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Predicting US Army First-Term Attrition After Initial Entry Training

TRADOC Analysis Center
700 Dyer Road
Monterey, CA 93943-0692

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Predicting US Army First-Term Attrition After Initial Entry Training

Authors

MAJ Anthony D. Smith
MAJ Karey Speten
Dr. Andrew Anglemyer
MAJ Jarrod Shingleton
Dr. Jon Alt

PREPARED BY:

ANTHONY D. SMITH
MAJ, US Army
TRAC-MTRY

APPROVED BY:

MICHAEL D. TETER
LTC, US Army
Director, TRAC-MTRY

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ABSTRACT

The United States Army recently announced a reduction of its 2018 recruiting goal due to a challenging recruiting environment and a shrinking population of eligible candidates. However, the Sergeant Major of the Army has stated that the current improvement in the retention of existing soldiers should mitigate the loss of new recruits. The goal of this research is to identify demographic and administrative factors of active component, first-term enlisted soldiers who have completed their Initial Entry Training (IET) to construct models to predict the probability of failure in completing their initial contractual obligation. We construct a binary logistic regression model, classification tree and a random forest classification model to predict a soldier's probability of first-term attrition based on the individual's unique service record. We design a web based graphic user interface that allows leaders, soldiers or recruiters to input demographic variables of current soldiers or recruits and get the predicted probability of attrition as an output. We find that a soldier's deployment history and the duration of the initial contract are significant predictors of whether a soldier will complete his or her first term. Knowledge of the key factors, and other influencing variables, assists the Army Resiliency Directorate in creation of models and tools to better advise U.S. Army leadership and development of intervention strategies and preventative measures to preclude the loss of first-term soldiers.

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LIST OF ACRONYMS AND ABBREVIATIONS

AAG	Army Analytics Group
AFQT	Armed Forces Qualification Test
ARD	Army Resiliency Directorate
ASVAB	Armed Services Vocational Aptitude Battery
AWD	Army Waiver Database
AUC	Area Under the Curve
BASD	Basic Active Service Date
CMF	Career Management Field
CTS-OCO	Contingency Tracking System – Overseas Contingency Operations
DA	Department of the Army
DCIPS	Defense Casualty Information Processing System
DMDC	Defense Manpower Data Center
DOD	Department of Defense
GAO	Government Accountability Office
GED	General Education Diploma
HOR	Home of Record
HRC	Human Resources Command
IET	Initial Entry Training
MEPCOM	Military Entrance and Processing Command
MOS	Military Occupation Specialty
MTOE	Modified Table of Organization and Equipment

PDE	Person-event Data Environment
PID	Person Identifier
TAPDB	Total Army Personnel Database
TSC	Test Score Category
TDA	Table of Distribution and Allowances
TRAC	TRADOC Analysis Center
TRADOC	Training and Doctrine Command
RF	Random Forest
ROC	Receiver Operating Characteristic
USAREC	United States Army Recruiting Command
VIF	Variance Inflation Factor

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This project is a great example of the teamwork and collaborative environment fostered between TRAC Monterey and the Naval Postgraduate School. Each member of the team brought their specific talents to the table and created a usable product for an outstanding sponsor.

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EXECUTIVE SUMMARY

The ability to successfully recruit and retain soldiers will be a challenge as long as there is an Army. Training civilians to become soldiers and then ensuring they complete their initial obligation is an expensive proposition and continually studied. The goal of this research is to identify demographic and administrative factors of active component, first-term enlisted soldiers who have completed their Initial Entry Training to construct models to predict the probability of failure in completing their initial contractual obligation. We construct a binary logistic regression model, classification tree and a random forest classification model to predict a soldier's probability of first-term attrition based on the individual's unique service record. We design a web based graphic user interface that allows leaders, soldiers or recruiters to input demographic variables of current soldiers or recruits and get the predicted probability of attrition as an output. We find that a soldier's deployment history and the duration of the initial contract are significant predictors of whether a soldier will complete his or her first term. Knowledge of the key factors, and other influencing variables, assists the Army Resiliency Directorate (ARD) in creation of models and tools to better advise U.S. Army leadership. The analysis from this project enhances ARD's ability to recommend intervention strategies and preventative measures to preclude the loss of first-term soldiers.

The accuracy rate of our predictive models is 83% and provide enough fidelity to warrant consideration of its use by Army planners. General attrition rate findings based on demographic predictor variables may help to inform force strength requirements, recruiting goals, and retention efforts. The flexible and repeatable nature of the random forest modeling technique provides analysts the ability to react quickly to changes in data availability and shifts in both policies and priorities.

Most importantly, this research provides ARD insight as the agency continues its efforts to improve soldier resiliency and, by extension, first-term attrition rates. Application of our predictive model to the administrative records of current enlistees could provide policy makers with probability estimates of all first-term soldiers and

facilitate the creation of intervention programs and prioritized resource strategies built upon a quantitative foundation.

SECTION 1. INTRODUCTION

1.1. PURPOSE

The goal of our research is to identify demographic and administrative factors available in every soldier's service record with potential to inform statistical models to predict a soldiers' probability of failing to complete their initial contractual obligation. We focus on answering the following two problem statements from the ARD: (i) What are the demographic and medical factors of personnel with highest probability of failure? and (ii) What is the mean number of total failures during the first enlistment term? We compare the effectiveness of logistic regression, classification and regression trees, and random forests. We demonstrate a proof of principle web-enabled decision support tool that employs the recommended model to predict the likelihood of attrition in an interactive manner with potential to support use cases in recruiting and by organizational leaders. We scope the analysis with the constraints, limitations and assumptions we describe in the next section.

1.2. CONSTRAINTS, LIMITATIONS, & ASSUMPTIONS

Constraints-*limit the study team's options to conduct the study*:

- We must complete all analysis in the Person-Event Data Environment (PDE).
- We must finish our research no later than 30 June 2018.

Limitations-*a study team's inabilities to investigate issues within the sponsor's bounds*:

- Analysis is limited to six data sets within the PDE.
    - Army Master, Transaction, Waiver, Contingency Operations, Casualty and Military Entrance databases.
- Data available lacks a consistent measure of attrition.

- Inconsistencies between the coding of the race variable exist between data sources and the large amount of missing data in the ethnicity variable limit the team's ability to make use of these variables previously identified as important to attrition.

Assumptions-*study specific statements that are taken as true in the absence of facts*:

- Data maintained within the PDE are accurate and represent complete soldier information for the six fiscal years analyzed.
- No significant changes occurred in a soldier's record that were not accurately captured by the quarterly snapshot dates available.
- Less than 1% of our total population have contractual obligation durations with "odd" values of one, two, seven, or eight years. We assume the standard enlistment contract is between three to six years. Since the odd values represent such a small percentage of the data, we remove these observations.
- In the creation of the predictor variables, 2.5% of the soldiers have the same odd contractual obligation values, which prevent selection of the soldier record with the correct end date of their first-term. We assume these entries are erroneous so we compute the average contractual period from the full population and assign the odd contractual obligation observations a value of 4 years.
- That soldiers successfully complete their initial obligation if their separation date was within three months of their first-term end date.

1.3. BACKGROUND & LITERATURE REVIEW

Recruiting and retaining for the Army will always be a challenge. Sergeant Major of the Army Daniel Dailey describes a positive development in first-term attrition rates:

"Retaining current soldiers has been more successful this year than in the past, with 86% staying on, compared with 81% in previous years" (Baldor, 2018, p. 1). On the other hand, the Army has announced its projected failure to meet its recruiting goal of 80,000 active soldiers in FY2018. The U.S. Army faces a significant challenge in recruiting and retention for the foreseeable future due to the low unemployment rate. According to Syeed and Whiteaker, "high obesity rates, drug use, criminal records and failing grades on the Army's aptitude test" complicate the challenge even further by reducing the eligible recruiting pool to "29% of the available population of 17-to 24-year-olds" (Syeed and Whiteaker, 2018). As highlighted by Sergeant Major Dailey's comment, reenlistments and retention of existing soldiers is key to long-term manning level sustainability and growth.

1.3.1. Previous Research

RAND Corporation and the Government Accountability Office (GAO) produced a large body of research on Army attrition over the last four decades. Their research consistently demonstrates that the most significant factors linked to attrition are a soldier's gender and whether they graduated high school or obtained a General Education Diploma (GED) (GAO, 1997). Specifically, females and GED recipients have a higher probability of failing to fulfill their initial service obligations than males and high school graduates (GAO, 1997). The general methods of analysis and data sources are similar across all the studies; however, the specific data sources and data manipulation methodologies are not well documented. A brief overview of their research will assist in better understanding U.S. Army attrition.

1.3.2. Government Accountability Office

The first report to examine military attrition rates after the enlistee population had stabilized for a decade following the elimination of the draft was published in 1997 and studied data collected by the Defense Manpower Data Center (DMDC) on service members from 1986 to 1994 (GAO, 1997). The research concluded that first-term attrition across all military services consistently averaged approximately 30%, but

cautioned the services against drawing definitive conclusions from the results because of the lack of consistency in the available data and arbitrary attrition goals created by each service. In his testimony before the Subcommittee on Military Personnel of the 105th Congress in 1997, Mark Gebicke of the GAO commented specifically on the inadequate quality of data available to researchers:

> DOD's [Department of Defense] [sic]current data on attrition is inconsistent and incomplete for two reasons. First, the services interpret DOD's definitions of separation codes differently and therefore place enlistees with identical situations in different discharge categories. …Second, DOD's separation codes—which represent DOD's primary source of service-wide data on why people are leaving the services—capture only the official reason for discharge. …In an attempt to standardize the services' use of these codes, DOD issued a list of the codes with their definitions. However, it has not issued implementing guidance for interpreting these definitions (Military Attrition, 1997, p. 6)

Gebicke testified again before the committee in 1998 and stressed the need for better analysis of separations by the DoD to improve military recruiting efforts. Additionally, he referenced specific findings from other GAO studies that "consistently [showed] that persons with high school diplomas [vice GED holders] and Armed Forces Qualification Test [AFQT] scores in the upper 50th percentile have lower first-term attrition rates" (Military Attrition, 1998, p. 3).

One of the studies referenced by Gebicke provides numerous descriptive summaries of the attrition data allowing for a baseline to check against the constructed dataset for our current research (GAO, 1998):

- First-term attrition rate from 1986 to 1998 was 31%
- 87% of enlistees signed 2-year, 3-year, or 4-year contracts
- In FY1993, female attrition rates were 51% compared to 37% for males

Many authors use the descriptive summaries of the data to specifically highlight the inconsistency of the separation codes applied across the services as mentioned in GAO's previous studies. Analysts group the separation codes into broad categories: misconduct, medical conditions, unsatisfactory performance, drug use, and pregnancy.

The large volume of approximately 1.7 million annual enlistees encourage the researchers to assume statistical similarity across the services when comparing the attrition rates in each of the categories. However, significant differences in attrition rates within categories were seen between the services across all fiscal years (GAO, 1998). This is the only document we find that clearly defines "attrition." The authors state that DoD has defined attrition "as the failure of an enlistee to complete his or her contractual obligation" (GAO, 1998, p. 16).

The most recently published report on overall DoD attrition rates is found within a 2017 GAO study focused on the attrition of first-term enlistees due to medical separations. The study compared first-term medical separations with overall first-term separation totals and reports that the overall attrition rate was steady from FY2005 to FY2015 across all services at an average of approximately 28% (Farrell, 2017, p. 14).

1.3.3. RAND Corporation

Buddin utilized new survey data from the 1979 Survey of Personnel Entering Military Service to enrich the typical service personnel record with additional variables (e.g., employment history, job match, job satisfaction, entry point decisions) (Buddin). His findings mirror results from other studies such as the link between attrition and the lack of a high school diploma and lower AFQT scores. The new survey data illuminates that the probability of attrition increases by 1% as the age of an enlistee at enlistment increased from 17. The results also indicate that unemployment prior to enlistment increased the attrition rate. Buddin also finds no relationship between job match or satisfaction and attrition.

Martin develops a predictive logistic regression model with Army personnel data provided by the DMDC. Martin's approach factors all numerical predictors (e.g., age, aptitude test scores) and collapses the factors into broad categories as to "maximize the difference in attrition between the dummy variable classes" (Martin, 1995, p. 35). Although his model ultimately has poor predictive power, he is content that it is at least no worse than other modeling attempts. Martin's work also provides interesting thoughts regarding the selection of variables in most attrition research. He points out that many

variables linked to attrition, such as gender, are unable to be affected by any change in policy. Martin believes that the variables are proxies for other correlated variables that may not be represented elsewhere in the data and should be considered as valid predictors even though the "true" variable is still unknown (Martin, 1995, p. 19).

Buddin focused his attention specifically on Army first-term attrition. The study data are very similar to the dataset used in our current research (cite). He used DMDC personnel data from FY1995 to FY2001 consisting of 550,000 observations (i.e., individual soldier enlistments) and incorporated extensive recruiting station and individual recruiter data provided by the U.S. Army Recruiting Command. He found that none of the recruiting information had any impact on attrition rates. While confirming overall attrition rates of 34% similar to other research, he found a higher attrition rate (51%) among women compared to men (31%) and a higher rate (50%) among GED holders versus high school graduates (32%) (Buddin, 1979, p. 74). Unlike previous research, he also detected higher rates of attrition among African-American and white non-Hispanic enlistees compared to Asian and Hispanic recruits.

1.4. TECHNICAL APPROACH

Based on our literature review and data available, we opt to use binary regression techniques along with classification methods to answer ARD's problem statement. We explore the use of logistic regression, classification trees and random forests on this problem.

After the creation of the cohort, we create training and test datasets allowing for the eventual validation of the "best" model. Since the research plan includes an analysis of fiscal year differences, we stratify the data by fiscal year of accession. Additionally, we stratify the data by the response variable. We ensure that both the training dataset and the test dataset have enough observations to allow for independent modeling over the spectrum of fiscal years and an appropriate number of observations for model training.

After stratifying the data, we employ a random 80/20 split, keeping 80% of the data as the training dataset for model building and selecting 20% of the observations as the testing dataset to test the generalizability of the models.

SECTION 2. DATA PREPARATION

This project uses six datasets accessed through the Person-Event Data Environment (PDE). The PDE was developed and is currently used by the Army Analytics Group (AAG) to support quick analysis projects for Senior Army Leadership, research data management and model validation for large Army studies. The system is designed as a self-service and collaborative environment, allowing those who need such data to retrieve and analyze the data with minimal support, and give Department of Defense (DoD) senior leaders timely and actionable information. PDE includes a project management suite that allows users to define a study, invite team members to join the study, specify data sets from a data catalog, conduct analyses and publish results with controlled or open availability (Jensen, 2016, pg 6).

2.1.1. Data Sources

2.1.1.1. ***Active Duty Military Personnel Master File***

The primary dataset we use to construct the cohort of enlisted soldiers for analysis is the Active Duty Military Personnel Master. The data consists of the demographic information contained in a soldier's service record and detailed information from a soldier's personnel file maintained by the Army Human Resources Command in the Total Army Personnel Database (TAPDB). Next, we merge the Active Duty Military Personnel Transaction dataset with our newly created Cohort Dataset. The transaction table captures the changes in a soldier's record such as enlistment into the Army, separation from the Army, and reenlistments. The table provides the documented separation codes we use in our analysis for determining if a soldier left the Army before the completion of the initial contractual obligation.

2.1.1.2. ***MEPCOM-700 and AWD Files***

Next, we add the MEPCOM-700 file. The data is derived from the system of record utilized by the Military Entrance and Processing Command (MEPCOM) during the recruitment process of a civilian applicant in all branches of service. The data contains additional demographic data not found in the Army's Master file such as scores from the Armed Services Vocational Aptitude Battery (ASVAB) testing and the number

of dependents at the time of enlistment. Related to the MEPCOM file, we also include the Army Waiver Database (AWD) maintained by the U.S. Army Recruiting Command (USAREC) containing information about administrative and medical waiver events granting a soldier admission into the Army.

*2.1.1.3. **DCIPS and CTS-OCO Files***

The final two datasets consist of events that occurred during a soldier's initial contractual period. The injury table reports data contained in the Defense Casualty Information Processing System: Injury file (DCIPS) and lists any injuries that occurred to a soldier while in a deployed status: both hostile and non-hostile types. Finally, we join on the Contingency Tracking System – Overseas Contingency Operations (CTS-OCO) dataset for a count of the number of deployments and number of days deployed for each soldier. Unlike the previously described datasets which provided mostly standardized codes, the variables we create from the injury and deployment tables represent logic-based calculations in determining the counts of events and ensuring only events that occurred prior to either the completion of the contractual period or early discharge are credited.

2.1.2. Variable Selection

After we join the tables together into a dataset containing one observation for each of the enlisted soldiers that joined the Army from FY2005 to FY2010, our Cohort Dataset contained 418,204 observations (soldiers) with 11 numerical predictor variables, seven binary variables, and 14 categorical variables. We initially explored all 32 variables available. Table 1 provides a list of the variables we use in the analysis.

Table 1 Variable Summary and Data Source Mapping

Variable	Data Source	Data Type	Factor Levels
AFQT Category	Master	Categorical	5
Age at Enlistment (Years)	Master	Numeric	N/A
ASVAB GT Score (Scale 3-150)	MEPCOM	Numeric	N/A
Citizenship Origination	Master	Categorical	3
Citizenship Status (Enlistment)	Master	Binary	2
Contract Duration (Years)	Master	Numeric	N/A

Variable	Data Source	Data Type	Factor Levels
Days Deployed (Qty)	CTS-OCO	Numeric	N/A
Dependents (Max Qty)	Master	Numeric	N/A
Deployments (Qty)	CTS-OCO	Numeric	N/A
Education Level (Enlistment)	Master	Categorical	4
Education Level (Max)	Master	Categorical	4
Education Tier	Master	Categorical	3
Fiscal Year (Enlistment)	Master	Categorical	6
Gender	Master	Binary	2
Height at Enlistment (Inches)	MEPCOM	Numeric	N/A
Home of Record Region	Master	Categorical	5
Hostile Injuries (Qty)	DCIPS	Numeric	N/A
Marital Status (Max)	Master	Categorical	3
Max Time-in-Grade (Months)	Master	Numeric	N/A
Military Occupation (Max)	Master	Categorical	21
Military Occupation Group	Master	Categorical	3
Non-Hostile Injuries (Qty)	DCIPS	Numeric	N/A
Prior Service	Transaction	Binary	2
Rank (Enlistment)	Master	Categorical	6
Rank (Max)	Master	Categorical	6
Unit Region (Max)	Master	Categorical	5
Unit Type (Max)	Master	Categorical	5
Waiver (Admin)	AWD	Binary	2
Waiver (Conduct)	AWD	Binary	2
Waiver (Drug)	AWD	Binary	2
Waiver (Medical)	AWD	Binary	2
Weight at Enlistment (Pounds)	MEPCOM	Numeric	N/A

2.1.2.1. ***Description of Variables***

This section describes the variables that are unintuitive from table 1. The *AFQT Category* represents the classification of an enlistee based on the percentile scores on the ASVAB. The U.S. Army Recruiting Command uses this to determine if a recruit is eligible to join the Army and identify the military occupational specialties for which an enlistee can pursue. MEPCOM defines test score categories: however, the Army determines which categories will be accepted (Department of the Army [DA], 2016, pp. 11-12). We combine the lowest score categories (TSC-IVB and TSC-V) as neither category is allowable for entrance into the Army.

Education Level reports the level of education achieved. We consolidated the codes from the Master data table to capture the four key educational milestones: high school completion, some college, undergraduate degree, and graduate degree. Since education levels can change over time, we construct two variables to consider both education level at enlistment and whether final education level impacted first-term attrition.

The military occupation variables capture the job skill of the soldier. The Career Management Field (CMF) is the first two numbers in a soldier's primary occupational specialty code. The CMF groups similar, but unique, specialties into broad categories such as infantry or supply. The *military occupation* variable is the individual soldier skill. We collapse factor levels with small counts into an *LD* (low density) category. We group the CMFs into much broader categories as defined in the Army force structure regulation (Department of the Army [DA], 2014, p. 11) with the *military occupation grp* variable. We show the military occupation definitions and groupings in Table 2.

Table 2 Military Occupation Map

Military Occupation Group	Military Occupation (CMF)	Description
Operations	11	Infantry
	12	Engineer
	13	Field Artillery
	14	Air Defense Artillery
	15	Aviation
	18	Special Operations Forces
	19	Armor
	31	Military Police
	74	Chemical
Operations Support	25	Signal
	35	Military Intelligence
Force Sustainment	42	Human Resources
	68	Health Services
	88	Transportation
	91	Ordnance

Military Occupation Group	Military Occupation (CMF)	Description
	92	Quartermaster
LD (Low Density)	27	Judge Advocate General
	29	Electronic Warfare
	36	Finance
	37	Psychological Operations
	38	Civil Affairs
	46	Public Affairs
	51	Acquisitions
	56	Chaplain
	71	Health Services (Lab)
	79	Recruiting

The *unit type* variable represents the difference in the mission and function of the unit to which a soldier was assigned at the end of their first-term. Generally, a unit authorized by a Modified Table of Organization and Equipment (MTOE) document is part of the Operating Force responsible for deployed warfighting functions while a unit defined by a Table of Distribution and Allowances (TDA) document belongs to the Generating Force responsible for non-deployable administrative, training, and strategic functions (Department of the Army [DA], 2013). A multi-component unit is manned by a mix of Active Component, Army Reserve, and National Guard members.

2.1.3. Building the Response Variable

In this section, we describe the process of building the response variable.

We start with 429,908 unique soldier records representing all enlisted soldiers who arrived at basic training in FY2005 to FY2010. Of those soldiers, we remove 11,704 due to an Initial Service Separation Code indicating that they were discharged from the Army prior to the completion of their Initial Entry Training. Next, we verify those who did not attrit using the Enlisted Career Status Code (42.71% for the cohort under study).

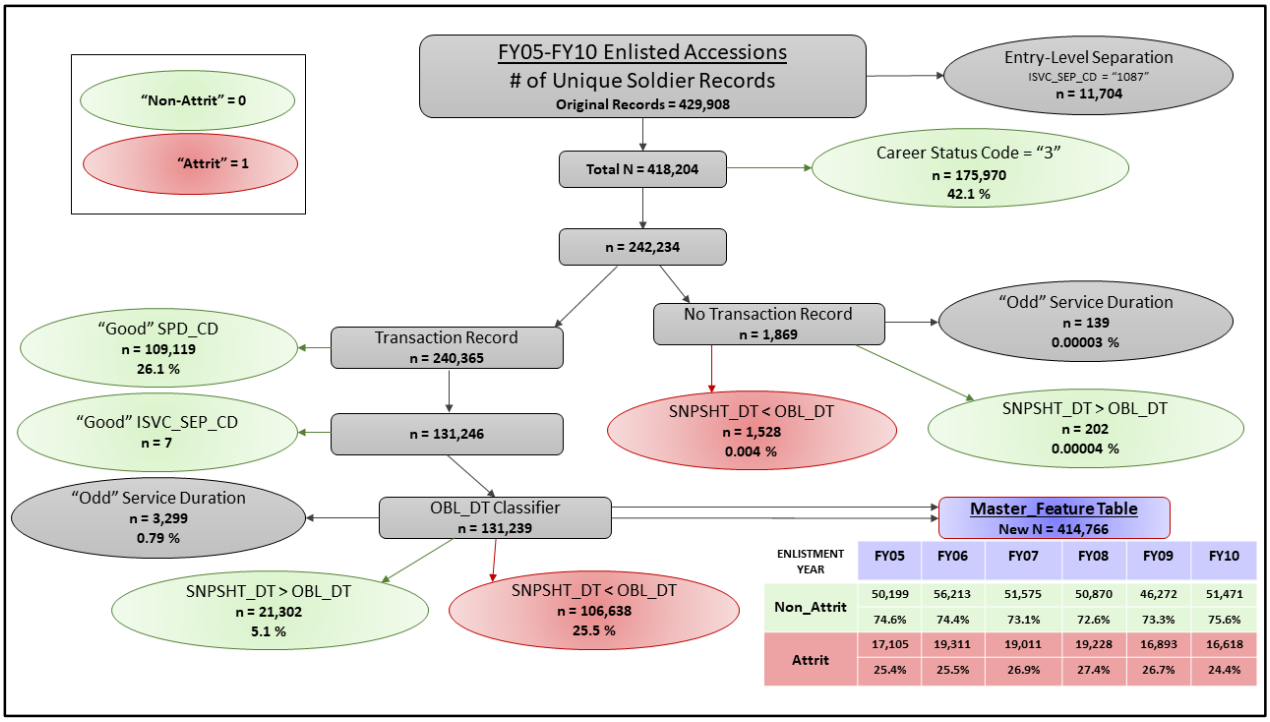
Next, we use the Separation and Discharge Code (SPD_CD) and Initial Service Separation Code (ISVC_SEP_CD) from the Transaction table. After joining the table to the new Master table, we find that 1,869 observations are missing Transaction table data. This prevented an examination of separation codes and another method is required. The

complete snapshot records allowed us to determine if a soldier completed their first-term if they simply had any record after their first-term end date. Unfortunately, there is no end date present in the data. We develop an algorithm to create the Calculated Obligation Date (CALC_OBL_DT) by adding the initially contracted number of years to the Basic Active Service Date (AFMS_DT) of each soldier. Once we calculate this value and adjust for the assumption of successful completion if a record existed within the final three months of the first-term, we classified 1,528 soldiers as having failed to meet their obligation ("attrit") and we remove them from the Master table.

Next, we examine the remaining 240,365 observations for "good" separation codes. Of the 172 unique SPD_CD categories and 55 unique ISVC_SEP_CD categories, we determine that 46 of them represent successful completion of the first-term of service (Appendix A). The separation codes allow us to classify another 26% of the total population as having successfully completed their contractual obligation period. At this point, we classify over two-thirds of our total population as successful without even referencing the extensive and questionable list of "bad" separation codes.

Finally, we need to classify the remaining 131,239 soldiers without referencing the separation codes. Instead, we use the derived CALC_OBL_DT as used for soldiers with no transaction data. We remove the 3,299 observations having no value for an initial obligation duration. Of the remaining observations, 83% had no record in the master data table beyond their CALC_OBL_DT. We classify the soldiers as having failed to meet their initial contractual obligation ("attrit").

We summarize our methodology of classification as a flowchart in Figure 1. Along with the classification walk-through, we provide a final summary table of our cohort dataset that includes the total number of observations and attrition rates per fiscal year. At a glance, the data appears valid as the number of accessions across fiscal years is steady and the attrition rates are consistent and near the 27-30% attrition rates reported in previous studies.



ENLISTMENT YEAR	FY05	FY06	FY07	FY08	FY09	FY10
Non_Attrit	50,199	56,213	51,575	50,870	46,272	51,471
	74.6%	74.4%	73.1%	72.6%	73.3%	75.6%
Attrit	17,105	19,311	19,011	19,228	16,893	16,618
	25.4%	25.5%	26.9%	27.4%	26.7%	24.4%

Figure 1 Classification Summary of the Response Variable

SECTION 3. ANALYSIS AND FINDINGS

3.1. COHORT DATASET OVERVIEW

We provide summary statistics for the response variable across all fiscal years in Table 3. The attrition rate of approximately 26% across the fiscal years was consistent with previous research (GAO, 1997).

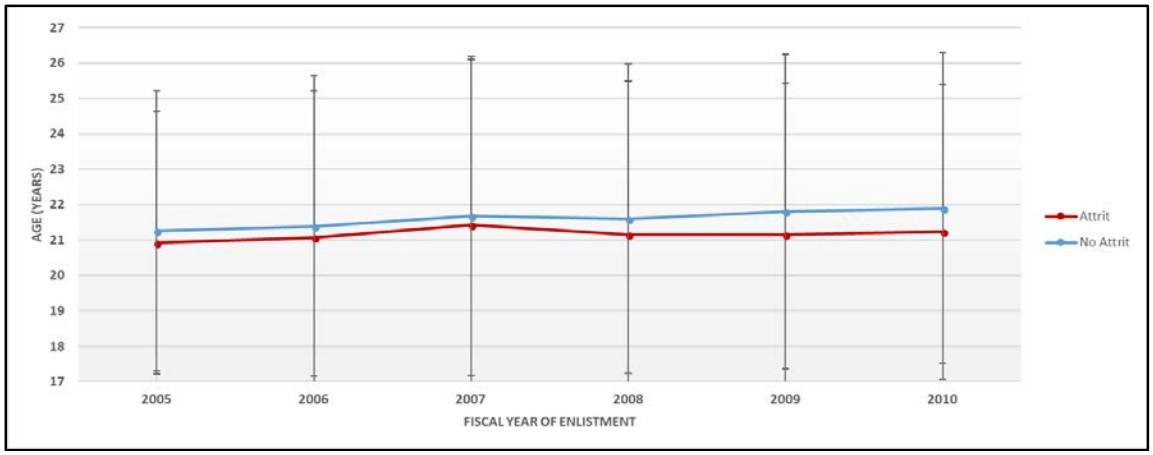
Table 3 Full Cohort Dataset—Attrition Rate by Fiscal Year of Enlistment

	2005	2006	2007	2008	2009	2010
Non-Attrit	50,199 (74.6%)	56,213 (74.4%)	51,575 (73.1%)	50,870 (72.6%)	46,272 (73.3%)	51,471 (75.6%)
Attrit	(25.4%) 17,105	(25.5%) 19,311	(26.9%) 19,011	(27.4%) 19,228	(26.7%) 16,893	(24.4%) 16,618

We provide a full summary of our cohort dataset in Appendix B. The numeric variables include the mean and standard deviation calculated for each of the fiscal years of accession. The binary and categorical factors contain data counts and proportions stratified by the fiscal year of accession for all factors and levels. We report missing data by a factor level of "NA" for the variables that had incomplete cases.

3.1.1. Numeric Variables Summary

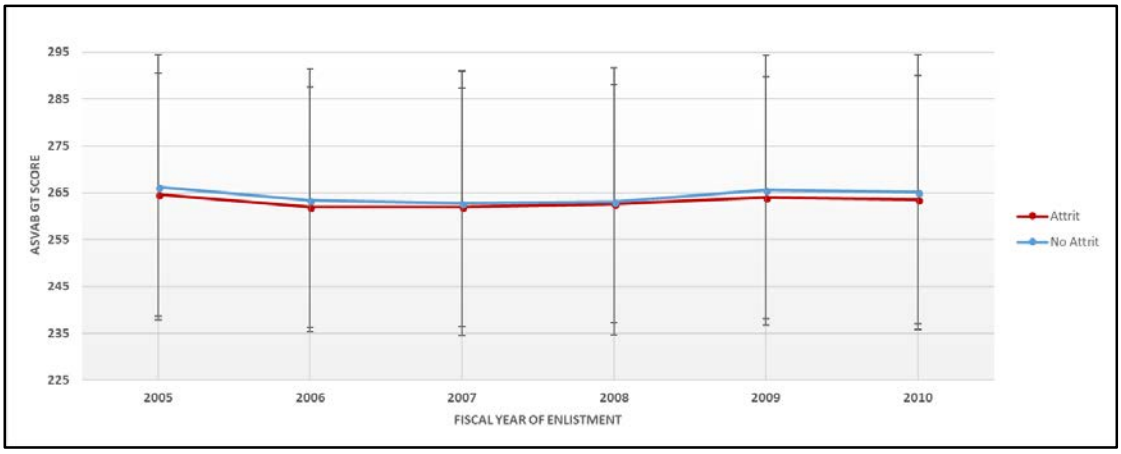
We summarize the numeric variables by stratifying the mean of the data for each of the fiscal years of enlistment. We show a higher average enlistment age of soldiers who successfully completed their first term (Figure 2) and the trend is consistent across all fiscal years of enlistment; however, the differences are all well within overlapping standard deviation bars.



Note: Error bars represent standard deviation.

Figure 2 Average Enlistment Age by Attrition Category

Unlike Martin's 1995 research, our data indicate very little difference in ASVAB scores between the attrition categories. Whereas Martin collapsed the AFQT percentiles into categories less than 65 and those greater than or equal to 65, our use of the ASVAB GT score similarly quantifies a recruit's performance. Once again, any difference in average GT scores was minor and well within the margin of error between the attrition categories (Figure 3).



Note: Error bars represent standard deviation.

Figure 3 Average ASVAB GT Score by Attrition Category

The average number of days deployed was different between the attrition categories (Figure 4). The difference could be an indicator of the sense of purpose and accomplishment that can result from performing the mission for which a soldier has

trained. However, it may only reflect the length of the initial contract and the related amount of time a soldier is eligible for possible deployment prior to discharge. Further analysis is required of the full deployment history of the soldiers to better understand this relationship. Incidentally, the sharp decrease in the average number of days deployed for soldiers completing their first-term matched expected results from the creation of our cohort dataset as U.S. Army deployment schedules slowed after the Iraq surge in 2007.

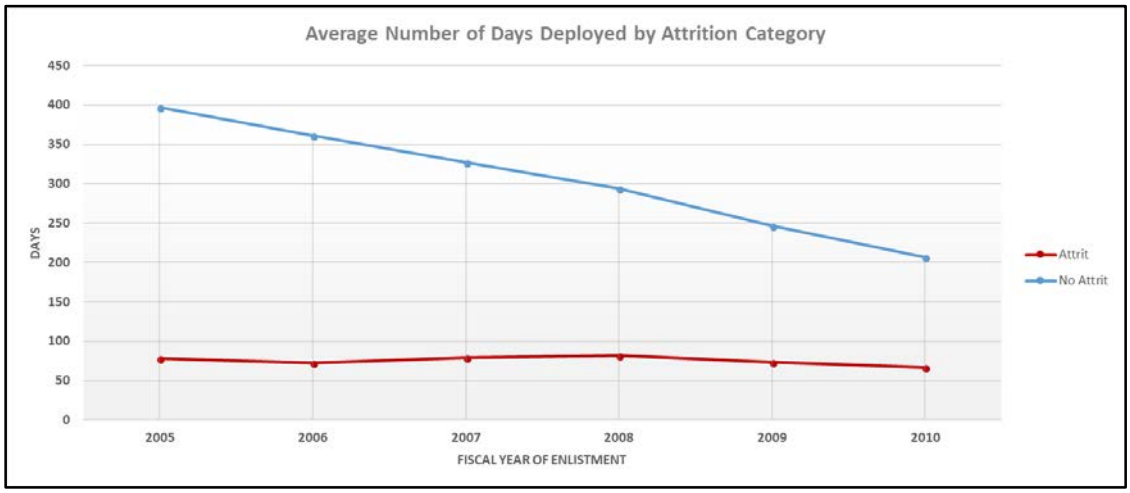


Figure 4 Average Number of Days Deployed by Attrition Category

We show that the remainder of the numeric variables exhibit even less of a difference between categories and provide little insight. However, we retain them in the cohort dataset for further statistical analysis.

3.1.2. Binary Variables Summary

Every identified, published attrition report noted that gender and the source of a high school certification are significant factors for determining a soldier's probability of successfully completing the first-term of enlistment. In our initial analysis of the binary data we examine the proportion of soldiers in each of these categories. Specifically, we expect to see a higher proportion of women and GED high school certifications among the population of soldiers who failed to complete their first term.

We find a difference in the proportion of women who fails to complete their first-term compared to men. Our average attrition rates across all fiscal years of enlistment for women of 40% and 24% for men are less than the results of 51% and 31% for women and men, respectively, reported in the 2005 attrition research of Buddin. We summarize our findings for each of the fiscal years of enlistment for males versus females in Figure 5. The female attrition rate ranged from 34% to 42% while the male attrition rate fell between 22% and 25%. The difference of our results compared to previous research is likely due to vague separation discharge codes and the lack of specific data methodology descriptions in the previous research.

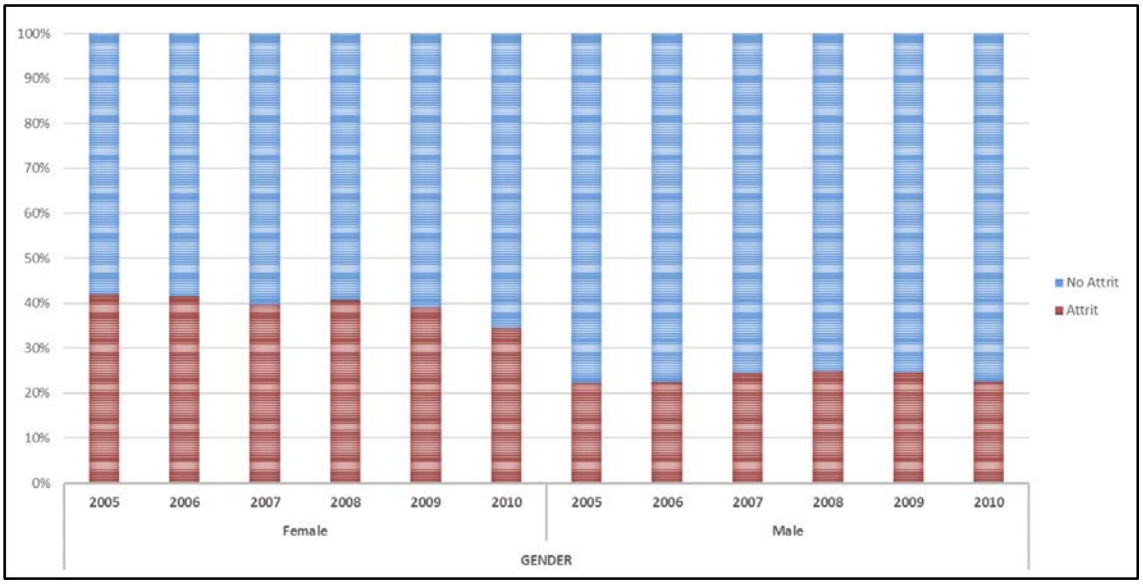
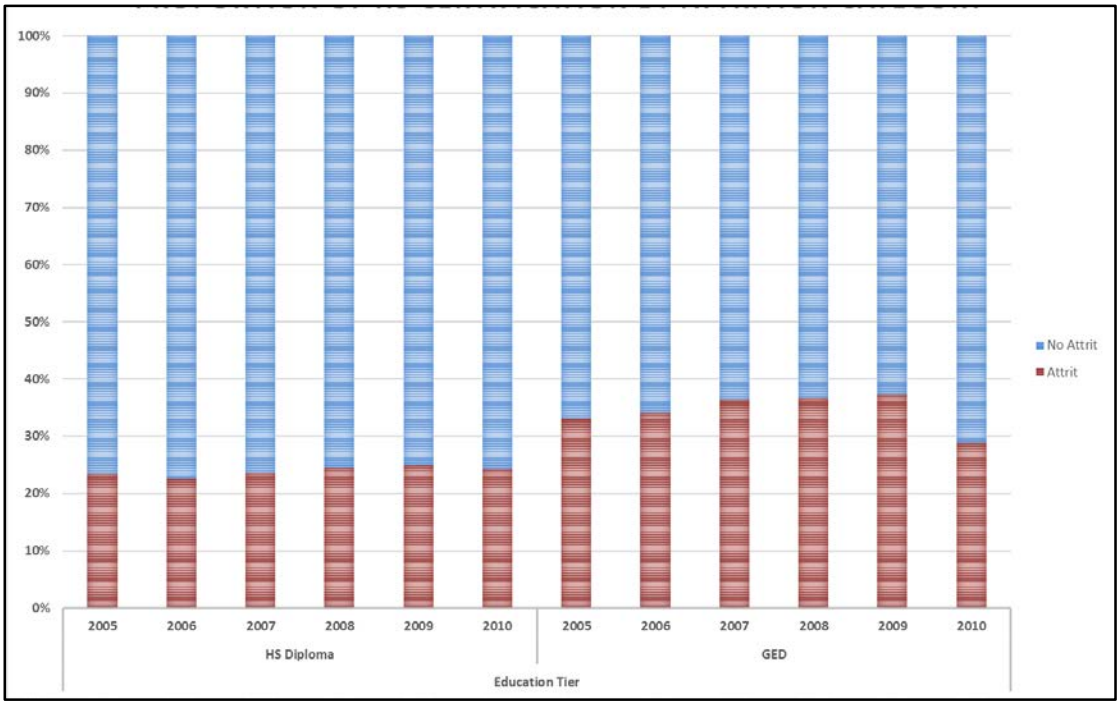


Figure 5 Proportion of Gender Levels by Attrition Category

As with our findings for gender, soldiers with a high school diploma had a lower attrition rate compared to soldiers holding a GED throughout our cohort dataset, though our rates are lower than the proportions found by Buddin (2005). High school graduates have a steady attrition rate of approximately 23% throughout the period of study while the attrition rate of enlistees receiving a GED fluctuates between 28% and 36% (Figure 6).



Note: Missing data and other high school certification levels have been omitted for clarity.

Figure 6 Proportion of High School Certification by Attrition Category

During the construction of our cohort dataset, we identify soldiers with prior service by the gain codes found within the Transaction table. These soldiers appear to have a significantly higher attrition rate than non-prior service soldiers (Figure 7). Though we initially include the prior service indicator in our analysis, we exclude the soldiers identified as prior service from the final models to prevent bias as these soldiers comprised less than 5% of our total population and we are unable to clarify the underlying data.

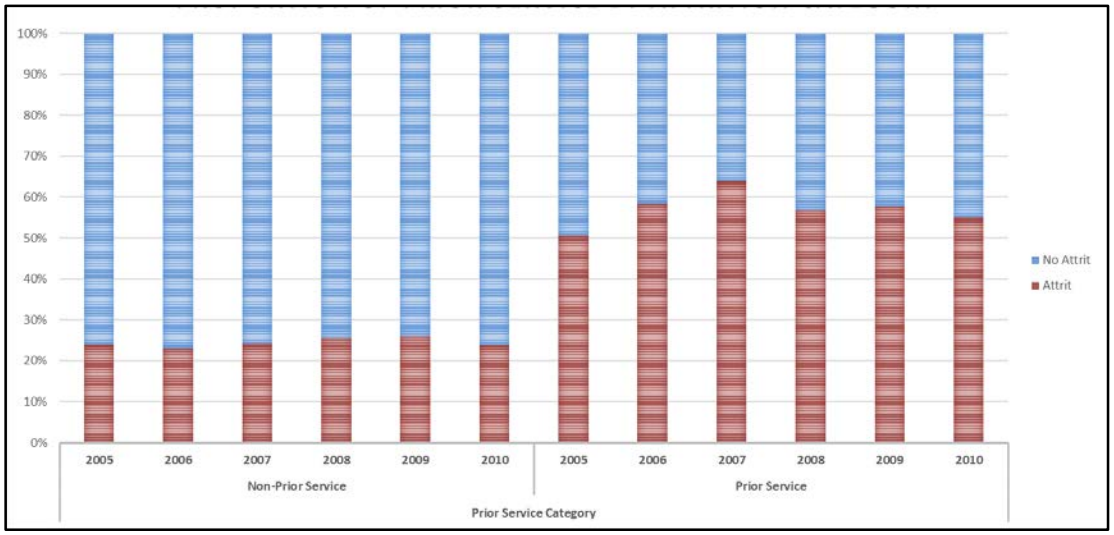


Figure 7 Proportion of Prior Service by Attrition Category

Our analysis of the waiver data revealed insignificant differences in the attrition rates between soldiers receiving waivers to allow enlistment and soldiers without waivers. Soldiers who receive a waiver and failed to complete their initial contractual obligation period represent less than 6% of the total population within the cohort dataset.

3.1.3. Categorical Variables Summary

In this section we highlight a Soldier's Home of Record at enlistment and marital status at the transition point out of the first term. The original personnel data reported a soldier's Home of Record state, which we collapse in our research to a region of the United States for modeling purposes. However, a look at the raw Home of Record state information is insightful. We display the overall attrition rate of individual states within the continental United States and illustrate an attrition rate 10% higher in the southern portion of the U.S. compared to other locations in Figure 8. Enlistees from West Virginia, Mississippi, and Louisiana appeared to be particularly prone to discharge from the Army before the end of their first term.

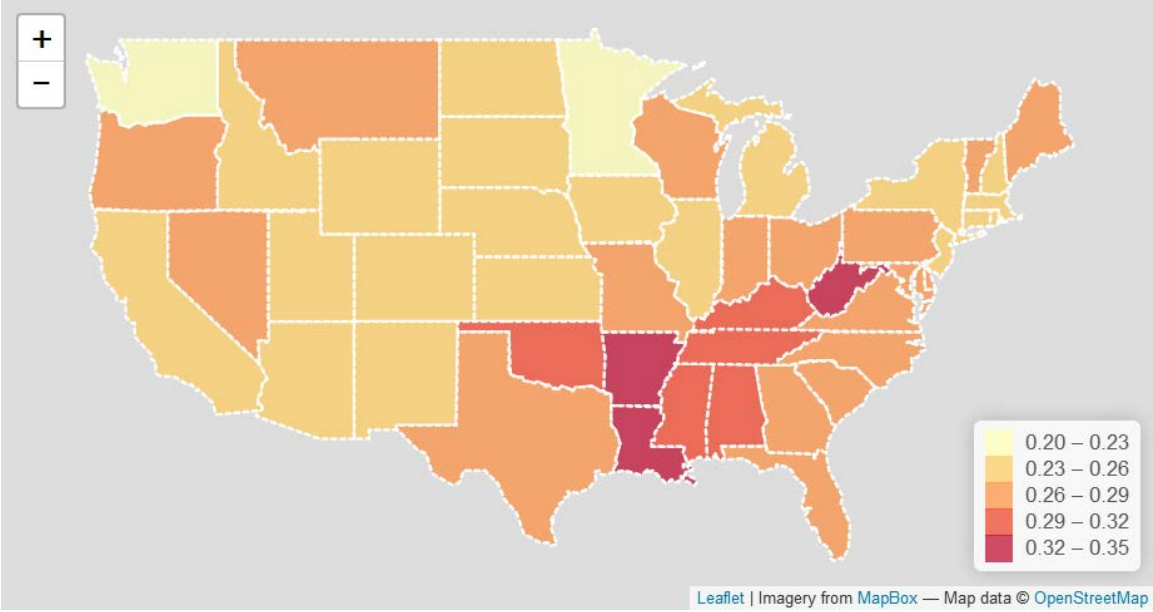
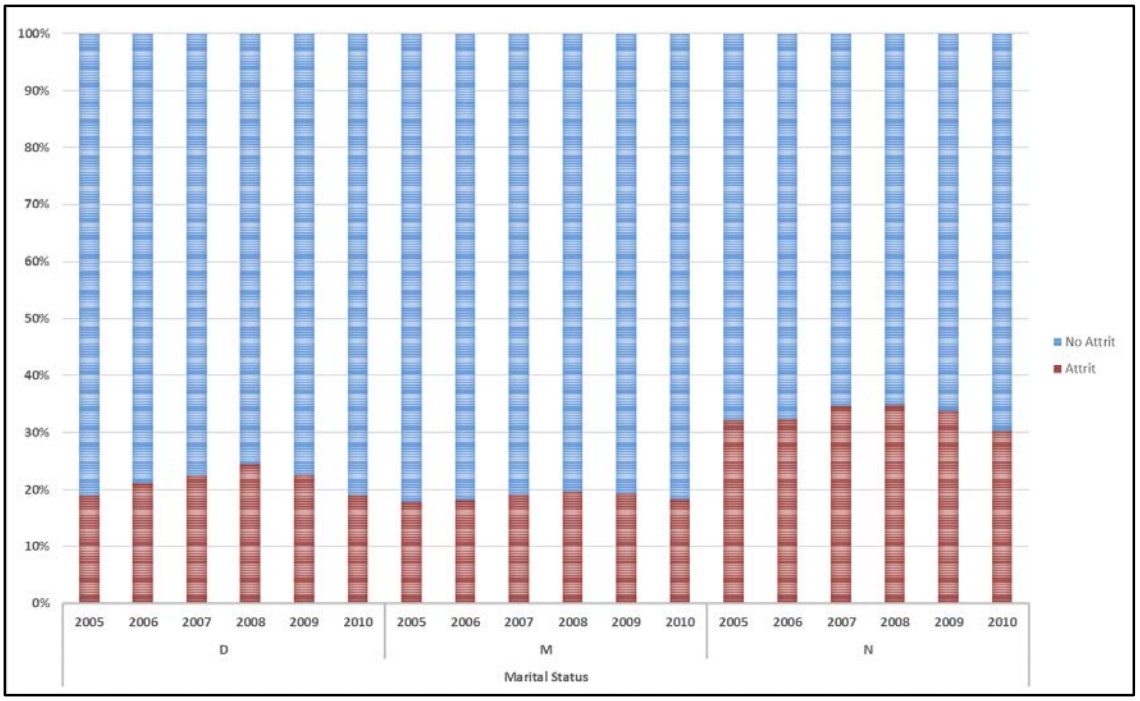


Figure 8 Attrition Rate by Home of Record

Our research considers the marital status of a soldier at the end of a successful first-term enlistment or at the point-of-failure for those soldiers who failed to complete the obligation period. The attrition rate of married or divorced soldiers averaged nearly 10% less than soldiers never having married (Figure 9). Unlike many of the categorical variables where differences in attrition rates are seen primarily in factor levels that include only a small amount of the total population, married and divorced soldiers make up nearly half of the cohort.



D-Divorced, M-Married, N-Never Married. "Other" category removed for clarity.

Figure 9 Proportion of Marital Status by Attrition Category

A notable exclusion from the list of insightful categorical variables includes the rank of a soldier at enlistment. The Army offers an incentive of higher ranks (paygrade and responsibility) to incoming recruits having certain academic achievements or referring additional enlistees. While this incentive may offer the benefit of higher recruitment volume, it does not appear that enlistees with a higher rank are more likely to complete their first-term than any other recruits.

3.2. MULTIVARIATE MODELING

Having split our cohort dataset into training and test sets, our initial modeling technique is a binary logistic regression to identify statistically significant variables and to generate model coefficients that may be used for a prediction tool. Additionally, we construct both a binary classification tree and random forests and compared the discrimination power of the models by examining their ROC curves.

3.2.1. Logistic Regression

We construct a binary logistic regression model utilizing an adapted backward stepwise regression with purposeful selection (Zhang, 2016). Also, we develop classification trees and random forest classification models for predictive power comparison utilizing the test dataset. We use the receiver operating characteristic (ROC) curves and Area Under the Curve (AUC) calculations as the measures of performance for model comparison. Our statistical methods include descriptive statistics and univariate analysis. Due to our large dataset, we address the issue of the "p-value problem." In large-sample studies, miniscule effects can be found as statistically significant. Previous research published in the Information Systems Research journal cautions against relying solely on p-values as they "can lead to claims of support for hypotheses of little or no practical significance" (Lin, Lucas Jr., & Shmueli, 2013, p. 906). In other words, results may have extreme statistical significance but no real-world applicability to the problem. We focus our analysis more on variable proportions, differences in effect sizes represented by the variable coefficients (marginal analysis), and charts representing descriptive statistic relationships rather than statistical significance. We select a p-value threshold of 0.001 and carefully consider each variable throughout the purposeful selection.

We begin our analysis with a look at the coefficient matrix output by our logistic regression model. We list the linear predictor estimates, log-odds, and probability in the model coefficient matrix (Table 4). The simplest interpretation is by understanding that variables with positive linear predictor estimate values increase the probability of first-term attrition, while negative estimate values decrease the probability. Thus, we see many

results that match our intuition. For instance, as the *contract duration* levels increase, the attrition probability increases. The most influential variable in the model, *days deployed*, is inversely related to the probability of attrition. Utilizing the probability, for each 30-day period that a soldier has deployed, his probability of first-term attrition is reduced by 30% if all other variables are fixed. Other findings of note include the increased probability of attrition for heavier enlistees and decreased probability for taller enlistees.

Table 4 Regression Model Coefficients Matrix

Variable Name	Linear Predictor Estimate	Linear Predictor Error	Log-Odds	Prob.	Pr(>|z|)
Contract Duration - 3 years	Ref.				
Contract Duration - 4 years	0.64	0.01	1.90	0.66	< 0.001
Contract Duration - 5 years	1.25	0.02	3.50	0.78	< 0.001
Contract Duration - 6 years	1.75	0.02	5.74	0.85	< 0.001
Prior Service - No	Ref.				
Prior Service - Yes	0.68	0.02	1.97	0.66	< 0.001
Military Occupation Group - Operations	Ref.				
Military Occupation Group - Operations Support	-0.55	0.02	0.58	0.37	< 0.001
Military Occupation Group - Force Sustainment	-0.31	0.01	0.73	0.42	< 0.001
Gender - Female	Ref.				
Gender - Male	-0.57	0.02	0.56	0.36	< 0.001
Rank (Enlistment) - CPL	Ref.				
Rank (Enlistment) - PFC	0.51	0.03	1.67	0.63	< 0.001
Rank (Enlistment) - PV1	1.02	0.02	2.77	0.73	< 0.001
Rank (Enlistment) - PV2	0.78	0.03	2.19	0.69	< 0.001
Rank (Enlistment) - SGT	0.95	0.08	2.59	0.72	< 0.001
Rank (Enlistment) - SSG	1.84	0.14	6.28	0.86	< 0.001
Waiver (Conduct) - No	Ref.				
Waiver (Conduct) - Yes	0.29	0.02	1.34	0.57	< 0.001
Waiver (Admin) - No	Ref.				
Waiver (Admin) - Yes	-0.41	0.03	0.66	0.40	< 0.001
Education Tier - High School diploma	Ref				
Education Tier - GED	0.55	0.01	1.74	0.64	< 0.001
Education Tier - No secondary school	0.61	0.06	1.83	0.65	< 0.001
Non-Hostile Injuries	0.34	0.05	1.41	0.58	< 0.001
Days Deployed	-0.01	0.00	0.99	0.50	< 0.001
Dependents	0.16	0.01	1.18	0.54	< 0.001
Height (Enlistment)	-0.01	0.00	0.99	0.50	< 0.001
Weight (Enlistment)	0.00	0.00	1.00	0.50	< 0.001

Variable Name	Linear Predictor Estimate	Linear Predictor Error	Log-Odds	Prob.	Pr(>|z|)
AFQT Category - II	Ref.				
AFQT Category - IIIA	0.20	0.01	1.23	0.55	< 0.001
AFQT Category - IIIB	0.26	0.01	1.29	0.56	< 0.001
AFQT Category - I	-0.35	0.03	0.71	0.41	< 0.001
AFQT Category - IVA	0.39	0.03	1.47	0.60	< 0.001
AFQT Category - IVB+	0.75	0.21	2.13	0.68	< 0.001
Citizenship Origination - Born in U.S.	Ref.				
Citizenship Origination - Naturalized	-0.74	0.04	0.48	0.32	< 0.001
Citizenship Origination - Outside U.S.	-0.23	0.04	0.80	0.44	< 0.001
Marital Status - Divorced	Ref.				
Marital Status - Married	0.06	0.03	1.06	0.51	0.044
Marital Status - Never Married	0.97	0.03	2.65	0.73	< 0.001
Marital Status - Other	0.25	0.20	1.29	0.56	0.202
Unit Type - TDA	Ref.				
Unit Type - MTOE	-0.89	0.01	0.41	0.29	< 0.001
Unit Type - Multi-Component	-1.91	0.11	0.15	0.13	< 0.001

3.2.2. Prediction

Since our research goal is to develop models useful in a predictive tool, we utilize the confusion matrix and the ROC curve to assess the quality of our predictions. The confusion matrix provides the quantities of correct predictions, false negatives, and false positives (Table 5). The *specificity* of the model is a measure of the proportion of soldiers correctly predicted to complete their first term where the probability cut-off for prediction of attrition is greater than 0.5. The specificity of the model on our training dataset is $\frac{206{,}519}{206{,}519+33{,}569} = 86\%$. The *sensitivity* of the model measures the proportion of soldiers that will fail to complete their first term that are correctly predicted by the model. We calculated our model sensitivity as $\frac{45{,}864}{45{,}864+18{,}255} = 71\%$. Additionally, the confusion matrix facilitates the calculation of the misclassification rate:

$$1 - \frac{206{,}519 + 45{,}864}{206{,}519 + 45{,}864 + 18{,}255 + 33{,}569} = 17\%.$$

Our misclassification rate on the training observations is low; accurately predicting 83% of the observations is very promising.

Table 5 Logistic Regression Training Dataset Confusion Matrix

Predicted Attrition Category	Observed Attrition Category	
	Non-Attrit	Attrit
Non-Attrit	206,519	33,569
Attrit	18,255	45,864

The confusion matrix is a static depiction of the predictive performance of our model. Another option is to vary the prediction cut-off threshold and examine the changes in the specificity and sensitivity in a ROC curve plot (Figure 10). The plot displays the false positive rate (1 - specificity) on the x-axis and the true positive rate (sensitivity) on the y-axis. The curve represents the change in the relationship between the two rates as the threshold varies. A very good test results in a curve pulled toward the top-left corner of the plot while a test performing no better than random chance will fall on the $y = x$ (diagonal) line. The color scale of the curve indicates the probability threshold assignment that produced the parametric point on the curve.

Another measure of performance of the model is the Area Under the Curve (AUC). As its name implies, this is a value signifying the approximated area of the polygon under the ROC curve. Since a worthless test falls on the diagonal line and the best test pulls to the upper left corner, the range of AUC is [0.5,1.0]. Obviously, a higher AUC value indicates a better performing model and an AUC value greater than 0.8 is typically considered very respectable.

Since the observations we use to build the model are now predicted by the model and we have a low misclassification rate, the training dataset ROC curve produced a high AUC value of 0.866 (Figure 10). The best probability threshold to balance specificity and sensitivity may be 0.59 depending on policy decisions to balance the costs and benefits of attrition intervention programs offered to soldiers that would complete their first term without preventative measures. We use the AUC value and misclassification rate throughout our modeling as the measures of performance for model comparison.

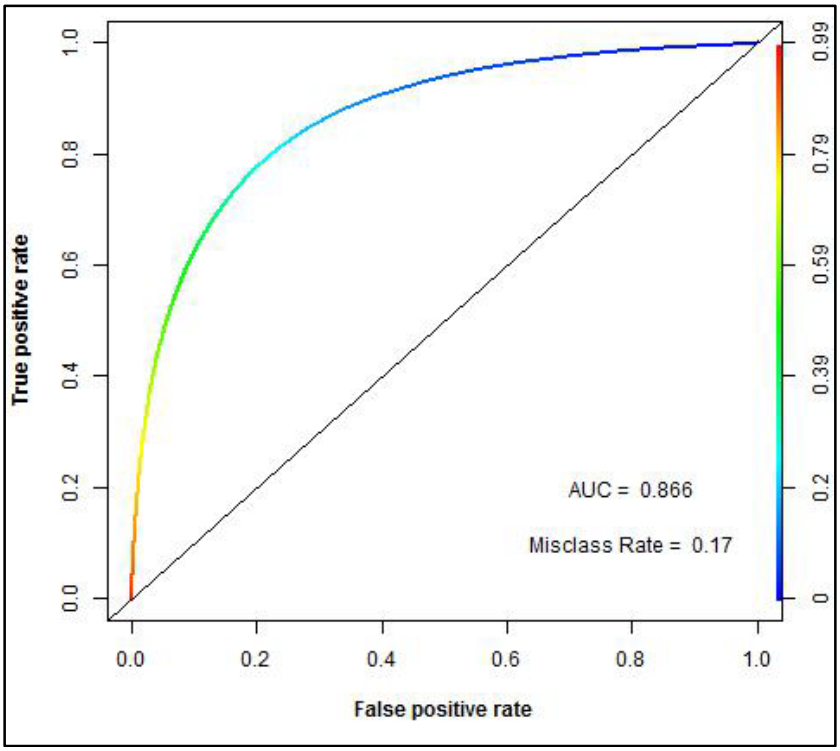


Figure 10 Attrition Classification by Logistic Regression - ROC Curve (Training)

Despite our large dataset, we use a 10-fold cross-validation technique to provide a better estimate of the classification rate (accuracy) of our model and a 95% confidence interval. 10-fold cross-validation consists of splitting the dataset into 10 folds, calculating the coefficients based on our modeling decisions with nine of the folds, and predicting the response variable for the fold kept out. After performing these actions for each of the folds, we average the accuracies and calculated the confidence interval. Our model results in an overall accuracy rate of 0.830 (95% confidence interval 0.827-0.833).

The final step of our regression analysis is to take the test dataset and use our model to predict the response variable. The model performs extremely well on the test dataset with a misclassification rate of 17.2% (Table 6) and an AUC value of 0.8719 (Figure 11). This shows our model is successful in predicting the probability of attrition on data that it has never seen.

Table 6 Logistic Regression Test Dataset Confusion Matrix

Predicted Attrition Category	Observed Attrition Category	
	Non-Attrit	Attrit
Non-Attrit	43,394	7,266
Attrit	3,934	10,661

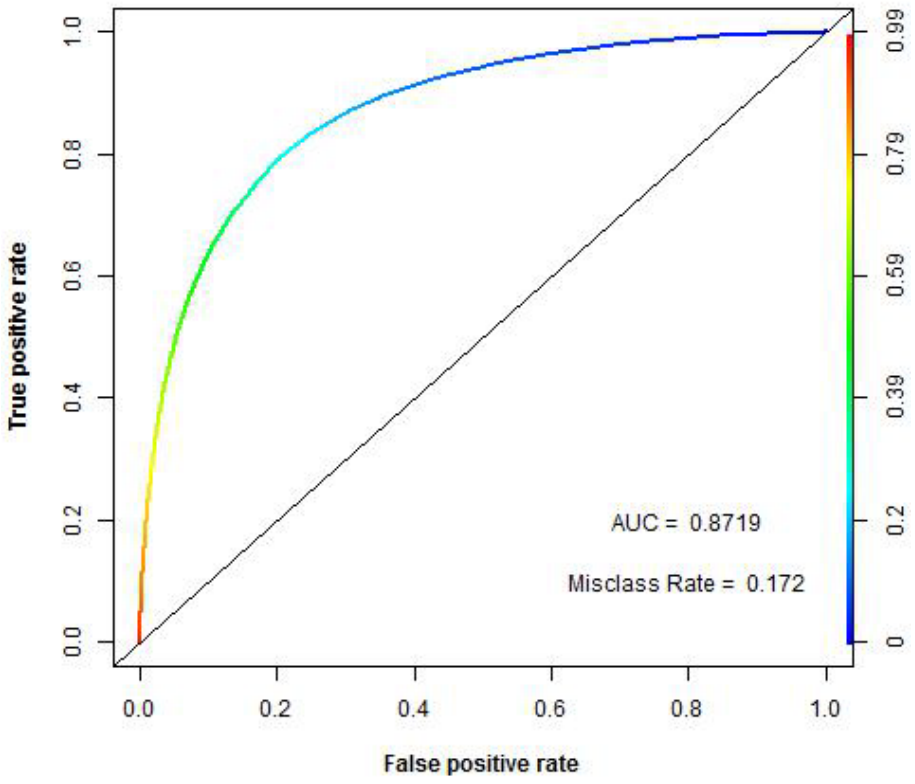


Figure 11 Attrition Classification by Logistic Regression—ROC Curve (Test)

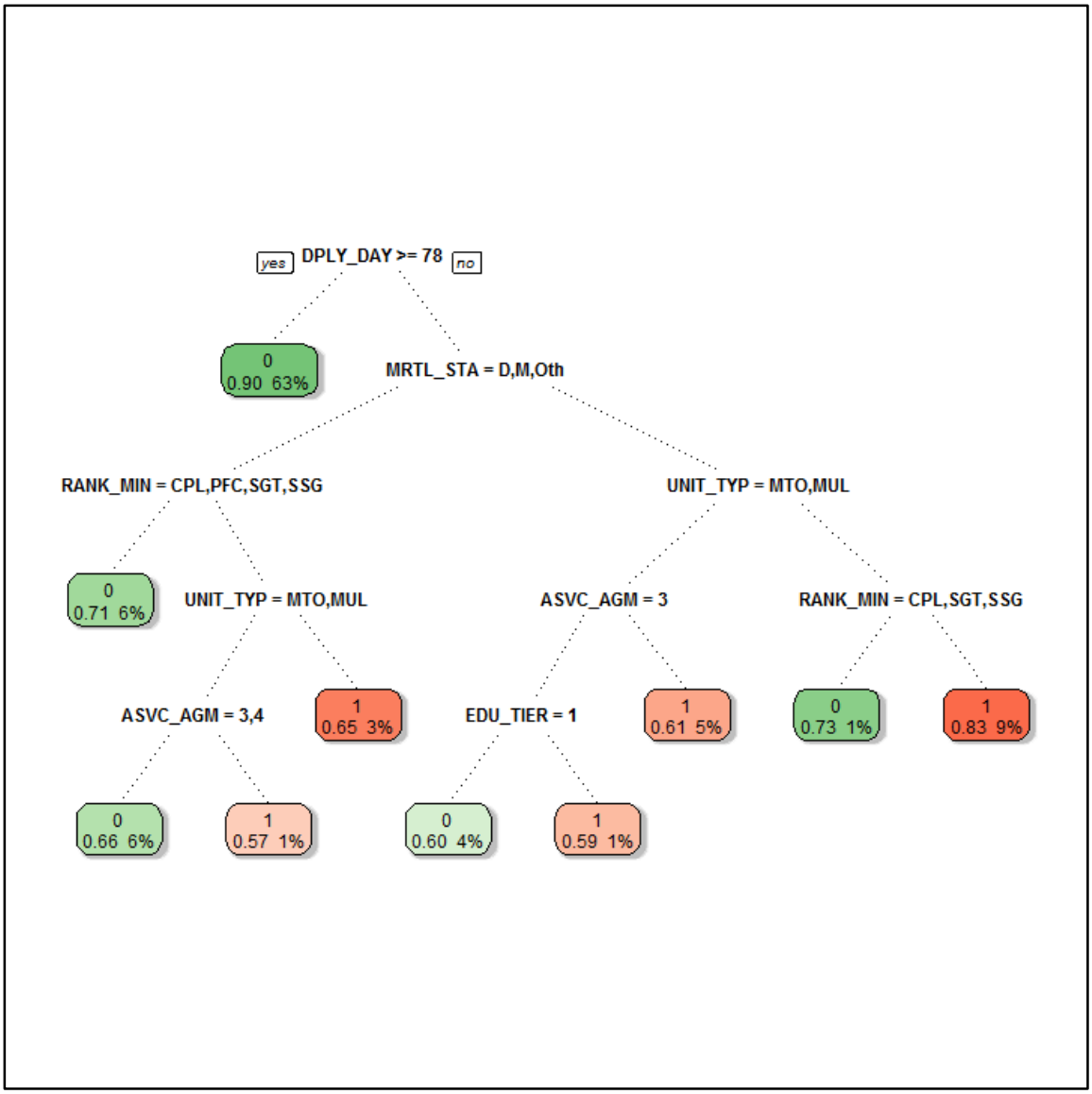
3.2.3. Classification Tree

We construct a classification tree for comparison to the logistic regression model. Like nonparametric statistics, a tree model requires few assumptions regarding the distribution of the data and is constructed by partitioning (splitting) the variables at the point that minimizes the residual sum of squares in the two branches of the nodes. Trees also handle missing values well and provide an analyst with an easily explained graphical representation of the relationships among the predictor variables. The leaves of the tree provide information about the observations that were classified into each leaf. The purity of the leaf is the proportion of observations within the leaf that match the “winning” class and the level of purity is indicated by color shading. This value can be thought of as the probability a soldier with matching predictor values leading to the leaf is going to match

the leaf classification. The percentage data reports the proportion of observations contained in each leaf.

Though trees require fewer assumptions and much less effort in variable selection, they still must be pruned to determine the best size of the tree. We fit a tree on our training dataset and select the smallest tree with a cross-validated error within one standard error of the minimum. In our tree, the complexity parameter is set to 0.0025 resulting in nine splits of our data. The first split is on *days deployed* which matched the most influential variable in the regression model (Figure 12). If a soldier is deployed for 78 days or more, he or she moves down the left branch into the leaf and has a 90% chance of completing his or her first term and the leaf contains 63% of the total dataset. Soldiers answering "Yes" to the implied questions posed at each node will always move down the left branch until reaching a leaf. Thus, a married soldier in the rank of PFC with no deployed days has a 71% chance of successfully completing his or her first term. Conversely, a single soldier in the rank of PFC with no deployed days belonging to an MTOE unit has an 83% chance of failing to complete his or her first term.

The tree mirrors the resulting influential variables identified in our regression analysis. Like the logistic regression, gender is a negligible factor in the classification tree and is not even included in the classification methodology. Also, the leaves representing a soldier's high school diploma source (*EDU_TIER)* only represent 5% of the observations and provided minimal classification information.



DPLY_DAY - Days Deployed, MRTL_STA - Marital Status (Divorced, Married, Other)

RANK_MIN - Rank at Enlistment, UNIT_TYP - Unit Type (MTOE, Multi-Compo)

ASVC_AGM - Contract Duration (years), EDU_TIER - High School Method (Diploma)

Figure 12 Attrition Classification Tree

We use the tree to predict the response variable of our test dataset. Though the performance of the model is very good, the ROC curve and AUC value of 0.8129 indicate that the classification tree model performs slightly worse than the logistic regression model.

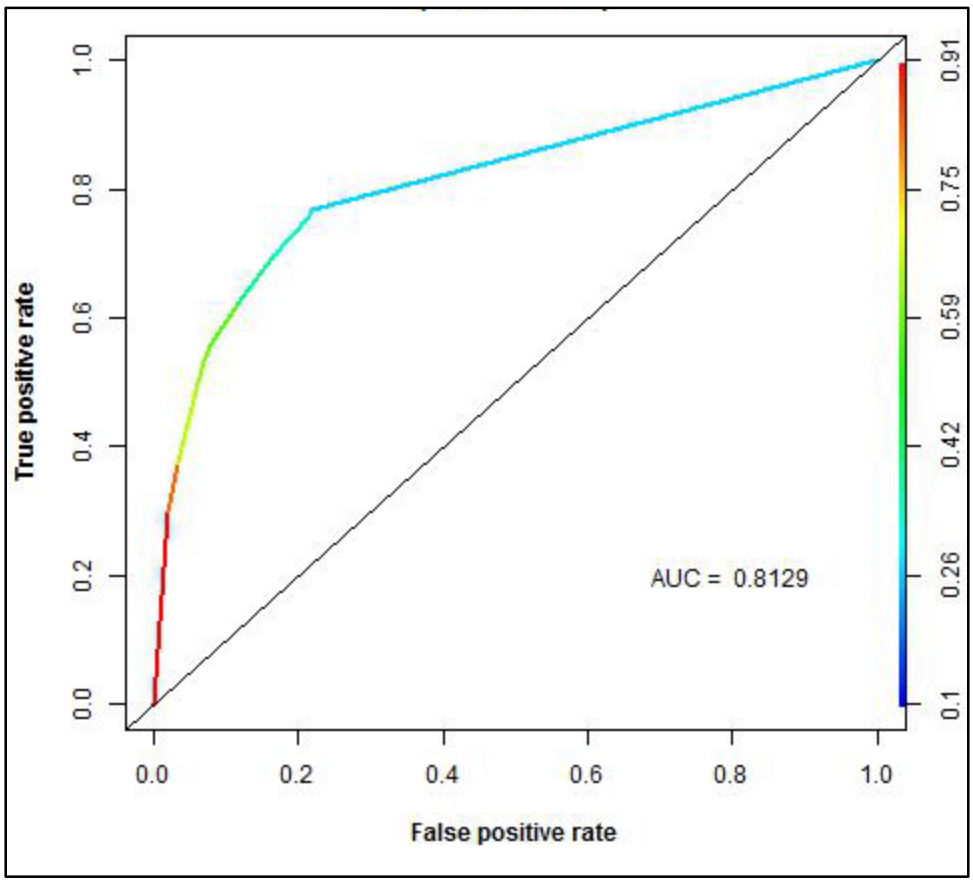


Figure 13 Attrition Classification by Classification Tree—ROC Curve (Test)

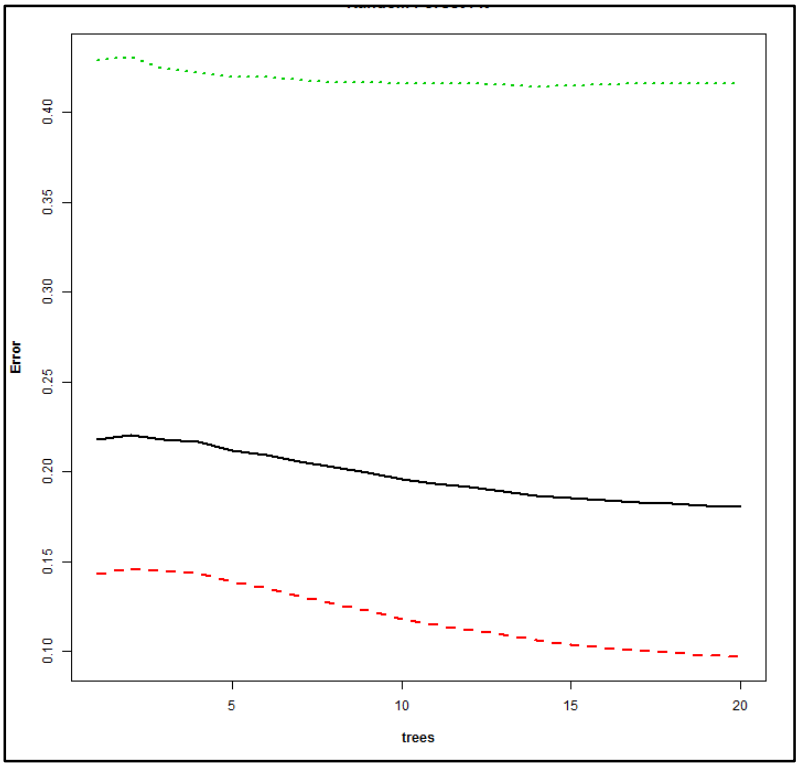
3.2.4. Random Forest

The final model we consider is a classification random forest (RF). The RF method consists of building numerous trees by randomly sampling the data with replacement. The trees are typically larger than a sole classification tree constructed by an analyst. At each split node, a random sample of predictors is chosen to ultimately test each of the predictor variables and prevent correlation between the trees in the forest. Finally, we make new predictions by pushing each predictor variable through each tree and averaging the predictions throughout the forest.

Two modeling parameters must be tuned in the implementation of the RF method. First, we need to identify the number of trees required in our forest to balance the computational complexity of the model while achieving the highest leaf purity. Second, we must select the number of predictor variable candidates considered at each split to capture the variability within the dataset without degrading the efficiency of the model.

RF modeling does not allow for missing values within the data without the use of estimate-generating algorithms to impute missing values. Since our dataset is very large and our examination of missing values indicates randomness, we remove the observations. Our final training dataset consists of 275,789 records for RF generation.

Our tuning process initially ran the model with 250 trees; however, the computation takes approximately 15 minutes. After analysis of the model error versus tree quantity plot, we find the number of trees required is only around 20 (Figure 14). The smaller forest greatly improves the speed of model construction, which allows for an efficient process to vary the number of predictor candidates considered at each split. The cross-validation techniques we employ show the stabilization of model accuracy with five predictor candidates considered at each split.



The solid line represents the overall model error by the number of trees in the forest. Dotted and dashed lines depict the error of unique “yes” and “no” responses.

Figure 14 Random Forest Error by Tree Quantity

Unlike classification tree models, which offer an intuitive visualization tree output, RFs are often considered “black box” solutions offering very little insight into the

underlying data relationships. However, the variable importance chart provides a window into the noteworthy variables within our data (Figure 15). Unsurprisingly, the most influential variables of the random forest model match the variables identified in the classification tree splits. A soldier's number of deployed days strongly influenced the prediction of first-term attrition while contract duration, marital status, unit type, and the soldier's rank at enlistment had similar influential effects.

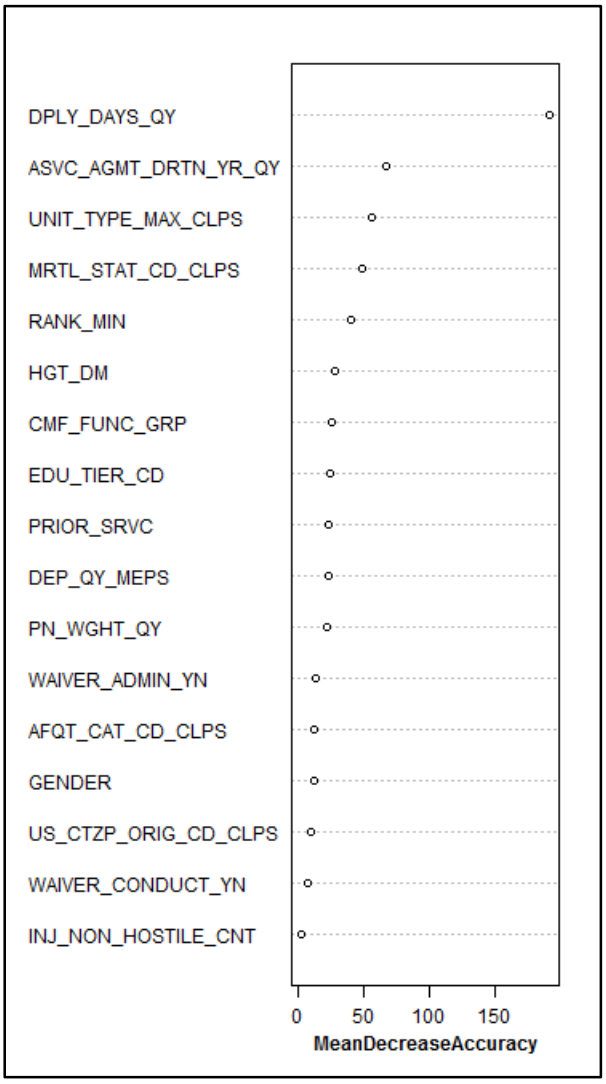


Figure 15 Random Forest Variable Importance

As expected, the predictive power of our RF model is higher than with a single classification tree. The predictive ability of a RF most often exceeds a single tree as multiple classification results are averaged for each set of predictor variables put through the forest. After predicting the observations in the test dataset, we find the superior ROC curve and AUC value of 0.8539 suggests using the RF instead of a classification tree in any future predictive tool (Figure 16) with a cut-off threshold near 0.63.

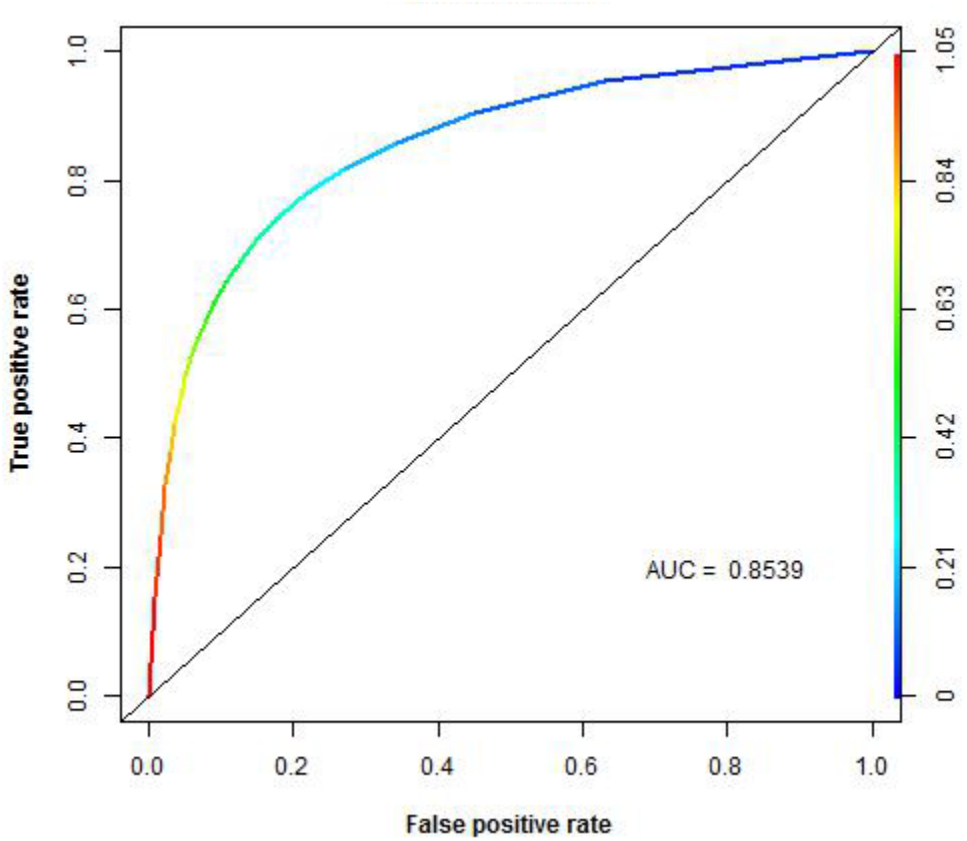


Figure 16 Attrition Classification by Random Forest—ROC Curve (Test Dataset)

3.2.5. Model Selection

We use the ROC curves and AUC calculations to determine the “best” model (Figure 17).

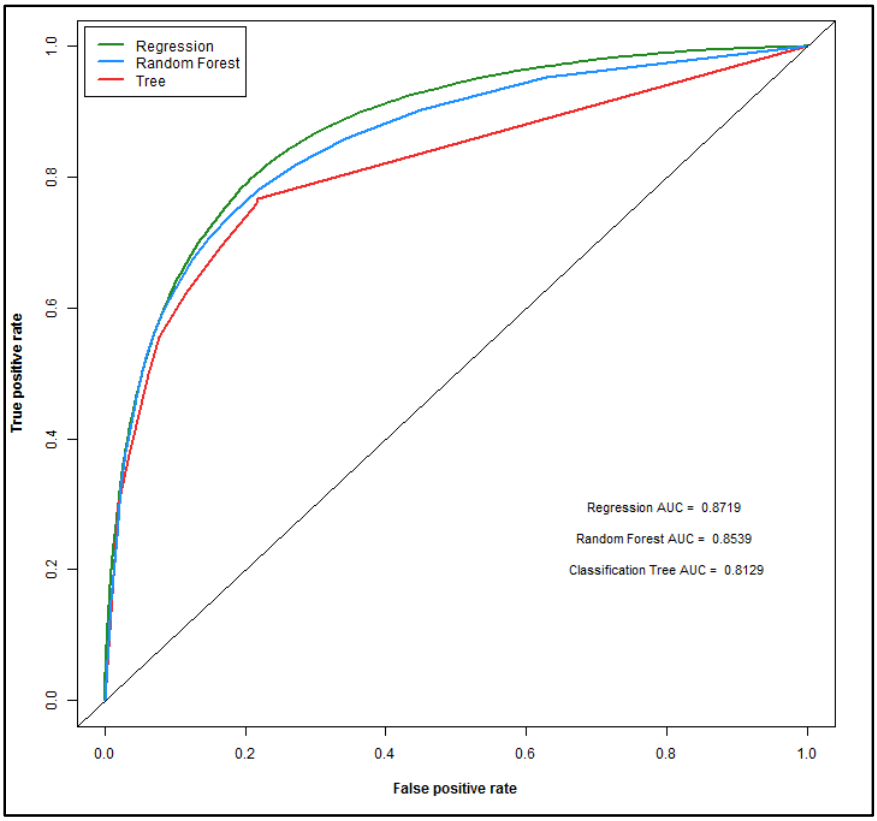


Figure 17 Model Comparison ROC Curves

The most influential predictor variables are consistent in each of our three models. While the logistic regression model utilizes the most predictors and factor levels, the classification tree model closely matches the accuracy performance with less than half of the predictors (Table 7). Though the RF model considers all of the same predictors as the logistic regression model, the most influential RF variables we identify in the table provide the majority of information determining the accuracy of the model.

Table 7 Variable Utilization by Model

Variable	Logistic Regression	Classification Tree	Random Forest
AFQT Category	x		
Citizenship Origination	x		
Contract Duration	x	x	x
Days Deployed	x	x	x
Dependents	x		x
Education Tier	x	x	x
Gender	x		
Height (Enlistment)	x		x
Marital Status	x	x	x

Variable	Logistic Regression	Classification Tree	Random Forest
Military Occupation Group	x		x
Non-hostile Injuries	x		
Prior Service	x		x
Rank (Enlistment)	x	x	x
Unit Type	x	x	x
Waiver (Admin)	x		
Waiver (Conduct)	x		
Weight (Enlistment)	x		x

In the interest of simplicity and accuracy, the RF model provides ARD analysts increased flexibility as the data catalog grows within the PDE and more soldier data is made available. Most importantly, an analyst can extract a single tree from a RF model and use it to provide stakeholders a visualization which is easy to understand and interpret. Additionally, ARD analysts could create simple flow charts that quickly allow Army leaders to assess the probability of a first-term soldier not completing his or her initial contractual obligation.

3.3. ATTRITION PREDICTION APPLICATION

We use an R Shiny Application with the three models in the background to allow users to predict the probability of attrition for individual soldiers as well as entire units. This application is a web based graphic user interface that allows leaders, soldiers or recruiters to input demographic variables of current soldiers or recruits and get the predicted probability of attrition as an output. The user can also look at all the variables included in the data in an easily readable table format. Lastly, if the user does not want to use the original cohort (FY05 to FY10), he or she can bring in new data from the PDE based on the new desired time span. Within this tab, users can execute everything we describe in Chapter 2.2 and Figure 1 which originally took months in minutes. The application is currently within the PDE, but users can easily extract the tool for implementation by itself or as part of a preexisting dashboard (Figures 19-22).

SECTION 4. CONCLUSION

4.1. DATA PREPARATION

The PDE is an extremely valuable resource for Army personnel analytics due to the consolidated data tables created from disparate data sources and the collaborative environment. However, the lack of comprehensive data definitions challenges users to fully understand the variables.

The universal application of separation codes continues to be a concern nearly four decades after the issue was first raised. Our research highlights the potential errors in the sole use of the codes to study attrition and offered a new methodology for identifying whether a soldier successfully completed his or her contractual obligation by examining the historical records of each soldier.

Careful selection of predictor variables is critical for accurately depicting a soldier's demographic and administrative history. The time-related snapshot data complicates the analysis and naïve variable assignment can lead to unexpected bias.

4.2. DATA ANALYSIS

U.S. Army first-term attrition rates were steady from FY2005 to FY2010 and averaged 26%. Our research confirms both the overall attrition rates and proportional rate differences between factor levels as reported in previous research. While 24% of male soldiers failed to complete their initial contract, 38% of female soldiers were discharged early. Enlistees with high school diplomas are 25% more likely to complete their first term than recruits holding a GED. Soldiers from Louisiana, Arkansas, and West Virginia fail to complete their first term at a 10% higher rate than states with the lowest attrition rates mostly found in the western United States. Single soldiers are also discharged early at a 10% higher rate than married or divorced enlistees.

The most influential predictor of first-term attrition is a soldier's deployment history. A soldier deployed more than three months has a 90% chance of completing the first term. Additionally, the length of a soldier's initial contract and marital status are key

discriminators in predicting the probability of completion of the first term. Longer contract periods increase the risk of attrition while married or divorced soldiers are less likely than single soldiers to attrit. A soldier's gender and ASVAB score have very little influence in predicting attrition. Additionally, whether a soldier received an enlistment waiver or not has a negligible effect on his or her probability of completing the first term.

Obviously, we do not advocate for the deployment of more soldiers, 10-year contracts, or marriage requirements. However, identifying soldiers with the highest probability of failure may significantly inform Army leadership in prioritizing resources and focusing intervention strategies at those soldiers most in need of assistance.

4.3. RECOMMENDATIONS

4.3.1. Implementation

The accuracy rate of our predictive models is 83% and provide enough fidelity to warrant consideration of its use by Army planners. The logistic regression model was the most accurate but the RF was nearly as accurate and may be easier to manipulate for ARD analysts. General attrition rate findings based on demographic predictor variables may help to inform force strength requirements, recruiting goals, and retention efforts. The flexible and repeatable nature of the RF modeling technique provides analysts the ability to react quickly to changes in data availability and shifts in both policies and priorities.

Most importantly, this research provides ARD insight as the agency continues its efforts to improve soldier resiliency and, by extension, first-term attrition rates. Application of our predictive model to the administrative records of current enlistees could provide policy makers with probability estimates of all first-term soldiers and facilitate the creation of intervention programs and prioritized resource strategies built upon a quantitative foundation.

A web-based predictive tool available to Army leaders at the lowest unit level would allow human resource professionals or junior Non-Commissioned Officers to

engage new soldiers during annual record reviews and monthly professional counseling sessions. Once the attrition probability assessment is completed for each soldier, the appropriate training, administrative actions, or other intervention strategies could be leveraged to best assist the soldier.

4.3.2. Future Research

We are unable to secure access to comprehensive enlistee medical data within the PDE for inclusion in this research. Once the data are available, we urge the addition of medical factors to our cohort dataset for further analysis. Though the broad categories of medical waiver data used in our research are too generalized to use for prediction, detailed medical information of new recruits may provide better models and a deeper understanding of attrition tendencies.

Our research and models consider predictor variables that evolve over the time a soldier has spent in the service. Predictive research tailored to Army accession policy analysis and the recruiting mission of USAREC requires the selection of only variables known at the time of a soldier's enlistment. We recommend the adaptation of our research to identify these variables and construct predictive models useful in understanding pre-enlistment recruits.

Finally, we recommend exploration of statistical modeling techniques not attempted in our research. Specifically, unsupervised models such as cluster analysis and principal components may assist researchers in better understanding the relationships in the data. Additionally, supervised techniques such as support vector machine or neural network design may provide higher accuracy rates in the predictive models.

APPENDIX A. SEPARATION CODES

Table 8 Successful Separation Code Definitions

Separation Code	Separation Code Type	Description
1001	ISVC_SEP_CD	Expiration Term of Service (ETS)
1002	ISVC_SEP_CD	ETS
1003	ISVC_SEP_CD	ETS
1008	ISVC_SEP_CD	ETS
1040	ISVC_SEP_CD	Transfer to Officer Program
1042	ISVC_SEP_CD	Enrollment in a service academy
1050	ISVC_SEP_CD	Retirement
1052	ISVC_SEP_CD	Retirement
1100	ISVC_SEP_CD	Reenlistment
948	SPD_CD	Enrollment in a service academy
FCA	SPD_CD	Resignation
FCB	SPD_CD	Resignation
FHC	SPD_CD	Reenlistment
FND	SPD_CD	Resignation
JBK	SPD_CD	ETS
JBM	SPD_CD	ETS
JCC	SPD_CD	ETS
JGH	SPD_CD	ETS
KBK	SPD_CD	ETS
KBM	SPD_CD	ETS
KCA	SPD_CD	Early Release Program (Voluntary Separation)
KCB	SPD_CD	Early Release Program (Special Separation Benefit)
KCC	SPD_CD	Early Release Program (Employment)
KCF	SPD_CD	ETS
KGM	SPD_CD	Transfer to Officer Program
KGX	SPD_CD	Transfer to Officer Program
KHC	SPD_CD	Reenlistment
KND	SPD_CD	Resignation
LBK	SPD_CD	ETS
LBM	SPD_CD	ETS
LCC	SPD_CD	ETS
LGH	SPD_CD	ETS
MBK	SPD_CD	ETS
MBM	SPD_CD	ETS
MCA	SPD_CD	Early Release Program (Voluntary Separation)

Separation Code	Separation Code Type	Description
MCB	SPD_CD	Early Release Program (Special Separation Benefit)
MCC	SPD_CD	Early Release Program (Employment)
MCF	SPD_CD	ETS
MDM	SPD_CD	ETS
MHC	SPD_CD	Reenlistment
RBD	SPD_CD	Retirement
RBE	SPD_CD	Retirement
RCC	SPD_CD	Retirement
SBB	SPD_CD	Retirement
SBC	SPD_CD	Retirement
VBK	SPD_CD	Retirement

APPENDIX B. COHORT DATASET SUMMARY

Table 9 Numeric Variable Summary: Mean (Std Dev) by Fiscal Year of Enlistment

	2005		2006		2007		2008		2009		2010	
	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit
Age (Enlistment)	21.26 (3.96)	20.93 (3.7)	21.39 (4.24)	21.08 (4.14)	21.67 (4.5)	21.43 (4.66)	21.6 (4.36)	21.15 (4.34)	21.81 (4.44)	21.16 (4.26)	21.9 (4.39)	21.23 (4.16)
ASVAB GT Score	266.22 (28.31)	264.61 (25.97)	263.38 (28.06)	261.91 (25.62)	262.78 (28.21)	261.95 (25.45)	263.13 (28.45)	262.58 (25.41)	265.57 (28.82)	263.99 (25.76)	265.1 (29.32)	263.53 (26.53)
Contract Duration	3.82 (0.9)	3.96 (0.92)	3.8 (0.9)	3.99 (0.98)	3.84 (0.91)	4.11 (1.02)	3.79 (0.93)	4.11 (1.05)	3.68 (0.9)	4.03 (1.07)	3.64 (0.89)	3.99 (1.07)
Days Deployed	396.92 (273.41)	78.45 (162.01)	361.14 (242.74)	72.77 (161.56)	327.29 (219.08)	79.26 (163.51)	293.83 (194.2)	81.6 (150.09)	246.46 (174.88)	73.11 (136.69)	206.68 (166.16)	66.37 (124.04)
Dependents	0.32 (0.82)	0.3 (0.78)	0.32 (0.84)	0.33 (0.85)	0.35 (0.88)	0.38 (0.92)	0.35 (0.89)	0.35 (0.9)	0.36 (0.89)	0.33 (0.87)	0.31 (0.82)	0.27 (0.77)
Deployments	2.5 (1.77)	0.57 (1.14)	2.27 (1.62)	0.5 (1.08)	2.17 (1.52)	0.55 (1.12)	1.97 (1.38)	0.58 (1.07)	1.6 (1.19)	0.51 (0.94)	1.29 (1.12)	0.47 (0.87)
Height at Enlistment	68.56 (3.22)	67.87 (3.51)	68.5 (3.22)	67.81 (3.54)	68.58 (3.24)	68.09 (3.48)	68.9 (3.23)	68.42 (3.44)	68.96 (3.2)	68.52 (3.43)	68.88 (3.24)	68.52 (3.45)
Hostile Injuries	0.04 (0.2)	0.02 (0.13)	0.03 (0.16)	0.01 (0.12)	0.02 (0.13)	0.01 (0.08)	0.02 (0.15)	0.01 (0.09)	0.03 (0.17)	0.01 (0.11)	0.02 (0.15)	0.01 (0.12)
Max Time-in-Grade	1.67 (0.88)	0.77 (0.73)	1.7 (0.96)	0.85 (0.77)	1.75 (0.89)	0.87 (0.81)	1.71 (0.88)	0.9 (0.81)	1.65 (0.86)	0.96 (0.84)	1.66 (0.85)	1.06 (0.85)
Non-Hostile Injuries	0.01 (0.07)	0.01 (0.09)	0.01 (0.07)	0.01 (0.08)	0.01 (0.08)	0.01 (0.07)	0.01 (0.09)	0.01 (0.09)	0.01 (0.1)	0.01 (0.1)	0.01 (0.1)	0.01 (0.12)
Weight at Enlistment	167.26 (30.91)	162.89 (32.69)	168.13 (31.87)	164.61 (33.45)	168.14 (32.21)	165.92 (33.85)	168.32 (31.99)	166.13 (34.14)	169.49 (32.03)	168.15 (34.94)	168.14 (30.97)	168.45 (33.92)

Table 10 Binary Variable Summary: Counts (Proportion of Attrition Category) by Fiscal Year of Enlistment

		2005		2006		2007		2008		2009		2010	
		No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit
Citizenship Status (Enlistment)	0	48750 (97.11)	16793 (98.18)	54693 (97.3)	19024 (98.51)	50112 (97.16)	18729 (98.52)	49297 (96.91)	18926 (98.43)	44813 (96.85)	16496 (97.65)	49463 (96.1)	16153 (97.2)
	1	230 (0.46)	42 (0.25)	320 (0.57)	54 (0.28)	440 (0.85)	44 (0.23)	871 (1.71)	69 (0.36)	1327 (2.87)	157 (0.93)	1788 (3.47)	236 (1.42)
	NA	1219 (2.43)	270 (1.58)	1200 (2.13)	233 (1.21)	1023 (1.98)	238 (1.25)	702 (1.38)	233 (1.21)	132 (0.29)	240 (1.42)	220 (0.43)	229 (1.38)
Gender	0	6264 (12.48)	4541 (26.55)	7189 (12.79)	5112 (26.47)	6823 (13.23)	4503 (23.69)	6476 (12.73)	4426 (23.02)	5748 (12.42)	3676 (21.76)	6734 (13.0)	3542 (21.3)
	1	43935 (87.52)	12564 (73.45)	49024 (87.21)	14199 (73.53)	44752 (86.77)	14508 (76.31)	44394 (87.27)	14802 (76.98)	40524 (87.58)	13217 (78.24)	44737 (86.9)	13076 (78.6)
Prior Service	0	48394 (96.4)	15255 (89.18)	53861 (95.82)	16013 (82.92)	49893 (96.74)	16021 (84.27)	49174 (96.67)	16985 (88.33)	45593 (98.53)	15966 (94.51)	51005 (99.09)	16047 (96.56)
	1	1805 (3.6)	1850 (10.82)	2352 (4.18)	3298 (17.08)	1682 (3.26)	2990 (15.73)	1696 (3.33)	2243 (11.67)	679 (1.47)	927 (5.49)	466 (0.91)	571 (3.44)
Waiver (Medical)	0	46708 (93.05)	15917 (93.05)	52497 (93.39)	18012 (93.27)	47582 (92.26)	17561 (92.37)	46845 (92.09)	17675 (91.92)	42773 (92.44)	15616 (92.44)	47769 (92.81)	15473 (93.11)
	1	3491 (6.95)	1188 (6.95)	3716 (6.61)	1299 (6.73)	3993 (7.74)	1450 (7.63)	4025 (7.91)	1553 (8.08)	3499 (7.56)	1277 (7.56)	3702 (7.19)	1145 (6.89)
Waiver (Conduct)	0	46457 (92.55)	15803 (92.39)	50662 (90.13)	17264 (89.4)	45042 (87.33)	16332 (85.91)	44964 (88.39)	16856 (87.66)	42487 (91.82)	15462 (91.53	49210 (95.61)	15816 (95.17)
	1	3742 (7.45)	1302 (7.61)	5551 (9.87)	2047 (10.6)	6533 (12.67)	2679 (14.09)	5906 (11.61)	2372 (12.34)	3785 (8.18)	1431 (8.47)	2261 (4.39)	802 (4.83)
Waiver (Admin)	0	47264 (94.15)	16520 (96.58)	52934 (94.17)	18517 (95.89)	47888 (92.85)	17921 (94.27)	47682 (93.73)	18222 (94.77)	43936 (94.95)	16161 (95.67)	49305 (95.79)	16020 (96.4)
	1	2935 (5.85)	585 (3.42)	3279 (5.83)	794 (4.11)	3687 (7.15)	1090 (5.73)	3188 (6.27)	1006 (5.23)	2336 (5.05)	732 (4.33)	2166 (4.21)	598 (3.6)
Waiver (Drug)	0	49739 (99.08)	16882 (98.7)	55571 (98.86)	18978 (98.28)	50772 (98.44)	18577 (97.72)	50104 (98.49)	18837 (97.97)	46074 (99.57)	16782 (99.34)	51470 (100)	16618 (100)
	1	460 (0.92)	223 (1.3)	642 (1.14)	333 (1.72)	803 (1.56)	434 (2.28)	766 (1.51)	391 (2.03)	198 (0.43)	111 (0.66)	1 (0)	0 (0)

Table 11 Categorical Variable Summary: Counts (Proportion of Attrition Category) by Fiscal Year of Enlistment

		2005		2006		2007		2008		2009		2010	
		No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit
Unit Region (Max)	Midwest	2650 (5.28%)	1525 (8.92%)	3003 (5.34%)	1516 (7.85%)	2598 (5.04%)	1678 (8.83%)	2721 (5.35%)	2057 (10.7%)	3187 (6.89%)	1574 (9.32%)	2735 (5.31%)	1305 (7.85%)
	Northeast	2391 (4.76)	722 (4.22)	2148 (3.82)	574 (2.97)	2985 (5.79)	921 (4.84)	2843 (5.59)	696 (3.62)	2370 (5.12)	515 (3.05)	2619 (5.09)	614 (3.69)
	South	27543 (54.87)	10622 (62.1)	33342 (59.31)	13080 (67.73)	28941 (56.11)	12415 (65.3)	29157 (57.32)	12313 (64.04)	26116 (56.44)	10983 (65.02)	29195 (56.72)	10161 (61.14)
	Territory	6 (0.01)	0 (0)	5 (0.01)	1 (0.01)	7 (0.01)	0 (0)	1 (0)	0 (0)	10 (0.02)	0 (0)	4 (0.01)	4 (0.02)
	West	11299 (22.51)	2792 (16.32)	11146 (19.83)	2679 (13.87)	11777 (22.83)	2861 (15.05)	11308 (22.23)	3130 (16.28)	9918 (21.43)	2463 (14.58)	12888 (25.04)	3423 (20.6)
	NA	6310 (12.57)	1444 (8.44)	6569 (11.69)	1461 (7.57)	5267 (10.21)	1136 (5.98)	4840 (9.51)	1032 (5.37)	4671 (10.09)	1358 (8.04)	4030 (7.83)	1111 (6.69)
Home of Record Region	Midwest	10857 (21.63)	3545 (20.72)	12423 (22.1)	4168 (21.58)	11035 (21.4)	3938 (20.71)	9814 (19.29)	3749 (19.5)	9113 (19.69)	3387 (20.05)	9790 (19.02)	3195 (19.23)
	Northeast	6005 (11.96)	2166 (12.66)	6772 (12.05)	2175 (11.26)	6152 (11.93)	2279 (11.99)	5936 (11.67)	2182 (11.35)	5646 (12.2)	2034 (12.04)	6033 (11.72)	1863 (11.21)
	South	20821 (41.48)	7652 (44.74)	23713 (42.18)	9060 (46.92)	22609 (43.84)	9223 (48.51)	22250 (43.74)	9046 (47.05)	19502 (42.15)	7756 (45.91)	22152 (43.04)	7812 (47.01)
	Territory	688 (1.37)	124 (0.72)	699 (1.24)	133 (0.69)	651 (1.26)	121 (0.64)	634 (1.25)	127 (0.66)	580 (1.25)	132 (0.78)	699 (1.36)	139 (0.84)
	West	11223 (22.36)	3500 (20.46)	11678 (20.77)	3545 (18.36)	10650 (20.65)	3287 (17.29)	10751 (21.13)	3726 (19.38)	10921 (23.6)	3491 (20.67)	12338 (23.97)	3537 (21.28)
	NA	605 (1.21)	118 (0.69)	928 (1.65)	230 (1.19)	478 (0.93)	163 (0.86)	1485 (2.92)	398 (2.07)	510 (1.1)	93 (0.55)	459 (0.89)	72 (0.43)
Military Occupation Group	OPNS	23978 (47.77)	7947 (46.46)	27478 (48.88)	8551 (44.28)	22746 (44.1)	8149 (42.86)	23359 (45.92)	8509 (44.25)	21256 (45.94)	7818 (46.28)	24456 (47.51)	7954 (47.86)
	OS	5960 (11.87)	1432 (8.37)	4993 (8.88)	1431 (7.41)	5297 (10.27)	2017 (10.61)	5892 (11.58)	2541 (13.22)	6570 (14.2)	2556 (15.13)	6829 (13.27)	2386 (14.36)
	FS	19012 (37.87)	6508 (38.05)	21836 (38.85)	8388 (43.44)	21970 (42.6)	8206 (43.16)	20028 (39.37)	7565 (39.34)	16736 (36.17)	6084 (36.01)	18484 (35.91)	5996 (36.08)
	NA	1249 (2.49)	1218 (7.12)	1906 (3.39)	941 (4.87)	1562 (3.03)	639 (3.36)	1591 (3.13)	613 (3.19)	1710 (3.7)	435 (2.58)	1702 (3.31)	282 (1.7)

		2005		2006		2007		2008		2009		2010	
		No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit
Rank (Max)	PV1	1199 (2.39)	5265 (30.78)	1386 (2.47)	5912 (30.61)	1397 (2.71)	6202 (32.62)	1375 (2.7)	5828 (30.31)	820 (1.77)	4612 (27.3)	625 (1.21)	3658 (22.01)
	PV2	965 (1.92)	3844 (22.47)	1227 (2.18)	4743 (24.56)	1143 (2.22)	4658 (24.5)	1062 (2.09)	4799 (24.96)	602 (1.3)	3862 (22.86)	430 (0.84)	3215 (19.35)
	PFC	2728 (5.43)	4197 (24.54)	3325 (5.92)	4754 (24.62)	3078 (5.97)	4217 (22.18)	2799 (5.5)	4399 (22.88)	1959 (4.23)	4178 (24.73)	1828 (3.55)	4683 (28.18)
	CPL	30882 (61.52)	3466 (20.26)	36453 (64.85)	3505 (18.15)	34656 (67.2)	3496 (18.39)	35272 (69.34)	3938 (20.48)	32532 (70.31)	3971 (23.51)	37214 (72.3)	4802 (28.9)
	SGT	12920 (25.74)	302 (1.77)	12823 (22.81)	334 (1.73)	10501 (20.36)	350 (1.84)	9629 (18.93)	220 (1.14)	9695 (20.95)	248 (1.47)	10706 (20.8)	255 (1.53)
	SSG	1505 (3)	31 (0.18)	999 (1.78)	63 (0.33)	800 (1.55)	88 (0.46)	733 (1.44)	44 (0.23)	664 (1.43)	22 (0.13)	668 (1.3)	5 (0.03)
Rank (Enlistment)	PV1	20438 (40.71)	9026 (52.77)	23077 (41.05)	10221 (52.93)	20691 (40.12)	9936 (52.26)	19672 (38.67)	9618 (50.02)	15577 (33.66)	7497 (44.38)	14859 (28.87)	6539 (39.35)
	PV2	11598 (23.1)	3979 (23.26)	14423 (25.66)	4813 (24.92)	13985 (27.12)	5085 (26.75)	15381 (30.24)	5716 (29.73)	14529 (31.4)	5308 (31.42)	15788 (30.67)	5000 (30.09)
	PFC	10394 (20.71)	2902 (16.97)	11519 (20.49)	3022 (15.65)	10807 (20.95)	2876 (15.13)	10680 (20.99)	3072 (15.98)	11050 (23.88)	3311 (19.6)	14713 (28.59)	4191 (25.22)
	CPL	6342 (12.63)	1053 (6.16)	5872 (10.45)	1020 (5.28)	5352 (10.38)	848 (4.46)	4647 (9.14)	707 (3.68)	4749 (10.26)	722 (4.27)	5694 (11.06)	859 (5.17)
	SGT	1130 (2.25)	119 (0.7)	1023 (1.82)	175 (0.91)	600 (1.16)	183 (0.96)	383 (0.75)	71 (0.37)	302 (0.65)	36 (0.21)	317 (0.62)	24 (0.14)
	SSG	297 (0.59)	26 (0.15)	299 (0.53)	60 (0.31)	140 (0.27)	83 (0.44)	107 (0.21)	44 (0.23)	65 (0.14)	19 (0.11)	100 (0.19)	5 (0.03)
Education Tier	1	42689 (85.04)	13065 (76.38)	43852 (78.01)	12788 (66.22)	39095 (75.8)	12070 (63.49)	39530 (77.71)	12839 (66.77)	40236 (86.96)	13342 (78.98)	49204 (95.6)	15789 (95.01)
	2	7086 (14.12)	3492 (20.42)	11828 (21.04)	6124 (31.71)	12000 (23.27)	6863 (36.1)	10490 (20.62)	6077 (31.6)	4791 (10.35)	2848 (16.86)	1843 (3.58)	743 (4.47)
	3	47 (0.09)	13 (0.08)	83 (0.15)	40 (0.21)	77 (0.15)	52 (0.27)	205 (0.4)	175 (0.91)	856 (1.85)	669 (3.96)	110 (0.21)	59 (0.36)
	NA	377 (0.75)	535 (3.13)	450 (0.8)	359 (1.86)	403 (0.78)	26 (0.14)	645 (1.27)	137 (0.71)	389 (0.84)	34 (0.2)	314 (0.61)	27 (0.16)

		2005		2006		2007		2008		2009		2010	
		No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit
AFQT Category	1	3545 (7.06)	803 (4.69)	3251 (5.78)	729 (3.78)	2967 (5.75)	648 (3.41)	2979 (5.86)	643 (3.34)	3266 (7.06)	692 (4.1)	3989 (7.75)	832 (5.01)
	2	17492 (34.85)	5587 (32.66)	18129 (32.25)	5703 (29.53)	16291 (31.59)	5705 (30.01)	16081 (31.61)	5976 (31.08)	15874 (34.31)	5573 (32.99)	17666 (34.32)	5451 (32.8)
	3A	12444 (24.79)	4854 (28.38)	12949 (23.04)	5050 (26.15)	11928 (23.13)	5181 (27.25)	11992 (23.57)	5418 (28.18)	11486 (24.82)	5084 (30.1)	11388 (22.13)	4488 (27.01)
	3B	14404 (28.69)	5148 (30.1)	19013 (33.82)	7142 (36.98)	17751 (34.42)	6790 (35.72)	17034 (33.49)	6487 (33.74)	14429 (31.18)	5265 (31.17)	17746 (34.48)	5739 (34.53)
	4A	2066 (4.12)	670 (3.92)	2453 (4.36)	641 (3.32)	2394 (4.64)	656 (3.45)	2038 (4.01)	528 (2.75)	841 (1.82)	241 (1.43)	407 (0.79)	95 (0.57)
	4Bplus	84 (0.17)	20 (0.12)	90 (0.16)	16 (0.08)	54 (0.1)	19 (0.1)	69 (0.14)	18 (0.09)	58 (0.13)	24 (0.14)	46 (0.09)	10 (0.06)
	NA	164 (0.33)	23 (0.13)	328 (0.58)	30 (0.16)	190 (0.37)	12 (0.06)	677 (1.33)	158 (0.82)	318 (0.69)	14 (0.08)	229 (0.44)	3 (0.02)
Citizenship Origination	A	46467 (92.57)	16358 (95.63)	52133 (92.74)	18560 (96.11)	47810 (92.7)	18223 (95.86)	46837 (92.07)	18374 (95.56)	41983 (90.73)	15864 (93.91)	45917 (89.21)	15458 (93.02)
	N	1370 (2.73)	217 (1.27)	1438 (2.56)	216 (1.12)	1294 (2.51)	222 (1.17)	1387 (2.73)	238 (1.24)	1578 (3.41)	258 (1.53)	2209 (4.29)	346 (2.08)
	C	926 (1.84)	218 (1.27)	1138 (2.02)	252 (1.3)	1082 (2.1)	293 (1.54)	1181 (2.32)	329 (1.71)	1257 (2.72)	395 (2.34)	1341 (2.61)	366 (2.2)
	NA	1436 (2.86)	312 (1.82)	1504 (2.68)	283 (1.47)	1389 (2.69)	273 (1.44)	1465 (2.88)	287 (1.49)	1454 (3.14)	376 (2.23)	2004 (3.89)	448 (2.7)
Education Level (Enlistment)	HS	42532 (84.73)	14597 (85.34)	45021 (80.09)	15935 (82.52)	46375 (89.92)	17781 (93.53)	45039 (88.54)	17867 (92.92)	39732 (85.87)	15552 (92.06)	42908 (83.36)	14824 (89.2)
	CLG	2458 (4.9)	836 (4.89)	2399 (4.27)	732 (3.79)	2237 (4.34)	760 (4)	2259 (4.44)	772 (4.01)	2539 (5.49)	804 (4.76)	3476 (6.75)	1094 (6.58)
	BAC	2368 (4.72)	415 (2.43)	2315 (4.12)	404 (2.09)	2611 (5.06)	424 (2.23)	2689 (5.29)	388 (2.02)	3330 (7.2)	453 (2.68)	4393 (8.53)	601 (3.62)
	GRAD	145 (0.29)	23 (0.13)	156 (0.28)	25 (0.13)	197 (0.38)	36 (0.19)	201 (0.4)	37 (0.19)	292 (0.63)	57 (0.34)	447 (0.87)	88 (0.53)
	NA	2696 (5.37)	1234 (7.21)	6322 (11.25)	2215 (11.47)	155 (0.3)	10 (0.05)	682 (1.34)	164 (0.85)	379 (0.82)	27 (0.16)	247 (0.48)	11 (0.07)

		2005		2006		2007		2008		2009		2010	
		No Attrit	**Attrit**	**No Attrit**	**Attrit**	**No Attrit**	**Attrit**	**No Attrit**	**Attrit**	**No Attrit**	**Attrit**	**No Attrit**	**Attrit**
Education Level (Max)	HS	44341 (88.33)	15285 (89.36)	50046 (89.03)	17694 (91.63)	45499 (88.22)	17778 (93.51)	44226 (86.94)	17892 (93.05)	38696 (83.63)	15516 (91.85)	41216 (80.08)	14745 (88.73)
	CLG	2773 (5.52)	828 (4.84)	2913 (5.18)	770 (3.99)	2866 (5.56)	750 (3.95)	3095 (6.08)	781 (4.06)	3580 (7.74)	847 (5.01)	5175 (10.05)	1161 (6.99)
	BAC	2520 (5.02)	432 (2.53)	2611 (4.64)	454 (2.35)	2583 (5.01)	421 (2.21)	2681 (5.27)	377 (1.96)	3289 (7.11)	438 (2.59)	4270 (8.3)	591 (3.56)
	GRAD	188 (0.37)	25 (0.15)	193 (0.34)	34 (0.18)	224 (0.43)	36 (0.19)	223 (0.44)	41 (0.21)	318 (0.69)	58 (0.34)	496 (0.96)	94 (0.57)
	NA	377 (0.75)	535 (3.13)	450 (0.8)	359 (1.86)	403 (0.78)	26 (0.14)	645 (1.27)	137 (0.71)	389 (0.84)	34 (0.2)	314 (0.61)	27 (0.16)
Marital Status (Max)	D	2051 (4.09)	481 (2.81)	2217 (3.94)	592 (3.07)	2069 (4.01)	598 (3.15)	1997 (3.93)	645 (3.35)	1621 (3.5)	472 (2.79)	1778 (3.45)	414 (2.49)
	M	24078 (47.97)	5238 (30.62)	27500 (48.92)	6094 (31.56)	26613 (51.6)	6260 (32.93)	25818 (50.75)	6283 (32.68)	23459 (50.7)	5610 (33.21)	25611 (49.76)	5736 (34.52)
	N	24033 (47.88)	11367 (66.45)	26455 (47.06)	12621 (65.36)	22867 (44.34)	12139 (63.85)	23031 (45.27)	12281 (63.87)	21168 (45.75)	10805 (63.96)	24061 (46.75)	10457 (62.93)
	OTHER	37 (0.07)	19 (0.11)	41 (0.07)	4 (0.02)	26 (0.05)	14 (0.07)	24 (0.05)	19 (0.1)	24 (0.05)	6 (0.04)	21 (0.04)	11 (0.07)
Unit Type (Max)	TDA	8267 (16.47)	7896 (46.16)	8608 (15.31)	9108 (47.16)	6617 (12.83)	8722 (45.88)	5726 (11.26)	8115 (42.2)	5277 (11.4)	6738 (39.89)	5719 (11.11)	5409 (32.55)
	MTOE	41673 (83.02)	8967 (52.42)	47387 (84.3)	10065 (52.12)	44768 (86.8)	10053 (52.88)	44882 (88.23)	10859 (56.47)	40849 (88.28)	10083 (59.69)	45610 (88.61)	11141 (67.04)
	MULTI	222 (0.44)	67 (0.39)	199 (0.35)	61 (0.32)	181 (0.35)	139 (0.73)	246 (0.48)	199 (1.03)	113 (0.24)	23 (0.14)	132 (0.26)	25 (0.15)
	NA	37 (0.07)	175 (1.02)	19 (0.03)	77 (0.4)	9 (0.02)	97 (0.51)	16 (0.03)	55 (0.29)	33 (0.07)	49 (0.29)	10 (0.02)	43 (0.26)

		2005		2006		2007		2008		2009		2010	
		No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit	No Attrit	Attrit
Military Occupation	LD	439 (0.87)	105 (0.61)	513 (0.91)	112 (0.58)	577 (1.12)	137 (0.72)	514 (1.01)	150 (0.78)	629 (1.36)	183 (1.08)	585 (1.14)	158 (0.95)
	11	10048 (20.02)	3562 (20.82)	10657 (18.96)	3328 (17.23)	8037 (15.58)	2731 (14.37)	8543 (16.79)	2849 (14.82)	8586 (18.56)	2972 (17.59)	9725 (18.89)	3179 (19.13)
	12	2156 (4.29)	645 (3.77)	3046 (5.42)	903 (4.68)	2211 (4.29)	802 (4.22)	3606 (7.09)	1288 (6.7)	2881 (6.23)	1027 (6.08)	2949 (5.73)	887 (5.34)
	13	2902 (5.78)	792 (4.63)	4265 (7.59)	1267 (6.56)	3471 (6.73)	1189 (6.25)	3291 (6.47)	949 (4.94)	2658 (5.74)	857 (5.07)	3501 (6.8)	1013 (6.1)
	14	506 (1.01)	222 (1.3)	1209 (2.15)	623 (3.23)	1041 (2.02)	482 (2.54)	1102 (2.17)	398 (2.07)	573 (1.24)	221 (1.31)	1311 (2.55)	409 (2.46)
	15	2148 (4.28)	616 (3.6)	2176 (3.87)	659 (3.41)	1841 (3.57)	680 (3.58)	1651 (3.25)	722 (3.75)	1908 (4.12)	804 (4.76)	2051 (3.98)	846 (5.09)
	18	498 (0.99)	77 (0.45)	320 (0.57)	2 (0.01)	204 (0.4)	2 (0.01)	231 (0.45)	2 (0.01)	258 (0.56)	4 (0.02)	325 (0.63)	2 (0.01)
	19	2881 (5.74)	870 (5.09)	2694 (4.79)	652 (3.38)	2575 (4.99)	807 (4.24)	2139 (4.2)	740 (3.85)	1935 (4.18)	825 (4.88)	2658 (5.16)	828 (4.98)
	25	3081 (6.14)	1158 (6.77)	2929 (5.21)	1136 (5.88)	2959 (5.74)	1328 (6.99)	3712 (7.3)	1807 (9.4)	4131 (8.93)	1799 (10.65)	3612 (7.02)	1417 (8.53)
	31	1971 (3.93)	897 (5.24)	1826 (3.25)	651 (3.37)	2373 (4.6)	1205 (6.34)	2065 (4.06)	1270 (6.6)	1766 (3.82)	926 (5.48)	1101 (2.14)	559 (3.36)
	35	2879 (5.74)	274 (1.6)	2064 (3.67)	295 (1.53)	2338 (4.53)	689 (3.62)	2177 (4.28)	733 (3.81)	2432 (5.26)	757 (4.48)	3194 (6.21)	969 (5.83)
	42	920 (1.83)	282 (1.65)	1291 (2.3)	406 (2.1)	1864 (3.61)	654 (3.44)	1411 (2.77)	567 (2.95)	794 (1.72)	245 (1.45)	726 (1.41)	225 (1.35)
	68	3465 (6.9)	633 (3.7)	4005 (7.12)	1531 (7.93)	3824 (7.41)	1689 (8.88)	3274 (6.44)	1516 (7.88)	3285 (7.1)	1278 (7.57)	3521 (6.84)	1138 (6.85)
	74	759 (1.51)	254 (1.48)	1141 (2.03)	452 (2.34)	871 (1.69)	236 (1.24)	647 (1.27)	272 (1.41)	573 (1.24)	166 (0.98)	742 (1.44)	227 (1.37)
	88	2558 (5.1)	821 (4.8)	3362 (5.98)	1256 (6.5)	3198 (6.2)	1250 (6.58)	2726 (5.36)	984 (5.12)	2075 (4.48)	779 (4.61)	2308 (4.48)	774 (4.66)
	91	6225 (12.4)	2531 (14.8)	6513 (11.59)	2534 (13.12)	6350 (12.31)	2112 (11.11)	5381 (10.58)	1897 (9.87)	5415 (11.7)	1851 (10.96)	6405 (12.44)	1989 (11.97)
	92	5515 (10.99)	2149 (12.56)	6297 (11.2)	2563 (13.27)	6279 (12.17)	2379 (12.51)	6813 (13.39)	2471 (12.85)	4663 (10.08)	1764 (10.44)	5055 (9.82)	1716 (10.33)
	NA	1248 (2.49)	1217 (7.11)	1905 (3.39)	941 (4.87)	1562 (3.03)	639 (3.36)	1587 (3.12)	613 (3.19)	1710 (3.7)	435 (2.58)	1702 (3.31)	282 (1.7)

APPENDIX C. UNIVARIATE MODEL RESULTS

Table 12 Univariate Summary of Binary/Categorical Variables: Count and Proportion by Attrition Category

	Variable	No Attrit	Attrit	Total	p-value
Fiscal Year (Enlistment)	2005	40187 (74.64 %)	13657 (25.36 %)	53844	Ref
	2006	45044 (74.55)	15376 (25.45)	60420	0.7432
	2007	41314 (73.16)	15155 (26.84)	56469	< 0.001
	2008	40704 (72.58)	15375 (27.42)	56079	< 0.001
	2009	37082 (73.38)	13450 (26.62)	50532	< 0.001
	2010	41123 (75.49)	13349 (24.51)	54472	0.0011
Prior Service	0 - “No”	238527 (75.61)	76942 (24.39)	315469	Ref
	1 - “Yes”	6927 (42.37)	9420 (57.63)	16347	< 0.001
Unit Region (Max)	Midwest	13570 (63.87)	7676 (36.13)	21246	Ref
	Northeast	12216 (79.27)	3195 (20.73)	15411	< 0.001
	South	139473 (71.52)	55534 (28.48)	195007	< 0.001
	Territory	23 (88.46)	3 (11.54)	26	0.0169
	West	54787 (79.75)	13912 (20.25)	68699	< 0.001
Home of Record Region	Midwest	50235 (73.99)	17657 (26.01)	67892	Ref

	Variable	No Attrit	Attrit	Total	p-value
	Northeast	29300 (74.28)	10143 (25.72)	39443	0.2926
	South	105092 (72.29)	40279 (27.71)	145371	< 0.001
	Territory	3182 (84.38)	589 (15.62)	3771	< 0.001
	West	54002 (76.24)	16827 (23.76)	70829	< 0.001
Military Occupation Group (Max)	Operations	114786 (74.59)	39095 (25.41)	153881	Ref
	Operational Support	28356 (74.26)	9827 (25.74)	38183	0.1845
	Force Sustainment	94559 (73.48)	34123 (26.52)	128682	< 0.001
Gender	0 - Female	31355 (60.42)	20542 (39.58)	51897	Ref
	1 - Male	214099 (76.49)	65820 (23.51)	279919	< 0.001
Citizenship Status	0 - U.S. Citizen	237869 (73.73)	84747 (26.27)	322616	Ref
	1- Non-Citizen	3981 (89.3)	477 (10.7)	4458	< 0.001
Rank (Max)	PV1	5457 (17.81)	25176 (82.19)	30633	Ref
	PV2	4254 (17.56)	19972 (82.44)	24226	< 0.001
	PFC	12590 (37.29)	21176 (62.71)	33766	< 0.001
	CPL	165848 (89.99)	18458 (10.01)	184306	< 0.001
	SGT	53011 (97.47)	1376 (2.53)	54387	< 0.001
	SSG	4294 (95.46)	204 (4.54)	4498	< 0.001
	PV1	91659	42169	133828	Ref

	Variable	No Attrit	Attrit	Total	p-value
Rank (Enlistment)		(68.49)	(31.51)		
	PV2	68568 (74.17)	23874 (25.83)	92442	< 0.001
	PFC	55203 (78.08)	15497 (21.92)	70700	< 0.001
	CPL	26230 (86.4)	4130 (13.6)	30360	< 0.001
	SGT	2968 (85.56)	501 (14.44)	3469	0.1734
	SSG	826 (81.22)	191 (18.78)	1017	< 0.001
Waiver (Medical)	0 - "No"	227569 (73.96)	80115 (26.04)	307684	Ref
	1 - "Yes"	17885 (74.11)	6247 (25.89)	24132	0.606
Waiver (Conduct)	0 - "No"	223280 (74.14)	77889 (25.86)	301169	Ref
	1 - "Yes"	22174 (72.35)	8473 (27.65)	30647	< 0.001
Waiver (Admin)	0 - "No"	231378 (73.71)	82513 (26.29)	313891	Ref
	1 - "Yes"	14076 (78.53)	3849 (21.47)	17925	< 0.001
Waiver (Drug)	0 - "No"	243147 (74.05)	85196 (25.95)	328343	Ref
	1 - "Yes"	2307 (66.43)	1166 (33.57)	3473	< 0.001

	Variable	No Attrit	Attrit	Total	p-value
Education Tier	1 - HS Diploma	203711 (76.16)	63762 (23.84)	267473	Ref

	Variable	No Attrit	Attrit	Total	p-value
	2 - GED	38563 (64.84)	20913 (35.16)	59476	< 0.001
	3 - Other	1097 (57.59)	808 (42.41)	1905	< 0.001
AFQT Category	1	15966 (82.08)	3485 (17.92)	19451	Ref
	2	81260 (74.95)	27159 (25.05)	108419	< 0.001
	3A	57981 (70.69)	24045 (29.31)	82026	< 0.001
	3B	80247 (73.36)	29146 (26.64)	109393	< 0.001
	4A	8113 (78.22)	2259 (21.78)	10372	< 0.001
	4Bplus	318 (79.9)	80 (20.1)	398	0.0234
Citizenship Origination	A - Born in U.S.	225055 (73.25)	82179 (26.75)	307234	Ref
	N - Born outside U.S.	7450 (86.6)	1153 (13.4)	8603	< 0.001
	C - Naturalized	5539 (79.07)	1466 (20.93)	7005	< 0.001
Education Level (Enlistment)	HS - High School	209433 (73.09)	77106 (26.91)	286539	Ref
	CLG - Some College	12261 (75.46)	3987 (24.54)	16248	< 0.001
	BAC - Baccalaureate	14140 (86.69)	2171 (13.31)	16311	< 0.001
	GRAD - Graduate	1124 (84.26)	210 (15.74)	1334	< 0.001
Education Level (Max)	HS - High School	211427 (72.8)	78975 (27.2)	290402	Ref
	CLG - Some College	16319 (79.92)	4099 (20.08)	20418	< 0.001

	Variable	No Attrit	Attrit	Total	p-value
	BAC - Baccalaureate	14345 (86.81)	2179 (13.19)	16524	< 0.001
	GRAD - Graduate	1280 (84.77)	230 (15.23)	1510	< 0.001
Marital Status (Max)	D - Divorced	9453 (78.59)	2576 (21.41)	12029	Ref
	M - Married	122658 (81.32)	28174 (18.68)	150832	< 0.001
	N - Never Married	113196 (67.08)	55556 (32.92)	168752	< 0.001
	Other	147 (72.41)	56 (27.59)	203	0.0347

	Variable	No Attrit	Attrit	Total	p-value
Unit Type (Max)	TDA	32112 (46.63)	36757 (53.37)	68869	Ref
	MTOE	212399 (81.31)	48824 (18.69)	261223	< 0.001
	MULTI	851 (68.24)	396 (31.76)	1247	< 0.001
Military Occupation (Max)	LD	2618 (79.48)	676 (20.52)	3294	Ref
	11	44576 (75)	14858 (25)	59434	< 0.001
	12	13543 (75.5)	4394 (24.5)	17937	< 0.001
	13	16091 (76.91)	4830 (23.09)	20921	0.0011
	14	4593 (70.79)	1895 (29.21)	6488	< 0.001
Military Occupation (Max)	15	9343 (72.98)	3460 (27.02)	12803	< 0.001
	18	1466 (95.19)	74 (4.81)	1540	< 0.001
	19	11932	3825	15757	< 0.001

	Variable	No Attrit	Attrit	Total	p-value
		(75.73)	(24.27)		
	25	16331 (70.53)	6824 (29.47)	23155	< 0.001
	31	8906 (66.91)	4405 (33.09)	13311	< 0.001
	35	12001 (79.99)	3002 (20.01)	15003	0.506
	42	5658 (74.42)	1945 (25.58)	7603	< 0.001
	68	17064 (73.42)	6178 (26.58)	23242	< 0.001
	74	3796 (74.62)	1291 (25.38)	5087	< 0.001
	88	12922 (73.5)	4660 (26.5)	17582	< 0.001
	91	29140 (73.82)	10335 (26.18)	39475	< 0.001
	92	27725 (72.73)	10394 (27.27)	38119	< 0.001

APPENDIX D. PURPOSEFUL VARIABLE SELECTION

The first step of the binary regression we employ is to construct a full model with all variables in order to identify the non-statistically significant variables: $\alpha = .01$ level. Though we use a significance level of 0.001 in the univariate model, by allowing for more candidate variables to be selected in the multivariate analyses using a more conservative significance level, we aim to reduce bias in our model by identifying all possible valid predictors. The model resulted in the identification of variables with multivariate *p*-values greater than 0.01: *unit region*, *home of record region*, *military occupation group*, *citizenship status*, *waiver (medical)*, and *waiver (drug)*. We removed these variables and we created new model.

Zhang (2016) describes the next step in the *Annals of Translational Medicine* in which he provides a strategy for purposeful selection of variables. In his words, "the coefficients of variables should be compared to coefficients in the original one. If a change of coefficients…is more than 20%, the deleted variables have provided important adjustment of the effect of remaining variables" (p. 3). These variables are called confounding variables and can provide an indication of correlation while potentially increasing the variance or introducing bias. The difference in the coefficients between our models is negligible for nearly all variables except for the military occupation variables.

Since the *military occupation group* is a collapsed form of the *military occupation*, it is natural to believe that removal of the term caused instability in the model. To test the theory, we reconstruct the model with *military occupation group* added back. As expected, the coefficients were nearly unchanged between models. Whereas most confounding variables should be kept in a model, our knowledge of the relationship between these variables led us to believe that the difference in coefficients was indicative of correlation. In the interest of a more parsimonious model, we remove the 17-level *military occupation* variable in favor of the 3-level *military occupation group*. Similarly, we identify the relationship between the *ASVAB GT Score* and the *AFQT Category* variables, which we derive from raw ASVAB line scores. Though the numeric *ASVAB GT Score*

would provide the simplest model, there are 11,527 missing values compared to only 1,757 missing values in the *AFQT Category* predictor, so we remove the *ASVAB GT Score* variable.

At this stage of the research, we make choices about variable selection based on known variable relationships and predictive use. For instance, the *Fiscal Year of Enlistment* indicator may be a statistically significant predictor in our training and test datasets. However, the historical data from FY2005 to FY2010 required for the determination of the response variable does not assist in predicting whether a current soldier who enlisted in FY2016 will complete the first term. Likewise, the rank of a soldier and the education level at the end of the first term is information that will not be available when using the model to predict a current soldier. We remove the variables *Fiscal Year of Enlistment, Rank (Max),* and *Education Level (Max)* and generate a new model to identify any variables that are no longer significant. *Age (Enlistment)* is no longer statistically significant and we remove it.

Our model now consists of only the statistically significant variables. The five variables with the highest importance metric are very different from the other variables (Table 13). Unfortunately, the most influential variable, *Max Time in Grade*, is a variable we create during the variable transformation of our cohort dataset and proves to be suspect under scrutiny. This concern combined with the challenge for a soldier to provide this input to a predictive tool leads us to remove the variable from the model.

Table 13 Max Time in Grade Importance Comparison

Model with Max Time in Grade		**Model without Max Time in Grade**	
Variable	**Score**	**Variable**	**Score**
Max Time in Grade	173.66	Contract Duration	97.50
Contract Duration	158.91	Days Deployed	82.58
Days Deployed	70.07	Unit Type (“MTOE”)	71.31
Prior Service (“Yes”)	51.80	Education Tier (“GED”)	40.34
Education Tier (“GED”)	31.12	Gender (“Male”)	32.44

Next, we converted the *Contract Duration* variable to a categorical factor from a numeric variable as it represents one of four discrete values from three to six years. Additionally, the variables *Education Level (Enlistment)*, *Hostile Injuries*, and *Deployments*, are no longer statistically significant and we remove them.

The final model consists of five numeric predictor variables and 40 levels of 12 categorical variables with importance scores assigned for non-reference variables. The variable importance table (Table 14) provides the variable names sorted in decreasing order of importance. The number of days a soldier spends deployed is clearly the most influential variable in the model. Soldiers with three- or four-year enlistment contracts may have very little time left in their first term after the initial entry training period and a deployment. The length of the initial contract is also very influential in the model. It is intuitive that a soldier's probability of leaving the Army before the end of the first term is impacted by the length of a soldier's first term. Interestingly, unlike previous research, the most influential variables did not include *gender* and *education tier*. We believe our broader variable selection may account for this.

Table 14 Logistic Regression Variable Importance

Variable Name	Importance Score
Days Deployed	195.3798
Contract Duration - 6 years	88.09909
Unit Type (Max) - MTOE	71.87137
Contract Duration - 5 years	68.46465
Contract Duration - 4 years	50.40338
Rank (Enlistment) - PV1	41.07629
Education Tier - GED	41.02178
Gender - Male	32.85909
Marital Status - Never Married	32.68731
Military Occupation Group - Operations Support	31.07285

Variable Name	Importance Score
Rank (Enlistment) - PV2	31.0492
Prior Service - Yes	30.14718
Military Occupation Group - Force Sustainment	25.81135
Dependents	23.2742
Rank (Enlistment) - PFC	20.11481
Citizenship Origination - Naturalized	19.03031
AFQT Category - IIIB	18.77884
Weight (Enlistment)	18.23063
Unit Type (Max) - Multi-Component	17.24774
Waiver (Conduct) - Yes	16.80668
Waiver (Admin) - Yes	15.18946
AFQT Category - IIIA	14.78308
AFQT Category - I	13.12183
Rank (Enlistment) - SSG	12.79808
Rank (Enlistment) - SGT	11.86484
AFQT Category - IVA	11.61668
Education Tier - Other	9.688365
Height (Enlistment)	6.240778
Non-Hostile Injuries	6.231266
Citizenship Origination - Outside U.S.	6.146431
AFQT Category - IVB+	3.67796
Marital Status - Married	2.014206
Marital Status - Other	1.277019

Prior to the examination of the model coefficients, we perform diagnostics to assess the underlying model assumptions. Binary logistic regression models do not face the restrictive assumptions required in linear models; however, we examine the model results for outliers and the presence of multicollinearity.

In his text, *Extending the Linear Model with R,* Faraway presents a method of visualization to subjectively gauge the goodness-of-fit of a logistic regression model (Faraway, 2016). We cannot use the deviance in a binary logistic regression model to test the fit, as the deviance is a function of the fitted probabilities. Our analysis requires the adaptation of his code to examine our model (Faraway, 2016, pp. 40-41). If the model is a good fit, we would expect the observed proportions of binned predictions to match the frequency of the event occurring within the bin. After we generated the linear predictor by our model, we grouped the predictors in 300 quantile bins. We counted the first-term attrition events (response variable), and we calculated the mean of the linear predictors with a 95% confidence interval inside each bin. Once plotted, we find a slight variation at the higher values of predicted probability, but the line mostly fell within the confidence interval hashes (Figure 18). Since the linear predictor line mostly falls within the 95% confidence interval hashes, there is no evidence that the model residual variance is excessive. Without consistent or excessive deviation, there is no evidence that the model residual variance is excessive.

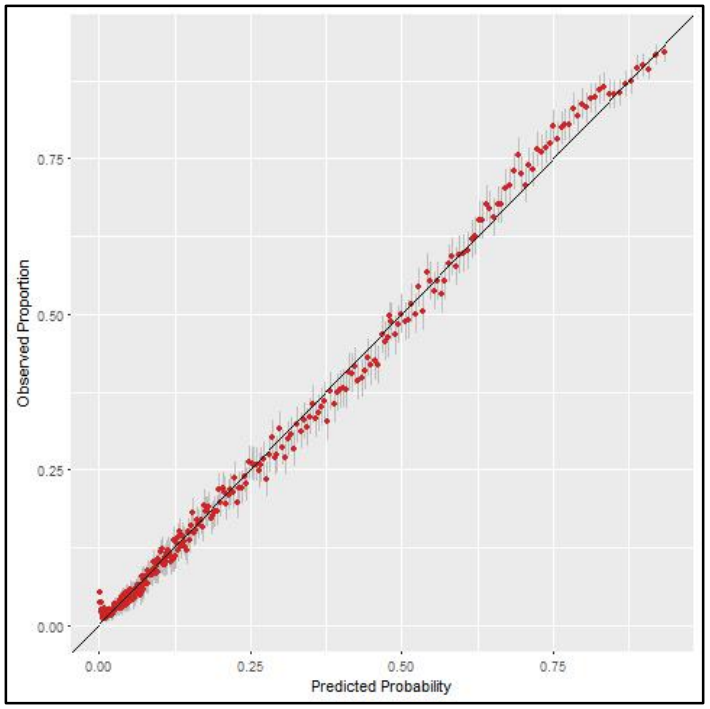


Figure 18 Binned Predicted Probabilities and Observed Proportions. Faraway (2016).

To check for multicollinearity within a binary logistic regression model, we examine the variable inflation factor (VIF). The variable inflation factor is a measure of the effect of correlation among two or more predictor variables within a regression model. The typical rule of thumb is variables with a VIF value greater than 10 are highly correlated and may cause problems within the model. In our model, none of the variables had a VIF value exceeding 1.5 and we proceed with our analysis of the model (Table 15).

Table 15 Regression Model Variable Inflation Factors

Variable Code	VIF Value
ASVC_AGMT_DRTN_YR_QY	1.057994
PRIOR_SRVC	1.01333

Variable Code	VIF Value
CMF_FUNC_GRP	1.062777
GENDER	1.333007
RANK_MIN	1.021972
WAIVER_CONDUCT_YN	1.017749
WAIVER_ADMIN_YN	1.115067
EDU_TIER_CD	1.03149
INJ_NON_HOSTILE_CNT	1.001179
DPLY_DAYS_QY	1.076537
DEP_QY_MEPS	1.175652
HGT_DM	1.430239
PN_WGHT_QY	1.250949
AFQT_CAT_CD_CLPS	1.026545
US_CTZP_ORIG_CD_CLPS	1.004612
MRTL_STAT_CD_CLPS	1.042209
UNIT_TYPE_MAX_CLPS	1.02462

APPENDIX E. SHINY APPLICATION SCREENSHOTS

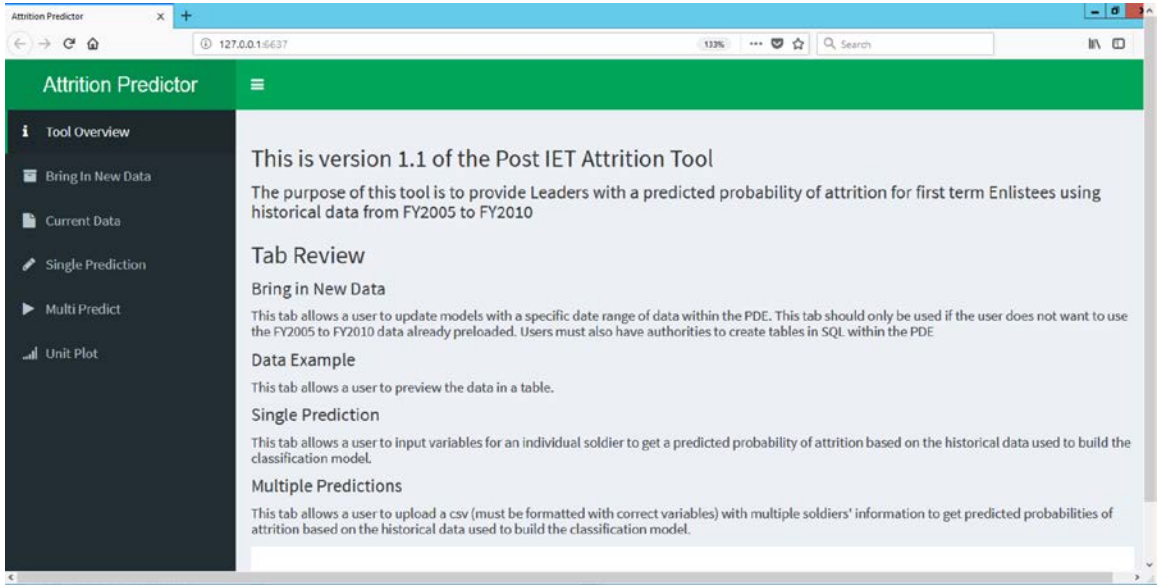


Figure 19 Launch Page for Attrition Prediction Tool

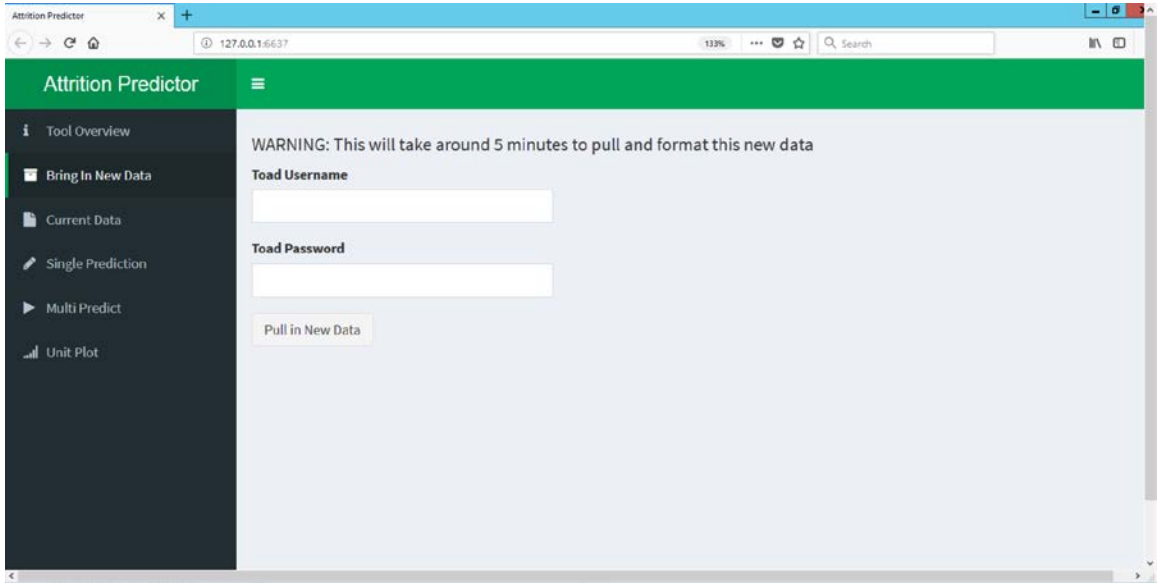


Figure 20 Bring in New Data Tab

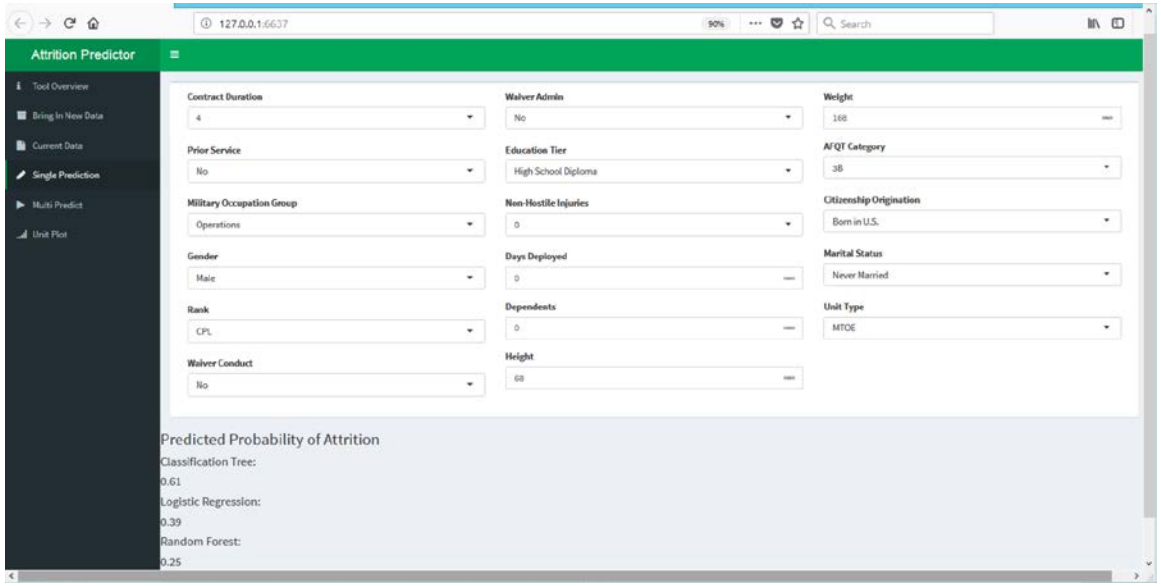
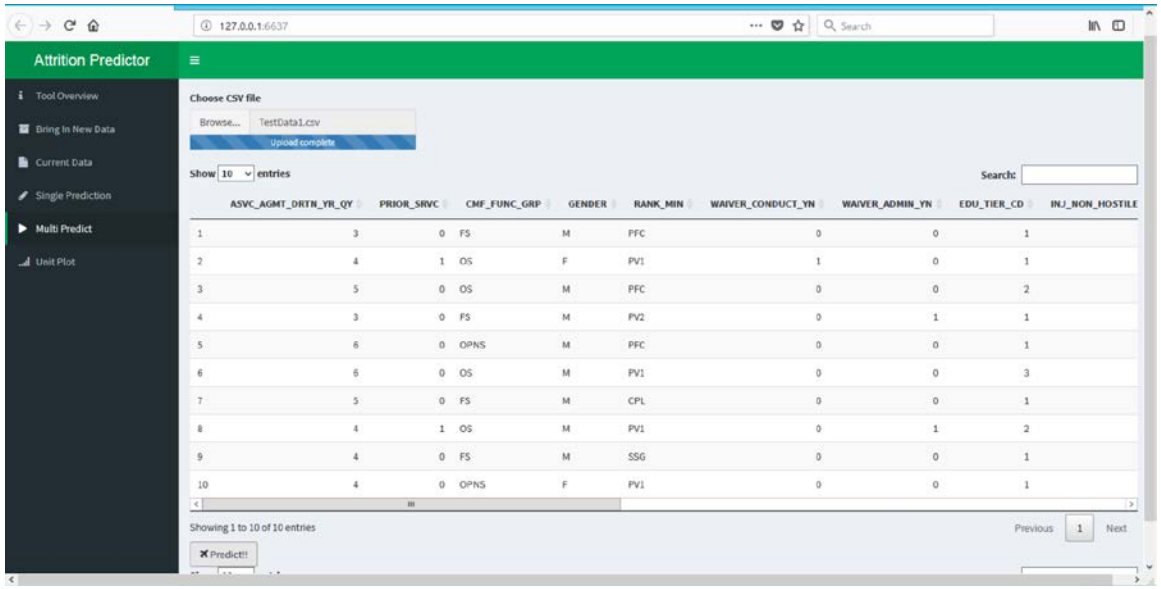


Figure 21 Individual Soldier Predictor Tab



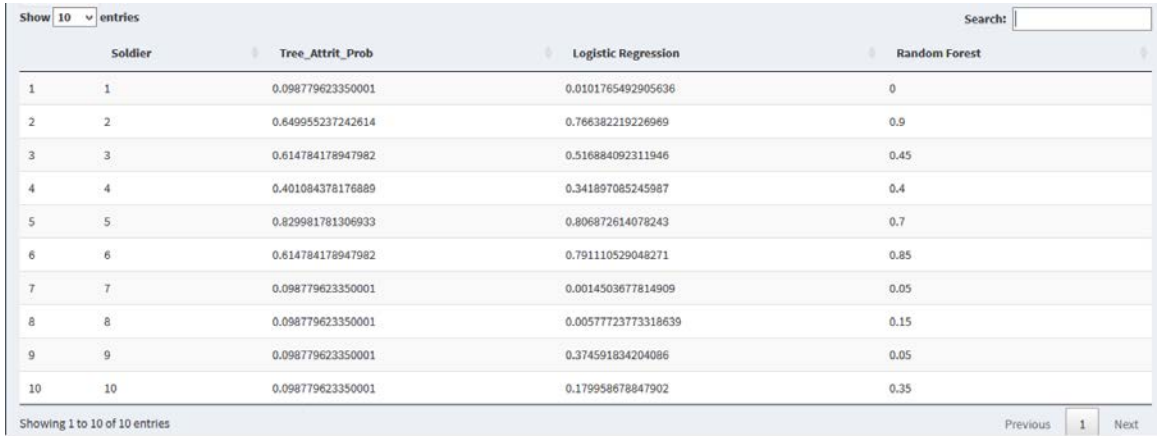


Figure 22 Unit Level Predictor Tab and Results

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