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Using a Nearest Neighbor Algorithm and Logistic Regression to Assess Hazard Identification in the U.S. Army Risk Management Process

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USING A NEAREST NEIGHBOR ALGORITHM AND LOGISTIC REGRESSION TO ASSESS HAZARD IDENTIFICATION IN THE U.S. ARMY RISK MANAGEMENT PROCESS

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ABSTRACT

This research considers whether a person's demographic and experiential attributes play a significant role in how they perceive the presence or absence of hazards in a given situation. The goal of the research is to show that participants with enlisted military experience, prior to being commissioned as a junior officer, would be more successful at identifying the hazards presented in military scenarios than those who had only been trained on the process via their pre-commissioning and initial entry courses of instruction. The research study involves the use of two surveys with realistic military scenarios including both Foot March and Maintenance scenarios. The data collected from the surveys was analyzed using data mining techniques, in particular Nearest Neighbor (NN) algorithm and Logistic Regression Model (LRM). NN determines how similar a participant's case is to an expert case and LRM analyzes the outputs in a way that allows us to see if any of the seven experiential and demographic attributes considered had a significant impact on a participant's ability to perform well on the assessment. While the results did not conclusively prove that experience or other demographic attributes had a statistically significant impact on a participant's overall performance, the results did suggest that the idea that those same attributes do not have an impact cannot be rejected. This research could provide useful feedback to the U.S. Army on the way they train and educate junior officers on their Risk Management process.

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DECLARATION

Some of the material contained in this thesis has appeared or will appear in the following refereed publications:

1. Karels, C., McCormick, H. and Hodhod, R. (2015, March). Application of fuzzy expert systems in assessing risk management in the US Army. *International Journal of Computer Applications* 113(6):10-16.

2. McCormick, H., and Hodhod, R. (2015). Using multiple regression tools to assess hazard identification in the U.S. Army risk management process. *Submission pending.*

1. Introduction

1.1 Background

Risk management (also referred to as RM) is defined by the U.S. Army as 'the process of identifying, assessing, and controlling risks arising from operational factors and making decisions that balance risk cost with mission benefits' [1]. In 1998 the Army introduced the first doctrinal publication on managing risk, the now obsolete Field Manual 100-14, in recognition of the need to standardize a methodology for identifying, quantifying, and mitigating the risks associated with training and combat activities [1]. Though the specifics and scope of this process have changed over the intervening years, the overarching goal of RM is still to manage the inherent risk as well as eliminate all unnecessary risk in all Army activities. While the Army has done much to improve this process with a goal toward making it more standardized and, as a consequence, less subjective, it has not significantly addressed a fundamental issue of this subjectivity, specifically why different individuals, presented with the same situation, perceive hazards differently. Conventional wisdom within the Army would argue that experience is the key to success in RM. Admittedly, having executed a specific task once or a number of times before can provide a risk manager a degree of perspective and historical knowledge that can certainly be leveraged when considering risk in similar future situations. But does this experience or any other demographic factors outside the scope of this task-specific experience shape an individual's perception of risk and ultimately their success in identifying hazards?

The aim of this thesis is to address these issues by analyzing the results of two scenario-based risk assessments completed by a population of newly-commissioned Infantry Officers who were attending the U.S. Army Infantry Basic Officers Leadership Course at Fort Benning, GA.

1.2 Research Question

The work done in this thesis aimed to answer the following research question: "Would the demographic attributes of the participants have a significant impact on their overall ability to correctly identify the hazards presented"? The hypotheses developed from this question are:

H_0: *Demographic attributes do not have an impact on the overall performance of the participants.*

H_1: *Demographic attributes do have an impact on the overall performance of the participants.*

To validate or refute the alternative hypothesis, data mining techniques such as Nearest Neighbor (NN) algorithm and logistic regression techniques are used. NN aims to determine a Degree of similarity (DoS) between an expert case and each participant's input. The DoS or scores were then analyzed against seven different demographic attributes of each participant using a Logistic Regression Model (LRM) with the intent of identifying any of the attributes that had a significant statistical impact on the participant's performance.

1.3 An overview of the Army RM process

The Army describes RM as the process for helping organizations and individuals make informed decisions to reduce or offset risk [1]. The current model is based on four underlying principles: integrate RM into all phases of missions and operations, make risk decisions at the appropriate level, accept no unnecessary risk, and apply RM cyclically and continuously. These four principles drive the cyclical and continuous five-step model as illustrated in Figure 1 below. Although each of these steps plays an important role in the process, for the purposes of this study, the scope of research is limited to the first step of the Army's RM process, *Identify the Hazards.* This is because without the ability to accurately identify the hazards present in the situation, a RM user cannot effectively assess or mitigate them in the subsequent steps of the process. In other words, you can't assess what you do not know is there. As Rotar and Kozar, stated in their work on the mechanics of an RM process, "The value of a risk management process is reduced without a clear understanding of the sources of risk and how they should be responded to" [2]. The U.S. Army's RM process, depicted below in Figure 1, is a five-step process which consists of identifying the hazards, assessing those hazards, developing controls and making risk decisions, implementing controls, and supervising and evaluating throughout the execution of the event.

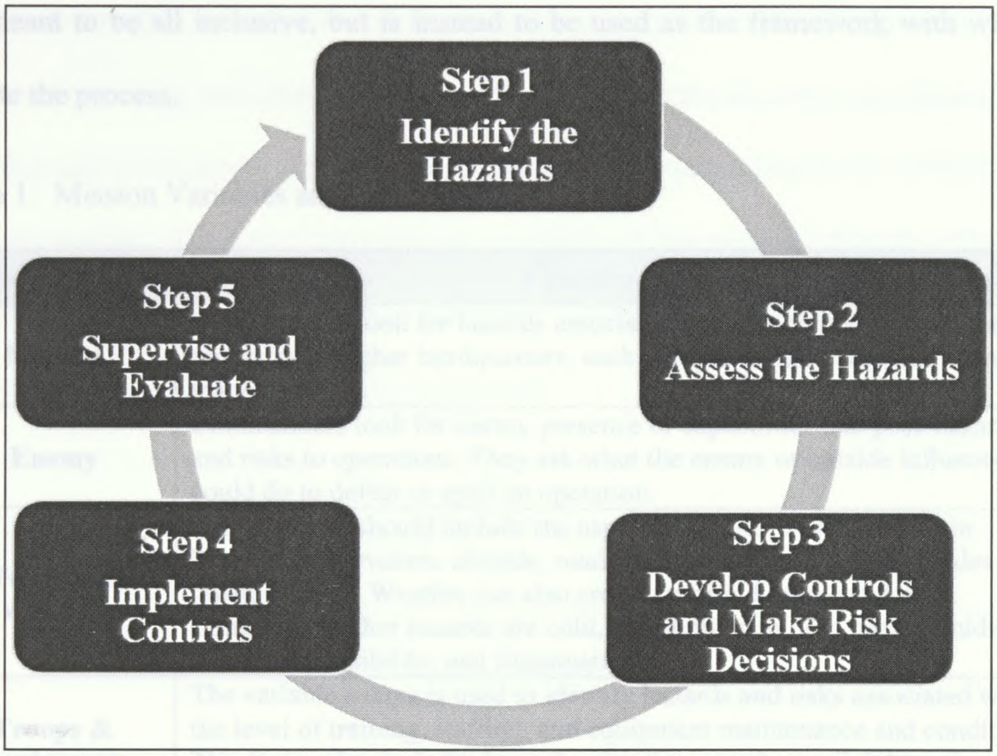

Figure 1: The Army Risk Management Process [1]

To assist risk managers in the first step of the RM process, the Army doctrine employs a series of considerations known as the *mission variables*. The mission variables are a construct that are taught as a tool or framework with which to identify and assess hazards present in a given situation. They consist of the Mission, the Enemy, the Troops and Equipment available for the task, the Time available to complete the task, the Terrain and weather in which the task will be executed, and any considerations involving the presence of Civilians on the battlefield. These variables are represented by the acronym METT-TC. During Step 1 of the RM process, each of the variables is considered as a possible hazard source. A list of considerations for each variable is provided by [1], an excerpt of which is illustrated below in Table 1. Note that this list is not meant to be all inclusive, but is instead to be used as the framework with which to initiate the process.

Table 1: Mission Variables and Considerations [1]

Mission Variable	Consideration(s)
Mission	Army leaders look for hazards associated with the complexity of plans and orders from higher headquarters, such as a particularly complex scheme of maneuver.
Enemy	Commanders look for enemy presence or capabilities that pose hazards and risks to operations. They ask what the enemy or outside influences could do to defeat or spoil an operation.
Terrain & weather	Army leaders should include the aspect of terrain. Common terrain hazards are elevation, altitude, road size and surfaces, curves, grades, and traffic density. Weather can also create specific hazards and risks. Common weather hazards are cold, ice, snow, rain, fog, heat, humidity, wind, dust, visibility, and illumination.
Troops & equipment available	The variable *troops* is used to identify hazards and risks associated with the level of training, staffing, and equipment maintenance and condition. This factor also includes hazards related to morale, availability of supplies, and services. Moreover, it includes hazards related to the physical and emotional health of each individual.
Time available	Subordinate commands need adequate planning and preparation time to develop and implement controls. Insufficient time for planning or preparation may lead to accepting greater risk. (For activities not directly related to operations, insufficient planning or preparation time usually results from haste rather than availability of time.)
Civilians on the Battlefield	The variable *civil consideration* expands the consideration of hazards and risks to include those that a tactical task may pose to the civilian populace and noncombatants in the operational area. It includes the critical requirement to protect civilians. The objective is to reduce collateral damage to civilians and noncombatants

These variables provide the baseline for a standardized, comprehensive method for identifying risks which is taught throughout the U.S. Army and were used in this study as a means of analyzing the participant population's input into the study, which is discussed in detail in Chapter 4.

The remainder of this thesis provides a detailed discussion of this effort. The next chapter provides a survey of existing research related to RM as well as some past and current efforts by researchers to provide RM systems in a variety of fields and industries.

Chapter 3 provides an overview of the research design and methodology including the recruitment strategy and data collection methods. Chapter 4 discusses the research tools used throughout the study. Chapter 5 highlights the characteristics and use of the LRM to produce results. Chapter 6 provides an analysis of the results. Finally, Chapter 7 provides discussion of the study, including limitations the study dealt with, and recommendations for future research in this area.

2. Related Work

Risk management has been an active research area in the past few decades. Despite the importance of this field in many domains such as insurance, investing, and information assurance, and others, the specific act of identifying risks in the U.S. Army has been under-examined. A survey of current RM literature and research shows that a variety of tools exist which intend to optimize the RM process by leveraging expert input to establish rules or parameters and then employ algorithmic or other functions modeled on how humans think in order to manage risk. Some of the more common of these RM processes employ such techniques as data mining, NN algorithms, regression, or expert systems (ES) such as neural networks, fuzzy logic, and even gaming systems to achieve their purpose.

Some leaders in the RM field have proposed various ESs to provide the expertise and objectivity required to effectively identify hazards and manage risk (some of the more successful of which are discussed in the second part of this section). However, a comprehensive study of existing literature relating to current RM processes underscores the idea that bias or subjectivity can play a significant role in how an RM user perceives risk. But is this necessarily bad? What if this subjectivity were based on experience or some other sources that lent itself to a better outcome? Unfortunately, little quantitative research is available that approaches, from the perspective mentioned above, the ability of an individual to successfully identify hazard. Indeed, in his perspective on quantitative risk assessment, George E. Apostolakis points out that "While it is relatively easy to ascribe an accident that has occurred to a bad safety culture, the fact that defining indicators of a good or bad safety culture in a predictive way remains elusive" [3]. The remainder of this section is dedicated to a review of data mining and ES designed to enable RM, as well as a survey of the current literature on the RM in the U.S. Army.

2.1 Existing systems for risk management

In [4], Bertrand Laporte proposed a data mining-based RM tool intended to assist customs agents responsible for inspecting baggage and personnel wanting to enter a country with accurately assessing who and what present the greatest hazards. He presented his idea based on the premise that by capturing specific data (some of which includes the contents of such documents and activities as verification certificates, detailed declarations, and the results of inspections for a specified reference period) and then effectively managing and mining that data, the user can establish accurate risk profiles based on "statistical regularities" that result.

Similar to LaPorte's concept, María Fernanda D'Atri, Darío Rodriguez, and Ramón García-Martínez presented a paper in which they employ data mining as a means of exploiting information based on intelligent systems to improve and optimize risk models used in the gas pipeline industry [5].

As mentioned previously, another popular way to counter the subjectivity inherent in so many RM systems (essentially an effort to level the playing field between those with experience in RM and those without) is to develop an ES that, to the extent possible, relies on expert input and logical inference to determine the hazards present and overall risk level associated with a given activity. A study of existing techniques employing ES to address and manage risk in a comprehensive manner reveals several credible proposals and existing applications in areas including supply chain management, financial management, insurance, and information assurance. An overview of each of these systems is provided in the following paragraphs.

In their paper [6] on quantifying risks in those supply chains, Samvedi, Jain, and Chan discuss the fact that processes for managing risk in supply chains are not immune to the same challenges that RM systems in nearly any field face. Indeed, they point out that "The major hindrance in analyzing risks comes from the fact that there is a lot of subjectivity involved". Their proposed use of an *analytical hierarchy process* (AHP) and a fuzzy *technique for order preference by similarity to the ideal solution* (TOPSIS) both recognized the subjectivity involved in the process and produced crisp output, ultimately producing a risk index and overall risk assessment which can be used to help decision makers deal with the risk present.

Baesens, et al. attempted to tackle risk in the financial industry by proposing the use of neural network rule extraction and decision tables as a viable means to evaluate the risk associated with extending credit to a given applicant in [7]. Though early attempts at using neural networks to evaluate credit risk were successful in evaluating the risk, the use of a neural network alone prevented the user from knowing how the classification was being made. This proved to be an issue as it prevented the financial institutions from meeting their legal obligations to justify why an individual's credit request had been denied. Baesens and his colleagues showed that the use of an appropriate neural network (in their case, either Neurorule or Trepan), combined with a decision table for visualization, can result in successful financial risk evaluation. The decision table served as a visualization tool that represented the neural network rule extraction process in a visual and understandable way, thus making it usable to the decision maker in justifying their decisions.

Like evaluating credit risk, selecting the appropriate mix of stock, bonds, etc that match an investor's acceptable level of risk can have an enormous impact on the success or failure of a financial manager. In [8] Shane, Fry, and Toro wrote about their development of a decision support system that uses two knowledge bases, a database, and a gaming system to effectively and efficiently match the appropriate portfolio to the investor. The first knowledge base, known as *Investment Suitability* addresses the appropriateness of an investment type with the personal attributes of the investor. A gaming system is used to determine overall investor risk tolerance. The second knowledge base, *Economic Conditions*, then analyzes and applies the effects of current market conditions against the *Investment Suitability* results. Finally, a *Portfolio Preference* database is consulted which contains historical portfolio mixes made by the advisor to see if any suitable options already exist. The output of these systems is then used to provide an informed recommendation to the investor on his or her optimal investment portfolio mix.

In [9], their paper studying the use of ES for RM in the insurance industry, Meyer, et al. conducted a study of two large insurance firms, John Hancock and Lincoln National, and their successful efforts in developing effective ES for decision support of underwriting insurance policies. In the case of John Hancock, which specializes in directly offering insurance policies to a large number of consumers, the use of an ES was focused on improving efficiency by employing a specially-developed set of heuristics which would allow a large number of more routine cases (based on the applicant's occupation, financial issues, medical conditions, etc) to be automatically approved, thereby reducing the workload of human underwriting experts to only those cases that fell outside of these norms. In the case of Lincoln National, the ES was designed to more efficiently combine what the authors classify as the procedural knowledge of the underwriting expert with the more theory-based inference done by the medical experts and actuaries employed by the company.

Fenz, Eckelhart, and Neubauer [10] developed an Automated Risk and Utility Management (AURUM) system to provide comprehensive RM support to those working in the area of Information Assurance (IA). Their system uses a Bayesian network to calculate threat probabilities, a risk determination, risk control identification, and evaluation. This process is intended to support decision makers in gaining a better understanding of the risks they face while also providing him or her with what can be achieved in terms of addressing the risks in relation to opportunity costs to other efforts or objectives.

While each of the ESs discussed above do indeed make strides in addressing the subjectivity issue associated with RM, they are mostly narrow in scope and serve to quantify the risks presented by known hazards. In other words, the ES themselves may analyze the hazards, but do so only once the experts have identified them. While admittedly useful to the individual risk manager, they fall short of providing the larger organization with any sort of understanding as to why the assessor or expert identified certain hazards when others did not. They are not, by design, analysis tools for use in addressing the challenges this study attempted to deal with. Until they can understand the root cause of the subjectivity involved in RM, organizations may never be able to attain the lofty goal of training and embedding risk management into the actual culture or fabric of the organization [11].

2.2 Current research on Risk Management in the U.S. Army

The U.S. Army provides a large number of publications in which each addresses RM and provide a good deal of detail relating to the process of RM, but do little to discuss or more importantly quantify any factors that might lead an individual to recognize, or fail to recognize, hazards in a given situation. These include, but are not limited to [1], [12], [13], [14], and [15]. The U.S. Army Safety Center publishes monthly and annual Army-wide accident statistics which can be used for trend analysis, but the researcher could not find any that delved into any demographic or psychographic data relating to the individual conducting the risk assessment for the event that led to the accident or injury in question [16].

Chris W. Johnson has authored two excellent works relating to RM in the military. His paper [17] discusses the U.S. Army's various RM processes. He goes as far as to point out that given a number of the Army's current processes (in this case relating specifically to aviation risk), "There are few guarantees that different personnel will identify similar hazards for the same mission elements". In his other paper [18], he discusses the idea that members of the military may tend to be more risk-seeking or tolerant. Dr. Johnson posits that "There seems to be very little direct evidence today that CRM (Composite Risk Management) techniques will be able to compensate for the risk preference biases that are often seen in military personnel". It can be argued that both of these points speak to the idea that when coupled with the uniformity provided by an effective RM process, subjectivity, depending on its source or cause, can either enhance or degrade the usefulness of that RM process.

In their work about examining the implementation of RM approaches in military operations, Liwång, Ericson, and Bang note that as powerful of a tool RM is, it can only be successful with an understood and shared definition of risk [19]. Unfortunately, they do not go as far as to delve into whether or not previous experience in considering risk plays a role in how one perceives it.

Kamperis, et al provide an interesting and informative analysis of quantitative and qualitative techniques for risk assessment in [20], but ultimately acknowledge that the common weakness of both techniques is that the assumptions used by those employing them can be highly subjective. While true, one could still argue that although that subjectivity is present, experience or some other demographic attribute associated with the assessor might provide a more informed version of subjectivity, which could actually result in a more accurate assessment of risk.

Some recent research and publications relating to RM in the civilian sector have focused on attempts to refine RM processes, with the idea that the simpler the process is to use, the more likely a supervisor or worker is to actually use the RM system as opposed to relying solely on their "wits" or experience. For example, in [21] Pinheiro, Cranor, and Anderson discuss RM in the oil and gas production industry and propose a modified approach to the legacy processes that includes a "simplified approach for determining risk". The approach may be simplified, but if the designer does not attempt to understand why some users are successful and others aren't, then there is still a knowledge gap that will keep the system from being as effective as possible. The next chapter introduces the reader to the research tools used to address the issues discussed above.

3.1 Research design

As described in the previous chapters, although there is abundant research on RM in different areas, such as the commercial insurance, banking, and investment sectors, it seems that research on RM in the U.S. Army has been under-examined. The question addressed in this thesis is: *Would the demographic attributes of the participants have a significant impact on their overall ability to successfully identify the hazards presented?* The research question leads to the following hypotheses:

H_0: Demographic attributes do not have an impact on the overall performance of the participants.

H_1: Demographic attributes do have an impact on the overall performance of the participants.

To address the research question, data was collected using a case study model featuring a within-group design in which each participant completed risk assessments based on two scenarios: a foot march and maintenance on a vehicle-based version. A qualitative study was conducted using RM worksheets with individual cases within the study consisting of the participants themselves (i.e. their biographical and experiential data), as well as their responses to the scenarios. The researcher employed theoretical replication by using comparable cases (all 2nd Lieutenants with recent RM training) to generate different results which were explained by differences between each case (i.e. their biographical and experiential data).

3. Research Design & Methodology

3.1 Research design

As described in the previous chapters, although there is abundant research on RM in different areas, such as the commercial insurance, banking, and investment sectors, it seems that research on RM in the U.S. Army has been under-examined. The question addressed in this thesis is: *Would the demographic attributes of the participants have a significant impact on their overall ability to successfully identify the hazards presented?* The research question leads to the following hypotheses:

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In order to prevent participant fatigue during the study, all participants were given one week to complete the assignment. The approximate duration required to complete the assignment was two hours. Additionally, the researcher attempted to minimize any bias resulting from learning effects by providing two separate scenarios for participants to complete, as well as by not dictating the order in which they should complete them.

3.2 Research methodology

As was discussed in the introduction to this thesis, there is little research available that directly addresses the question of why different individuals tend to identify different hazards, even when viewing the same situation. The researcher aimed to address this issue by providing a group of participants with identical risk scenarios, having them conduct their individual risk assessments on their scenarios, and then analyzing their results to determine what demographic attributes might have a statistically significant impact on the participants' performance.

3.2.1 Recruitment strategy

Participants in this research consisted of U.S. Army and Marine officers, all in the grade of 2nd Lieutenant, who were attending the Infantry Basic Officer Leadership Course (IBOLC) through the U.S. Army Maneuver Center of Excellence (MCoE) and the Infantry School at Fort Benning, GA. IBOLC serves as initial entry training for all newly commissioned officers in the Infantry branch. This is the first training that 2nd Lieutenants receive after earning their commissions from either a service academy (USMA), the Reserve Officers Training Corps (ROTC), or the Officer Candidate School

(OCS). The goal of IBOLC is to educate, train, and inspire Infantry Lieutenants so that upon IBOLC graduation, they demonstrate the competence, confidence, physical and mental toughness, and moral/ethical fiber necessary to lead platoons in any operational environment [22]. Immediately prior to participating in the study, participants received a formal block of instruction intended to prepare them for a subsequent homework assignment requiring each student to read through two realistic scenarios and then complete the RM process on each scenario using a DA Form 7566, the Army's Composite Risk Management Worksheet.

Participants in this study were contacted through their IBOLC chain of command and asked to participate on a voluntary basis. It is important to note that while the assignment to complete the RM scenarios was administered by the participants' instructors as part of their normal classroom Risk Management curriculum, participation in the study was voluntary. In addition to the assigned homework, those who chose to participate in the study received and completed a biographical questionnaire, as well as an Informed Consent Form.

3.2.2 Data collection

Data considered for the study consisted of responses derived from risk assessments completed by study participants in response to a realistic military training scenario provided by the researcher. The construct for assessing risks and identifying any hazards presented throughout the scenarios was organized into four categories, each of which were derived from portions of the U.S. Army's mission variables, which are comprised of Mission, Enemy, Terrain, Troops and equipment available, Time available, and Civilians on the battlefield, also known as METT-TC. The reader should note that only four of the six mission variables were considered. This is because the scenarios that drove the input for the system were based on training situations and as such did not require the participant to consider the variables of Enemy or Civilians on the battlefield. Therefore, the researcher used a condensed version of METT-TC, specifically one that accounted for the elements of Mission, Terrain, Troops and equipment available, and Time available, or MTT-T. Each of these four categories contained a series of binary attributes that represented a possible hazard condition within that category. The condition of each was such that it was either identified as present or not present. If a hazard was identified, the researcher categorized it into one of the four categories discussed above. A fifth category of data collected represented the demographic attributes associated with each participant, reflecting the biographical and experiential data associated with the participant represented.

4. Research Tools

A data analysis model has been proposed to analyze the data collected from the surveys as shown in Figure 2. The researcher used data mining via a Nearest neighbor (NN) in order to calculate the Degree of similarity (DoS) between each participant's input and an expert case. These DoS, or scores, were later used for identifying subgroups of a participant population who demonstrated similar tendencies in identifying or failing to identify hazards as part of an RM process, and then analyzing those subgroups in order to identify any trends based on characteristics (i.e. *demographic*, *experiential*, etc) present within the similarly responding groups.

The individual records were input into a NN algorithm in the form of individual cases and were compared against an expert case in order to calculate the similarity between them. A NN process stores all available cases to project a numerical target based on the similarity measure or distance function [23]. These distance functions became the DoS for each case. Demographic attributes (with the exception of *name*) were not introduced into the NN algorithm—they existed as a metric so that individual records within data clusters could later be extracted for use. The output was then grouped according to DoS parity. Selected clusters or groupings were then analyzed to determine any common trends based on the demographic attributes associated with the member individuals.

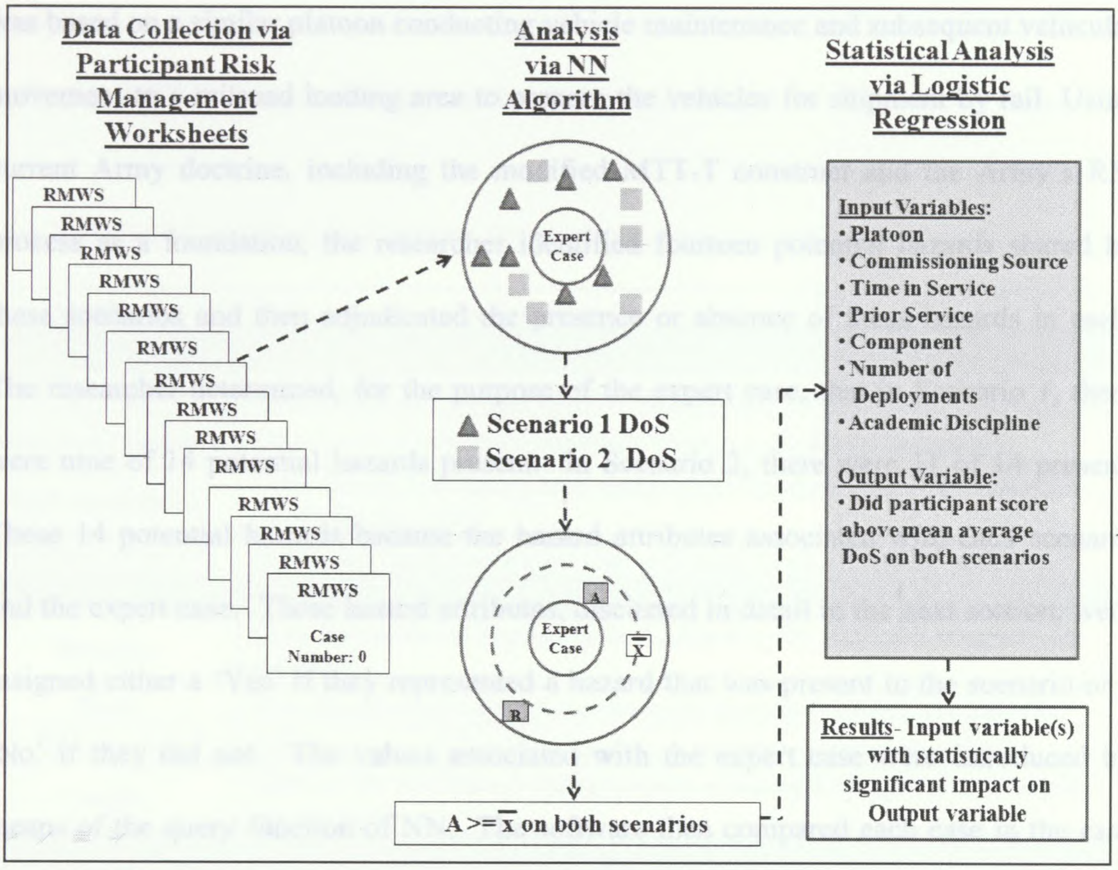

Figure 2: Data analysis model

4.1 Nearest Neighbor (NN) algorithm

The system leveraged the NN algorithm offered by the off-the-shelf *myCBR* tool [24] to calculate the DoS between each participant case and an expert case provided by the researcher. myCBR is an open-source similarity-based retrieval tool that can model and test similarity measures between cases [25]. These inputs, each of which constituted one member case, were derived from the responses of 72 separate study participants in response to the two different risk management scenarios. The first, Scenario 1, was based on a U.S. Army infantry platoon preparing for and conducting a tactical foot march, or ground-based movement, for training. The second, Scenario 2, was based on a similar platoon conducting vehicle maintenance and subsequent vehicular movement to a railroad loading area to prepare the vehicles for shipment by rail. Using current Army doctrine, including the modified MTT-T construct and the Army's RM process as a foundation, the researcher identified fourteen potential hazards shared by these scenarios and then adjudicated the presence or absence of these hazards in each. The researcher determined, for the purpose of the expert case, that in Scenario 1, there were nine of 14 potential hazards present. In Scenario 2, there were 11 of 14 present. These 14 potential hazards became the hazard attributes associated with each scenario and the expert case. These hazard attributes, discussed in detail in the next section, were assigned either a 'Yes' if they represented a hazard that was present in the scenario or a 'No' if they did not. The values associated with the expert case were introduced by means of the query function of NN. The software then compared each case in the case base to the expert case and returned a corresponding similarity value for each case. The similarity values were then used to determine groupings of similar responses, which the researcher used to identify any experiential or biographical trends amongst the clustered participants as part of a later phase of the study.

4.1.1 Attributes in NN algorithm

There were a total of 14 hazard identification attributes and seven biographical, experiential, and administrative demographic attributes considered in this study. Biographical attributes were recorded for participant identification and later data analysis, but (with the exception of each participant's name) were not considered in relation to the NN algorithm in order to minimize skewing in the DoS calculation. Table 2 below provides a description of each hazard attribute used in the system, listed under its applicable MTT-T category (designated by the shaded rows).

Table 2: Hazard Identification Attribute Descriptions

Attribute	Description
Mission	
C2 Span of Ctrl	Can leaders sufficiently control organization throughout movement?
Mission Complexity	Does level of mission complexity present a challenge or hazard?
SOP Availability	Does the platoon have a well understood Standard Operating Procedure (SOP) for this task?
Guidance from HQ	Did higher headquarters provide sufficient level of detailed guidance?
Terrain & Weather	
Weather	Does the predicted weather pose a hazard to the platoon throughout the mission?
Route	Does the planned route or terrain to be traversed present any hazards?
Illumination	Will limited visibility (fog, darkness, etc) impact mission safety?
Traffic	Does traffic (civilian or military) pose a hazard to the platoon throughout the mission?
Troops & Equipment Available	
PLT Task Experience	Does the platoon as a whole have sufficient experience in this task?
Condition of Soldiers and Equip	Are soldiers adequately conditioned? Do soldiers have appropriate and adequate equipment for task?
Ldr Experience	Does the platoon leadership that is present have sufficient experience in this task?
Key Pax Availability	Are all key and critical personnel available to participate in mission?
Time Available	
Planning Time Available	Does the leadership have sufficient time to plan the mission?
Time to Complete Mission	Does the platoon have sufficient time to complete the mission safely?
Biographical Data	
Name	Participant's name

Hazards were either considered present (as represented by a 'Yes') or not present (as represented by a 'No'). Each hazard attribute was assigned the attribute type *symbol*. The value was either a match for the expert value, in which case it was assigned a value of 1, or a non-match, in which it was assigned a value of 0. One attribute, *name*, was assigned the attribute type *string* and assigned an _*undefined* value in the expert case, which was done to allow the attribute to be associated with each case (in order to track which case was which), but with minimal skewing of the degree of similarity data that was returned. Table 3 below provides a detailed listing of attribute names, types, and values, including the 'Query (Expert) Value' column which represents the expert value for each attribute in each scenario as determined by the researcher for the narrative or scenario provided to each participant. The values represented in each column were used to populate the Query function of the system for each scenario.

Table 3: Listing of the name, type, value range, and query (expert) value for each attribute considered.

			Query (Expert) Value		
Attribute	**Type**	**Inputs**	**Foot march**	**Maintenance**	**Algorithm Assigned Values**
C2 Span of Ctrl	Symbol	Yes or No	No	No	0 or1
Condition of Soldiers and Equip	Symbol	Yes or No	Yes	Yes	0 or1
Guidance from HQ	Symbol	Yes or No	No	No	0 or1
Illumination	Symbol	Yes or No	Yes	Yes	0 or1
Key Pax Availability	Symbol	Yes or No	Yes	Yes	0 or1
Ldr Experience	Symbol	Yes or No	Yes	Yes	0 or1
Mission Complexity	Symbol	Yes or No	No	No	0 or1
Name	String	name	_undefined	_undefined	name
PLT Task Experience	Symbol	Yes or No	Yes	Yes	0 or1
Planning Time Available	Symbol	Yes or No	No	Yes	0 or1
Route	Symbol	Yes or No	Yes	Yes	0 or1
SOP Availability	Symbol	Yes or No	Yes	Yes	0 or1
Time to Complete Mission	Symbol	Yes or No	No	Yes	0 or1
Traffic	Symbol	Yes or No	Yes	Yes	0 or1
Weather	Symbol	Yes or No	Yes	Yes	0 or1

4.1.2. Results for NN algorithm

4.1.2.1. Data validation

To validate the data we have, a sample test was done using 15 participants for Scenario 1 and ran their inputs in all 14 hazard attributes against the expert case. Same test was repeated using 15 participants for Scenario 2. All attributes returned acceptable results (acceptable being defined as no *unknown* or *undefined* values being returned for any attribute). The researcher then repeated the tests for both Scenarios 1 and 2 using the same inputs and query values to ensure that the system reproduces the same results, given the same inputs and parameters. There were no anomalies between the first and second rounds of testing for either set of cases or query function.

4.1.2.2 Output from NN algorithm

The overall DoS were then calculated by comparing the attribute values of each individual participant's data against the expert's data. The algorithm assigned a DoS value to each participant based on the proximity of its attribute values to those of the expert data values used in the query. The greater the value of the DoS that the algorithm assigned, the greater the number of attribute values that matched between the individual case and the expert case. No similarity functions or weights were assigned to any attributes or the query values as each hazard attribute was of equal value and the only possible outcomes for the *symbol* attributes was either 'Yes' or 'No'.

Figure 3 contains a sample screen shot of four cases, including their individual values and corresponding DoS based on the Foot March (Scenario 1) and expert values as illustrated previously in Table 3.

	FM (No Bio)33	FM (No Bio)40	FM (No Bio)42	FM (No Bio)41
Similarity	0.93	0.86	0.86	0.86
C2 Span of Ctrl	Yes	No	No	No
Condition of Soldiers and Equip	Yes	No	Yes	Yes
Guidance from HQ	No	No	No	No
Illumination	Yes	Yes	No	Yes
Key Pax Availability	Yes	Yes	No	No
Ldr Experience	No	No	No	No
Mission Complexity	No	No	No	No
Name	Lichtfuss	Garner	Naber	Semonis
PLT Task Experience	Yes	No	Yes	No
Planning Time Available	No	No	No	No
Route	Yes	Yes	Yes	Yes
SOP Availability	Yes	No	No	No
Time to Complete Mission	No	No	No	No
Traffic	Yes	Yes	Yes	Yes

Figure 3: Example Case Outputs and Degrees of Similarity

In the example above Lichtfuss, case *FM(No Bio)33*, correctly identified 12 of the 14 hazards and received a 0.93 DoS, while Garner, Naber, and Semonis (participant data 40-42 respectively) correctly identified 10 out of 14 hazards and were assessed a 0.86 degree of similarity. The four cases above serve as a representative example of the 72 cases per scenario that were compared using the NN algorithm to compute the degree of similarity between the four cases and the expert case.

In the next chapter, the researcher discusses how the outputs from the NN algorithm were analyzed using a Logistic Regression Model to determine the significance of any of the demographic attributes on a participant's score.

5. Logistic Regression Model to analyze NN outputs for analysis

In the previous step, the study data was mined using NN algorithm to determine each participant's performance as compared to an expert case. The researcher employed the algorithm to calculate the Degree of similarity (DoS) between the participants' inputs and that of an expert case. The outputs of the NN algorithm (consisting of individual DoS) were then collected for analysis using Logistic Regression Model (LRM) using XLMiner data mining software to determine if any of the seven biographical or experiential attributes had a statistically significant impact on the population's success in identifying hazards. The LRM allows the researcher to establish a relationship between a binary outcome variable and a group of predictor variables. It models the logit-transformed probability as a linear relationship with the predictor variables and employs the equation below. When executed, the logistic regression of y on $x_1,\ldots, x_k$ estimates parameter values for $\beta_0, \beta_1, \ldots, \beta_k$ via maximum likelihood method. [26]

$$\text{logit}(p) = \log(p/(1-p)) = \beta_0 + \beta_1 * x1 + \ldots + \beta_k * xk$$

Explanation of terms:

y = binary outcome variable indicating failure/success with 0/1

p = the probability of y to be 1, p = prob(y=1)

$x_1, .., x_k$ = set of predictor variables

In this model, y reflected whether the participant had received a "passing" score or not. A passing score was defined as having scored above the mean average DoS on both scenarios 1 and 2. A non-passing score was defined as a participant failing to achieve a

DoS above the mean average on either of the two scenarios or both scenarios. x1,…x7 were the seven demographic attributes associated with each participant.

The overall LRM process consisted of three steps: Coding the data for analysis, organizing the data for input into the regression model, and finally running the regression model. The first two steps are discussed in detail in the following subparagraphs.

5.1 Data coding

The biographical and experiential data discussed in Chapter 3 was organized into seven areas of consideration. These areas were: platoon assignment, commissioning source, academic discipline, if the participant had any prior military service before being commissioned (not including pre-commissioning training or education), actual time in military service, whether they received a reserve or active duty commission, and number of deployments. For analytical purposes, this data was then coded, as illustrated in Tables 4 and 5 below.

Table 4: Biographical Attribute Coding

Attribute	**Coding Options**
Platoon Assigned to	1, 2, or 3
Commissioning Source	Service Academy, ROTC, or OCS
Prior Service	Yes or No
Component	Active Component or Reserve Component
Academic Discipline	0,1,2,3,4, or 5 (*)*See table 5 below for explanation*
Time in Service	< 1 year, 1-3 years, or >3years
Number of Deployments	0, 1, 2, or 3

Table 5: Breakdown of participants' academic majors by discipline

Discipline	Code Number	Majors Included
No Major	0	No major declared
Physical Science	1	Biology Chemistry Exercise Science Geo Science
Social Sciences	2	Political Science Psychology Criminal Justice Sociology Languages Law International / Foreign Relations Defense & Strategic Studies
Business	3	Economics Business Management Culinary Management
Math/Technology/Engineering	4	Mathematics Technology Engineering Operational Research
History	5	History

5.2 Organizing data for input into the regression model

Input into the regression model consisted of the values for each of the seven demographic attributes for each participant. Output consisted of the dependent variable AVG_1. AVG_1 represented those participants who attained a "passing" score overall. Table 6 below extends the previous coding methodology to illustrate the corresponding input variables represented in the regression model. The results are discussed in Chapter 6 of this thesis.

Table 6: LRM input and output variables

Attribute	Coding Options	Input Variable
Platoon Assigned to	1, 2, or 3	PLT_1, PLT_2, PLT_3
Commissioning Source	Service Academy, ROTC, or OCS	COM_1, COM_2, COM_3
Prior Service	Yes or No	PSVC_1, PSVC_2
Component	Active or Reserve Component	COMP_1, COMP_2
Academic Discipline	0,1,2,3,4, or 5	AD_0, AD_1, AD_2, AD_3, AD_4, AD_5
Time in Service	< 1 year, 1-3 years, or >3years	TIS_1, TIS_2, TIS_3
Number of Deployments	0, 1, 2, or 3	DEPL_0, DEPL_1, DEPL_2, DEPL_3
Attribute	**Coding Options**	**Output Variable**
DoS > mean on both scenarios	Pass	AVG_1

6. Results

This study employed two data mining techniques in an attempt to determine if any of the demographic attributes of the participants had a significant impact on their overall ability to identify the hazards presented in two military operation-based scenarios. The first employed a NN algorithm to determine the DoS between 72 different participant's responses to the two scenarios and an expert case. The second employed logistic regression of those outputs to test for a relationship between a binary outcome variable and a group of predictor variables. In other words, the logistic regression should determine if any of seven demographic attributes associated with the participants had a statistically significant impact on their overall success in attempting to match the expert case.

6.1 NN algorithm results

The NN algorithm was run on the input of each of the two different scenarios. The results are below in Figures 4 and 5. In each figure, the X-axis represents the case number for each participant (0-71). The Y-axis represents the range of DoS for that scenario. Y-values represent each participant's DoS. The horizontal, dashed line represents the mean average DoS for that scenario.

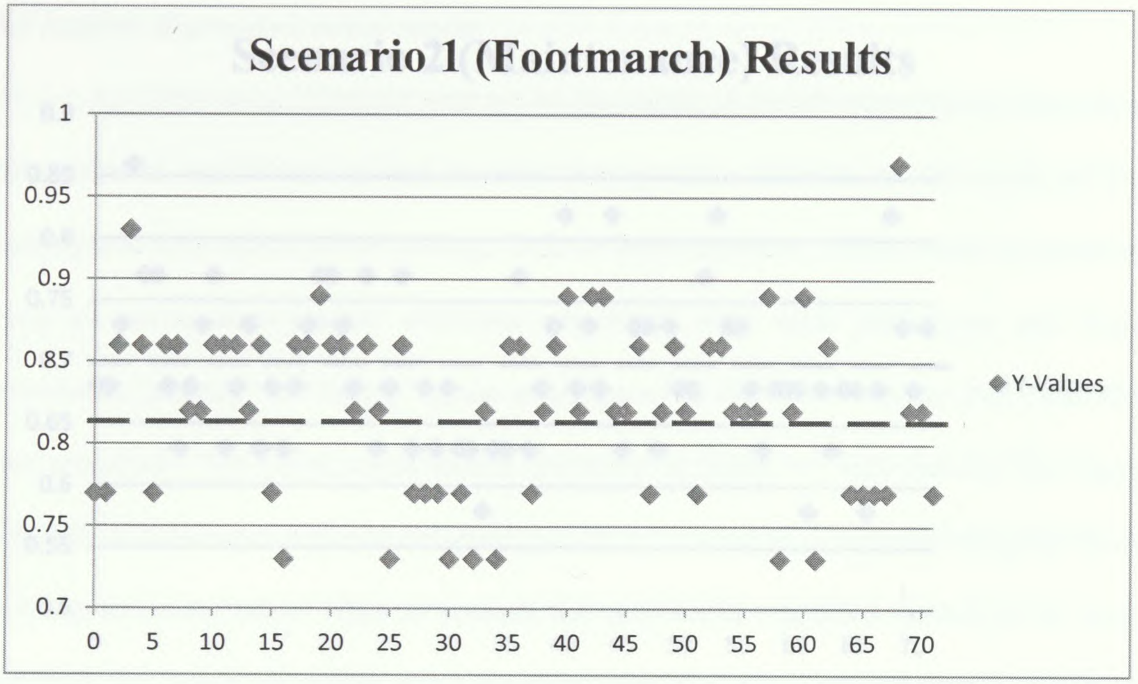

Figure 4: Scenario 1 NN Results

As seen in Figure 4, the mean average DoS for Scenario 1 was 0.8191861. The high DoS was a 0.97 achieved by case number 68. The low DoS was a seven-way tie of 0.73 registered by case numbers 16, 25, 30, 32, 34, 58, and 61. A total of 48 participants scored above the mean average DoS.

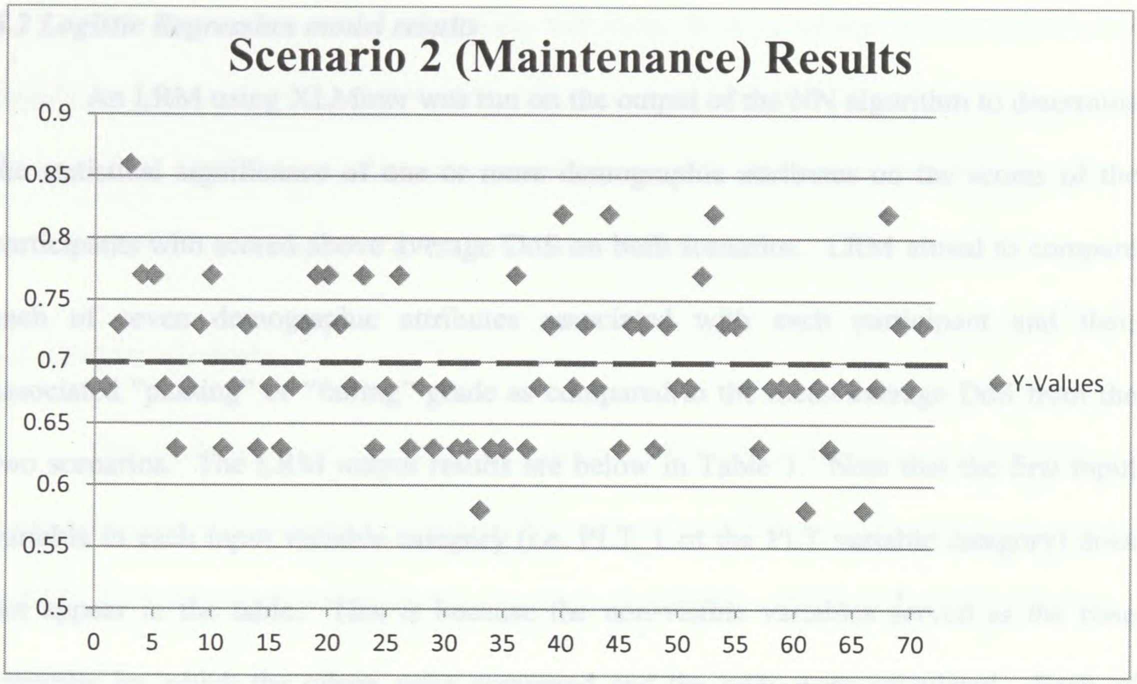

Figure 5: Scenario 2 NN Results

Figure 5 shows the mean average DoS for Scenario 2 was 0.695972. The high DoS was a 0.86 achieved by case number 3. The low DoS was a three-way tie of 0.58 registered by case numbers 33, 61, and 66. A total of 28 participants scored above the mean average DoS for this scenario.

Overall, participants scored better on Scenario 1, which had mean average DoS 0.1232141 degrees higher than that of Scenario 2. Further, 67% of participants scored above the mean average DoS for Scenario 1 while only 39% did the same on Scenario 2. Twenty-five participants scored above the mean average DoS on both scenarios.

6.2 Logistic Regression model results

An LRM using XLMiner was run on the output of the NN algorithm to determine the statistical significance of one or more demographic attributes on the scores of the participants who scored above average DoS on both scenarios. LRM aimed to compare each of seven demographic attributes associated with each participant and their associated "passing" or "failing" grade as compared to the mean average DoS from the two scenarios. The LRM output results are below in Table 7. Note that the first input variable in each input variable category (i.e. PLT_1 of the PLT variable category) does not appear in the table. This is because the non-visible variables served as the base variables by which the others were compared and the odds were calculated. Each of these variables was still considered in the calculation, as well as the output and results.

Table 7: LRM Output Results

Input Variables	P-Value
PLT_2	0.11525
PLT_3	0.16371
PSVC_1	0.321222
COMP_1	0.369528
TIS_2	0.370832
COM_3	0.383773
DEPL_1	0.68538
AD_5	0.883773
Intercept	0.888516
DEPL_2	0.891042
DEPL_3	0.90257
AD_2	0.907533
AD_3	0.908714
AD_4	0.909825
AD_1	0.919134
COM_2	0.949266
TIS_3	0.982466

The results from the LRM show that there is no attribute with a statistically significant impact (p value of <=.05). These results suggest that none of the seven demographic attributes significantly contributed to a participant performing above average when identifying hazards on a risk assessment.

6.3 Analysis of results

This study intended to answer the question, 'Would the demographic attributes of the participants in this study have a significant impact on their overall ability to correctly identify the hazards presented in the scenarios provided?', which lead to the following hypotheses:

H_0: Demographic attributes do not have an impact on the overall performance of the participants.

H_1: Demographic attributes do have an impact on the overall performance of the participants.

As illustrated in Chapter 6, the results of the research showed that none of the demographic attributes considered as part of the study had a significant statistical impact on a participant's ability to achieve a "passing" score. The researcher therefore has to conclude that, given the hypotheses established at the outset of this study, the research failed to reject the null hypothesis but did not prove the alternative hypothesis. This means that while the results did not conclusively prove that experience or other demographic attributes had a statistically significant impact on a participant's overall performance, the results do suggest that the idea that those same attributes do not have an impact cannot be rejected.

Considering the fact that the least Time in Service for any participant was 4 months, while the greatest was 13 years, the conventional wisdom that the longer or more often an individual has been around a process, the better they will be at it does not appear to stand the rigors of statistical analysis, at least in this study's case. Similarly, the notion that any prior service time at all would increase a participant's performance could not be proven. Less than half of participants with prior enlisted time scored above average in both scenarios. Further studies would need to be done to prove this conclusively since this fact may merely suggest that their prior service was in a grade junior enough that they were never formally exposed to the RM process.

Finally, it must be noted that the absence of a statistically significant correlation between the participants' performance and the demographic attributes considered for each participant could be attributed to the fact that immediately prior to being provided the scenarios and RM products, each study participant received a standardized block of instruction on the U.S. Army RM process. This block of instruction, which includes instruction on using the METT-TC construct for identifying hazards (as was discussed in Chapter 1), may have served its intended purpose by mitigating any significant experiential differences that existed between the participants.

7. Discussion

This study is as a result of over 18 years of the researcher learning, teaching, participating in, and observing the U.S. Army's RM process in action. Throughout that time, the researcher has tried to gain an understanding of why different people perceive the presence or absence of hazards so differently. The conventional wisdom so often prevalent within the Army that experience is the key to success in RM may stand true, but that does not answer the question of what kind of experience? Prior service in the military? Experience gained while attending a particular commissioning source? The overwhelming majority of literature available today on the subject of RM acknowledges that there is inherent subjectivity in nearly every RM process in existence. But what if this subjectivity were based on experience or some other source that lent itself to a better outcome? Are there certain attributes or experiences that assist a person in accurately identifying hazards? That is what this study was intended to address. The study analyzed the results of two scenario-based risk assessments completed by a population of newly-commissioned Infantry Officers who were attending the U.S. Army Infantry Basic Officers Leadership Course at Fort Benning, GA. Input was analyzed using both a NN algorithm to produce DoS from an expert case for each respondent in each scenario. Those outputs then served as variables in a LRM intended to identify any of seven attributes that may have had a statistically significant impact on a respondent's success. Ultimately the results proved that none of the seven demographic attributes considered as part of the study had a significant statistical impact on a respondent's ability to achieve a "passing" score. As was discussed in Chapter 6, the researcher had to conclude that, given the hypotheses established at the outset of this research study, the research results failed to reject the null hypothesis but did not prove the alternative hypothesis. This means that while the results did not conclusively prove that experience or other demographic attributes had a statistically significant impact on a respondent's overall performance, the results do suggest that the idea that those same attributes do not have an impact cannot be rejected.

7.1 Limitations of the study

This study was constrained by three primary limitations. First was the relatively small sample size of 72 respondents. A larger sample size may have shown that one or more of the demographic attributes had a significant impact. Unfortunately, due to the time of year in which the study was conducted, the IBOLC class in session at the time of the study was smaller than normal. Additionally, the time of year also resulted in a class mix that was much heavier on service academy graduates than other timeframes would have been. This is due to the graduation dates of each of the commissioning sources. The U.S. Military Academy graduates in early May and those officers have priority for class seats in the early summer IBOLC classes. Lieutenants receiving their commission through ROTC typically fill the bulk of mid to late summer IBOLC classes, with OCS commissionees filling in throughout the year due to their cyclic graduation dates. This resulted in a disproportional number of service academy commissionees serving as participants. Finally, the actual instrument used for gathering data, the DA Form 7566, Composite Risk Management Worksheet, was designed to serve as a risk management tool, not a test instrument as it was in the study. As such, it was not designed using an approach based in a proven research methodology to ensure that it fully captures the scope of anticipated learned knowledge or performance measures when used in a data collection role. Although it served its purpose in this study based on its familiarity to all respondents and its doctrinal foundation, future studies may consider an alternative set of test measures that are first validated as test instruments by checking for internal consistency.

7.2 Recommendations for further work

It must be noted that one potential reason for the lack of any statistically significant impact by the demographic might have occurred as a result of the RM training provided by the IBOLC instructors prior to the respondents completing their risk assessments. This standardized block of instruction may have had a mitigated effect on the disparity that could be caused by varying backgrounds, experiences, etc, and essentially caused a "leveling of the playing field" in the participants' ability to identify hazards. If this were the case, it would seem to speak highly of the Army's current RM Chain Teaching model used to instruct service members on RM. This study however, did not directly address this idea, and the researcher recommends this as a topic for further study utilizing a pre/post-test methodology. This study could analyze the impacts of the standardized instruction by recording the participants' results from two scenarios completed prior to their receiving the standardized block of RM instruction. Once they have received the instruction, the researchers could present the participants with two more scenarios, similar in nature to the first two, and use the differences in performance data to determine what, if any, impacts the standardized block of RM instruction had on the population's ability to correctly identify hazards. Finally, the researcher recommends that a similar study can be conducted but with alternative demographic attributes such as respondent age, specific Military Occupational Specialty (MOS) if the respondent had served previously in the military, specific college major (versus academic discipline category such as the researcher used), etc, in order to determine if there might be a correlation between those attributes and how the participants react to different RM scenarios in the U.S. Army.

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