorable attitudes will have the highest scores while individuals with the least favorable (or unfavorable) attitudes will have the lowest. [McIver and Carmines, 1981, pp. 22-23]

B.2.3. LIKERT SCALE IMPLEMENTATION

Ideally, a Likert Scale evaluation is given to a large group of individuals (N of at least 100). After survey completion the individual items are aggregated by item, similar groupings, and total score. A Likert scale is termed as a summated instrument scale meaning that the composite items are summed to produce a total score. Summated scales contain:

- Multiple items whose results are combined, averaged, or summed.
- Individual items that measure an aspect which possesses a property that may be represented by an underlying, quantitative measurement continuum.
- The individual items have no "correct" answer differentiating a summated scale from a multiple choice test
- Each individual item contains a statement to which the respondents are asked to select an answer that best serves to represent their rating. [Spector, 1992]

Items (i.e., questions) are selected for use in a Likert Scale survey according to their capability to be discriminated between high and low scores on total score through use of a group-difference procedure. The difference in items means between high- and low-scoring groups (e.g., highest and lowest quartiles). The best discriminating items are then selected to constitute the survey, and a comprehensive scale score is obtained by summing individual items scores for the selected items. Likert Scale methodology implementation involves computation of:

- Total score(s)
- Item-total score correlations
- Alpha reliability of the final set of items. [Dawis, 1997]

B.2.4. LIKERT SCALE DATA ANALYSIS

There are many different views on the processes to evaluate the data derived from Likert Scales. "In fact, there is no common standard accepted by the scientific community for the correct interpretation and analysis of such data. Interpretation and analysis often seem to be in a mismatch." [Göb et al., 2007, p. 602] Both ordinal scale based evaluations and interval/cardinal scale derived statistics are commonly used. Examples of these disparate views include:

- Likert scales fall within the ordinal level of measurement. That is, the response categories have a rank order, but the intervals between values cannot be presumed equal…The legitimacy of assuming an interval scale for Likert-type categories is an important issues because the appropriate descriptive and inferential statistics differ for ordinal and interval variables, and if the wrong statistical technique is used, the researcher increases the chance of coming to the wrong conclusion about the significance (or otherwise) of his research. [Jamieson, 2004, p. 1217]

- Likert scales are treated as yielding interval data by the majority of marketing researchers. [Brown, 1998, p. 3-12]
- Likert scaling presumes the existence of an underlying (or latent or natural) continuous variable whose value characterizes the respondent's attitudes and opinions. If it were possible to measure the latent variable directly, the measurement scale would be, at best, an interval scale…It is probably that the Likert scale will be ordinal, but in any event, the population could be totally ordered by the magnitude of the latent variable. [Clason and Dormody, 1994, p. 31-32]
- Measurement versus statistics. There is an old and continuous debate…the proponents of measurement hold that level of measurement (nominal, ordinal, interval, and ratio) constrains the kind of statistical procedures that can be applied to the numerical data. The proponents of statistics maintain that the level of measurement in not a constraining factor. Those who accept the latter view tolerate the use of parametric statistics with scores from quasi-interval scales that actually are at the ordinal level of measurement, a common practice that is criticized by proponents of the former view. [Dawis, 1987, p. 487]
- In methodological considerations it is generally acknowledged that attitude measuring scales should be considered ordinal. Nevertheless, many studies use cardinal statistics as sample means, sample variances, *t*-tests to analyze attitude data. [Göb et al., 2007, p. 602]

- Under certain conditions, treating ordinal data is considered permissible or not permissible; however, no clear specification exists to identify the needed conditions for making a determination. [Vigderhous, 1977]

Likert Scale results have been considered as interval measurements for analysis of MCAS results. Much of the analysis conducted by Schimpf's study of the relationship between MCAS and Naval Aviation Mishaps [Schimpf, 2004b] and Goodrum's Assessment of the Maintenance Safety Climate in U.S. Navy Fleet Logistics Support Wing Squadrons [Goodrum, 1999] utilized statistical analysis to derive values such as means and standard deviations of responses to MCAS questions.

B.3. RELIABILITY

In research, the term reliability denotes "repeatability" such that a test result is considered reliable if it would repeatedly produce the same result when assessing the same object. [Trochim, 2006] Reliability, measured by computed coefficient values, demonstrates whether the test was correctly designed such that a certain collection of items accurately yield interpretable statements about individual differences. [Cronbach, 1951] Specific definitions of test reliability are defined by unique descriptors:

- Coefficient of Stability-the degree to which the test score indicates unchanging individual differences in any traits. This may be evaluated through use of retest methodology i.e., giving the same test twice to the same group.

- Coefficient of Stability and Equivalence-the degree to which the test score indicates unchanging individual differences in the general and group factors defined by the test. Equivalent or parallel tests are techniques used to determine stability and equivalence
- Coefficient of Equivalence-the degree to which the test score indicate the status of the individual at the present instant in the general and group factors defined by the test. Internal consistency tests are generally measures of equivalence. This coefficient predicts the correlation of the test with a hypothetical equivalent test, as like the first test as the parts of the first test are alike. Split-half methodology correlates half the test items with the remaining items to determine if the separate half-tests have equal standard deviations. This is used to assess equivalence of simultaneously administered parallel tests that provides an estimate of internal consistency.
- Hypothetical Self-Correlation-is the degree to which the test score indicate individual differences in any traits at the present moment. This requires independent simultaneous identical tests for evaluation. [Cronbach, 1947]

An internal consistency reliability estimate provides the reliability of the instrument by computing how well the items that reflect the same construct yield similar results. Internal consistency reliability is a measure of how consistent the results are for different items for the same construct within the measure. [Trochim, 2006] Methodologies for computing internal consistency reliability include: interitem correlation, average item-total correlation, split-half reliability, and Cronbach's Alpha Test.

Cronbach adapted work by Kuder-Richardson to develop the means for computing a split half coefficient of equivalence. The use of Cronbach's alpha test is a measure of internal consistency to evaluate reliability. It may be conducted with only a single test administration to furnish a distinctive estimate of the reliability of a given test. Cronbach's alpha is the average value of the reliability coefficients one would have obtained for all possible combinations of items when split into two half-tests. [Gliem and Gliem, 2003]. The equation for determining Cronbach's alpha is:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum s_i^2}{S^2}\right) \qquad \text{(EQ 50)}$$

where k=number of items
s_i^2=variance for item i
S^2=total test variance

Cronbach defined the coefficient alpha to be:

- The mean of all possible split-half coefficients
- The value expected when two random samples of items from a pool like those in the given test are correlated
- The lower bound of the coefficient or precision (i.e., instantaneous accuracy) and lower bound for coefficient of equivalence obtained by simultaneous administration of two tests having matched items
- The estimate and lower bound to the proportion of test variance attributable to common factors among the items (i.e., the index of common factor concentration

- The upper bound to the concentration in the test of the first factor among the items. [Cronbach, 1951, pp. 331-332]

Table 65 depicts the scale of reliability determined by calculating Cronbach's Alpha coefficient for internal consistency [George & Mallery, 2003, p. 231].

Table 65. Cronbach's Alpha Coefficient Reliability Scale

Alpha (α) Value	Reliability
> 0.9	Excellent
> 0.8	Good
> 0.7	Acceptable
> 0.6	Questionable
> 0.5	Poor
$\leq$ 0.5	Unacceptable

B.4. SKEWNESS

Numerous common statistical tests for skewness when applied to discrete probability distributions will result in a non-parametric value of zero when the median is equal to the mean. The outcome is zero when the median equals the mean for calculating both the formal definition of skewness that derives the third moment of the distribution and Pearson's skewness coefficient [Tabor, 2010]. These equations are depicted below:

3rd Moment of Distribution:

$$\frac{1}{n}\sum(x-\bar{x})^3 \Big/ \sqrt[3]{\frac{1}{n}\sum(x-\bar{x})^2}$$

(EQ 51)

Pearson Skewness Coefficient

$$3\,(mean - median)/_{standard\ deviation}$$

(EQ 52)

Tabor compared 11 different statistic formulas for computing skewness in terms of their power for detecting skewness using samples from strongly, moderately, and slightly skewed populations. The lower rank value is indicative of the higher the power for detecting a skewed population (i.e., rank 1 = most power). The tested statistics, estimates of power, and average rankings are provided, below, in Table 66.

Table 66. Comparison of Statistical Formulas for Skewness (Tabor, 2010)

Population Skew		Strong	Moderate	Slight	Aver-age Rank
Name	Statistic	Power (Rank)	Power (Rank)	Power* (Rank)	
A	$\frac{mean}{median}$	0.42 (8)	0.21 (8)	0.098 (6)	7.33
B	$\frac{\max - median}{median - min}$	0.84 (2)	0.31 (1)	0.107 (5)	2.67
C	$\frac{Q_3 - median}{median - Q_1}$	0.28 (9)	0.10 (9.5)	0.065 (10)	9.5
D	$\frac{\max - Q_3}{Q_1 - min}$	0.85 (1)	0.26 (5.5)	0.090 (7)	4.5
E	$\frac{\frac{1}{2}(min + max)}{median}$	0.56 (5)	0.30 (2)	0.126 (1)	2.67
F	$\frac{\frac{1}{2}(Q_1 + Q_2)}{median}$	0.13 (11)	0.10 (9.5)	0.066 (9)	9.83
G	$\frac{\frac{1}{2}(min + max)}{\frac{1}{2}(Q_1 + Q_3)}$	0.49 (6.5)	0.27 (4)	0.118 (2)	4.17
H	$\frac{min + Q_1 + median + Q_3 + max}{5}$	0.49 (6.5)	0.26 (5.5)	0.110 (4)	5.33
I	$\frac{1}{n}\Sigma(x-\bar{x})^3 \Big/ \sqrt[3]{\frac{1}{n}\Sigma(x-\bar{x})^2}$	0.68 (3)	0.28 (3)	0.113 (3)	3
J	$\frac{3(mean - median)}{standard\ deviation}$	0.64 (4)	0.22 (7)	0.085 (8)	6.33
K	$\frac{(Q_3 - median) - (median - Q_1)}{Q_3 - Q_1}$	0.26 (10)	0.09 (11)	0.061 (11)	10.67

Note: * - Power estimates were taken to additional decimal place to support ranking

APPENDIX C. NAVAL AVIATION SQUADRON ORGANIZATIONAL DESCRIPTION AND DECOMPOSITION.

C.1. INTRODUCTION

The study commenced with a detailed analysis and decomposition of a Naval Aviation squadron to determine its function, objectives, and organizational constraints. This dissertation contains the initial systems analysis and mapping to support the groundwork for selection of the type of computation model that was developed here within. For the purpose of this research, a squadron is comprised of the personnel, aircraft, supplies, and support equipment placed under the responsibility of a Commanding Officer (CO). The CO bears absolute responsibility for his command and is entrusted with the commensurate authority to successfully accomplish assigned duties. [U.S. Naval Regulations, 1990, p. 47, paragraph 0802] The squadron's purpose is to provide trained aircrew and Ready For Tasking (RFT) aircraft for assigned missions. Mission type orders are used to communicate the superior commander's general intention and specifically direct the subordinated commander to accomplish an operational effect to support that intention. [Major Fischer, 1995, p. 6] Missions are assigned to individual units for accomplishment. Within Naval Aviation, these unit elements are normally squadrons although they may be assigned to wings that are the aggregated entity of numerous squadrons. A squadron is a complex organization that consists of numerous departments and divisions whose actions must be coordinated. Major sub-divisions within a squadron include:

- Maintenance: Provides RFT aircraft in support of the Operations Department. It is responsible for conducting scheduled and unscheduled repairs as well as preventative upkeep. Maintenance contains the largest share of squadron personnel. Its functions include production center assignment and coordination, material/supply support, tool control, quality assurance, and ground support for aircraft launch, recovery, and between flight aircraft servicing. The maintenance department was the significant focus of this research effort.
- Operations: Plans, schedules, and executes operational flights to complete mission assignments from higher command and internal squadron requirements.
- Safety: Implements Command Aviation Safety program to enhance readiness by preserving material resources and human lives through application of written policies, plans, and policies couples with the attitudes and practices that promote aviation safety. [OPNAVINST 3750.7R, 2001, p. 2-1]

A depiction is shown in Figure 33.

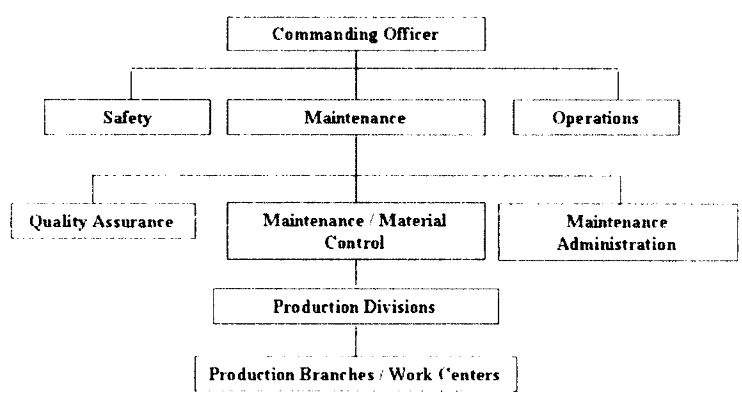

Figure 33. Squadron Organization

C.2. MAINTENANCE DEPARTMENT ROLES AND RESPONSIBILITIES

The functions and objectives of the major units within the maintenance department are described below:

- Maintenance Officer (MO). A squadron department head who leads, manages, and supervises the department. The Mo is responsible to the CO for the accomplishment of the department's mission and aided by the Assistant Maintenance Officer (AMO). Per HFACS-ME (Table 4), the MO has impact on the first order effects for management conditions, maintainer conditions, and working conditions. The MO also has responsibility for accomplishment of personnel training that may influence human errors resulting from maintainer acts due to inadequacies in their (technical) knowledge, skill, and judgment.
- Maintenance Material Control. A division within the maintenance department led by the Maintenance Material Control Officer (MMCO). The MMCO reports directly to the MO and is responsible for the coordination and accomplishment of the department's productive effort and material support. Actions taken by Maintenance Material Control have bearing on management conditions and working conditions through tasking the squadron work centers,
- Maintenance Administration. Assigned under the direction of the AMO, this division provides administrative services for the entire department. Work product includes correspondence, establishment and control of reporting and record keeping systems, information and publication distribution, and clerical support. The Maintenance Administration division impacts management conditions.

- Quality Assurance (QA). The QA division is manned by highly skilled personnel responsible for monitoring and ensuring the quality of the department's workmanship. This is conducted through inspections and audits to prevent the occurrence of defects. QA covers all maintenance actions from start to completion. Prevention is essential to thwart maintenance failure and extends to personnel safety, equipment preservation, and throughout the entire maintenance effort. Additional actions include data collection and analysis. "Prevention is about regulating events rather than being regulated by them. QA is a planned and systematic pattern of actions necessary to provide adequate confidence the product will perform satisfactorily in service, and the monitoring and analyzing of data to verify the validity of these actions." [CNAFINST 4790.2, Vol. 1, 2005, p. 14-2] The QA division has oversight over all HFACS-ME first order categories: Management Conditions, Maintainer Conditions, Working Conditions, and Maintainer Acts.
- Production Division, Branches, and Work Centers. Divisions are the largest functional component within the department that may be further divided into smaller groups of branches and work centers that are tasked to accomplish specific assignments. These units receive tasking from Maintenance Material Control to accomplish required scheduled and unscheduled actions in order to prepare an aircraft for flight and Ready For Tasking. Each functional entity is responsible for a functional area to which maintenance personnel are assigned. An example of common production components is shown in Table 67.

Table 67. Maintenance Production Units

Division	Branch	Work Center
Aircraft	Power Plants	Engines
		Propellers
	Airframe	Structures
		Hydraulics
		Corrosion Control
	Aviation Life Support Systems	Egress / Environmental Systems
Avionics / Armament	Electronics	Communications, Navigation, Radar
		Fire Control
	Electrical / Instrument	
	Reconnaissance / Photo	
Ordnance		
Line	Plane Captain	
	Troubleshooter	
	Support Equipment	

The individual units that conduct the maintenance production have influence on all HFACS-ME sub categories.

C.3. ORGANIZATIONAL RELATIONSHIPS

Two types of relationships, line and staff, exist between functional entities internal and external to the maintenance department. A line relationship is used to describe the interaction between senior supervisory personnel and their subordinates. Line interaction by the supervisor includes direct tasking of work assignments to subordinates, performance appraisal, and responsibility for subordinates actions / work product to higher levels within or outside the squadron. Subordinate responsibilities in a line relationship include task completion and providing feedback as to assigned work status (to include impediments). Line relationship describes responsibilities and communications inherent in direction and management of a hierarchical aligned organization. (e.g., department, division, branch, and work center). The staff relationship exists between an advisory staff supervisor and a production line supervisor. "Staff elements are designed to be integral elements of the organization, wholly concerned with the exercise of servicing and supporting production elements." [CNAFINST 4790.2, Vol. 1, 2005, p. 8-1] Staff relationships provide the effective means for information flow across hierarchical levels and outside the line relationship. Line and staff relationships within the squadron are depicted in Figure 34.

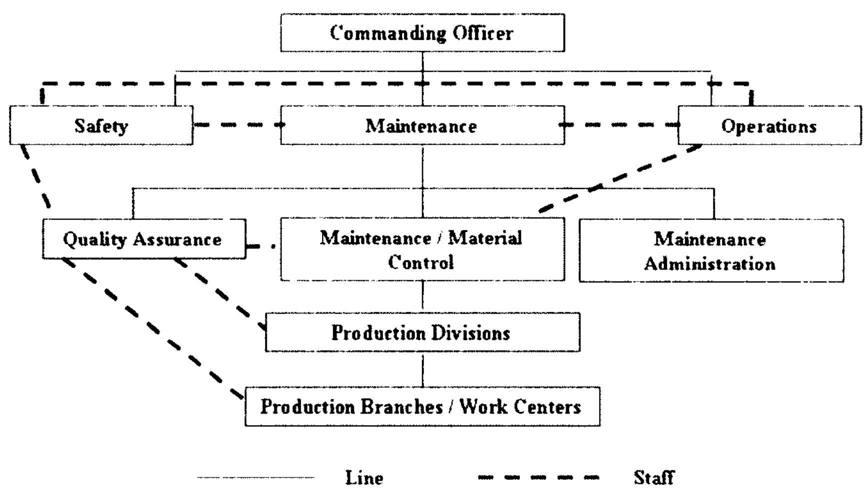

Figure 34. Squadron Line and Staff Relationships

C.4. COMMAND RELATIONSHIPS

Squadrons as organizations are subordinate entities with line relationships to two separate superior commands; one which exercises administrative control, the other executes operational control. Administrative commands execute staff control of the resources and logistics support required by the subordinate unit to execute its operational tasking. Administrative commanders are responsible for the aircraft material readiness, manpower, personnel training, administration, and inspection of subordinate commands. Administrative commands are typically aligned as Type Wings comprised of similar aircraft type, models, and series. Operational commanders exert line control, provide tasking and authoritative direction to subordinate squadrons to accomplish assigned missions that tactically employs their capabilities. Common operational commands are Navy carrier air wings or Marine Air Groups. Their responsibilities include the operational readiness, inspection, and overall performance of squadrons under their command. As both administrative and operational commanders have overlapping responsibilities for subordinate unit safety and maintenance, their influence will require examination for incorporation in the design of the computation model.

C.5. GOVERNING MAINTENANCE INSTRUCTION AND GOALS

There are numerous instructions and regulations that govern policies, procedures, and responsibilities of a Naval Aviation squadron. The primary foundation for conducting maintenance on aircraft is the Naval Aviation Maintenance Program (NAMP). The NAMP instruction is the overarching document that governs all Naval Aviation maintenance.

> "The maintenance of naval aircraft has continually changed and evolved over the lifetime of Naval Aviation. Aircraft maintenance processes and procedures have become increasingly complex as aircraft and aircraft systems have become more complicated...The NAMP was established by Chief of Naval Operations to provide an integrated system for performing aeronautical equipment maintenance and related support functions." [CNAFINST 4790.2, 2006, p. 1]

The Navy currently uses two distinct domains to differentiate the degree of repair capability to be accomplished. Organizational level maintenance is considered "on flight line", that is, routine preventative procedures done at specifically defined intervals or unscheduled repairs to restore non-properly functioning equipment. Unscheduled repairs are limited in scope primarily to replacement of major components or replaceable assemblies. Fleet Readiness Centers (FRCs) conduct more in-depth, "off flight line" repairs and have the capability to fix the components and replaceable assemblies making them Ready For Issue (RFI) for squadron use. This research was limited to organizational level aircraft maintenance.

The NAMP sets forth a standardized organization that assigns explicit responsibilities to "ensure effective management within a framework of authority, functions, and relationships necessary to achieve improvements in performance, economy of operation, and quality of work." [CNAFINST 4790.2, 2006, Volume 1, p. 8-1] The goal of a properly implemented standardized maintenance organization is to improve the following key characteristics:

1. Personnel performance and training.
2. Aircraft, equipment, and system readiness.
3. Maintenance integrity and effectiveness for all material.
4. Safety.
5. Maintenance manpower and materials usage.
6. Maintenance work scheduling and planning
7. Work performance management and evaluation.
8. End product quality.

9. Combat readiness attainment and retention.

10. Personnel and aircraft continuity throughout inter-command transfers.

11. Environmental compliance.

APPENDIX D. MAINTENANCE CLIMATE ASSESSMENT SURVEY

Table 68. Close-Ended MCAS Questions

Number	Question
Process Auditing (PA)	
1	The command adequately reviews and updates safety procedures.
2	The command monitors maintainer qualifications and has a program that targets training deficiencies.
3	The command uses safety and medical staff to identify / manage personnel at risk.
4	Collateral Duty Inspectors (CDIs) / Quality Assurance Representatives (QARs) routinely monitor maintenance evolutions.
5	Tool Control and support equipment licensing are closely monitored.
6	Signing off personnel qualifications is taken seriously.
Reward System And Safety Culture (RS / SC)	
7	Our command climate promotes safe maintenance.
8	Supervisors discourage Standard Operating Procedures (SOP), Naval Aviation Maintenance Program (NAMP) or other procedure violations and encourage reporting safety concerns.
9	Peer influence discourages SOP, NAMP or other violations and individuals feel free to report them.
10	Procedural violations of SOP, NAMP, or other procedures are not common in this command.
11	The command recognizes individual safety achievement through rewards and incentives
12	Personnel are comfortable approaching supervisors about personal problems / illness.
13	Safety Non-Commissioned Officer (NCO), QAR, and CDI are sought after billets
14	Unprofessional behavior is not tolerated in this command.
Quality Assurance (QA)	
15	The command has a reputation for quality maintenance and set standards to maintain quality control.
16	QA and Safety are well respected and are seen as essential to mission accomplishment.
17	QARs / CDIs sign-off after required actions are complete and are not pressurized by supervisors to sign-off.
18	Maintenance on detachments is of the same quality as that at home station.
19	Required publications / tools / equipment / are available, current, serviceable, and used.
20	QARs are helpful, and QA is not "feared in my unit.

Table 68 (Continued)

Number	Question
Risk Management (RM)	
21*	In my squadron, multiple job assignments and collateral duties adversely affect maintenance.
22	Safety is part of maintenance planning, and additional training / support is provided as needed.
23	Supervisors recognize unsafe conditions and manage hazards associated with maintenance and the flight line.
24	I am provided adequate resources, time, and personnel to accomplish my job.
25	Personnel turnover does not negatively impact the command's ability to operate safely.
26	Supervisors are more concerned with safe maintenance than the flight schedule, and do not permit cutting corners.
27	Day / Night Check have equal workloads, and staffing is sufficient on each shift.
28	Supervisors shield personnel from outside pressures and are aware of individual workload.
29	Based upon my command's current assets / manning it is not over-committed
Command and Control (C2)	
30	My command temporarily restricts maintainers who are having problems.
31	Safety decisions are made at the proper levels, and work center supervisor decisions are respected.
32	Supervisors communicate command safety goals and are actively engaged in the safety program.
33	Supervisors set the example for following maintenance standards and ensure compliance.
34	In my command, safety is a key part of all maintenance operations, and all are responsible / accountable for safety.
35	Safety education and training are comprehensive and effective.
36	All maintenance evolutions are properly briefed, supervised, and staffed by qualified personnel.
37	Maintenance Control is effective in managing all maintenance activities.

Table 68 (Continued)

Number	Question
Communication / Functional Relationships (C / FR)	
38	Effective communication exists up / down the chain of command.
39	I get all the information I need to do my job safely.
40	Work center supervisors coordinate their actions with other work centers in maintenance.
41	My command has effective pass-down between shifts.
42	Maintenance Control troubleshoots / resolves gripes before flight.
43	Maintainers are briefed on potential hazards associated with maintenance activities.

*-Question is written with negative connotation asking individual to score their agreement-disagreement with a condition that adversely affects safety.

The MCAS used Likert scale response options as shown in Table 69.

Table 69. Likert Scale Response Option and Values

Option	Value
Strongly Disagree	1
Disagree	2
Neutral	3
Agree	4
Strongly Agree	5

APPENDIX E. BAYESIAN NETWORK MODEL DATA FROM MAINTENANCE CLIMATE ASSESSMENT SURVEYS BY MODEL OF ORGANIZATIONAL SAFETY EFFECTIVENESS SPECIFIC CHARACTERISTIC

E.1. PROCESS AUDITING CHARACTERISTIC DATA RESULTS FOR BAYESIAN NETWORK MODELS

Table 70. BNM Computational Model #1 Process Auditing Characteristic Nodal Probability Distribution

FMO =	YES	NO
PMR Q_1	0.2658	0.2494
PMR Q_2	0.2415	0.2501
PMR Q_3	0.2327	0.2507
PMR Q_4	0.2600	0.2498
CMR Q_1	0.3738	0.2343
CMR Q_2	0.1149	0.2577
CMR Q_3	0.1882	0.2612
CMR Q_4	0.3231	0.2468

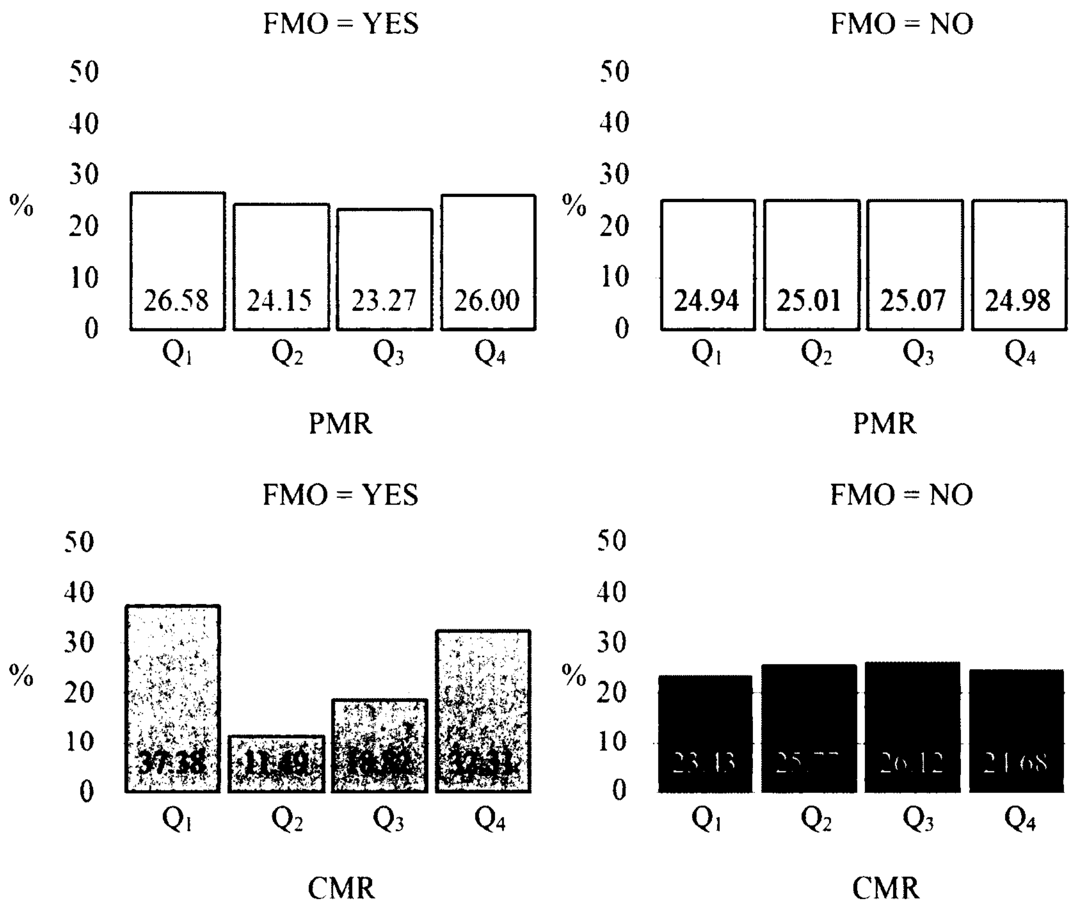

Figure 35. BNM Computational Model #1 Process Auditing Characteristic Nodal Conditional Probabilities

Table 71. BNM Computational Model #2 Process Auditing Characteristic Nodal Probability Distribution

FMO =	YES	NO
PMR Q_1	0.2707	0.2490
PMR Q_2	0.2401	0.2502
PMR Q_3	0.2343	0.2506
PMR Q_4	0.2549	0.2502
CMR Q_1	0.3739	0.2343
CMR Q_2	0.1141	0.2578
CMR Q_3	0.1877	0.2613
CMR Q_4	0.3243	0.2466

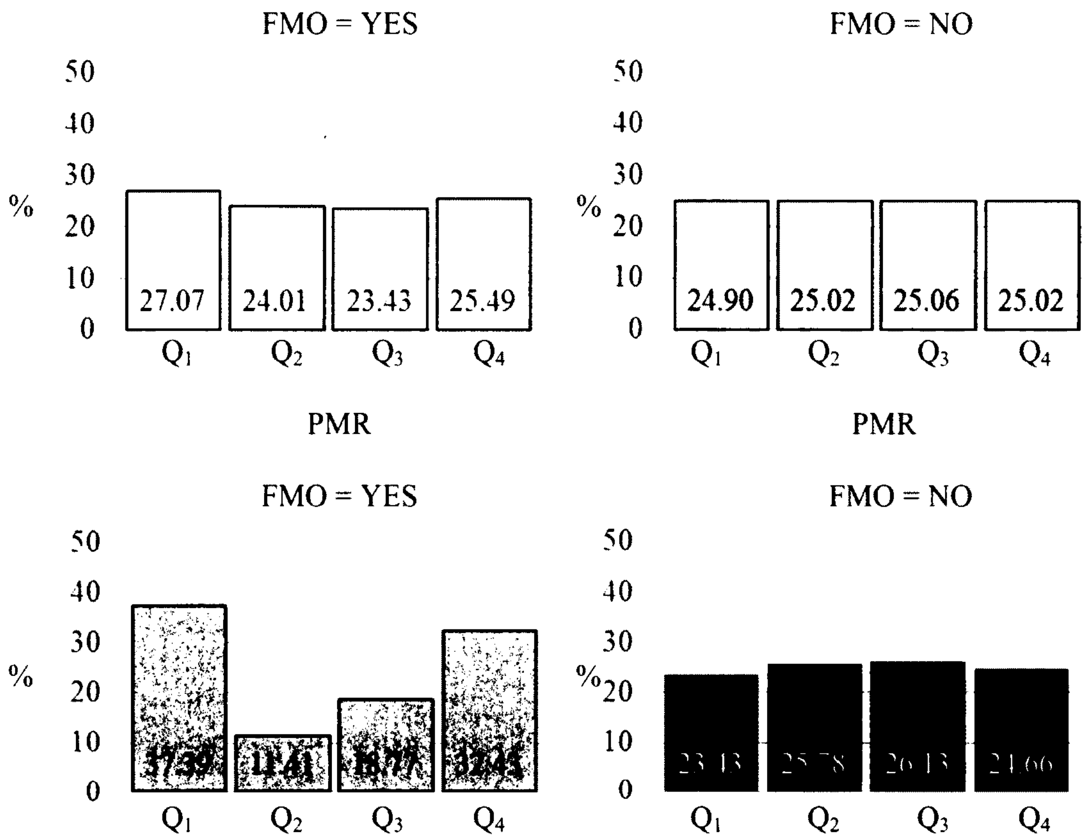

Figure 36. BNM Computational Model #2 Process Auditing Characteristic Nodal Conditional Probabilities

Table 72. BNM Computational Model #3 Process Auditing Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2695	0.2417
CMR Q_2	0.2687	0.2455
CMR Q_3	0.2014	0.2595
CMR Q_4	0.2603	0.2533
IMT Higher	0.3090	0.3112
IMT Neutral	0.3604	0.3854
IMT Lower	0.3306	0.3034

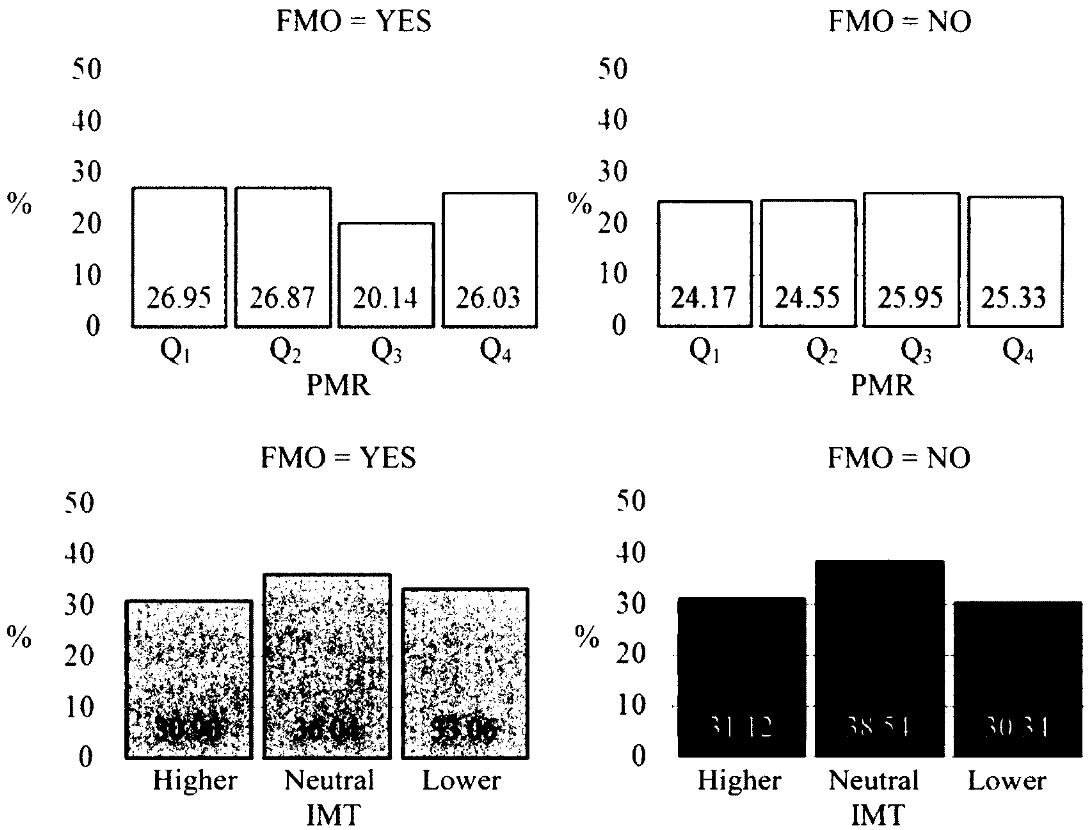

Figure 37. BNM Computational Model #3 Process Auditing Characteristic Nodal Conditional Probabilities

Table 73. BNM Computational Model #4 Process Auditing Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2680	0.2417
CMR Q_2	0.2705	0.2455
CMR Q_3	0.2014	0.2595
CMR Q_4	0.2601	0.2533
IMT Higher	0.2976	0.3118
IMT Neutral	0.3894	0.3838
IMT Lower	0.3130	0.3044

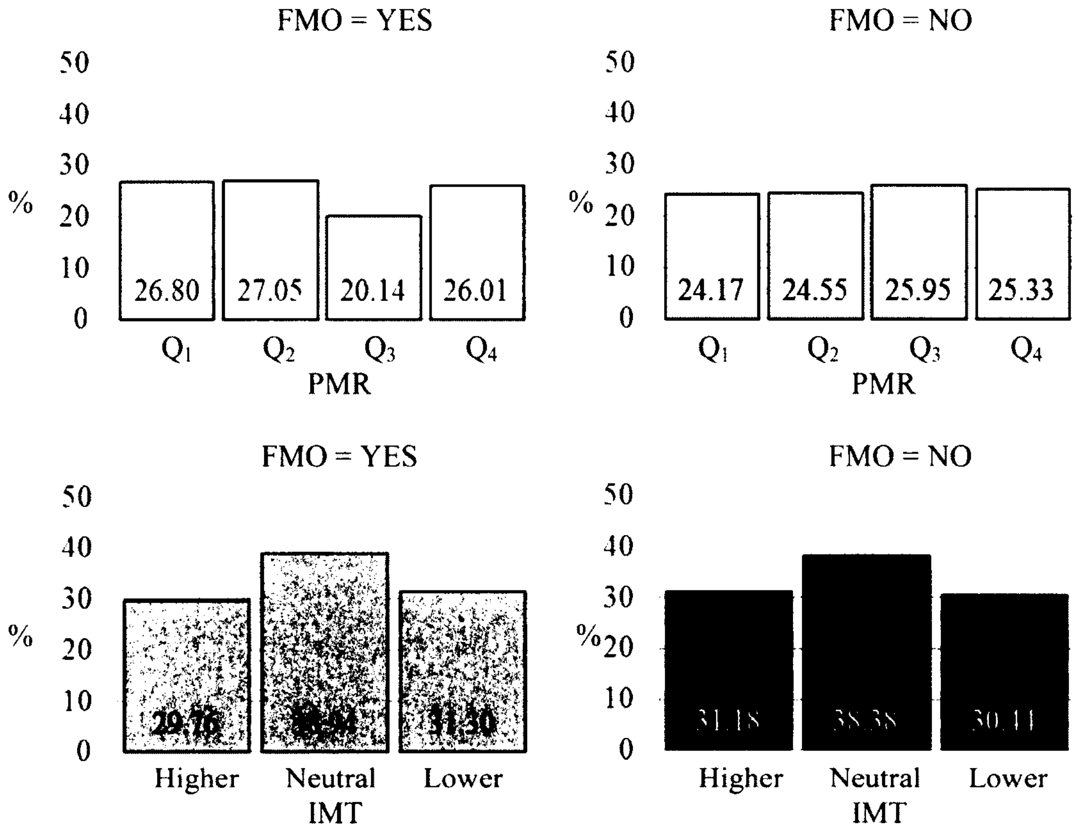

Figure 38. BNM Computational Model #4 Process Auditing Characteristic Nodal Conditional Probabilities

Table 74. BNM Computational Model #5 Process Auditing Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2701	0.2424
CMR Q_2	0.2691	0.2458
CMR Q_3	0.2013	0.2593
CMR Q_4	0.2595	0.2525
IMT Higher	0.3086	0.3108
IMT Neutral	0.3611	0.3860
IMT Lower	0.3302	0.3032

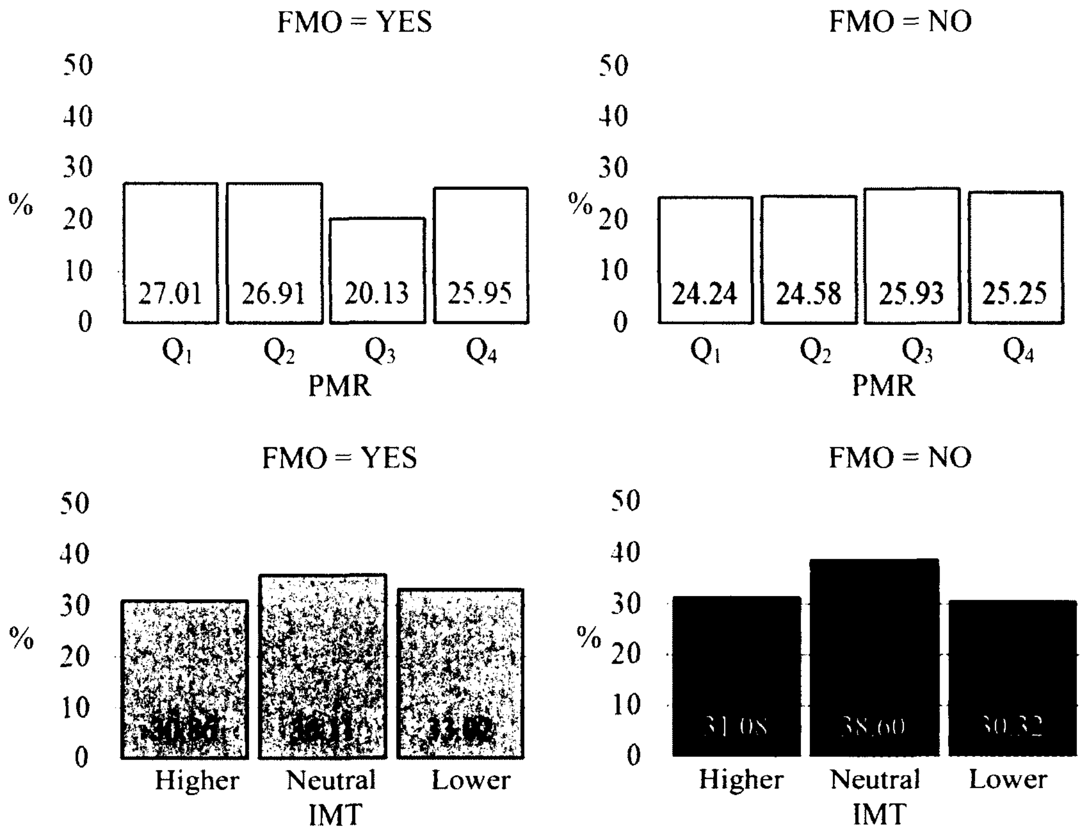

Figure 39. BNM Computational Model #5 Process Auditing Characteristic Nodal Conditional Probabilities

E.2. REWARD SYSTEM AND SAFETY CULTURE CHARACTERISTIC DATA RESULTS FOR BAYESIAN NETWORK MODELS

Table 75. BNM Computational Model #1 Reward System and Safety Culture Characteristic Nodal Probability Distribution

FMO =	YES	NO
PMR Q_1	0.2675	0.2492
PMR Q_2	0.2357	0.2505
PMR Q_3	0.2433	0.2500
PMR Q_4	0.2535	0.2503
CMR Q_1	0.3525	0.2321
CMR Q_2	0.1508	0.2485
CMR Q_3	0.1868	0.2642
CMR Q_4	0.3099	0.2532

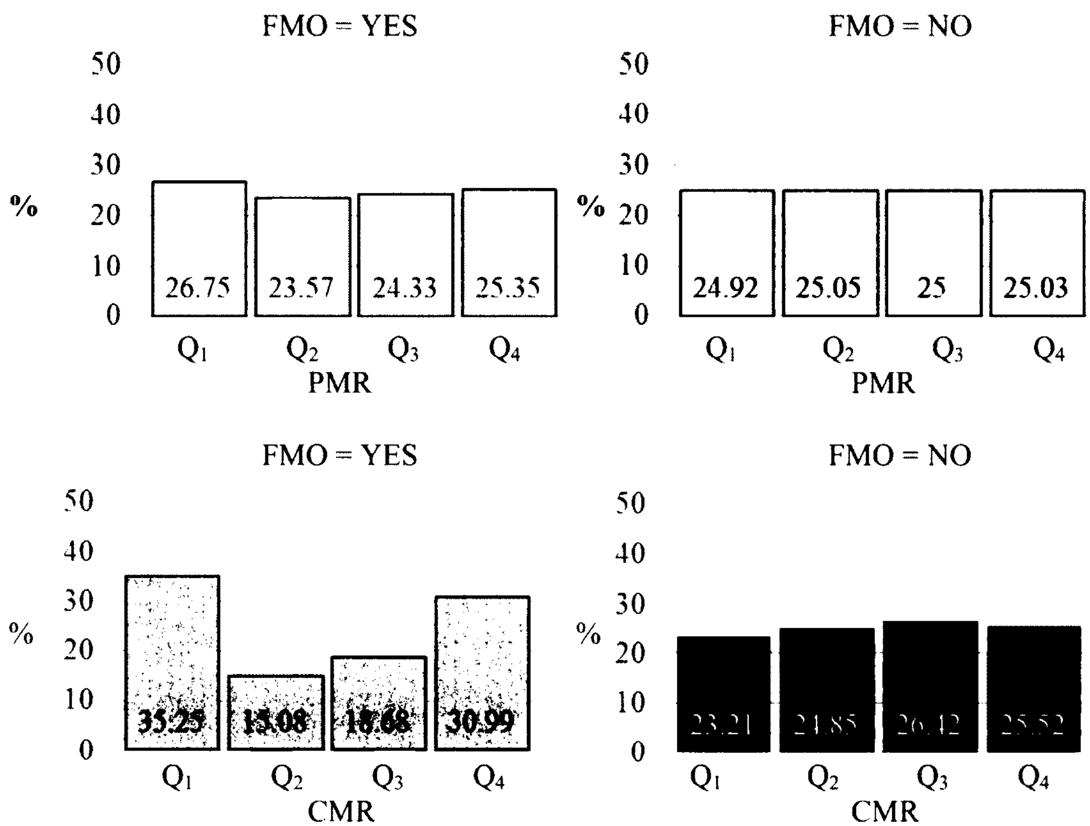

Figure 40. BNM Computational Model #1 Reward System and Safety Culture Characteristic Nodal Conditional Probabilities

Table 76. BNM Computational Model #2 Reward System and Safety Culture Characteristic Nodal Probability Distribution

FMO =	YES	NO
PMR Q_1	0.2635	0.2495
PMR Q_2	0.2456	0.2498
PMR Q_3	0.2407	0.2502
PMR Q_4	0.2502	0.2505
CMR Q_1	0.3506	0.2323
CMR Q_2	0.1514	0.2484
CMR Q_3	0.1853	0.2643
CMR Q_4	0.3127	0.2550

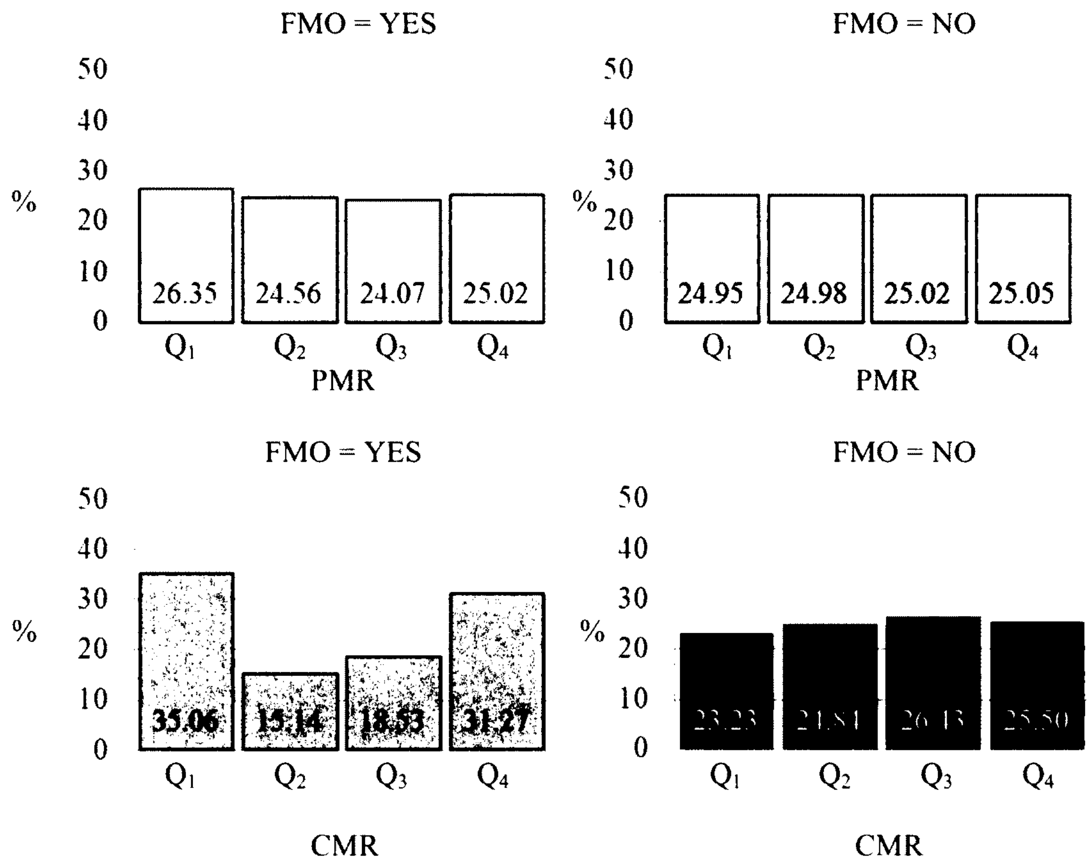

Figure 41. BNM Computational Model #2 Reward System and Safety Culture Characteristic Nodal Conditional Probabilities

Table 77. BNM Computational Model #3 Reward System and Safety Culture Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2130	0.2413
CMR Q_2	0.2306	0.2414
CMR Q_3	0.2556	0.2589
CMR Q_4	0.3008	0.2584
IMT Higher	0.3916	0.3267
IMT Neutral	0.3668	0.3625
IMT Lower	0.2416	0.3108

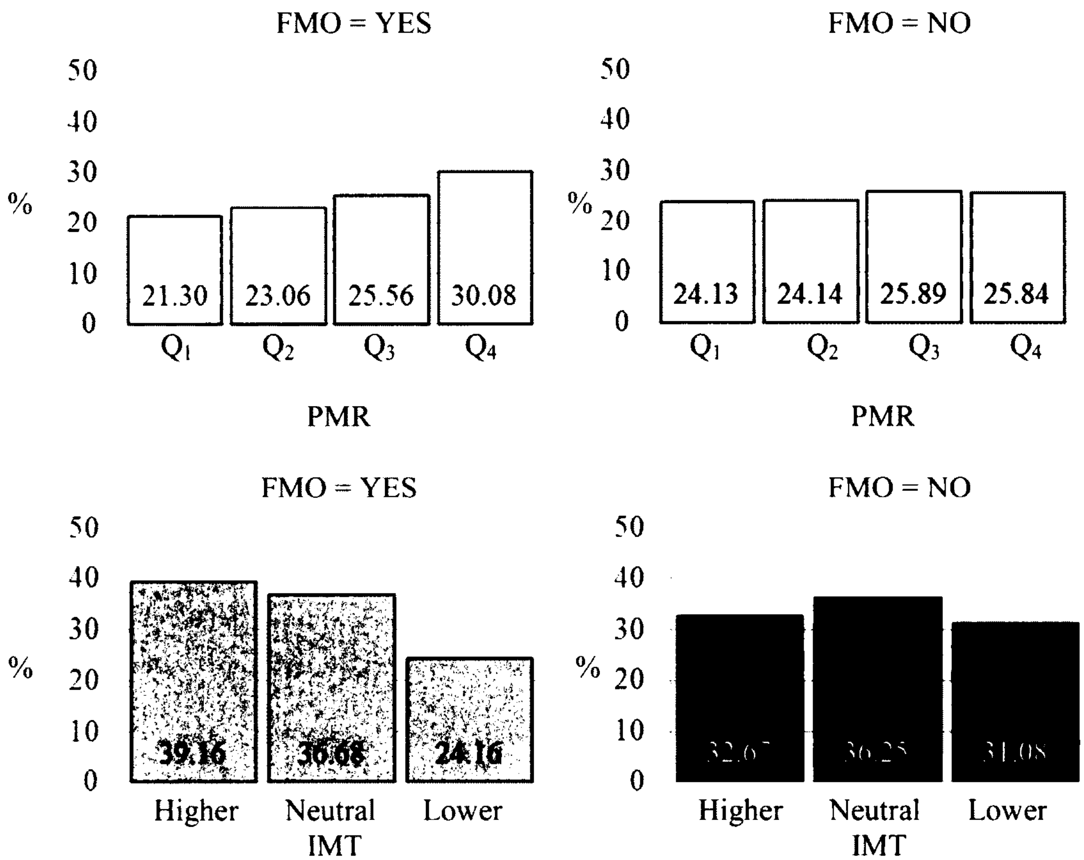

Figure 42. BNM Computational Model #3 Reward System and Safety Culture Characteristic Nodal Conditional Probabilities

Table 78. BNM Computational Model #4 Reward System and Safety Culture Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2115	0.2414
CMR Q_2	0.2352	0.2411
CMR Q_3	0.2557	0.2590
CMR Q_4	0.2976	0.2585
IMT Higher	0.3467	0.3291
IMT Neutral	0.3656	0.3625
IMT Lower	0.2877	0.3084

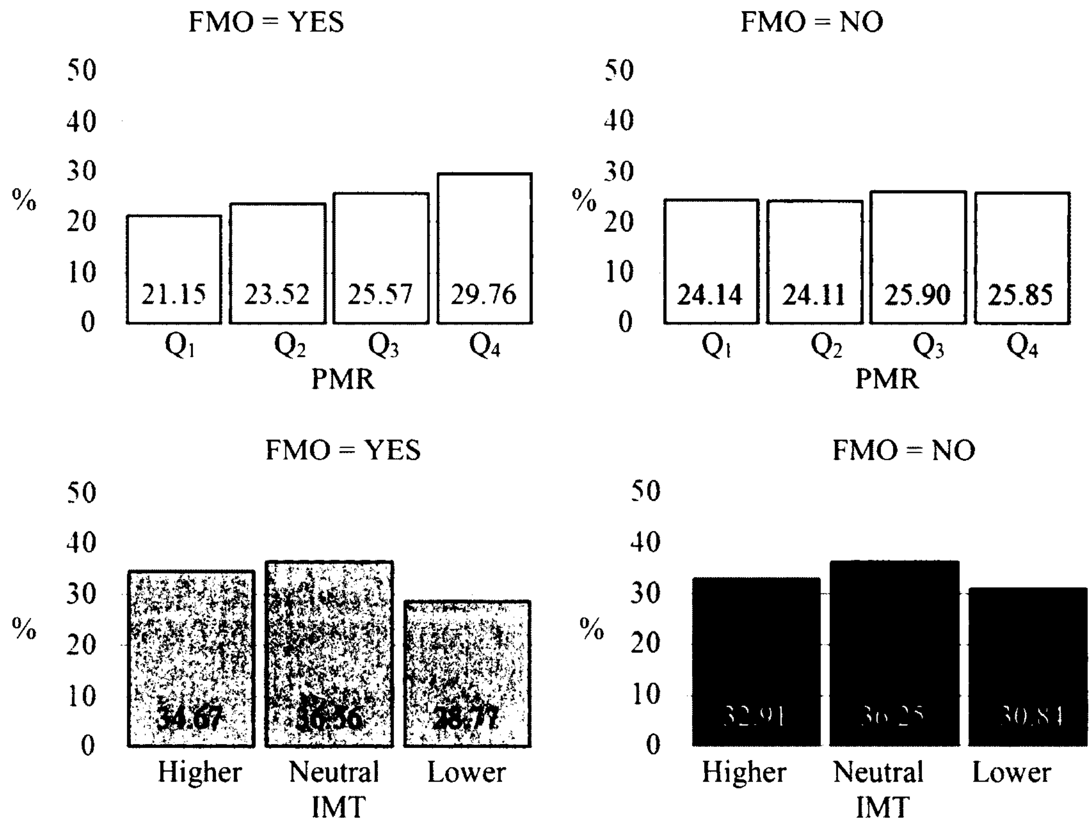

Figure 43. BNM Computational Model #4 Reward System and Safety Culture Characteristic Nodal Conditional Probabilities

Table 79. BNM Computational Model #5 Reward System and Safety Culture Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2141	0.2426
CMR Q_2	0.2313	0.2417
CMR Q_3	0.2556	0.2591
CMR Q_4	0.2990	0.2566
IMT Higher	0.3901	0.3251
IMT Neutral	0.3676	0.3632
IMT Lower	0.2423	0.3117

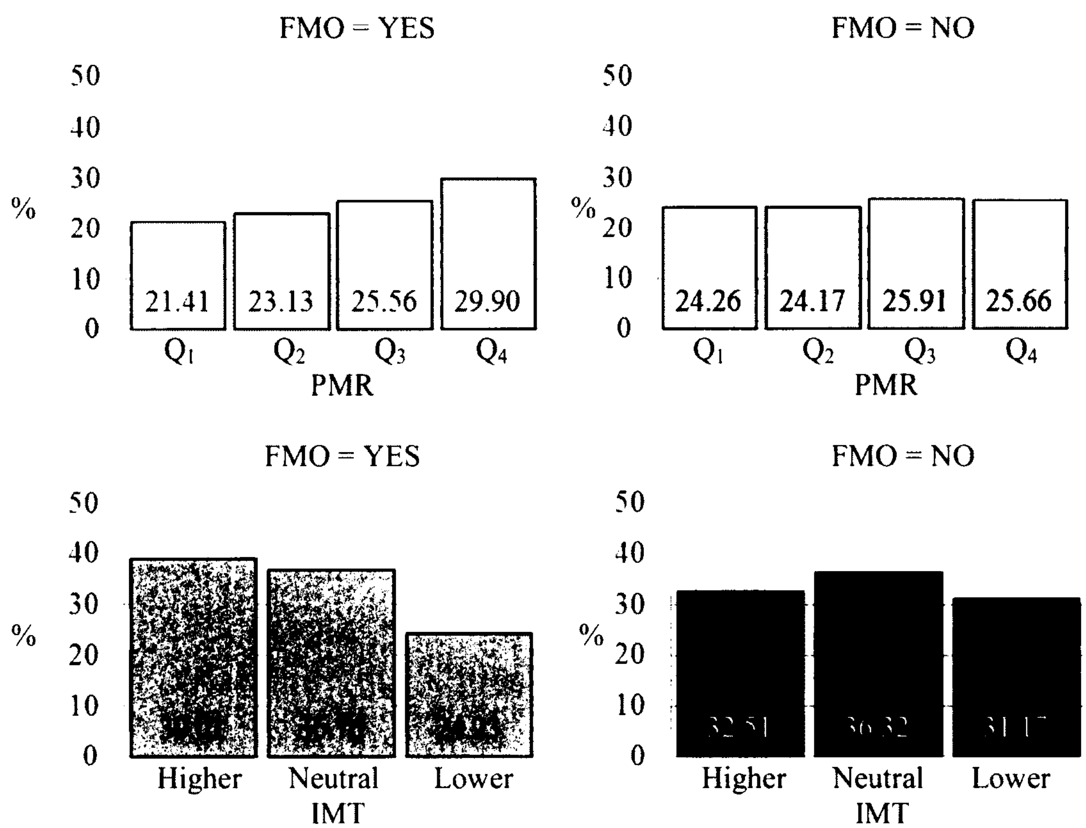

Figure 44. BNM Computational Model #5 Reward System and Safety Culture Characteristic Nodal Conditional Probabilities

E.3. QUALITY ASSURANCE CHARACTERISTIC DATA RESULTS FOR BAYESIAN NETWORK MODELS

Table 80. BNM Computational Model #1 Quality Assurance Characteristic Nodal Probability Distribution

FMO =	YES	NO
PMR Q_1	0.2705	0.2490
PMR Q_2	0.2493	0.2495
PMR Q_3	0.2410	0.2501
PMR Q_4	0.2392	0.2514
CMR Q_1	0.3464	0.2373
CMR Q_2	0.1873	0.2617
CMR Q_3	0.1856	0.2525
CMR Q_4	0.2807	0.2485

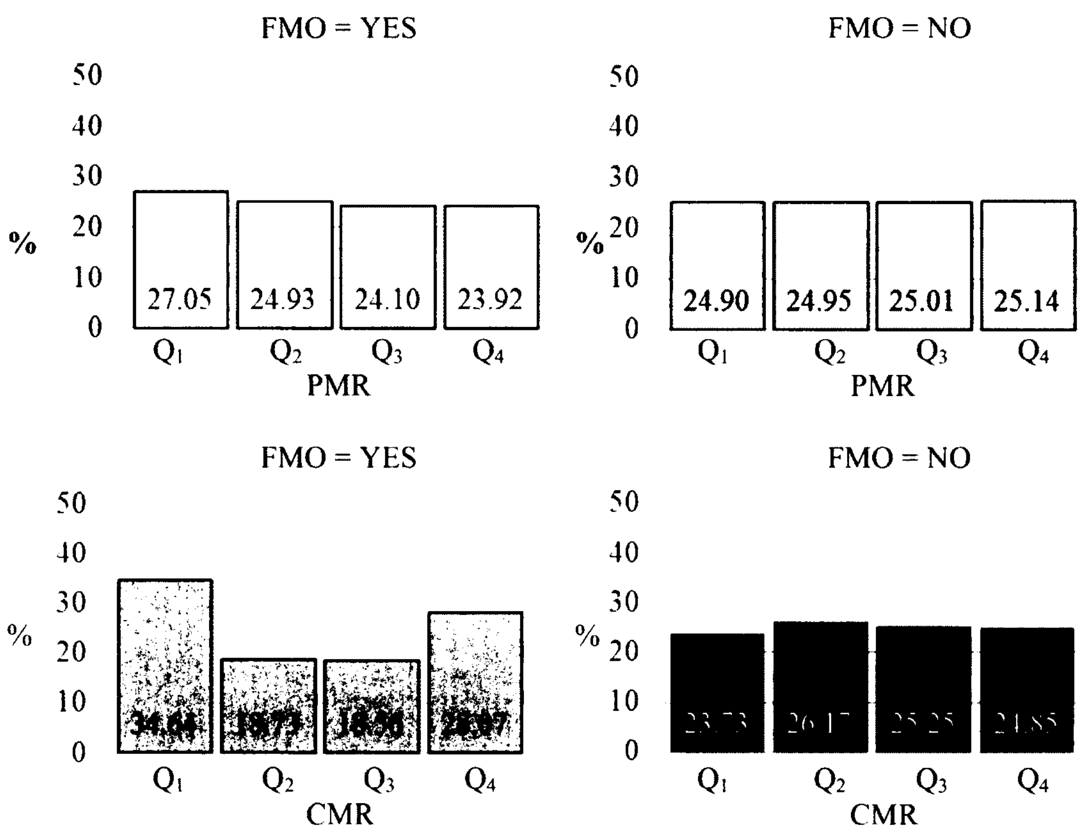

Figure 45. BNM Computational Model #1 Quality Assurance Characteristic Nodal Conditional Probabilities

Table 81. BNM Computational Model #2 Quality Assurance Characteristic Nodal Probability Distribution

FMO =	YES	NO
PMR Q_1	0.2737	0.2488
PMR Q_2	0.2405	0.2502
PMR Q_3	0.2443	0.2499
PMR Q_4	0.2415	0.2511
CMR Q_1	0.3470	0.2372
CMR Q_2	0.1884	0.2616
CMR Q_3	0.1849	0.2526
CMR Q_4	0.2797	0.2486

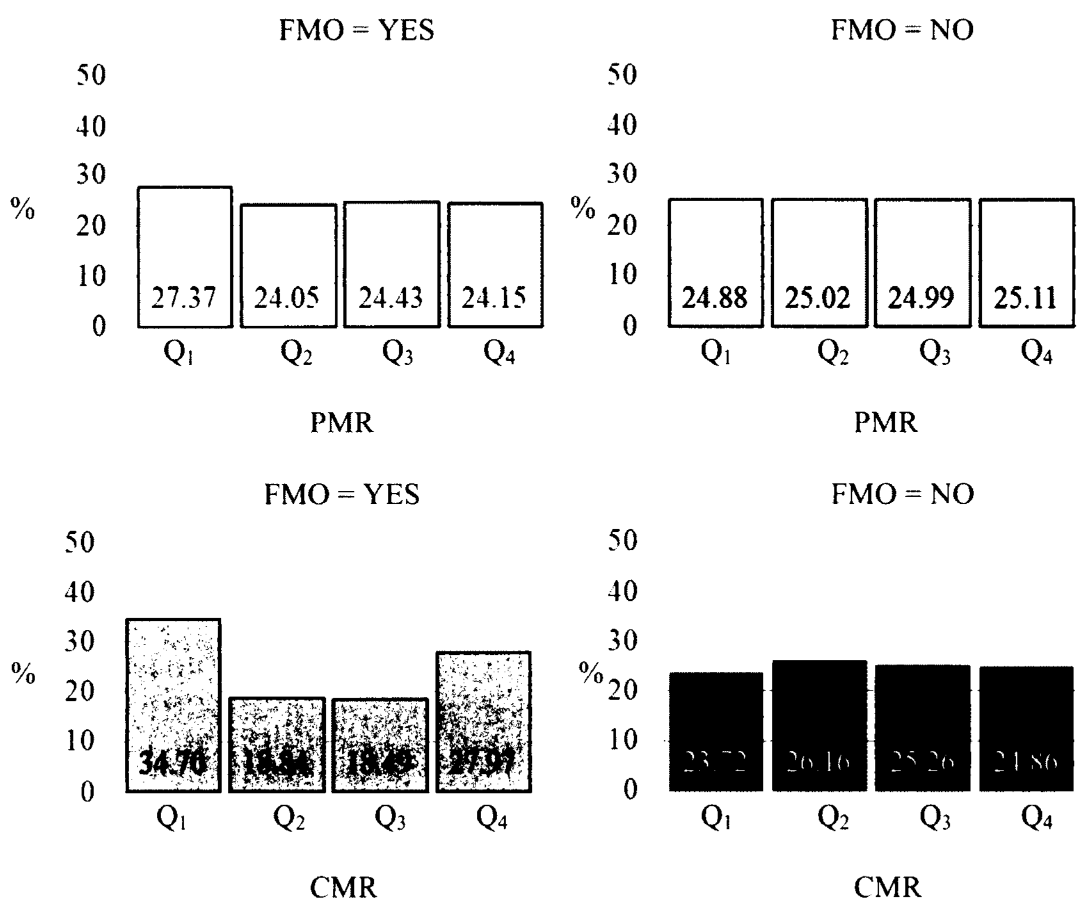

Figure 46. BNM Computational Model #2 Quality Assurance Characteristic Nodal Conditional Probabilities

Table 82. BNM Computational Model #3 Quality Assurance Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.1719	0.2464
CMR Q_2	0.4065	0.2475
CMR Q_3	0.1408	0.2530
CMR Q_4	0.2808	0.2531
IMT Higher	0.2258	0.3197
IMT Neutral	0.4669	0.3743
IMT Lower	0.3073	0.3059

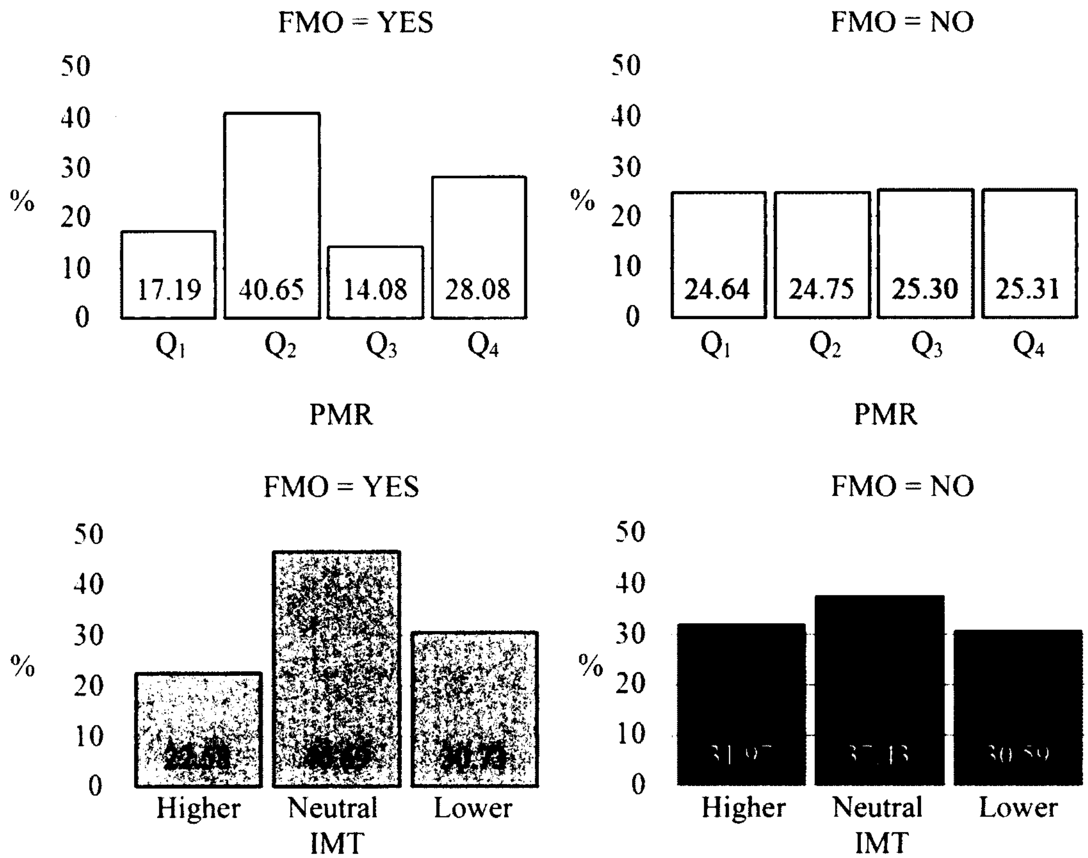

Figure 47. BNM Computational Model #3 Quality Assurance Characteristic Nodal Conditional Probabilities

Table 83. BNM Computational Model #4 Quality Assurance Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.1748	0.2462
CMR Q_2	0.4014	0.2478
CMR Q_3	0.1423	0.2529
CMR Q_4	0.2815	0.2531
IMT Higher	0.3231	0.3145
IMT Neutral	0.3726	0.3794
IMT Lower	0.3043	0.3061

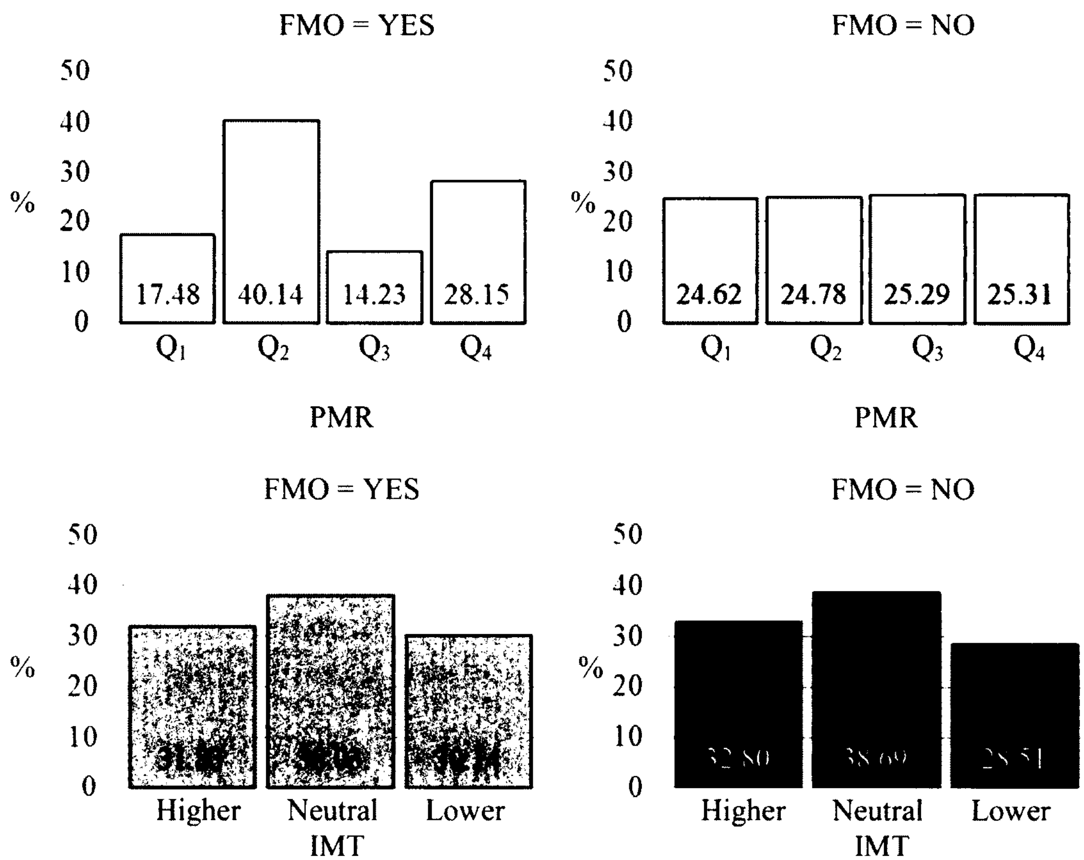

Figure 48. BNM Computational Model #4 Quality Assurance Characteristic Nodal Conditional Probabilities

Table 84. BNM Computational Model #5 Quality Assurance Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.1727	0.2477
CMR Q_2	0.4058	0.2470
CMR Q_3	0.1411	0.2533
CMR Q_4	0.2804	0.2520
IMT Higher	0.2251	0.3184
IMT Neutral	0.4680	0.3747
IMT Lower	0.3069	0.3069

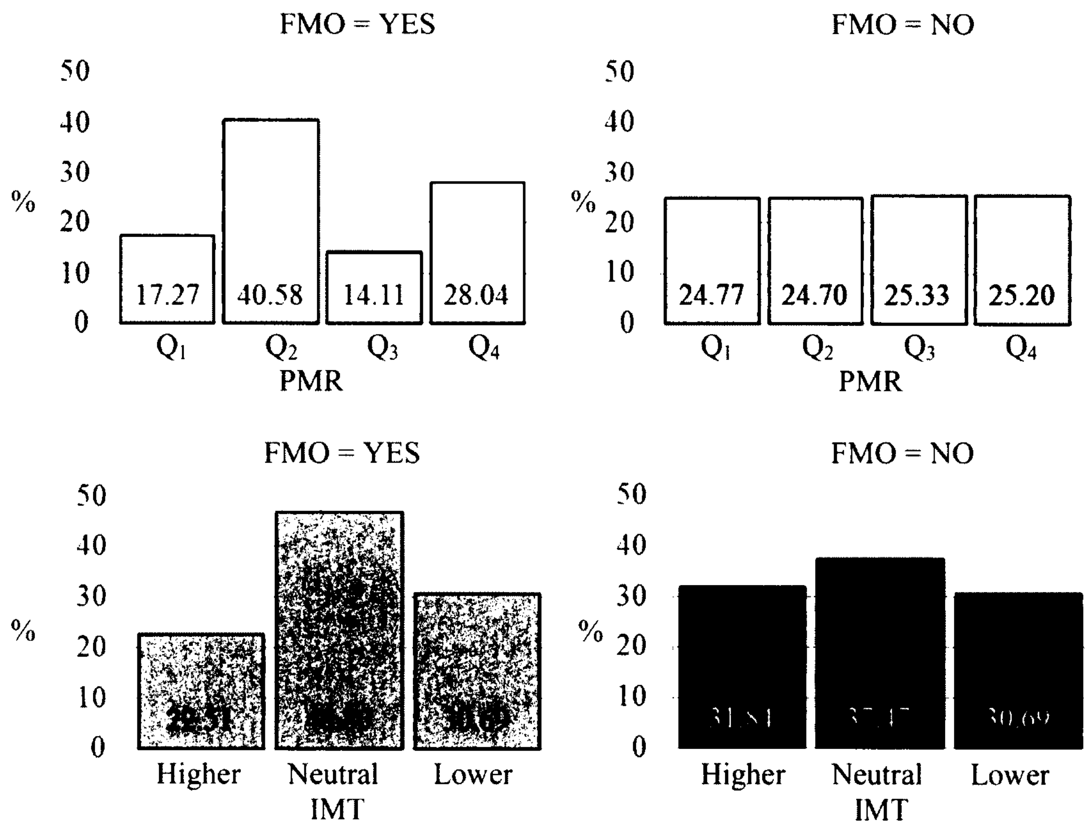

Figure 49. BNM Computational Model #5 Quality Assurance Characteristic Nodal Conditional Probabilities

E.4. RISK MANAGEMENT CHARACTERISTIC DATA RESULTS FOR BAYESIAN NETWORK MODELS

Table 85. BNM Computational Model #1 Risk Management Characteristic Nodal Probability Distribution

FMO =	YES	NO
PMR Q_1	0.2847	0.2479
PMR Q_2	0.2409	0.2501
PMR Q_3	0.2360	0.2505
PMR Q_4	0.2384	0.2514
CMR Q_1	0.3491	0.2106
CMR Q_2	0.1924	0.2544
CMR Q_3	0.1704	0.2699
CMR Q_4	0.2881	0.2651

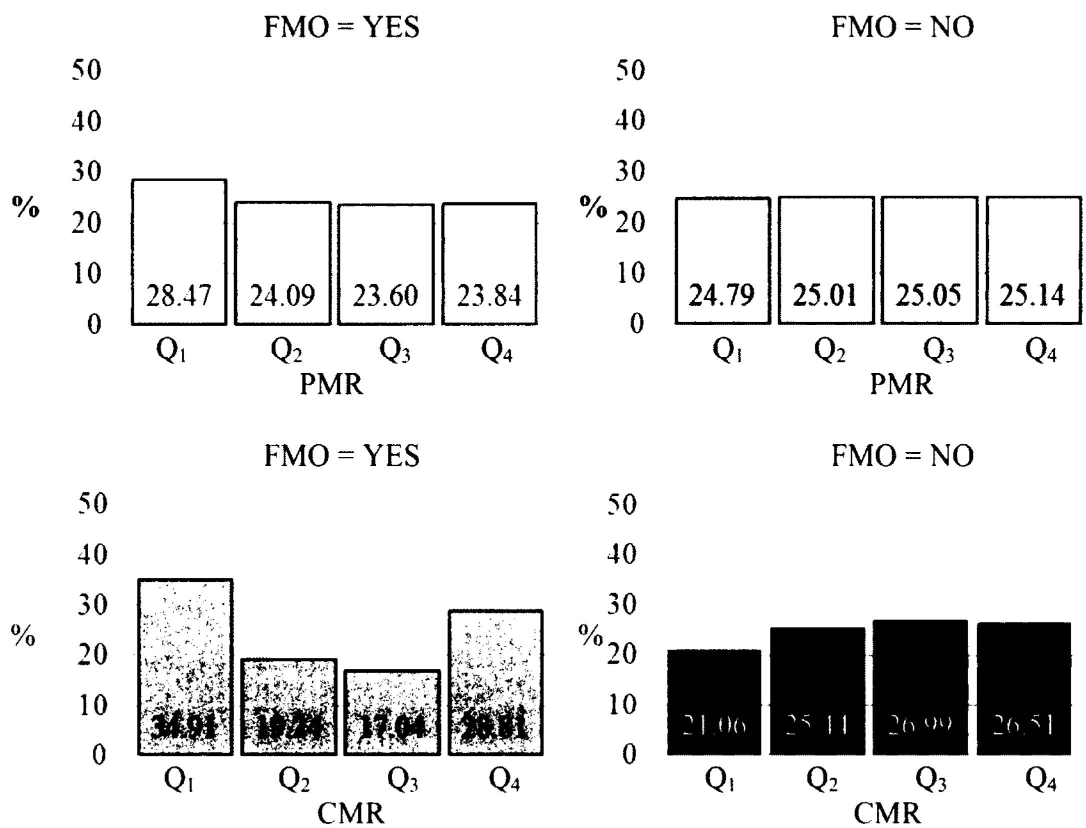

Figure 50. BNM Computational Model #1 Risk Management Characteristic Nodal Conditional Probabilities

Table 86. BNM Computational Model #2 Risk Management Characteristic Nodal Probability Distribution

FMO =	YES	NO
PMR Q_1	0.2761	0.2486
PMR Q_2	0.2447	0.2498
PMR Q_3	0.2419	0.2501
PMR Q_4	0.2373	0.2515
CMR Q_1	0.3468	0.2108
CMR Q_2	0.1901	0.2545
CMR Q_3	0.1729	0.2697
CMR Q_4	0.2902	0.2650

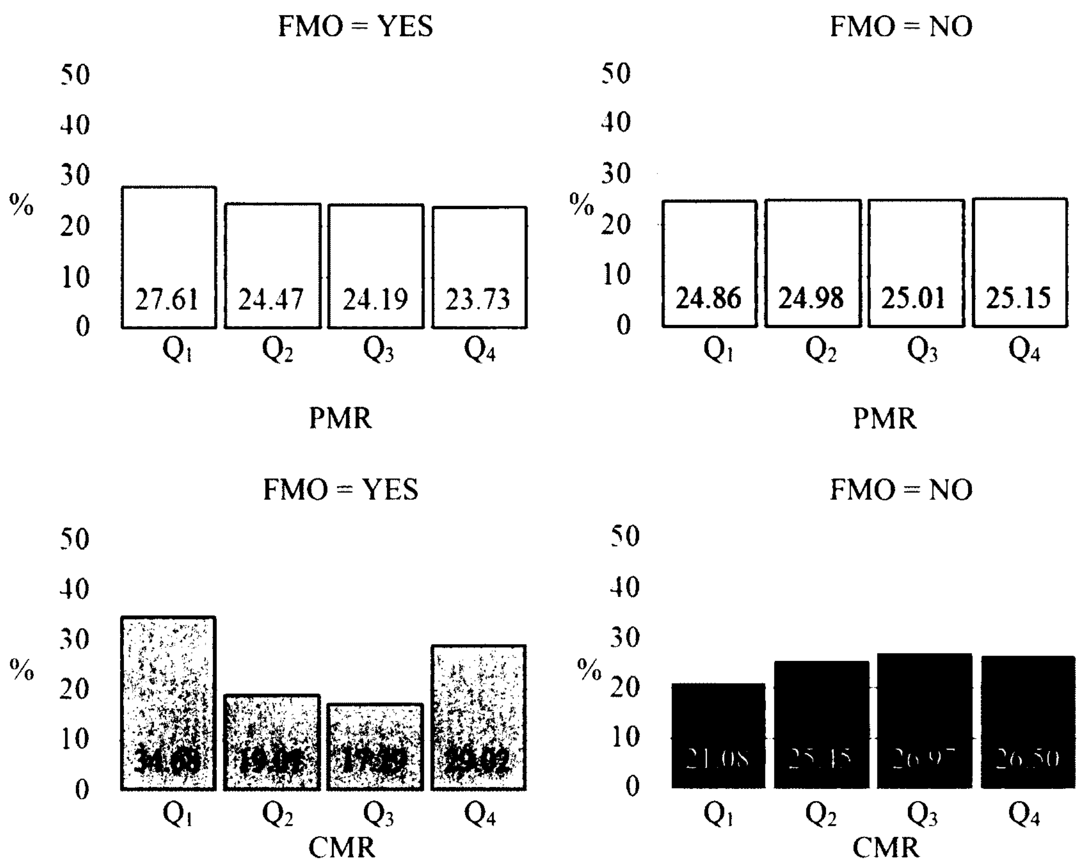

Figure 51. BNM Computational Model #2 Risk Management Characteristic Nodal Conditional Probabilities

Table 87. BNM Computational Model #3 Risk Management Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2991	0.2178
CMR Q_2	0.2030	0.2532
CMR Q_3	0.2659	0.2619
CMR Q_4	0.2320	0.2671
IMT Higher	0.4029	0.3473
IMT Neutral	0.2604	0.3708
IMT Lower	0.3367	0.2819

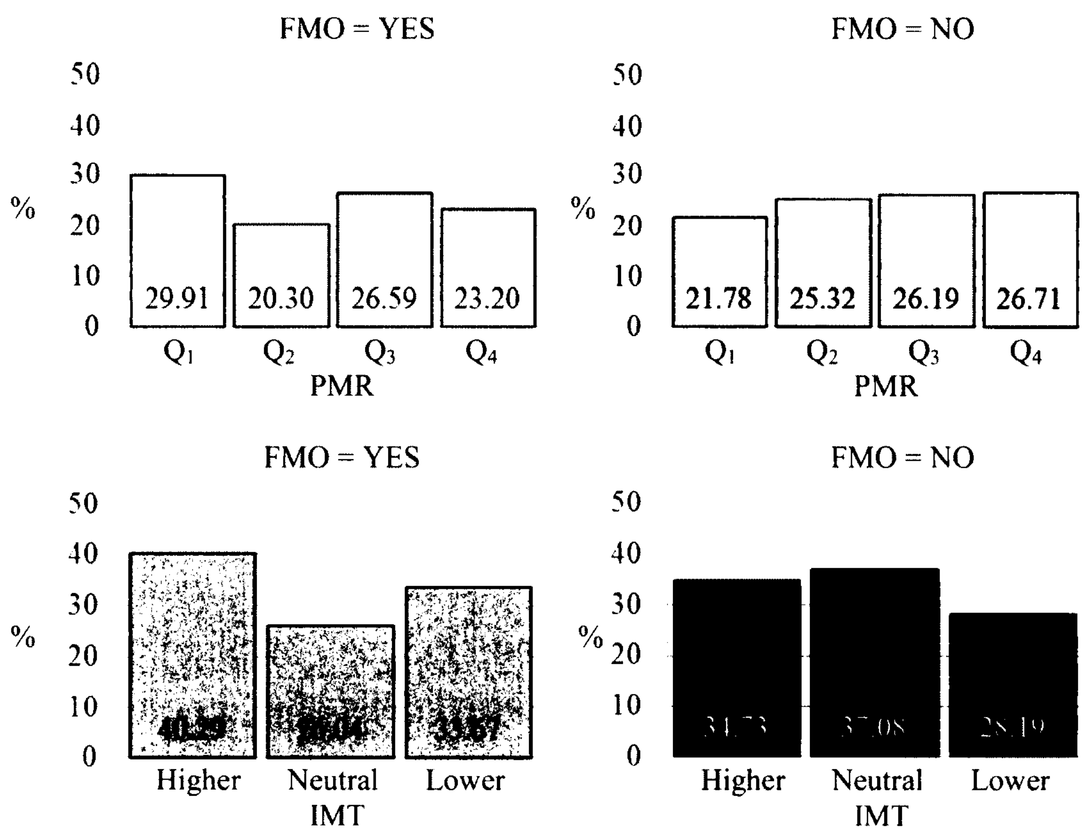

Figure 52. BNM Computational Model #3 Risk Management Characteristic Nodal Conditional Probabilities

Table 88. BNM Computational Model #4 Risk Management Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2962	0.2179
CMR Q_2	0.2065	0.2530
CMR Q_3	0.2646	0.2620
CMR Q_4	0.2327	0.2671
IMT Higher	0.3195	0.3517
IMT Neutral	0.3735	0.3648
IMT Lower	0.3070	0.2835

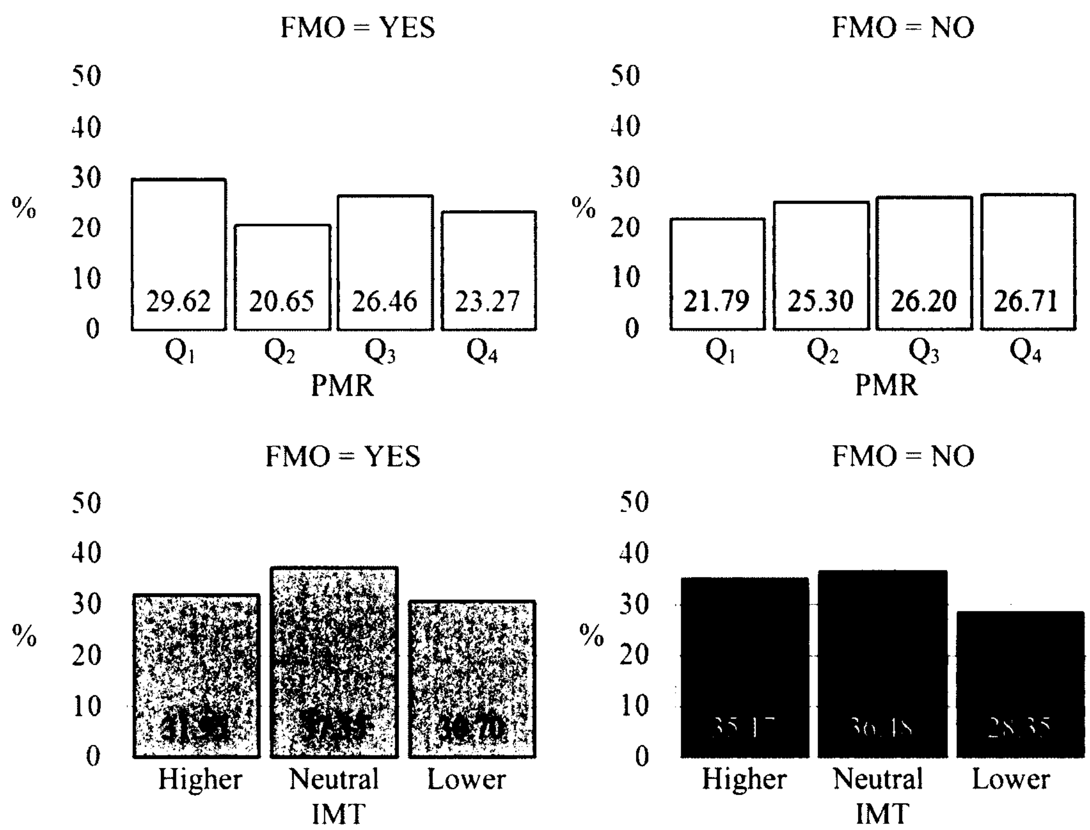

Figure 53. BNM Computational Model #4 Risk Management Characteristic Nodal Conditional Probabilities

Table 89. BNM Computational Model #5 Risk Management Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2996	0.2181
CMR Q_2	0.2029	0.2531
CMR Q_3	0.2658	0.2620
CMR Q_4	0.2317	0.2668
IMT Higher	0.4027	0.3471
IMT Neutral	0.2607	0.3710
IMT Lower	0.3366	0.2819

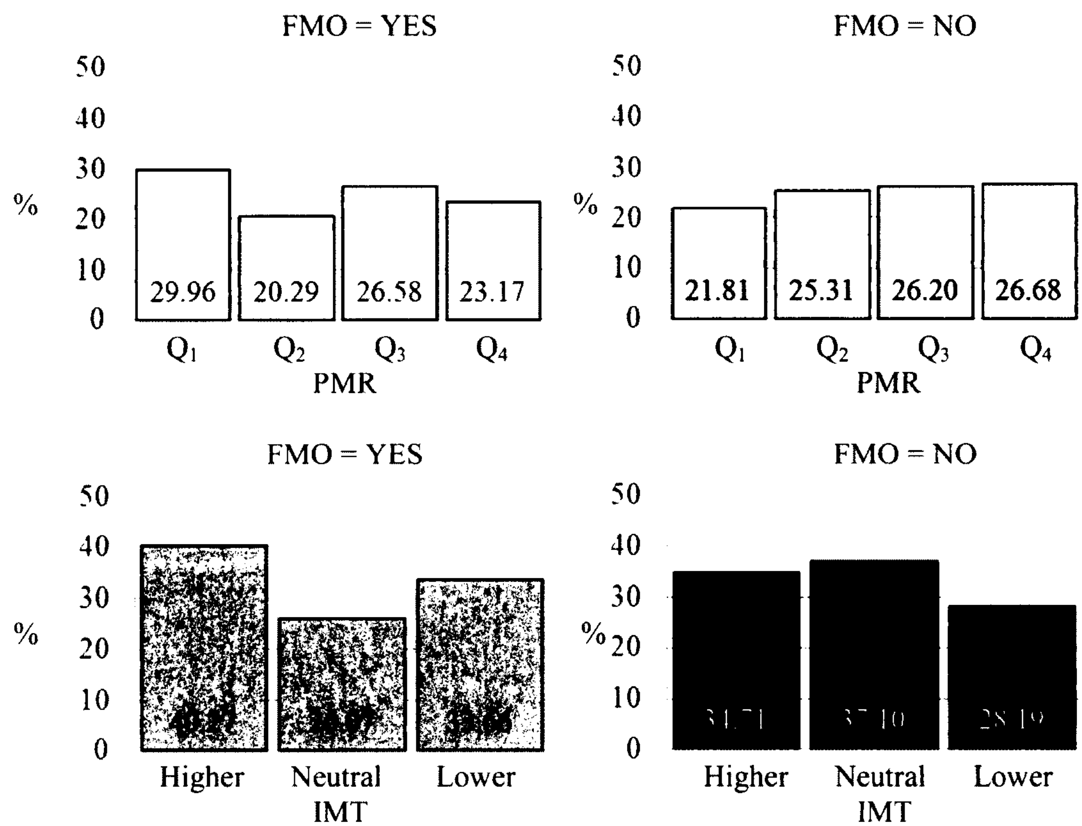

Figure 54. BNM Computational Model #5 Risk Management Characteristic Nodal Conditional Probabilities

E.5. COMMAND AND CONTROL CHARACTERISTIC DATA RESULTS FOR BAYESIAN NETWORK MODELS

Table 90. BNM Computational Model #1 Command and Control Characteristic Nodal Probability Distribution

FMO =	YES	NO
PMR Q_1	0.2731	0.2488
PMR Q_2	0.2303	0.2509
PMR Q_3	0.2482	0.2496
PMR Q_4	0.2484	0.2507
CMR Q_1	0.3749	0.2262
CMR Q_2	0.1537	0.2623
CMR Q_3	0.1708	0.2539
CMR Q_4	0.3006	0.2576

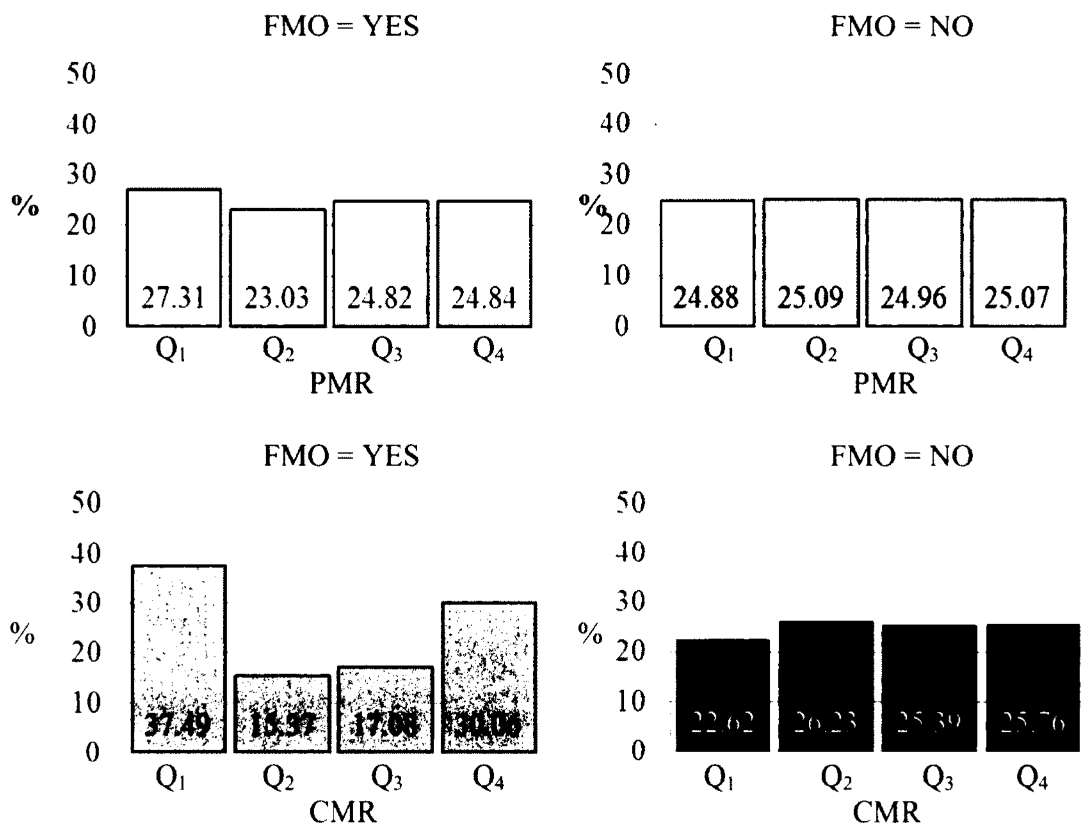

Figure 55. BNM Computational Model #1 Command and Control Characteristic Nodal Conditional Probabilities

Table 91. BNM Computational Model #2 Command and Control Characteristic Nodal Probability Distribution

FMO =	YES	NO
PMR Q_1	0.2715	0.2489
PMR Q_2	0.2388	0.2503
PMR Q_3	0.2443	0.2499
PMR Q_4	0.2454	0.2509
CMR Q_1	0.3736	0.2263
CMR Q_2	0.1546	0.2622
CMR Q_3	0.1693	0.2540
CMR Q_4	0.3025	0.2575

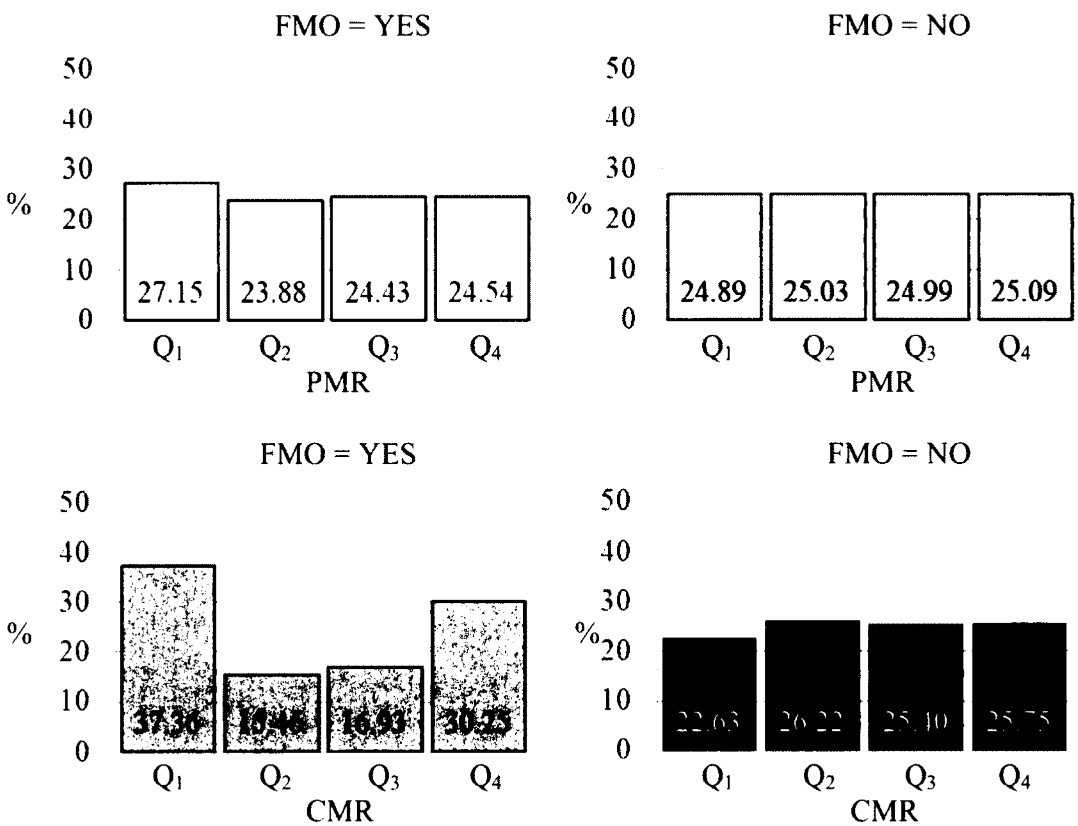

Figure 56. BNM Computational Model #2 Command and Control Characteristic Nodal Conditional Probabilities

Table 92. BNM Computational Model #3 Command and Control Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2728	0.2343
CMR Q_2	0.2622	0.2535
CMR Q_3	0.2039	0.2494
CMR Q_4	0.2611	0.2627
IMT Higher	0.2805	0.3180
IMT Neutral	0.3931	0.3983
IMT Lower	0.3264	0.2837

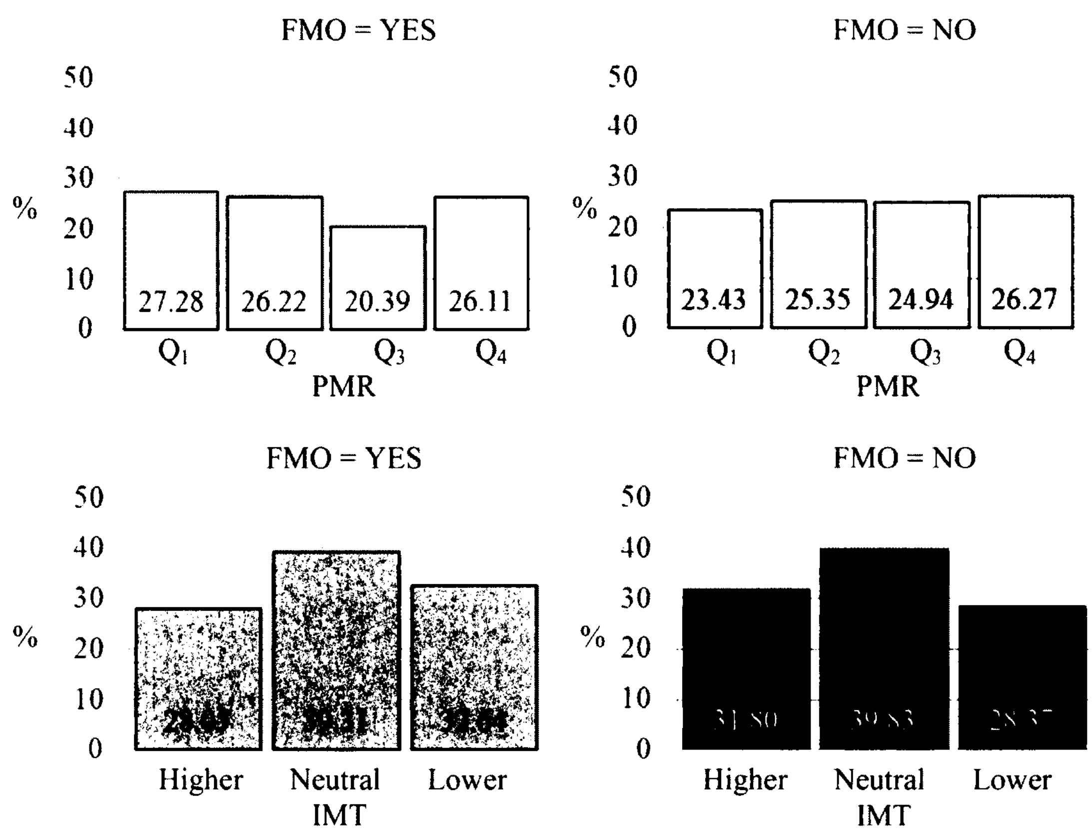

Figure 57. BNM Computational Model #3 Command and Control Characteristic Nodal Conditional Probabilities

Table 93. BNM Computational Model #4 Command and Control Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2707	0.2344
CMR Q_2	0.2670	0.2533
CMR Q_3	0.2033	0.2495
CMR Q_4	0.2590	0.2628
IMT Higher	0.3001	0.3170
IMT Neutral	0.4011	0.3978
IMT Lower	0.2988	0.2852

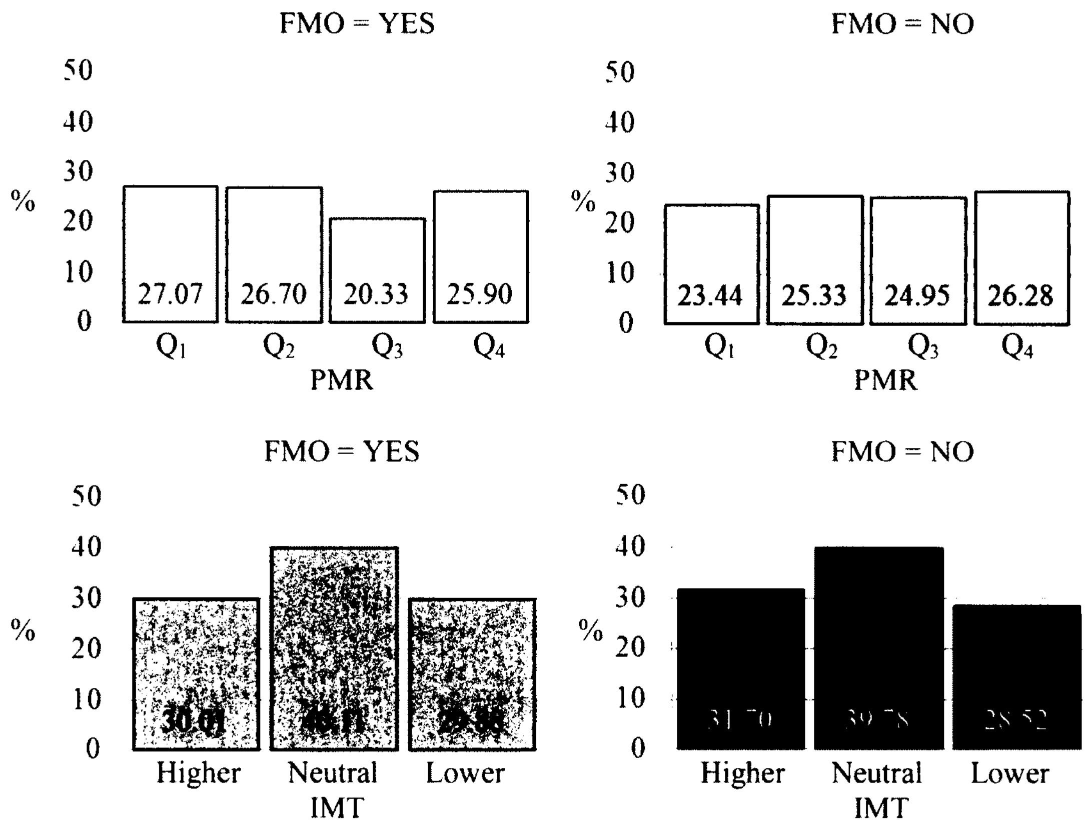

Figure 58. BNM Computational Model #4 Command and Control Characteristic Nodal Conditional Probabilities

Table 94. BNM Computational Model #5 Command and Control Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2741	0.2353
CMR Q_2	0.2621	0.2535
CMR Q_3	0.2041	0.2498
CMR Q_4	0.2597	0.2614
IMT Higher	0.2796	0.3174
IMT Neutral	0.3939	0.3987
IMT Lower	0.3265	0.2839

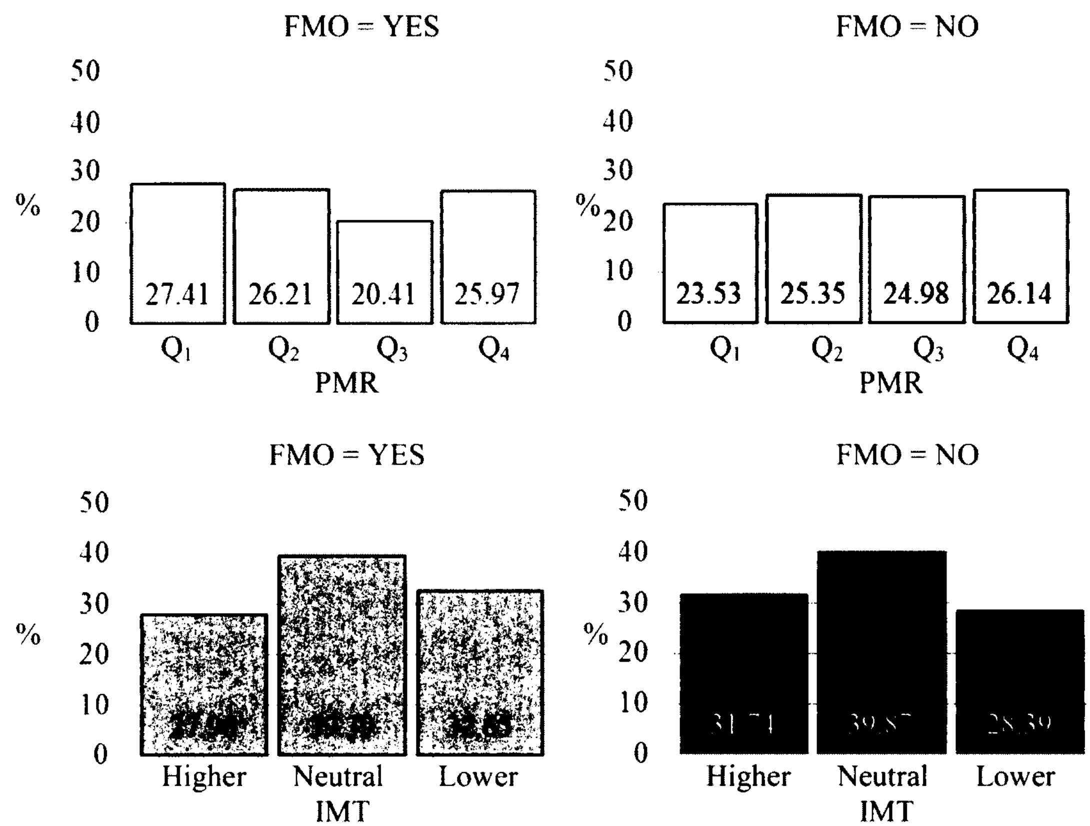

Figure 59. BNM Computational Model #5 Command and Control Characteristic Nodal Conditional Probabilities

E.6. COMMUNICATION / FUNCTIONAL RELATIONSHIPS CHARACTERISTIC DATA RESULTS FOR BAYESIAN NETWORK MODELS

Table 95. BNM Computational Model #1 Communication / Functional Relationship Characteristic Nodal Probability Distribution

FMO =	YES	NO
PMR Q_1	0.2613	0.2497
PMR Q_2	0.2400	0.2502
PMR Q_3	0.2280	0.2511
PMR Q_4	0.2707	0.2490
CMR Q_1	0.3520	0.2227
CMR Q_2	0.1366	0.2665
CMR Q_3	0.1517	0.2576
CMR Q_4	0.3597	0.2532

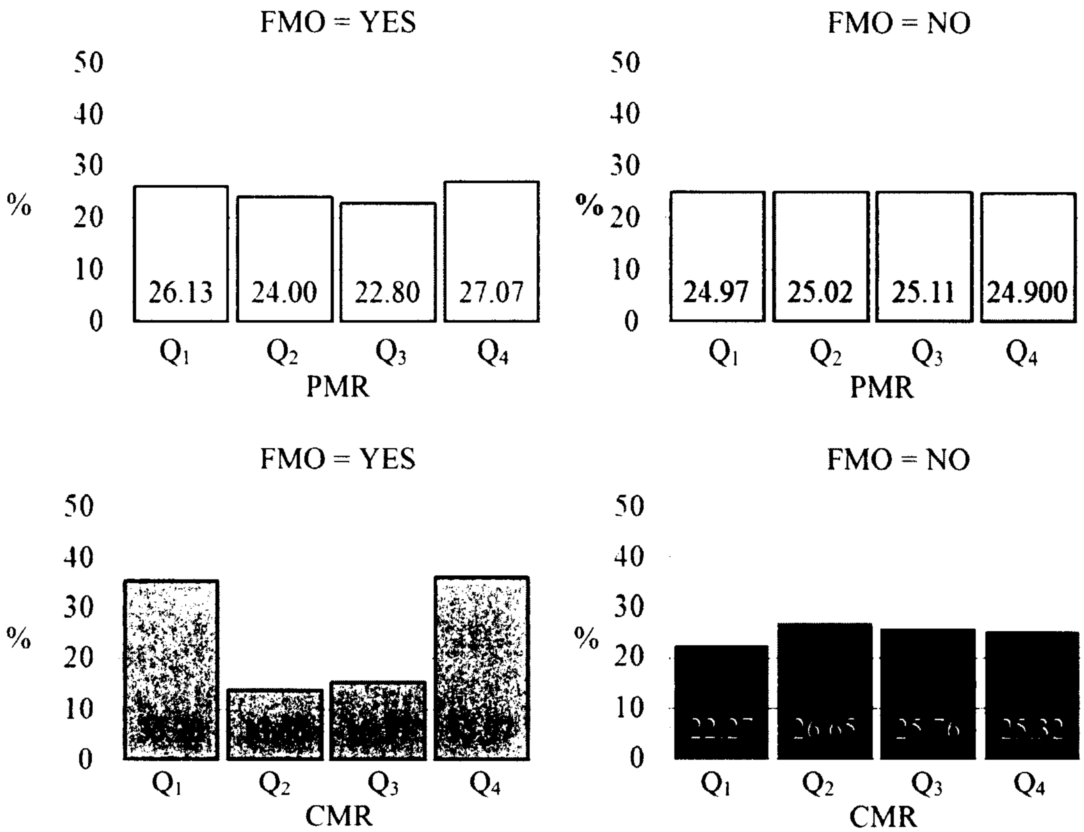

Figure 60. BNM Computational Model #1 Communication / Functional Relationship Characteristic Nodal Conditional Probabilities

Table 96. BNM Computational Model #2 Communication / Functional Relationship Characteristic Nodal Probability Distribution

FMO =	YES	NO
PMR Q_1	0.2623	0.2496
PMR Q_2	0.2371	0.2504
PMR Q_3	0.2334	0.2507
PMR Q_4	0.2672	0.2493
CMR Q_1	0.3521	0.2227
CMR Q_2	0.1371	0.2665
CMR Q_3	0.1490	0.2578
CMR Q_4	0.3618	0.2530

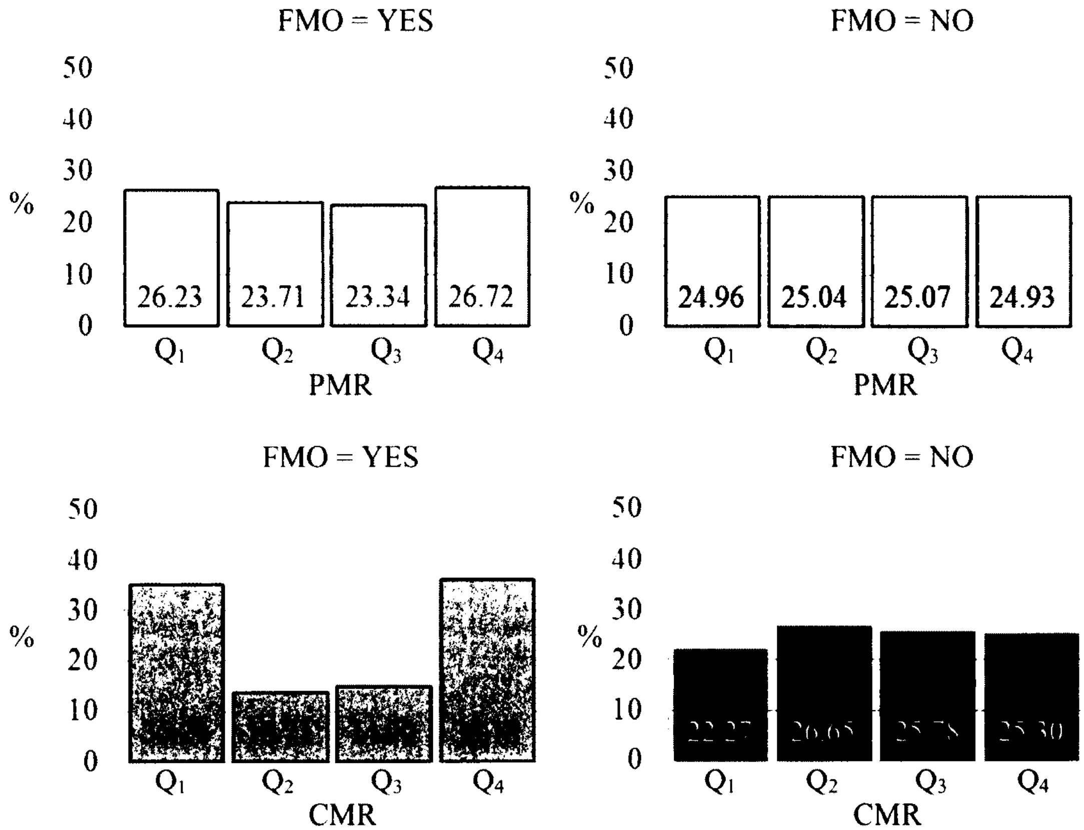

Figure 61. BNM Computational Model #2 Communication / Functional Relationship Characteristic Nodal Conditional Probabilities

Table 97. BNM Computational Model #3 Communication / Functional Relationship Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2023	0.2360
CMR Q_2	0.3535	0.2530
CMR Q_3	0.1730	0.2531
CMR Q_4	0.2712	0.2579
IMT Higher	0.3268	0.3328
IMT Neutral	0.3291	0.3818
IMT Lower	0.3441	0.2854

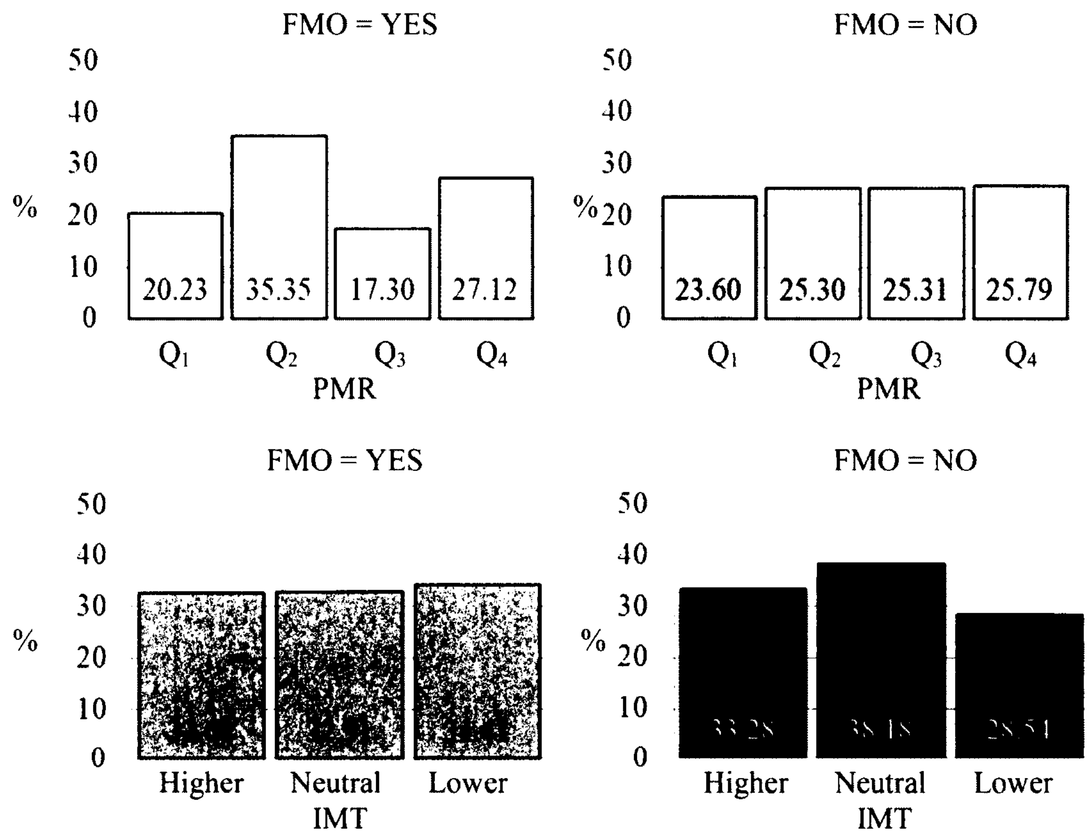

Figure 62. BNM Computational Model #3 Communication / Functional Relationship Characteristic Nodal Conditional Probabilities

Table 98. BNM Computational Model #4 Communication / Functional Relationship Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2007	0.2361
CMR Q_2	0.3568	0.2528
CMR Q_3	0.1731	0.2531
CMR Q_4	0.2694	0.2580
IMT Higher	0.3390	0.3322
IMT Neutral	0.3700	0.3796
IMT Lower	0.2910	0.2882

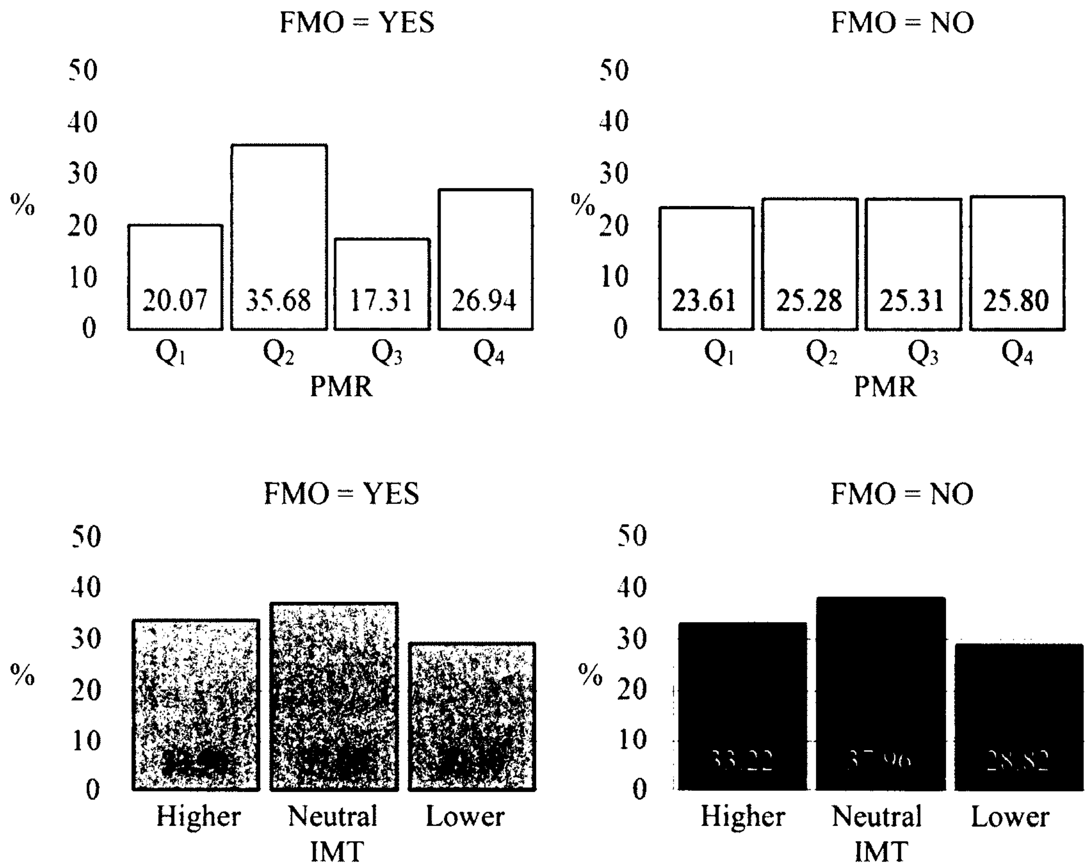

Figure 63. BNM Computational Model #4 Communication / Functional Relationship Characteristic Nodal Conditional Probabilities

Table 99. BNM Computational Model #5 Communication / Functional Relationship Characteristic Nodal Probability Distribution

FMO =	YES	NO
CMR Q_1	0.2026	0.2368
CMR Q_2	0.3541	0.2536
CMR Q_3	0.1726	0.2524
CMR Q_4	0.2707	0.2572
IMT Higher	0.3257	0.3315
IMT Neutral	0.3302	0.3829
IMT Lower	0.3441	0.2856

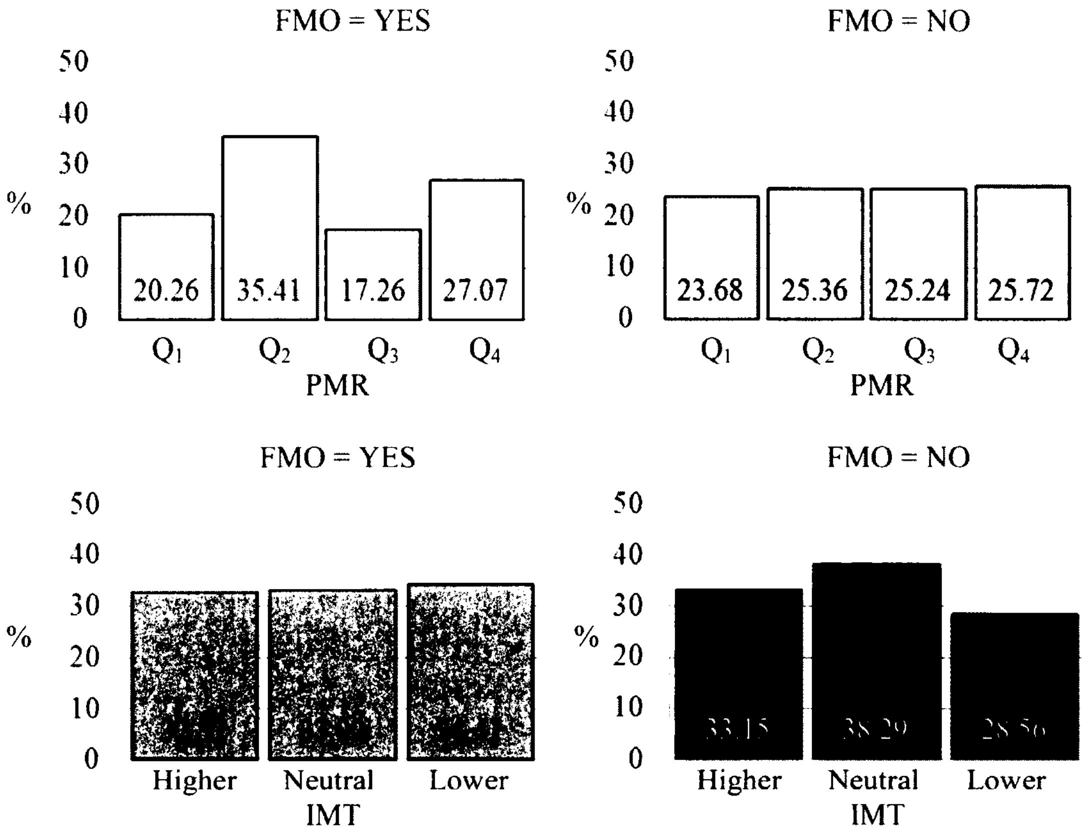

Figure 64. BNM Computational Model #5 Communication / Functional Relationship Characteristic Nodal Conditional Probabilities

APPENDIX F. BAYESIAN NETWORK MODEL DATA SUPPORTING ANSWER TO RESEARCH QUESTION 2

Table 100. Attributes of Probability Density Distributions of BNM #1 Output when FMO = YES

Model	MOSE Charac –teristic	Proba – bility Variable	Depiction	Mode	Skew-ness$_1$	Skew-ness$_2$	Slope
BNM #1	All	PMR	Bimodal	Q_1, Q_4	1.0101	1.0050	-0.1725
		CMR	Bimodal	Q_1, Q_4	0.9728	0.9864	-1.2525
BNM #1	PA	PMR	Bimodal	Q_1, Q_4	0.9712	0.9856	-0.1450
		CMR	Bimodal	Q_1, Q_4	1.0462	1.0231	-1.2675
BNM #1	RS/SC	PMR	Bimodal	Q_1, Q_4	0.9873	0.9936	-0.3500
		CMR	Bimodal	Q_1, Q_4	0.9869	0.9934	-1.0650
BNM #1	**QA**	**PMR**	**Unimodal**	**Q_1**	**0.9238**	**0.9619**	**-0.7825**
		CMR	Bimodal	Q_1, Q_4	0.8737	0.9369	-1.6425
BNM #1	**RM**	**PMR**	**Unimodal**	**Q_1**	**0.9026**	**0.9513**	**-1.1575**
		CMR	Bimodal	Q_1, Q_4	0.8467	0.9234	-1.5250
BNM #1	C2	PMR	Unimodal	Q_1	0.9865	0.9932	-0.6175
		CMR	Bimodal	Q_1, Q_4	0.8918	0.9459	-1.8575
BNM #1	C/FR	PMR	Bimodal	Q_1, Q_4	0.9948	0.9974	0.2350
		CMR	Bimodal	Q_1, Q_4	1.0467	1.0233	0.1925

Table 101. Attributes of Probability Density Distributions of BNM #1 Output when FMO = NO

Model	MOSE Charac –teristic	Proba – bility Variable	Depiction	Mode	Skew-ness$_1$	Skew-ness$_2$	Slope
BNM #1	All	PMR	Uniform	None	0.9992	0.9996	0.0125
		CMR	Unimodal	Q_2	1.0568	1.0284	0.8075
BNM #1	PA	PMR	Uniform	None	1.0020	1.0010	0.0100
		CMR	Unimodal	Q_3	1.0325	1.0163	0.3125
BNM #1	RS/SC	PMR	Uniform	None	1.0012	1.0006	0.0275
		CMR	Unimodal	Q_3	1.0807	1.0404	0.5775
BNM #1	QA	PMR	Uniform	None	1.0060	1.0030	0.0600
		CMR	Unimodal	Q_2	1.0040	1.0020	0.2800
BNM #1	RM	PMR	Uniform	None	1.0080	1.0040	0.0875
		CMR	Unimodal	Q_3	1.1505	1.0753	1.3625
BNM #1	C2	PMR	Uniform	None	1.0012	1.0006	0.0475
		CMR	Unimodal	Q_2	1.0471	1.0235	0.7850
BNM #1	C/FR	PMR	Uniform	None	1.0004	1.0002	-0.0175
		CMR	Unimodal	Q_2	1.0442	1.0221	0.7625

Table 102. Attributes of Probability Density Distributions of BNM #2 Output when FMO = YES

Model	MOSE Charac –teristic	Proba – bility Variable	Depiction	Mode	Skew-ness$_1$	Skew-ness$_2$	Slope
BNM #2	All	PMR	Bimodal	Q_1, Q_4	0.9767	0.9883	-0.3025
		CMR	Bimodal	Q_1, Q_4	0.9751	0.9876	-1.1750
BNM #2	PA	PMR	Bimodal	Q_1, Q_4	0.9577	0.9789	-0.3950
		CMR	Bimodal	Q_1, Q_4	1.0492	1.0246	-1.2400
BNM #2	RS/SC	PMR	Bimodal	Q_1, Q_4	0.9643	0.9821	-0.3325
		CMR	Bimodal	Q_1, Q_4	0.9920	0.9960	-0.9475
BNM #2	**QA**	**PMR**	**Unimodal**	**Q_1**	**0.9448**	**0.9724**	**-0.8050**
		CMR	Bimodal	Q_1, Q_4	0.8678	0.9339	-1.6825
BNM #2	**RM**	**PMR**	**Unimodal**	**Q_1**	**0.9201**	**0.9601**	**-0.9700**
		CMR	Bimodal	Q_1, Q_4	0.8625	0.9313	-1.4150
BNM #2	**C2**	**PMR**	**Unimodal**	**Q_1**	**0.9596**	**0.9798**	**-0.6525**
		CMR	Bimodal	Q_1, Q_4	0.8932	0.9466	-1.7775
BNM #2	C/FR	PMR	Bimodal	Q_1, Q_4	1.0024	1.0012	0.1225
		CMR	Bimodal	Q_1, Q_4	1.0442	1.0221	0.2425

Table 103. Attributes of Probability Density Distributions of BNM #2 Output when FMO = NO

Model	MOSE Charac –teristic	Proba – bility Variable	Depiction	Mode	Skew-ness$_1$	Skew-ness$_2$	Slope
BNM #2	All	PMR	Uniform	None	1.0016	1.0008	0.0225
		CMR	Unimodal	Q_2	1.0568	1.0284	0.8000
BNM #2	PA	PMR	Uniform	None	1.0032	1.0016	0.0300
		CMR	Unimodal	Q_3	1.0321	1.0161	0.3075
BNM #2	RS/SC	PMR	Uniform	None	1.0028	1.0014	0.0250
		CMR	Unimodal	Q_3	1.0803	1.0401	0.5675
BNM #2	QA	PMR	Uniform	None	1.0040	1.0020	0.0575
		CMR	Unimodal	Q_2	1.0048	1.0024	0.2850
BNM #2	RM	PMR	Uniform	None	1.0064	1.0032	0.0725
		CMR	Unimodal	Q_3	1.1492	1.0746	1.3550
BNM #2	C2	PMR	Uniform	None	1.0032	1.0016	0.0500
		CMR	Unimodal	Q_2	1.0471	1.0235	0.7800
BNM #2	C/FR	PMR	Uniform	None	1.0000	1.0000	-0.0075
		CMR	Unimodal	Q_2	1.0442	1.0221	0.7575

Table 104. Attributes of Probability Density Distributions of BNM #3 Output when FMO = YES

Model	MOSE Charac –teristic	Proba – bility Variable	Depiction	Mode	Skew-ness$_1$	Skew-ness$_2$	Slope
BNM #3	All	PMR	Unimodal	Q_2	0.8818	0.9409	-0.1400
		IMT	Unimodal	Neutral	0.9259	0.9629	-1.2800
BNM #3	PA	PMR	Bimodal	Q_1, Q_4	0.8580	0.9290	-0.2300
		IMT	Unimodal	Neutral	1.0442	1.0221	0.7200
BNM #3	RS/SC	PMR	Unimodal	Q_4	1.2543	1.1271	2.1950
		IMT	Unimodal	Higher	0.7391	0.8696	-5.0000
BNM #3	QA	PMR	Bimodal	Q_2, Q_4	0.7289	0.8645	2.7225
		IMT	Unimodal	Neutral	1.1775	1.0887	2.7167
BNM #3	RM	PMR	Bimodal	Q_1, Q_3	0.9916	0.9958	-1.6775
		IMT	Bimodal	Hi, Low	0.8758	0.9379	-2.2067
BNM #3	C2	PMR	Bimodal	Q_1, Q_4	0.8692	0.9346	-0.2925
		IMT	Unimodal	Neutral	1.0962	1.0481	1.5300
BNM #3	C/FR	PMR	Bimodal	Q_2, Q_4	0.7992	0.8996	1.7225
		IMT	Unimodal	Low	1.0352	1.0176	0.5767

Table 105. Attributes of Probability Density Distributions of BNM #3 Output when FMO = NO

Model	MOSE Charac –teristic	Proba – bility Variable	Depiction	Mode	Skew-ness$_1$	Skew-ness$_2$	Slope
BNM #3	**All**	**PMR**	**Unimodal**	**Q_4**	**1.0695**	**1.0348**	**1.0300**
		IMT	Unimodal	Neutral	0.9199	0.9600	-1.3900
BNM #3	PA	PMR	Unimodal	Q_3	1.0525	1.0263	0.3867
		IMT	Unimodal	Neutral	0.9845	0.9923	-0.2600
BNM #3	RS/SC	PMR	Unimodal	Q_3	1.0717	1.0358	0.5700
		IMT	Unimodal	Neutral	0.9687	0.9843	-0.5300
BNM #3	**QA**	**PMR**	**Unimodal**	**Q_4**	**1.0247**	**1.0124**	**0.2233**
		IMT	Unimodal	Neutral	0.9730	0.9865	-0.4600
BNM #3	**RM**	**PMR**	**Unimodal**	**Q_4**	**1.1231**	**1.0616**	**1.6433**
		IMT	Unimodal	Neutral	0.8772	0.9386	-2.1800
BNM #3	C2	PMR	Bimodal	Q_2, Q_4	1.0500	1.0250	0.9467
		IMT	Unimodal	Neutral	0.9337	0.9668	-1.1433
BNM #3	C/FR	PMR	Unimodal	Q_1	1.0450	1.0225	0.7300
		IMT	Unimodal	Neutral	0.9095	0.9547	-1.5800

Table 106. Attributes of Probability Density Distributions of BNM #4 Output when FMO = YES

Model	MOSE Charac –teristic	Proba – bility Variable	Depiction	Mode	Skew-ness$_1$	Skew-ness$_2$	Slope
BNM #4	All	PMR	Unimodal	Q_2	0.8667	0.9334	-0.1600
		IMT	Unimodal	Neutral	0.9668	0.9834	-0.5633
BNM #4	PA	PMR	Bimodal	Q_2, Q_4	0.8570	0.9285	-0.1975
		IMT	Unimodal	Neutral	1.0313	1.0156	0.5133
BNM #4	RS/SC	PMR	Unimodal	Q_4	1.2386	1.1193	2.1525
		IMT	Unimodal	Neutral	0.8886	0.9443	-1.9667
BNM #4	QA	PMR	Bimodal	Q_2, Q_4	0.7355	0.8678	2.6675
		IMT	Unimodal	Neutral	0.9668	0.9834	-0.5633
BNM #4	RM	PMR	Bimodal	Q_1, Q_3	0.9893	0.9946	-1.5875
		IMT	Unimodal	Neutral	0.9753	0.9877	-0.4167
BNM #4	C2	PMR	Bimodal	Q_1, Q_4	0.8598	0.9299	-0.2925
		IMT	Unimodal	Neutral	0.9974	0.9987	-0.0433
BNM #4	C/FR	PMR	Bimodal	Q_2, Q_4	0.7937	0.8969	1.7175
		IMT	Unimodal	Neutral	0.9084	0.9542	-1.6000

Table 107. Attributes of Probability Density Distributions of BNM #4 Output when FMO = NO

Model	MOSE Charac –teristic	Proba – bility Variable	Depiction	Mode	Skew-ness$_1$	Skew-ness$_2$	Slope
BNM #4	**All**	**PMR**	**Unimodal**	**Q_4**	**1.0704**	**1.0352**	**1.0300**
		IMT	Unimodal	Neutral	0.9177	0.9589	-1.4300
BNM #4	PA	PMR	Unimodal	Q_3	1.0525	1.0263	0.3867
		IMT	Unimodal	Neutral	0.9853	0.9927	-0.2467
BNM #4	RS/SC	PMR	Uniform	Q_3	1.0725	1.0363	0.5700
		IMT	Unimodal	Neutral	0.9594	0.9797	-0.6900
BNM #4	**QA**	**PMR**	**Unimodal**	**Q_4**	**1.0243**	**1.0121**	**0.2300**
		IMT	Unimodal	Neutral	0.9177	0.9589	-1.4300
BNM #4	**RM**	**PMR**	**Unimodal**	**Q_4**	**1.1236**	**1.0618**	**1.6400**
		IMT	Unimodal	Neutral	0.8723	0.9362	-2.2733
BNM #4	C2	PMR	Bimodal	Q_2, Q_4	1.0504	1.0252	0.9467
		IMT	Unimodal	Neutral	0.9384	0.9692	-1.0600
BNM #4	**C/FR**	**PMR**	**Unimodal**	**Q_4**	**1.0454**	**1.0227**	**0.7300**
		IMT	Unimodal	Neutral	0.9157	0.9579	-1.4667

Table 108. Attributes of Probability Density Distributions of BNM #5 Output when FMO = YES

Model	MOSE Charac –teristic	Proba – bility Variable	Depiction	Mode	Skew-ness$_1$	Skew-ness$_2$	Slope
BNM #5	All	PMR	Unimodal	Q_2	0.8758	0.9379	-0.1950
		IMT	Unimodal	Neutral	0.9257	0.9628	-1.2867
BNM #5	PA	PMR	Bimodal	Q_1, Q_4	0.8546	0.9273	-0.2650
		IMT	Unimodal	Neutral	1.0444	1.0222	0.7200
BNM #5	RS/SC	PMR	Unimodal	Q_4	1.2452	1.1226	2.1225
		IMT	Unimodal	Higher	0.7425	0.8712	-4.9267
BNM #5	QA	PMR	Bimodal	Q_2, Q_4	0.7286	0.8643	2.6925
		IMT	Unimodal	Neutral	1.1782	1.0891	2.7267
BNM #5	RM	PMR	Bimodal	Q_1, Q_3	0.9900	0.9950	-1.6975
		IMT	Bimodal	Hi, Low	0.8760	0.9380	-2.2033
BNM #5	C2	PMR	Bimodal	Q_1, Q_4	0.8650	0.9325	-0.3600
		IMT	Unimodal	Neutral	1.0984	1.0492	1.5633
BNM #5	C/FR	PMR	Bimodal	Q_2, Q_4	0.7963	0.8981	1.7025
		IMT	Unimodal	Low	1.0375	1.0187	0.6133

Table 109. Attributes of Probability Density Distributions of BNM #5 Output when FMO = NO

Model	MOSE Charac –teristic	Proba – bility Variable	Depiction	Mode	Skew-ness$_1$	Skew-ness$_2$	Slope
BNM #5	**All**	**PMR**	**Unimodal**	**Q_4**	**1.0627**	**1.0314**	**0.9533**
		IMT	Unimodal	Neutral	0.9205	0.9602	-1.3767
BNM #5	PA	PMR	Unimodal	Q_3	1.0483	1.0242	0.3367
		IMT	Unimodal	Neutral	0.9849	0.9925	-0.2533
BNM #5	RS/SC	PMR	Unimodal	Q_3	1.0648	1.0324	0.4667
		IMT	Unimodal	Neutral	0.9736	0.9868	-0.4467
BNM #5	QA	PMR	Unimodal	Q_3	1.0214	1.0107	0.1433
		IMT	Unimodal	Neutral	0.9773	0.9886	-0.3833
BNM #5	**RM**	**PMR**	**Unimodal**	**Q_4**	**1.1222**	**1.0611**	**1.6233**
		IMT	Unimodal	Neutral	0.8776	0.9388	-2.1733
BNM #5	C2	PMR	Bimodal	Q_2, Q_4	1.0458	1.0229	-0.3600
		IMT	Unimodal	Neutral	0.9352	0.9676	1.5633
BNM #5	**C/FR**	**PMR**	**Unimodal**	**Q_4**	**1.0392**	**1.0196**	**0.6800**
		IMT	Unimodal	Neutral	0.9122	0.9561	-1.5300

VITA

Harry Michael Robinson, a Philadelphia native, earned his commission through the Navy Reserve Officer Training Corps upon graduation from the Pennsylvania State University in 1982 with a Bachelor of Science in Computer Science. Subsequent to earning his wings as a Naval Flight Officer, he completed operational squadron tours in the VAW-126 "Seahawks" and VAW-123 "Screwtops". He served as Commanding Officer for the VAW-125 "Tigertails" participating in Operations Nobble Eagle and Enduring Freedom. Harry deployed onboard the aircraft carriers USS Kennedy (CV 67), USS America (CV 66), USS Eisenhower (CVN 69), and USS Washington (CVN 73). He assumed responsibilities as the Commander, Airborne Command Control and Logistics Wing followed by assignment as the Commanding Officer of the Naval Air Warfare Center Training Systems Division / Naval Support Activity Orlando, Florida. Harry logged over 4,000 flight hours in more than 30 military aircraft. He retired at the rank of Captain from the U.S. Navy after 28 years of service.

Prior to appointment as the Veterans Health Administration Simulation Learning Education and Research Network (SimLEARN) National Program Manager, Harry was a Senior Associate with Booz Allen Hamilton, where he served as the Advanced Analytics Modeling and Simulation lead supporting Team Orlando, a collaborative alliance of governmental and non-profit agencies, including the Department of Defense and Veterans Affairs, working to leverage simulation technology to improve employee performance

Harry earned a Master's of Science in Aviation Systems from the University of Tennessee in 1992 and completed the Naval War College Command and Staff Course. He was graduated from the U.S. Navy Test Pilot School and completed a Medical Modeling and Simulation Certificate Program from the Naval Postgraduate School Modeling Virtual Environment and Simulation Institute.

Department of Modeling, Simulation and Visualization Engineering
1300 Engineering and Computational Sciences Building
Old Dominion University
Norfolk, Virginia 23529