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Can-Do Vs. Will-Do Factors: Predicting the Gold-Standard Marine

March 2022

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Prepared for the Naval Postgraduate School, Monterey, CA 93943

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ABSTRACT

The Marine Corps has historically used the high school diploma and Armed Services Vocational Aptitude Battery scores to define a high-quality enlisted Marine. This industrial-era approach fails to consider the enlistee holistically, despite evidence that a combination of cognitive and non-cognitive assessments paints a more complete picture of an enlistee. In addition to utilizing outdated recruitment methods, the current manpower system fails to identify where a particular Marine falls on a range of skills, with the extremes being generalist and specialist. Using factor analysis, machine learning, and multivariate logistic regression, this research utilizes existing personnel data to develop proxy variables that support Marine Corps efforts to better predict which enlistees will be gold-standard Marines, as well as predicting whether an enlisted Marine is a generalist or specialist. Given that proxy variables are generated to replace data that is provided by the Tailored Adaptive Personality Assessment System (TAPAS), the Marine Corps should validate the predictive accuracy of these models using TAPAS data once it is available. The bottom line is that this research provides evidence that the current manpower and recruiting systems can be refined to support more accurate decision making that will enable the Marine Corps to achieve future manpower and operating environment requirements.

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TABLE OF CONTENTS

LIST OF FIGURES

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LIST OF TABLES

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LIST OF ACRONYMS AND ABBREVIATIONS

ACCPDS	Active Component Common Personnel Data System
AFQT	Armed Forces Qualification Test
ASVAB	Armed Services Vocational Aptitude Battery
AVF	All-Volunteer Force
CFT	Combat Fitness Test
CMC	Commandant of the Marine Corps
CPG	Commandant’s Planning Guidance
DOD	Department of Defense
DLAB	Defense Language Aptitude Battery
EPME	Enlisted Professional Military Education
IST	Initial Strength Test
LASSO	Least Absolute Shrinkage and Selection Operator
MCMAP	Marine Corps Martial Arts Program
MCO	Marine Corps Order
MCRC	Marine Corps Recruiting Command
MCRCO	Marine Corps Recruiting Command Order
MCRISS	Marine Corps Recruiting Information Support System
MOS	Military Occupational Specialty
M&RA	Manpower & Reserve Affairs
PFT	Physical Fitness Test
PME	Professional Military Education
TAPAS	Tailored Adaptive Personality Assessment System
TFDW	Total Force Data Warehouse

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I. INTRODUCTION

A. OVERVIEW

The Marine Corps continues to compete with the other military services in the recruitment of high-quality enlistees. Until recent years, the Marine Corps has failed to holistically collect and analyze all pertinent data on enlistees to predict which enlisted Marines will be gold-standard Marines during their first, and most-likely only, term in the Marine Corps. The Commandant of the Marine Corps (CMC) and other researchers highlight that the future operating environment demands smart, high-performing enlisted Marines. Using education credentials to predict performance as a Marine, however, can be limiting. Fortunately, the use of a combination of cognitive and non-cognitive tests, in addition to knowledge on education credentials, offers the potential for the Marine Corps to improve its ability to predict future performance. Moreover, the Marine Corps can potentially use this information to further refine educational requirements and identify the preferred range of skills that future enlistees must possess or be capable of possessing to be considered gold-standard.

B. PURPOSE OF THIS STUDY

The primary purpose of this study is to develop a predictive model that will improve the Marine Corps' ability to identify and recruit enlistees with the highest probability of displaying elite performance. The secondary goal is to use those same predictors to predict whether an enlisted Marine will be a generalist or a specialist. More specifically, this thesis focuses on answering the following primary and secondary research questions.

1. Primary Research Question

- What combination of "will-do" factors, "can-do" factors, aptitude scores, and educational credentials currently recorded in multiple Marine Corps' databases can be used to accurately predict which enlisted Marines will become gold-standard Marines?

Nye et al. (2012) provides a framework for defining "will-do" and "can-do" factors. Specifically, Nye et al. (2012) uses soldiers' scores on Army-wide and MOS-specific job knowledge tests to build a composite score for their can-do factors. For will-do factors, the authors use performance data such as scores on physical fitness tests and indicators of disciplinary problems and misconduct. From here on out, a high performing gold-standard Marine is defined as a Marine with in-service proficiency and conduct marks of 4.5 and above.

2. Secondary Research Question

- Are gold-standard Marines more likely to be generalists or specialists? Can education credentials be used to predict who will be a generalist or a specialist?

C. SCOPE AND LIMITATIONS

1. Scope

This research focuses on first term enlisted Marines that enlisted into the Marine Corps between 1 January 2010 and 31 December 2017. Historical quality metrics, such as education credentials and aptitude tests, and personality metrics that were developed from accession and performance data are used to predict which enlistees would be gold-standard Marines. This research does not utilize any information on subsequent enlistments or Marines whose initial accession date fall outside the above date range.

Furthermore, this research only focuses on first term enlisted Marines since the Marine Corps invests significant amounts of resources into their enlistment and development. Gold-standard Marines are commonly not identified until much later in their first terms after they have displayed consistent, superior performance. To mimic this process, I use predictors that the institution would have access to when making manpower decisions. Given the plethora of enlistment and performance data, research on this population of Marines has the potential to reap significant returns when it increases the Marine Corps' ability to make more effective recruitment and retention decisions.

2. Limitations

A robust and reliable data set that contains individual Armed Services Vocational Aptitude Battery (ASVAB) component scores and Tailored Adaptive Personality Assessment System (TAPAS) facet scores that are collected during the recruiting process is essential to provide the Marine Corps with a holistic picture of an enlistee and the enlistee's future potential. However, the data set from the Total Force Data Warehouse (TFDW) for this research contains only the ASVAB Armed Forces Qualification Test (AFQT) score and no TAPAS facet scores. This research uses available literature on the TAPAS to develop factors that provide the best, but limited, representation of TAPAS information. For example, the facet of emotional stability could be inferred from whether or not an enlistee requires waivers for law violations or misconduct. The developed factors serve as proxy variables for TAPAS, but do not necessarily contain all information that is available through the multiple TAPAS facet scores. Individual facet scores that identify an enlistee's potential for personality traits, such as achievement, responsibility, and intellectual efficiency, will support stronger and more effective recruiting and retention decisions.

D. RESULTS

The primary hypothesis in this research is whether the Marine Corps can use education-, personality-, and performance-related factors to predict which enlisted Marines would become a gold-standard Marine. In fact, all proxy factors, except the factor for lifestyle waivers, are significant predictors at the one percent level. Figure 1 depicts which factor indices (developed via factor analysis using variables drawn from TFDW) and demographic characteristics increases the odds of an enlistee being a gold-standard Marine. This indicates that identifying a more holistic set of underlying personality and aptitude traits enables and improves the Marine Corps' ability to identify which enlistees will be gold-standard Marines by the end of their first term.

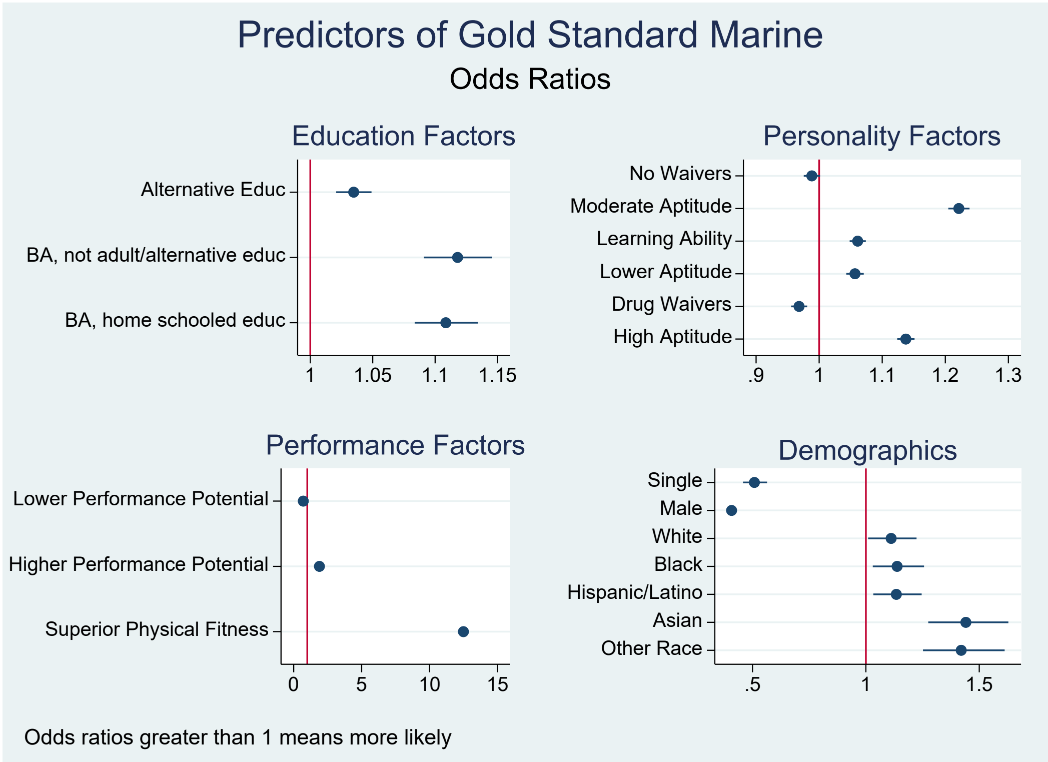

Figure 1. Odds Ratios for Predicting Gold-Standard Marines

The secondary hypothesis in this research is that the Marine Corps can predict whether enlisted Marines are more likely to be generalists or specialists. The fact of the matter is that using a simplistic criterion of grouping by military occupation specialty (MOS) as a measure of being a generalist or specialist enables the Marine Corps to predict which enlisted Marines have a higher likelihood of being a generalist or specialist. For example, MOSs in the 04XX logistics field generally execute general logistics support and are therefore coded as generalists. MOS in the 26XX and 27XX intelligence fields tend to execute more technical and complicated responsibilities and are therefore coded as specialists. Figure 2 depicts that the Marine Corps can predict whether an enlisted Marine will be a generalist or specialist using the same factors developed to predict gold-standard Marines. An additional component of the secondary question is whether education credentials can be used to predict generalists or specialists. At the end of the day, the only education credential that significantly supports predicting the likelihood of becoming a generalist vs. a specialist is the adult/alternative diploma.

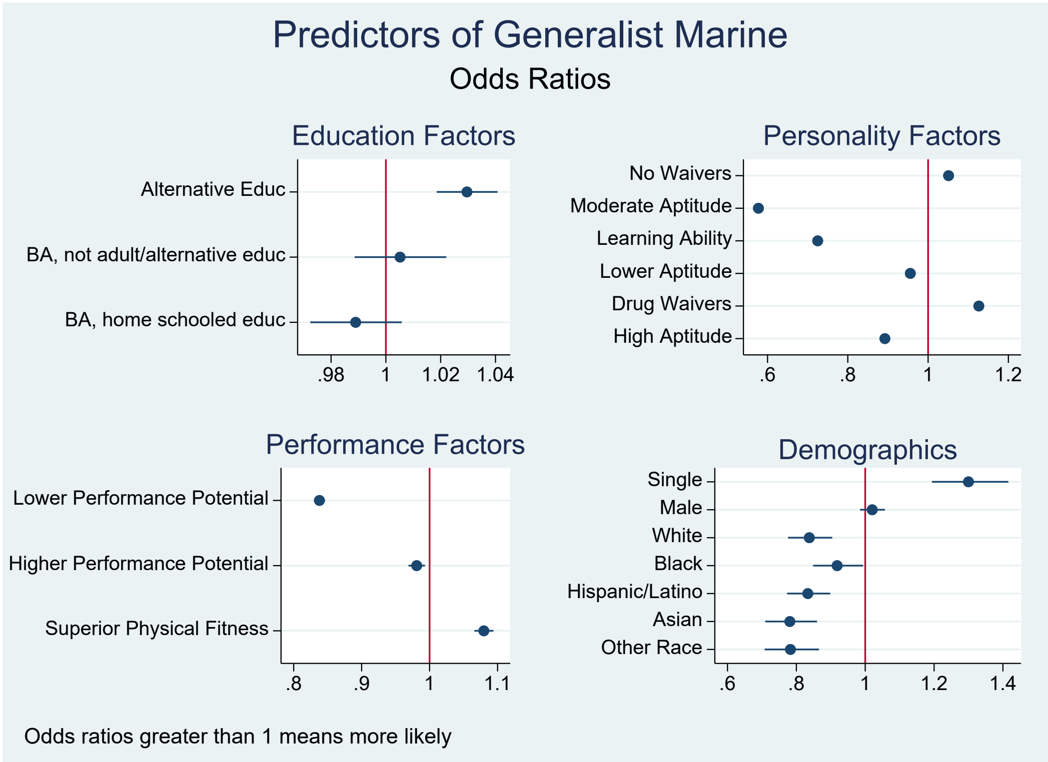

Figure 2. Odds Ratios for Predicting Generalist Marines

E. OVERVIEW OF CHAPTERS

This study is composed of six chapters. Chapter II comprises the background information on the Department of Defense (DOD) and Marine Corps, including planning, recruiting and educational policies and initiatives. Chapter III is a literature review that is separated into five sections. The first two sections cover major manpower economic models and DOD education and attrition. The last three sections contain a literature review of relevant research on intelligence, range of skills, and the TAPAS. Chapter IV provides an explanation of the data and methodologies used in this research, including an explanation of the specific steps taken to prepare the data for analysis. Chapter V describes the steps first taken to execute factor analysis and then the steps taken to execute machine learning and multivariate logistic regressions on the retained factors and variables. This research concludes with Chapter VI, which provides relevant findings and recommendations for future research.

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II. BACKGROUND

A. OVERVIEW

This chapter provides important historical details on the DOD and the Marine Corps' processes for recruiting and educating high quality enlistees. The first section describes the all-volunteer force (AVF) and how the DOD executes its responsibilities to man this force despite various challenges. This is followed by a section discussing the Commandant's Planning Guidance (CPG) and the insight it offers into current Marine Corps priorities and how the institution needs to adapt to meet future manpower requirements. The section on Professional Military Education (PME) provides a brief history of the enlisted professional military education (EPME) system and details concerns about the adequacy of this system. Finally, the last section explains specific aspects of the Marine Corps Recruiting Command (MCRC) processes for identifying the pool of enlistees that are categorized as high quality.

B. THE ALL-VOLUNTEER FORCE AND NEED FOR SUSTAINED INVESTMENT IN RECRUITING

The 2020 CNA report by Gilroy et al. provides an historical analysis on the overarching DOD perspective on the recruiting challenges that all branches of the U.S. military face as they try to fill their ranks with the enduring quotas of recruits, while simultaneously adhering to the legal mandates imposed on the services in terms of the quantity and quality of recruits. All things considered, the services have demonstrated the ability to consistently achieve their recruiting mission over time. However, the services continue to face a dilemma that forces each branch to decide between using constrained recruiting resources to focus on recruiting the quantity of recruits to fill spaces caused by attrition and separation or to focus on recruiting quality recruits that satisfy the growing metrics established by the DOD and the service (Gilroy et al., 2020). The bottom line is that the services must do both. They must fill the ranks with the minimum number of recruits to satisfy end strength requirements established by Congress, while concurrently ensuring they meet or surpass the quality dimensions mandated by Congress.

The end strength requirement of the AVF is established in the National Defense Authorization Act passed by Congress each year. However, the quality aspect of recruiting is a little more abstract, and Gilroy et al. (2020) explains that quality of a prospective recruit is determined not only by the education credential possessed by the recruit but also by the recruit's aptitude scores as measured by the ASVAB. Over time, the DOD has gained a better appreciation of the fact that higher percentages of recruits with a high school diploma stay the course and complete their initial enlistment contracts (Gilroy et al., 2020). Naturally, the DOD compares this group of recruits that achieve a higher standard with those recruits that possess no credential or an alternative credential, even though the alternative credential is considered equivalent to a high school diploma. Similarly, recruits whose AFQT score falls within the range of Category I through Category IIIA are expected to achieve superior levels of performance, relative to recruits whose score falls in Category IIIB or below (Gilroy et al., 2020). Ultimately, this focus on quality metrics has led the DOD to develop and implement additional evaluations that must be administered during the recruiting process to fill in gaps and paint a more holistic picture of the recruits' quality. One example of an assessment referenced by Gilroy et al. (2020) is the TAPAS, a personality assessment system, that was initially developed by the Army but is now being used by the other services in varying capacities. A more detailed analysis of TAPAS is provided in Chapter II.

Gilroy et al. (2020) highlights the challenges that recruiters face when trying to identify the ideal recruit, referencing GEN Maxwell Thurman's recruiting principles. Recruiters face a unique challenge of trying to understand the actual population they are immersed in and recruiting from, and specifically, they must continuously develop their understanding of the tangible and intangible factors that drive youth enlistment. The DOD must continue to identify levers that the services can leverage to pinpoint traits beyond simple education credentials and aptitude. The essence of the analysis by Gilroy et al. (2020) is that the services have achieved a fairly accurate ability to recruit high percentages of recruits that satisfy certain quality metrics. Unfortunately, all this analysis does not address the fact that despite having such a large pool of high-quality recruits, the services continue to experience attrition. While some attrition is natural and desired, the DOD must strive to maximize its ability to identify those recruits that have a higher propensity of completing their initial enlistment contract.

In the end, Gilroy et al. discuss a series of policy decisions that impact the services' ability to achieve recruiting mission. Of particular interest is the policy of approving waivers that enable recruits to enlist, despite having a history of conditions that may indicate an inability to successfully complete their first term contract (Gilroy et al., 2020). Historically, there is no evidence that the services have attempted to use these various waivers to identify personality traits that may be better indicators of future success or failure. The bottom line is that the services are attempting to meet quantity requirements, while maximizing their ability to predict who will be a high-quality recruit and leaving open the option of deviating from some metrics in order to meet recruiting mission.

C. COMMANDANT'S PLANNING GUIDANCE

As is customary, at the beginning of each commandant of the Marine Corps' tenure, the commandant will publish the CPG to provide a unity of action for the Marine Corps for the following four-year period. This unity of action is essential because the operating environment is continually fluctuating, and the Marine Corps has grown accustomed to hearing that it must adapt and change in order to be postured to effectively execute the requirements levied upon it in this chaotic operating environment. In July 2019, General David H. Berger, 38th Commandant of the Marine Corps, published his CPG and identified force design and education and training as two essential areas where change was required in order to better posture the Marine Corps to effectively execute its role as "the nation's naval expeditionary force-in-readiness" (Berger, 2020, p. 1).

In the past, it was sufficient for an enlistee simply to possess the minimum educational credential and aptitude scores on the ASVAB. The enlisted Marines of the past performed well and, in most cases, met or surpassed the expectations that the Marine Corps had for them. However, the current CPG raises concerns that the Marine Corps needs to reevaluate its manpower processes to ensure that the service begins to identify and retain talented enlistees that possess more knowledge and skills (Berger, 2020). General Berger (2020) reminds the Marine Corps that future fights will demand more from enlistees. Not only does the Marine Corps need to rid itself of legacy capabilities, such as tanks, that lack relevance for the future engagements the Marine Corps will find itself in, but the Marine Corps also needs to retain more high-quality Marines. The Marine Corps needs to specifically focus on retaining those Marines that can think critically, exercise sound initiative, desire self-improvement, and that possess or have the potential to gain essential skills, such as cognitive flexibility, that enable them to solve complex problems in a variety of unique environments (Berger, 2020).

Enlisted Marines will be expected to be more educated and possess a breadth of skills that enable them to operate fluently in all environments (Berger, 2020). These expectations raise the concern that not only does the Marine Corps need to improve its ability to identify enlistees that possess these traits, but the Marine Corps also needs to ensure the PME system can meet the future demands placed upon it by Marine Corps leadership. The CPG identifies an outdated PME system in the Marine Corps that is built around a combination of receptive training model and directive training model, where enlistees are lectured at and then guided through a series of predetermined methods that have historically solved problems (Berger, 2020). The Marine Corps' future successes in the realm of talent management will hinge on the ability of the Marine Corps to develop a system through which Marines can control their own learning and use generative learning to identify and solve problems that will not necessarily be predefined (Berger, 2020).

Ultimately, the CMC offers a renewed perspective that the Marine Corps needs to refocus its efforts on building up a force of generalist Marines that have a solid foundation of education in the art and science of naval warfare (Berger, 2020). Berger goes on to emphasize how the Marine Corps needs to develop a more holistic understanding of learning, clearly translate that understanding into doctrine, and create opportunities for Marines to learn how to use their skills in environments that demand teamwork and faster decision making to resolve real-world problems. Despite this focus on creating a more common understanding of the skills and knowledge required to be an effective naval expeditionary force, the CMC highlights throughout the CPG that the manpower structure also needs to be updated to ensure that it brings to the surface those Marines that possess specialized skills that are invaluable to the Corps (Berger, 2020). The bottom line is that the Corps wants the most well-rounded Marines that can observe real-word problems, think outside the box, and develop solutions that will contribute to the Marine Corps' ability to be victorious in future conflicts.

D. PROFESSIONAL MILITARY EDUCATION

The Marine Corps' current PME system, including officer and EPME, was formally codified under the Marine Corps University in the late 1980s under the guidance and direction of the 29th Commandant of the Marine Corps, General Alfred M. Gray Jr. General Gray recognized that the future success of the Marine Corps would be dictated by new fluid and chaotic operating environments and that the Marine Corps needed better trained and educated personnel that had a bias for action (Marine Corps University, n.d.). The EPME system continues to be developed to ensure that higher caliber enlisted Marines are equipped with the essential knowledge and skills that maximize their potential to successfully represent the Marine Corps throughout the world.

As specified in Marine Corps Order (MCO) 1553.4B (2008), the Marine Corps takes the following stance in regard to all PME

> The Marine Corps PME philosophy is that PME is a career long study of the foundations of the military profession. PME is designed to equip Marines with the analytical skills necessary to exercise sound military judgment in contemporary operations. The Marine Corps PME program is a progressive learning system designed to educate Marines by-grade throughout their careers. (Headquarters, United States Marine Corps [HQMC], 2008, p. 2)

In essence, the Marine Corps' position is that PME is all-inclusive. All enlisted Marines of all grades are expected to actively engage in EPME. First, this engagement ensures that all enlisted Marines are equipped with skills that enable them to execute their assigned responsibilities more effectively within the hierarchy of the Marine Corps. Second, completion of EPME enables the Marine Corps to use it as a signaling mechanism for promotion and selection purposes. While commands across the Marine Corps are being directed to support and implement policies and plans to ensure all Marines complete PME requirements, there is a simultaneous effort to hold the individual Marine accountable for his or her PME progress by reporting metrics on PME to future selection boards (HQMC, 2008).

The push for accountability and need to ensure all Marines build a consistent foundation of thinking, analysis, and judgment ultimately forces the Marine Corps to consider whether all EPME alternatives are equal. Logically, there are going to be constraints in terms of time and space that are placed on individual Marines and units that prevent EPME from being completed as the Marine Corps philosophy lays it out (HQMC, 2008). MCO 1553.4B addresses this concern by authorizing commands to certify that individual Marines have satisfied all PME requirements if they completed one of the PME equivalent courses. While this no doubt helps the Marine Corps move closer to achieving General Alfred Gray's intent by adhering to the philosophy as described in MCO 1553.4B, some potentially serious assumptions and concerns begin to surface.

A notable assumption that surfaces is that the foundation of EPME received at different courses is truly consistent, and the Marines that graduate return to the Marine Corps with a similar set of skills, within an acceptable range. A second assumption is that the number and the types of equivalent courses are sufficient to meet the demands of the Marine Corps and long-term goals of the individual Marine. Lastly, this leads to the assumption that the greater DOD and Marine Corps philosophies are in fact correct and that all Marines, regardless of the length of their career, need to complete PME in order to fully contribute to the Marine Corps' ability to achieve victory in combat. This last assumption is based on yet another assumption, and that is the concern that the Marine Corps is unable to predict which Marines are likely to elect to continue to serve in the military and thus require additional future military education. Ultimately, this leads the Marine Corps to its current position, as detailed in MCO 1553.4B, where all Marines are expected to learn and will begin to build a foundation of military education until they exit the military service.

E. MCRCO 1100.1 MARINE CORPS RECRUITING COMMAND ENLISTMENT PROCESSING MANUAL

MCRC explains in its mission statement in Marine Corps Recruiting Command Order (MCRCO) 1100.1 that "the immediate impact that recruiting has on the Marine Corps requires that standards for enlistment be strictly set to ensure that future Marines will maintain our tradition of excellence" (Marine Corps Recruiting Command [MCRC], 2011, p. 1-4). MCRCO 1100.1 goes on to provide guidance and direction to the MCRC force on all the demographic, aptitude, and moral traits that a qualified enlistee must possess. If the enlistee fails to satisfy any of the detailed qualifications, MCRCO 1100.1 provides further guidance on determining if an enlistee may qualify for a waiver, or combination of waivers, that will ultimately enable an enlistee to attend Marine Corps Recruit Training in pursuit of earning the title United States Marine.

The bottom line is that MCRC wants the highest quality enlistees to apply in order to increase the Marine Corps' return on investment and to reduce the future burden on the Marine Corps in terms of excess administrative requirements and adverse actions. MCRC insinuates that the highest quality enlistees are young, single with no dependent children, U.S. citizens, and graduates of a traditional brick-and-mortar high school (MCRC, 2011). MCRC further refines its implied definition of high-quality enlistees by clarifying that they possess a spotless criminal history, have no history of drug or alcohol use, are physically fit, and possess a superior mental aptitude (MCRC, 2011). This list of characteristics and standards is very impressive; however, it must be understood that not all characteristics have equal significance. While MCRC emphasizes the importance of education by stating that "traditional education strongly correlates with success at recruit training and completion of the first term of enlistment," it fails to clarify if education by itself is the most significant predictor of the quality of the enlistee (MCRC, 2011, pp. 3–37).

MCRC gets closer to the command's real intent at recruiting high-quality enlistees in the section on physical aptitude when it begins to delve into the concern that enlistees must be capable and prepared to endure future physical demands (MCRC, 2011). The significance of this thought process is that MCRC is attempting to collect current data on enlistees and use it as a screening tool to ensure enlistees reflect the standards that all

Marines are expected to emulate, and then use that data to make future predictions about the enlistees' performance in the Marine Corps at various benchmarks. Historically, many DOD agencies, including MCRC, have had a hyper focus on using the data to predict attrition at the earliest stages of an enlistee's career, specifically attrition during recruit training or during their first enlistment. However, there is no historical evidence in MCRCO 1100.1 that MCRC has devoted resources to refining its ability to identifying traits of those Marines that successfully complete their first enlistment. It would be ideal for MCRC to identify those with the highest return on investment or those that achieved the highest performance as rated by various metrics that are recorded later in the enlistees' career. In the end, this results in MCRC using a very limited approach by seeking out the enlistees that the organization identifies as being the highest quality as measured by attrition earlier in their career and premature performance metrics.

F. SUMMARY

The AVF has proven that the DOD can produce quantity over quality when it comes to enlistees. However, the Marine Corps needs enlistees that more completely fit the whole Marine concept, not just minimum entry standards. This stronger foundation will support the Marine Corps' future investment in education and training, enabling the Marine Corps to reap greater benefits from first term Marines. The Marine Corps has tried to use historical tools to dial-in and identify the ideal combination of education credentials and aptitude scores needed by successful enlistees. However, if history has shown us anything, it is the fact that traditional measurements of success have not included all the traits that the Marine Corps needs to examine in order to fully define what it means to be a high-quality enlistee.

III. LITERATURE REVIEW

A. OVERVIEW

This chapter describes literature related to key aspects of this study. The first section begins with a survey on manpower economics and discusses the focus of historical models. Then, the next section provides a brief overview of education and attrition from the DOD perspective. The third section provides an overview of cognition and intelligence and highlights areas that the Marine Corps is particularly concerned about. The fourth section provides an analysis of research on range of skills and the ability of generalists and specialists to complete various tasks. The chapter concludes with a summary of how the Navy has used TAPAS to better understand enlistees.

B. SURVEY OF THE LITERATURE ON MANPOWER ECONOMICS

In his CPG, General Berger (2020) stated that "our manpower system was designed in the industrial era to produce mass, not quality" (p. 7). Asch and Hosek (2007) note that since the official end of the Cold War in 1989, the DOD has reduced the quantity requirement, yet not necessarily focused on improved quality. The authors survey the extensive literature on defense manpower economics, and reference high-quality enlistments in their discussion of the supply of defense manpower. However, their focus is on the DOD's ability to meet high-quality enlistments and not necessarily how the DOD defines high-quality. In fact, the survey chapter brings together research studies where high-quality enlistments are "defined as high school diploma graduates who score in the upper half of the Armed Forces Qualification (AFQT) distribution" (Asch & Hosek, 2007, p. 1078). As articulated by General Berger, the system is stagnant, and the DOD has made no changes in how it defines high-quality over the last 15 years.

In their study of enlistment supply, Asch and Hosek (2007) explain that the DOD has historically used two very limited models, which are not holistic in nature. The first model does not consider individual personality traits of the enlistee in any way and attempts to predict if an individual will enlist simply based on demographic and environmental variables. The second model is an aggregate model that is even more ambiguous in that it simply references high-quality or low-quality recruits without any discussion of the strengths or weaknesses of these categories (Asch & Hosek, 2007). The authors do touch on some interesting points, such as college opportunities or veteran influences, that might explain the propensity of individuals to enlist in the military. The authors focus on non-demographic traits highlights the fact that there are underlying personality traits, such as openness to experience or agreeableness, that can be used to better define a high-quality recruit and subsequently be used to predict which individuals have a higher propensity to enlist.

Similarly, when it comes to retention, Asch and Hosek (2007) describe a broken system that simply focuses on how monetary benefits, unemployment rates, and other variables drive a service member's choice to reenlist. The authors again highlight areas where the retention models need to be improved by including more subjective variables, such as individual effort, that paint a more complete picture of service members. However, the retention models still have a heavy focus on monetary compensation and benefits, such as traditional military pay, career sea pay, and education benefits (Asch & Hosek, 2007).

In their discussion of personnel management, Asch and Hosek (2007) touch on programs used by the DOD that might influence enlistees' decisions to separate from the service. For example, the authors discuss literature on separation programs that might inadvertently result in high-quality service members separating from the military. However, even this discussion limits its focus of quality to education credentials and the AFQT score. Given that education credentials primarily document past performance and ASVAB scores are not a full measure of an enlistee's traits and abilities, the definition of high-quality needs to be expanded. This thesis is focused on supporting the DOD and Marine Corps' ability to identify whom to recruit in a more holistic fashion. The focus on developing a holistic picture of a recruit means improving upon traditional models that rely on limited variables, such as education credentials and ASVAB scores, with knowledge on range of skills and other non-cognitive variables of interest, to predict which service members are likely to perform well in service.

C. EDUCATION AND ATTRITION

Meanwhile, a RAND study by Hosek et al. (1989) focuses on variables that could explain potential differences in attrition behavior among individuals that were categorized as high school seniors or high school graduates at the time of the individual's enlistment. The authors identify that their research will be considered a success if they are able to improve the DOD's ability to differentiate attritors from non-attritors. They explain that while the term attrition may normally carry negative connotations, it can benefit the military services if the services are capable of separating the chaff from the wheat by categorizing service members given various performance and personality metrics. Hosek et al. claim that their research fills in a gap of knowledge in previous work by not only considering the enlistee's original likelihood of attrition, but also examining the enlistee's likelihood of attrition conditional upon them enlisting. By examining the enlistment and attrition choices sequentially, the authors are allowing for selectivity bias in the youth population at enlistment. On the other hand, previous work has already provided the DOD with the ability to predict an enlistee's likelihood of attrition given they enlisted.

Using data from two independent surveys, Hosek et al. (1989) created a choice-based sample of 5,847 individuals, where they took data on 4,718 enlistees and supplemented the sample by adding in data on 1,129 non-enlistees. The authors explain that even though this method has its drawbacks, specifically oversampling, their findings should hold because "the oversampling is corrected during statistical estimation" (Hosek et al., 1989, p. 19). The authors elected to use a model that accounts for both enlistment and attrition in order to remove selectivity bias as a concern by minimizing the possibility of unobservable variables (Hosek et al., 1989). However, Hosek et al. themselves assert that readers will not find unobservable variables in their data set, such as "personality traits (e.g., willingness to take direction)" (Hosek et al., 1989, p. 2). Given that certain standard data gathered by the DOD has the potential to be used as proxy variables for some of these unobservable variables, the authors still fail to account for all predictor variables that will ultimately impact an enlistee's probability of enlistment and attrition. In the end, the authors' sequential probit model with enlistment and attrition as outcomes simply controls for these potential unobservable variables in the residual (Hosek et al., 1989).

One of the most interesting points introduced by the authors in their research is the concept of which actors, the enlistee and/or the military, maintain the decision-making authority in enlistment and attrition processes (Hosek et al., 1989). During the enlistment phase, the enlistee is the primary decision maker. Despite this undesired non-traditional power dynamic, the military and enlistee will both benefit from a greater understanding of the factors that influence an enlistee's decision to enlist, such as self-awareness of personality traits associated with preferences for civilian life or military service. This is important because both parties will later be advocating for their position during the attrition decision. Given that the ultimate causes of attrition are not necessarily known, it is in the best interest of all parties to engage in an enlistment decision on the front end that is mutually beneficial.

Considering the need to better understand what drives an enlistee's decision to enlist in the first place, Hosek et al.'s results indicate that the perceived costs and benefits of future education are some of the most significant variables that drive high school seniors and graduates to make different enlistment decisions. Strangely though, these same educational expectations result in both groups electing to make similar attrition decisions. This finding points back to the need to identify the underlying unobservable personality traits that the authors allege are not impacting an individual's decisions to enlist or attrite after they have controlled for other variables, such as age, aptitude scores, family demographics, etc.

The bottom line is that the authors fail to dig deeply into the topic of unobservable variables that if accounted for, whether through specific measurements or proxy variables, would paint a clearer picture of what drives an individual to make different choices about their future. While the researchers categorize these individuals into different groups, the so-called unobservable variables may indicate more similarities or more specific differences that the researchers could use to build a model that more accurately predicts enlistment and attrition. The authors confirm this fact when they state that the decisions made by individuals in these two groups are potentially associated with "preexisting attributes" which the authors state would need to be examined "with other data than ours" (Hosek et al., 1989, p 9). In the end, the authors claim omitting unobservables may not be creating a bias by referring to the lack of correlation between the unobservable variables or residuals in the different levels of their sequential probit model. The lack of correlation may indicate that an enlistees' experiences in the military provide more insight into the enlistees' decision to end their military service, rather than pre-existing traits of the service member prior to enlistment. While the unobservable variables may not have been important for the authors to predict attrition given enlistment, the variables are important to this research as they have the potential to improve the Marine Corps' ability to predict who will be a gold-standard Marine.

Fast forward to 2020, and the current state of knowledge on enlistment and attrition has not increased significantly. Marrone (2020) emphasizes that the DOD continues to be relegated to using traditional data types (i.e., economic, demographic, aptitude scores) to make enlistment and attrition predictions. For example, given the finite amount of data that can be retrieved accurately at accession, the DOD barely beats 50/50 odds in predicting if an enlistee will attrite or not (Marrone, 2020). This is an indication that observable variables, such as an enlistee's sex, education certificate, and AFQT score, at the time of accession do not paint the full picture of the enlistee. It is essential that other variables, such as personality traits, are identified, measured, and recorded so that the DOD can improve its ability to predict enlistment, attrition, and, in the case of this research, elite performance.

D. COGNITION AND INTELLIGENCE

1. Marine Corps Learning Requirements

The Marine Corps expects all enlisted Marines to willingly embrace PME so that the Marine Corps can equip these Marines with a common foundation from which they can think critically and exercise educated judgment. Augier and Barrett (2021) understand this well and describe a Marine Corps that is hyper focused on PME, resulting in an obsession with how Marines need to acquire knowledge versus how they need to utilize it to tackle future problems. The authors explain that in the future, the Marine Corps desires Marines to come out of the PME system with a willingness to agree to disagree and an open-mindedness that there is not a one-size-fits-all solution to problems. Unfortunately, if the

Marine Corps was truly embracing the “strategic corporal” concept that has been talked about for years, then the PME system would already be producing the critical thinkers and problem solvers that the future operating environment demands. In the end, one of the most insightful contributions by the authors is their statement that “the most important dimensions of warfighter knowledge are cognitive skills and attitudes” (Augier & Barrett, 2021, p. 2).

Augier and Barrett (2021) emphasize that if the Marine Corps is going to develop the desired quality of Marines for the future, then learning needs to become “more challenging, slower, and frustrating” (p. 4). This raises a separate concern regarding whether Marines have the prerequisite knowledge needed to fully engage in this modified learning structure. The bottom line is that Marines were assessed into the Marine Corps using the ASVAB, which is an aptitude test that only tests for cognitive skills that are based on knowledge gained from prior experience (Roberts et al., 2000). As already discussed, the Marine Corps needs to move away from a PME system that only educates Marines on solving canned problems. Augier and Barrett (2021) explain that future Marines need to have a growth mindset, be willing to adapt how they think, and feel comfortable engaging in a thinking process that demands critical thinking, imagination, and innovation. Clearly, there is a disconnect between the cognitive skills the ASVAB measures and the cognitive skills the Commandant is envisioning his Marines possessing.

All this is not to say that the ASVAB is not achieving what it was designed to do in the past. According to the official site for the ASVAB program, the AFQT component of the ASVAB is designed to measure “general cognitive ability” (ASVAB, 2021). There is a wide body of ASVAB research that concludes that this test is valid for assessment and classification purposes; however, the Marine Corps needs to test enlistees for cognitive abilities that are demanded but not measured by the ASVAB. This research is focused on identifying indicators of the demanded cognitive skills, such as cognitive flexibility and fluid intelligence, or combinations of cognitive skills that will enable the Marine Corps to recruit those Marines that are predicted to be gold-standard Marines after accession. If this can be completed, the Marine Corps can achieve many of the changes that Augier and

Barrett stress are essential for a transformation of the PME system from its industrial era structure to an adaptable and efficient system.

2. Identifying and Measuring Key Leadership Traits

The research by Straus et al. (2018) into the ability of the Army to measure and develop desired leadership traits is particularly relevant to this research. Straus et al. (2018) draw together a comprehensive body of research on this topic to provide insights into which traits can be improved or developed through training and education and which specific testing methods the Army should utilize to gain valid measurements of the traits in question. Figure 3 provides a summary view of Straus et al.'s findings on the malleability of some of the traits discussed in the author's research. Furthermore, the authors find that tests, such as forced-choice tests and surveys, that have the highest reliability and validity should be administered (Straus et al., 2018). While Straus et al. (2018) chose to cut out some traits that are of particular interest to this research, such as cognitive flexibility and frame-switching capabilities, the authors established a strong foundation upon which future research can be built. In fact, research that will be discussed at the end of this chapter by Pema et al. supports much of the research and findings discussed in the report by Straus et al.

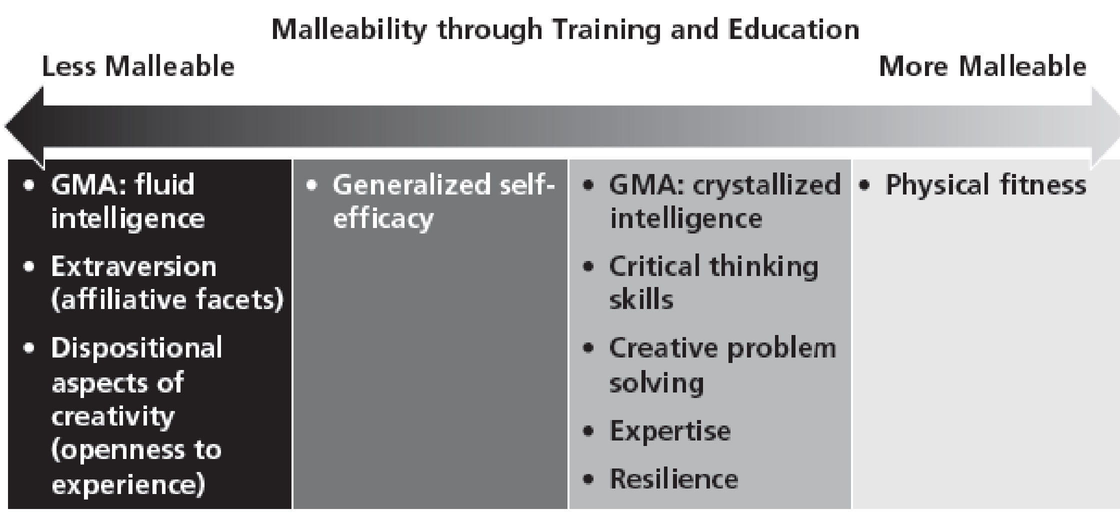

Figure 3. Degree of Malleability of ALRM Constructs. Source: Straus et al. (2018).

The first variable of interest that Straus et al. (2018) covered that is relevant to this research is general mental ability, which the authors further broke down into crystallized and fluid intelligence. Straus et al. (2018) found that the Army can use targeted training and education to influence crystallized intelligence after an enlistee has been assessed. This is favorable for the Army given that it can develop higher standards based on the baseline measures of the crystallized intelligence that the ASVAB already measured (Roberts et al., 2020). Fluid intelligence, which is not measured by the ASVAB, enables a person to use reason and logic to solve novel problems. Straus et al. (2018) documents that fluid intelligence cannot be significantly influenced through training and education, which should be concerning to the DOD given that the authors also report that an individual's overall level of fluid intelligence dissipates after reaching its cap around 22 to 25 years of age.

A second group of variables that are particularly relevant to this research due to their potential to be used to measure elite performance fall under what Straus et al. (2018) refers to as presence. The authors define presence as "how others perceive leaders in terms of overall appearance and behavior" (Straus et al. 2018, p xv). While perception is not necessarily important to this research, the components that formulate the presence trait are important. For example, Straus et al. (2018) explains that past research supports the use of physical fitness as a measure of mental and physical strength. A combination of mental and physical strength are most certainly important characteristics of service members and are likely to be variables that can be used to identify gold-standard Marines. Furthermore, physical fitness and resilience are traits that can be developed over time. While the authors do an extremely thorough job of analyzing the malleability of these traits, the list of methods used to measure them is exhaustive. It is highly unlikely that there is going to be an interest across the military services to levy more tests and batteries upon recruiters and the military entrance facilities.

Straus et al. (2018) provides a series of recommendations for methods that the Army could filter through to get the most return from the investment in additional testing administration. One recommended test that is discussed by the authors is TAPAS. TAPAS is discussed in further detail at the end of this chapter but the important part to emphasize now is the fact that this test is currently the ideal test to use because it is a forced-choice test that prevents the enlistee from faking and giving answers that the enlistee thinks are desirable. Consistent administration of the TAPAS test and ASVAB is essential because it will provide the military services and researchers with a combination of measures of most of the malleable traits that Straus et al. (2018) explains are used to categorize or identify leaders. Given that the DOD currently uses education credentials and ASVAB scores as primary signals of the quality of recruit, Straus et al. (2018) stress that there are still many gaps in the knowledge of what leadership traits are most important and how those traits should be measured. TAPAS most certainly closes part of this gap; however, it is possible that there may be other tests that can effectively isolate and identify components of fluid intelligence, extraversion, or other traits that the author identifies as being on the lower end of the spectrum of malleability.

E. RANGE OF SKILLS

1. Skill Efficiency of Generalists and Specialists

Public and private sector employers of all sizes are consistently evaluating prospective employees to determine if the new hire has the skills necessary to competently and effectively execute all tasks demanded by the employer. In conducting this analysis, the employer must determine what benefits the organization will reap from hiring the new candidate and what compensation must be offered by the employer in exchange for the candidate's level of skills. In the case of the DOD, a majority of the enlistees are fresh out of high school and possess no specialized skills. This unique situation results in the DOD having to determine the enlistee's potential to gain skills.

Keeping this information in mind, Buchen et al. (2020) highlights some important considerations that employers, such as the DOD, should make when determining if it is worth paying additional monetary benefits for more specialized skills, or the potential for more specialized skills. Buchen et al. (2020) explains that employees must be categorized as either a generalist or specialist from the perspective of the employer. Like the research by Fahrenkopf et al. that follows, Buchen et al. (2020) explains that a match between the skills requirement of the employer and the skills possessed by the employee is significant.

Fahrenkopf et al. refers to this as a job-skills match and provides a much more elaborate explanation in their research. However, Buchen et al. (2020) focuses on the employee's efficiency in multitasking and creates a clear case for why employers favor specialists over generalists.

Buchen et al. (2020) focuses on a scenario where there are two employees whose average skill abilities are only marginally different and the employee with the slightly higher average is the generalist, the other being the specialist. Essentially, the authors establish that generalists are favored when the difference is sizeable and specialists will be favored when the difference in average skill abilities is only marginal, or even negative (Buchen et al., 2020). Intuitively this makes sense because if the generalist has significantly higher average skills, then the employer's compensation system does not have to address special skills and simply compensates the employee as a generalist. In other words, the employer is not paying for special titles and credentials. On the other hand, if the difference in average skill abilities is only marginal, the employer is benefiting from similar levels of employee efficiency but also gaining access to specialized skills.

The weakness of this research lies in the fact that it emphasizes the importance of job-skill match after the employee has been introduced to the organization. Employer screening should have already identified employees with specialized skill sets and correctly aligned them to occupations that demanded that skill set. If no specialized skill sets are required, the employer would be knowingly violating the job-skill match requirement. Furthermore, the screening is likely to categorize two employees with marginally different average skill sets as either a generalist or a specialist. The true benefit of this research lies more in how it can be applied to the hiring and screening process. If employers can correctly measure average skill abilities and determine if an employee is a generalist or specialist, then they can make more informed decisions regarding job-skill match at the beginning of the employment contract.

This thesis focuses on doing exactly that, predicting if an enlistee is a generalist or a specialist and whether a gold-standard Marine is more likely to be a generalist or a specialist. Assuming the Marine Corps can accurately categorize enlistees into these two groups regardless of how small the difference in the average skill abilities is, it is doubtful that enlistees fresh out of high school with little job experience are going to display a large variance. In this case, the research by Buchen et al. (2020) would likely recommend that the Marine Corps recruit specialists due to the smaller variance. However, this research will only support that case if the specialist is also predicted to be a gold-standard Marine. If there is a small variance in average skill abilities and gold-standard Marines are predicted to be generalists, then the Marine Corps will be in a dilemma.

2. Employer Preferences for Generalists and Specialists

A 2020 study by Fahrenkopf et al. uniquely contributes to the body of knowledge on range of skills by utilizing a laboratory experiment to examine several factors that individual workers and organizations must consider when making employment decisions. Fahrenkopf et al.'s (2020) findings support the notion that when considering the post-employment performance of an organization, organizational performance will be substandard for those organizations that hire specialists, relative to those organizations that elect to hire generalists. Furthermore, the authors' research supports the belief that organizations will experience superior performance if they hire employees whose skills are closely matched with the occupational requirements and skill structure of the organization (Fahrenkopf et al., 2020). In fact, the authors document that, on average, groups with a generalist work structure that brought in generalist workers produced 125 percent more products than a group with a specialist work structure that brought in a specialist worker (Fahrenkopf et al., 2020). While it is noted that specialists had a lower probability of transferring their unique knowledge once hired into a new organization, regardless of its structure, both generalists and specialists are capable of transferring knowledge to their new teams.

Combining Fahrenkopf et al.'s findings on the improved productivity of organizations that employ generalists, with past research that documents that generalists are more sought due to their breadth of skills, it begs the question of why the Marine Corps wants to employ specialists at all (2020). The answer lies within past research on specialists, which the authors explain has proven that specialists are faster learners (Fahrenkopf et al., 2020). If the Marine Corps is focused on getting the most bang for their buck from an enlistee, it would then benefit the Marine Corps to utilize past research to justify utilizing its resources to identify specialists. This is not likely to be the case given that the Marine Corps expects all Marines to use their knowledge and skills for the greater good of the whole organization. Furthermore, if generalists are predicted to have a higher probability of transferring knowledge, relative to specialists, the Marine Corps is likely to experience future benefits and costs savings from enlisting Marines that are categorized as generalists.

Fahrenkopf et al. (2020) state that their "findings are most likely to generalize to situations where individuals move between organizations where work is done by groups" (p. 1616). While most enlistees are not likely to be coming from a traditional work organization in the context that the authors are referring to, it is assumed that most enlistees are more likely to identify as generalists due to the structure of traditional brick-and-mortar high schools. In this structure, students are expected to learn a wide range of skills because there is no difference in the type and quality of work that each student is expected to complete. This also creates an opportunity to determine if all types of students, such as home-schooled students, have an equal likelihood of being categorized as a generalist.

The overarching theme of the research by Fahrenkopf et al. (2020) is that organizations that are receiving a specialist employee can expect degraded performance, relative to an organization that receives a generalist employee. However, the degraded performance that any organization is going to experience from employee turnover can be minimized by striving to maximize the job-skills match between the employee and the organization (Fahrenkopf et al. 2020). With these facts in mind, this research is focused on identifying possible indicators of generalists and specialists, such as education credentials. From that point, the goal is to determine if those Marines who are potentially identified as gold-standard Marines are more likely to be generalists or specialists.

F. TAILORED ADAPTIVE PERSONALITY ASSESSMENT SYSTEM

The research by Pema et al. (2014) is highly relevant to this research because it explains how the Navy has used TAPAS to develop a more complete understanding of who is enlisting in the Navy and why. Pema et al. (2014) use many of the same observable variables that are used in this research but focus on answering three areas of concern that this research will not address. First, the authors identify that the Navy is already using existing aptitude tests to identify high-quality recruits; however, TAPAS scores reveal new information about recruits that is not already explained by current screening mechanisms (Pema et al., 2014). Next, the authors determine that certain TAPAS test scores are more accurate predictors of accession decisions or Delayed Entry Program attrition (Pema et al., 2014).

Given that TAPAS was still a new screening mechanism at the time the authors conducted their research, Pema et al. (2014) was only able to utilize 13,846 observations from their sample of one year of accession data. Despite the lack of a robust data set, the authors make several pivotal insights, which are reflected in Figure 4. Pema et al. (2014) document that when controlling for ASVAB scores, the Will-Do factors, such commitment, predict a lower probability that an enlistee will assess. Similarly, Pema et al. (2014) find that Can-Do factors, such as job knowledge, provide additional predictive accuracy on accessions when included with controls for ASVAB scores. An advantage that the authors have over this research is that they are able to access the specific TAPAS facet scores that provide additional insights above and beyond what the TAPAS composite score provides. For example, the authors find that the facet scores for achievement and intellectual efficiency provide additional predictive accuracy on enlistment decisions (Pema et al., 2014).

Accession	Without Cognitive Controls		With Cognitive Controls	
	Probit	Partial Effect	Probit	Partial Effect
Will Do	0.00573*** (0.00102)	0.00227*** (0.00040)	-0.00271** (0.00111)	-0.00106** (0.00043)
Can Do	-0.00220** (0.00110)	-0.00087** (0.00044)	0.00477*** (0.00119)	0.00187*** (0.00047)

Figure 4. Accession Probabilities of TAPAS Composite Scores. Adapted from Pema et al. (2014).

The challenge with the authors' approach and findings is that it forces the Navy to try to fit a model to the data. If the Navy uses a combination of cognitive controls and the

Can-Do score, they get one set of results on a potential enlistee's decision to access into the Navy. If the Navy uses the Will-Do score in another case without controlling for cognitive scores, they get similar results. The ambiguous nature of the facet scores and a lack of an extensive research base is likely why an overall TAPAS composite score has also been developed.

G. SUMMARY

Previous work has focused heavily on explaining how the DOD can use various monetary benefits to influence the behavior of quality enlistees, which are those individuals that meet minimum education and aptitude requirements. As more and more research is conducted, it becomes more apparent that historical definitions of enlistee quality fail to capture all the details about personality traits that were previously referred to as unobservable traits. Educational credentials and ASVAB scores are important, but other traits, such as cognitive flexibility and fluid intelligence, need to be measured as they are of interest to the Marine Corps given its focus on developing a smarter and more agile force. In addition to developing a more in-depth understanding of these key traits, prior research is also expanding the knowledge on the relevance of generalists and specialists in today's military. As the DOD expands it knowledge and begins to develop new assessments, such as TAPAS, it enables the Marine Corps to move one step closer to predicting which Marines will be gold-standard Marines.

IV. DATA AND METHODOLOGY

This is a quantitative study that utilizes data from a single source for all first-term enlisted Marines. This chapter will describe this data and the steps taken to clean and merge the databases in order to build the sample of first-term Marines for analysis using the version 17.0 Basic Edition of the STATA software program. The final section of this chapter provides an explanation of the methodology used to complete this study.

A. TOTAL FORCE DATA WAREHOUSE

All data for this study comes from the Marine Corps' Total Force Data Warehouse (TFDW). TFDW is a centralized data repository for data from multiple other systems utilized by the Marine Corps. TFDW stores this data in tables that contain detailed information on applicants and Marines throughout their careers, regardless of the duration of the career. Much of the data stored in TFDW is stored for individual applicants and Marines based on a sequence number. Each sequence number is a specific snapshot for the applicant or Marine that is taken on an exact date each month.

The tables utilized for this analysis come from the Active Component Common Personnel Data System (ACCPDS), Marine Corps Recruiting Information Support System (MCRISS), and other personnel systems. The data tables contain demographic, accession, performance, and separation information on enlisted Marines that accessed into the Marine Corps between 2010 and 2017. Reenlistment eligibility and other reenlistment data are not utilized in this analysis. Appendix A contains a detailed list of all variables used in this analysis and applicable descriptions.

B. DATA PREPARATION

Manpower & Reserve Affairs (M&RA) provides the data from TFDW as panel data. Each individual Marine is identified in each table using an encrypted identification number provided by M&RA. The main data files that are the foundation of the analytical data set are Marine population snapshots that covered sequence 244 taken on 31 October 2007 to sequence number 389 taken on 31 July 2021. Given that there are multiple snapshots of individual Marines within these tables, these Marine tables are appended and then the data collapsed to provide a single observation per Marine covering the population of interest. The 11 other tables that M&RA provides with the demographic, accession, performance, and separation information are then individually collapsed and each table merged with the main Marine table to develop the final data set used for this analysis. The merged data set contains 553,281 individual observations before any observations are dropped.

To arrive at the final analytical data set of 179,733 observations, sample exclusion restrictions and missing data are validated. First, 187,126 observations are dropped for having an accession date prior to 1 January 2010, and 140,132 observations are dropped for having an accession date after 31 December 2017. I then drop 16 observations for not having an AFQT score in any of the data tables.

Next, the data is cleaned to address conflicting values for the race variables to develop mutually exclusive indicators. In building the final data set, all races that are not non-Hispanic White, non-Hispanic Black, Hispanic-Latino, or Asian are grouped under the indicator variable Other. In multiple cases, individuals identify themselves as one of the traditional four races and as one of the races grouped under Other. In this case, the entry for the traditional race is kept and the value for Other replaced with a zero. Other is replaced with zero for 150,780 individuals listed as non-Hispanic White, 22,099 individuals listed as non-Hispanic Black, 50,128 individuals listed as Hispanic-Latino, and 4,663 individuals listed as Asian.

The next step is to ensure that all Marines had an entry for their scores for average proficiency and average conduct marks for their period of service. Given that all Marines are required to have proficiency and conduct marks while they serve in the ranks of E-1 to E-4, there is no logical reason to have a missing value for this variable so cases where that occurred, these observations are dropped. There are 14,826 observations with a missing value for the average service conduct marks and 1 additional observation with a missing value for the average service proficiency marks.

Using similar logic, all new recruits are required to complete the Initial Strength Test (IST) so there is no scenario where a Marine should have a missing value for any of the components of the IST. 406 observations are dropped for a missing value for IST crunches and 26 observations are dropped for a missing value for IST run. 115 observations are dropped for male recruits with a missing value for pull-ups. 184 observations are dropped for female recruits that had a missing value for the flexed arm hang or pull-ups.

Again, using similar logic, all Marines are required to possess an MOS and complete martial arts training, marksmanship training, and annual physical fitness and combat fitness tests. 86 observations are dropped for not having any marksmanship qualification listed in the tables provided by M&RA. 177 observations are dropped for not having any score listed for the combat fitness test (CFT). Lastly, 40,633 observations are dropped for not having any value listed for any belt under the Marine Corps Martial Arts Program (MCMAP). The final adjustments are made based on the military occupational specialty (MOS) variable. 677 observations are dropped for having an invalid MOS listed in the system. The final data set after all adjustments contains 179,733 observations with entries for all variables that required a valid entry.

C. DESCRIPTIVE STATISTICS

Table 1 lists the demographic descriptive statistics for the sample used in this analysis. The descriptive statistics for education credentials, cognitive and non-cognitive test metrics, accession waivers, and performance metrics are discussed in the results chapter. Overall, the descriptive statistics for this sample are indicative of what is seen in the entire Marine Corps.

The mean age in this sample is 23.8 years, which is reasonable given that this analysis is only looking at first term Marines. 91.5 percent of the sample is male, and 98.6 percent of the sample has a marital status of single. In terms of racial variables within the sample, 63.1 percent of the sample is non-Hispanic White, 9.8 percent is non-Hispanic Black, 24.3 percent is Hispanic-Latino, and 2.2 percent is Asian.

Table 1. Demographic Descriptive Statistics

Sample Demographics	Observations	Mean	Standard Deviation	Min	Max
Age	179732	23.837	2.450	17	40
Male	179733	0.915	0.279	0	1
Single	179733	0.986	0.116	0	1
Non-Hispanic White	179733	0.631	0.482	0	1
Non-Hispanic Black	179733	0.098	0.297	0	1
Hispanic-Latino	179733	0.243	0.429	0	1
Asian	179733	0.022	0.147	0	1
Other Race	179733	0.023	0.149	0	1

D. METHODOLOGY

Upon arriving at the final analytical data set, quantitative analysis is performed using the statistical software STATA to answer the research questions. I use factor analysis to answer the primary research question relating will-do versus can-do factors, since this method reveals underlying correlations between factors. Factor analysis is an appropriate tool to use given the Marine Corps' need to select groupings of variables that can be used to identify gold-standard Marines. Furthermore, factor analysis is utilized for this portion of the research due to the limitations with gaining access to TAPAS data and the need to create factors that serve as proxy variables for characteristics or traits that are unobservable, but are contained in existing variables collected by the Marine Corps. Factor analysis is particularly useful given the need to compress various education, aptitude, physical performance tests, enlistment waivers, and other performance variables that are commonly collected into a few factors that are relevant to this research and easily interpreted ("Overview for Factor Analysis," 2019). Once I discover the underlying correlations between the raw variables and construct the factors, I use latent factors to estimate relationships with performance and indicators of gold-standard Marines.

In conducting factor analysis, I utilize a variance criterion and scree plots to identify the appropriate number of latent factors. To minimize the number of factors, the cumulative variance that must be accounted for by each grouping of factors is limited to approximately

90 percent. This criterion is applied equally to all iterations of the factor analysis that are further discussed in the following chapter. To illustrate the validity of retaining the optimum number of latent factors, scree plots are generated to identify where the plot flattened out. Only those latent factors that lie above the flatter part of the plot are retained. The scree plots for the three factor groupings discussed in the next chapter are contained in Appendix B.

Following the factor analysis, the secondary questions are answered using the Least Absolute Shrinkage and Selection Operator (lasso) machine learning technique and logistic or logit regression. The first step in this phase of the analysis is to split the data into a training set and a validation set. The training set is first used to build the predictive model, and the validation set is then used to ensure that the model is performing as expected on a set of data that was unavailable to STATA when it was building the predictive model.

I compare the performance of two different lasso selection algorithms in logistic lasso: cross-validation and adaptive selection. More generally lasso selects predictors or variables by considering the trade-off between data fitting and the statistical penalty of having too many variables. Lasso makes this tradeoff explicit by optimally selecting predictors that maximize the logistic regression data fit or likelihood function while subtracting from this likelihood function a penalty term that reflects the size and variance of the logit coefficients. Lasso is a selection algorithm that first retains variables with a coefficient greater than zero and then further reduces those retained predictors by estimating a penalty function that controls or tunes the data fitting. The lasso algorithm effectively supports this research's goal of building an accurate and useful predictive model. Cross-validation lasso is the standard lasso while adaptive lasso implements two steps of the cross-validation. There are multiple ways to specify the form of the penalty function in the objective function of logistic lasso. Cross-validation assumes a uniform penalty weight across the estimated coefficients while adaptive lasso allows different penalty weights to different variables. The bottom line is that lasso minimizes the number of variables that will be used by the Marine Corps to predict which enlistees will be gold-standard Marines in the logistic regression. I estimate both selection algorithms and use the one that has a higher predictive power.

The final analysis step taken in this research is to estimate a multivariate logistic regression model to illustrate the predictive effects of each variable deemed valid by the prior lasso algorithm. In particular, I estimate the following logistic equation

$$P(y_i = 1) = \pi_i = \frac{e^{x_i\beta}}{1+e^{x_i\beta}}$$

where y equals 1 if an enlistee is a gold-standard Marine and is 0 otherwise, π is the predicted probability Marine i is a gold-standard Marine, and x represents the factors or variables that were retained during the cross-validation lasso. Examples of factors and variables that are retained include demographic variables, such as being male, and education latent factor 1, described further in the following chapter. Included in the predictors are variables that are observed throughout an enlisted Marine's first term as the institution learns more about the individual, including good conduct medal.

E. SUMMARY

This research relies heavily on data from TFDW, which is collected from many different sources and stored within complex tables. This data requires a significant amount of cleaning and processing in order to ensure it is in a format that facilitates analysis. Despite the significant amount of cleaning required, the sample of observations within the final data set is representative of the population of Marines that are being analyzed. With that in mind, factor analysis and machine learning are the most appropriate tools to utilize to answer the research questions. In this research, factor analysis, cross-validation lasso, and multivariate logistic regression are sequentially utilized to determine the Marine Corps' ability to predict which enlistees will be gold-standard Marines.

V. RESULTS AND ANALYSIS

A. FACTOR ANALYSIS

This section details the three sets of factor analysis. For each grouping of related factors, the descriptive statistics are provided, and any notable statistics are highlighted in the explanation. Below I also explain and interpret the factor loadings used to construct the latent factors for the predictive analysis. It should be noted that scaling is not used in this factor analysis and that the factor analysis is used to group raw variables that are correlated.

1. Education Related Factors

The first factor analysis is executed on the education variables in the final data set. Table 2 reports the descriptive statistics for the education variables. 99.5 percent of the sample are considered to have graduated and possess a credential. 95.1 percent of the sample possess a traditional high school diploma. The graduation percentage and traditional high school diploma percentage are high as expected. The next two highest credentials in this sample are associates degree and bachelor's degree, each at 1.3 percent. The various other non-traditional education credentials did not contain percentages over 1 percent of the total sample.

Table 2. Education Descriptive Statistics

	Observations	Mean	Standard Deviation	Min	Max
<u>Education Variables</u>					
Less Than High School (HS) Diploma	179733	0.000	0.013	0	1
Other Non-Traditional HS Credential	179733	0.000	0.003	0	1
Distance Learning Diploma	179733	0.003	0.051	0	1
Non-HS Graduate with One Semester of College	179733	0.007	0.083	0	1
Current HS Student/Not a Senior	179733	0.000	0.000	0	0
Adult/Alternative Diploma	179733	0.009	0.093	0	1
Occupational Program Certificate	179733	0.000	0.012	0	1
Associates Degree	179733	0.013	0.112	0	1

	Observations	Mean	Standard Deviation	Min	Max
<u>**Education Variables**</u>					
GED	179733	0.000	0.019	0	1
Exit Exam Failure	179733	0.000	0.009	0	1
Professional Nursing Diploma	179733	0.000	0.000	0	0
Homeschool Diploma	179733	0.008	0.088	0	1
HS Certificate of Attendance	179733	0.000	0.004	0	1
Bachelor’s Degree	179733	0.013	0.114	0	1
HS Diploma	179733	0.951	0.215	0	1
Currently Enrolled/Other Than HS Diploma	179733	0.000	0.000	0	0
Master’s Degree	179733	0.001	0.025	0	1
Post Master’s Degree	179733	0.000	0.004	0	1
Current HS Senior	179733	0.000	0.004	0	1
Doctorate Degree	179733	0.000	0.003	0	1
First Professional Degree	179733	0.000	0.002	0	1
National Guard Youth Challenge Program with GED	179733	0.000	0.012	0	1
No Education Credential	179733	0.000	0.000	0	0
Unknown Credential	179733	0.000	0.000	0	0
Graduated	179733	0.995	0.073	0	1

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Factor4	Factor5
educ_cert1					
educ_cert5					
educ_cert7	0.1736				
educ_cert8	0.2767			-0.4684	
educ_certB	0.3113	-0.5357			
educ_certC					
educ_certD	0.2341				0.4094
educ_certE					
educ_certF					
educ_certH	0.3047		-0.5255		
educ_certJ					
educ_certK	0.3740	0.2186	0.2143	0.2103	-0.1661
educ_certL	-0.9089				
educ_certN					
educ_certR					
educ_certS					
educ_certU					
educ_certW					
educ_certX					
grad					

(blanks represent abs(loading)<.1)

Figure 5. Education Factor Loadings

Even though the scree plot shows that the curve begins to flatten out after the first factor, the first three factors are retained based on the criterion of close to 90 percent variance explained. These factors combined account for 84.9 percent of the cumulative variance in the education data. Figure 5 lists the loadings for the education factors. Education factor 1 accounts for 55.7 percent of the variance in the data. Larger values of education factor 1 represent enlistees that possess alternative education credentials, as the indicators for non-HS graduate but with some college (educ_cert8), Adult/Alternative Diploma (educ_certB), and Homeschool (educ_certH) all load high. In addition, the traditional high school diploma (educ_certL) has a high negative loading on education factor 1, while a BA (educ_certK) also loads positive on this factor. For the analyses below, I interpret education factor 1 as an index of enlisted Marines who possess education credentials that are non-traditional/alternative, since the traditional Marine has a high school diploma (95%, as shown in Table 1).

Meantime, education factor 2 accounts for an additional 14.9 percent of the variance and describes enlistees that pursue higher education (educ_certK). The adult/alternative diploma loads negatively on education factor 2. Education factor 3 is the remaining education-related factor that was retained and accounts for the final 14.3 percent of the cumulative variance. This factor also describes enlistees that pursue higher education; however, this factor is negatively related to the home school diploma. Below I interpret education factors 2 and 3 as reflecting enlistees who pursue higher education credentials.

2. Will-Do and Can-Do Factors

The second factor analysis is executed on the cognitive, non-cognitive, physical fitness, and accession variables in the final data set that are associated with the will-do and can-do variables that are generated when the Marine Corps collects TAPAS data. As alluded to earlier, I am unable to distinguish between will-do and can-do variables in this research; therefore, these variables are grouped under a single set of personality factors. Table 3 contains the descriptive statistics for the will-do and can-do associated variables. The cognitive test metrics in this analysis include the AFQT score, ASVAB AFQT

Categories, and Defense Language Aptitude Battery (DLAB) score. The AFQT scores range from 0 to 99 with the mean score in the sample being 62.5. The ASVAB AFQT categories and their respective ranges are Category 1 (93-99), Category 2 (65-92), Category 3a (50-64), Category 3b (31-49), Category 4a (21-30), Category 4b (16-20), Category 4c (10-15), and Category 5 (0-9). 99.9 percent of the observations in the sample fall within ASVAB Category 3b and above.

The accession waivers section contains the descriptive statistics for the major categories of waives that an enlistee enters the Marine Corps with. 48.4 percent of the sample entered the Marine Corps with a waiver. Of those enlistees that access into the Marine Corps with a waiver, 48.2 percent enlist with a waiver for drugs and 11.5 percent enlist with a waiver for a law violation. Of note, 40.5 percent of the enlistees with a waiver, required a waiver for reasons other than misconduct, law violations, etc. These other reasons include, but are not limited to, waivers for age, dependents, prior service, medical/physical, and alien/hostile country.

Table 3. Will-Do and Can-Do Descriptive Statistics

	Observations	Mean	Standard Deviation	Min	Max
Cognitive Test Metrics					
ASVAB AFQT Score	179733	62.450	17.573	0	99
AFQT Category 1	179733	0.049	0.216	0	1
AFQT Category 2	179733	0.395	0.489	0	1
AFQT Category 3a	179733	0.300	0.458	0	1
AFQT Category 3b	179733	0.255	0.436	0	1
AFQT Category 4a	179733	0.001	0.024	0	1
AFQT Category 4b	179733	0.000	0.009	0	1
AFQT Category 4c	179733	0.000	0.006	0	1
AFQT Category 5	179733	0.000	0.010	0	1
Defense Language Aptitude Battery Score	13726	91.203	18.540	1	151
Physical Fitness Metrics					
ist_crunches	179733	85.424	326.513	0	101066
ist_hang	20969	35.553	53.673	0	6547
ist_pull_ups	170616	11.916	7.189	0	1674
ist_run	179733	11.207	1.861	0	95
Accession Waivers					
Mental Qualification Waiver	86926	0.000	0.003	0	1
Law Violation Waiver	86926	0.115	0.318	0	1
Drug Waiver	86926	0.482	0.500	0	1

	Observations	Mean	Standard Deviation	Min	Max
Minimum Education Waiver	86926	0.000	0.003	0	1
Other Waiver	86926	0.405	0.491	0	1

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6
asvab_cat1			0.1154			0.9874
asvab_cat2		0.7441		0.5927		-0.2958
asvab_cat3a				-0.9935		-0.1013
asvab_cat3b		-0.9297		0.3500		
asvab_cat4a						
asvab_cat4b						
asvab_cat4c						
asvab_cat5						
afqt_scr_qy		0.8418	0.1560	0.2047		0.3160
dlab			0.9752			
mos		0.1280				
ist_crunches						
ist_run						
mq_waiver						
lv_waiver	-0.1957					
drug_waiver	-0.6036				0.7489	
meduc_waiver						
other_waiver	-0.5021				-0.8381	
miss_dlab			-0.9782			
miss_mq_wa~r	0.9978					
miss_lv_wa~r	0.9978					
miss_drug_~r	0.9978					
miss_meduc~r	0.9978					
miss_other~r	0.9978					

(blanks represent abs(loading)<.1)

Figure 6. Will-Do and Can-Do Factor Loadings

Using both the scree plot and the criterion of 90 percent again, I retain the first six factors. These factors account for 86.8 percent of the cumulative variance in the will-do and can-do data. Figure 6 lists the loadings for the non-cognitive factors. Non-cognitive factor 1 represent enlistees that did not require waivers, as the positive loadings on missing waiver indicators show. Large negative values for non-cognitive factor 1 represent enlistees that require lifestyle waivers, as the indicators for drug waivers and other waivers have high negative loadings. Additionally, law violations load negative on this factor. For the analyses below, I interpret non-cognitive 1 as an index of enlisted Marines who enlist without waivers.

Similarly, large values for non-cognitive factor 2 represent enlistees that perform moderately well on aptitude tests, as the indicators for ASVAB Category 2 (asvab_cat2, equivalent to 65^{th}-92^{nd} percentile) and AFQT score (afqt_scr_qy) load high. ASVAB Category 3b (asvab_cat3b, 31–49^{th} percentiles) has a high negative loading on non-cognitive factor 2, while MOS also loads positive on this factor. I interpret non-cognitive factor 2 as an index of enlisted Marines with a moderate aptitude for superior performance.

The loadings for non-cognitive factor 3 are similar to non-cognitive factor 2; however, large values for non-cognitive factor 3 represent an enlistee required to take additional aptitude tests and also scores high on traditional aptitude tests, as the indicator for the DLAB (dlab) has a high positive loading on non-cognitive factor 3. As stated, the ASVAB Category 1 (asvab_cat_1, 93–99^{th} percentiles) and AFQT score (afqt_scr_qy) load positive on this factor as well. I interpret non-cognitive factor 3 as an index of enlisted Marines with higher learning abilities.

Non-cognitive factor 4 is also similar to the previous two non-cognitive factors with the exception that large values for non-cognitive factor 4 represent an enlistee that fails to perform in the highest AFQT tier. The indicators for ASVAB Category 2 (asvab_cat2), ASVAB Category 3b (asvab_cat3b), and AFQT score (afqt_scr_qy) load positive on non-cognitive factor 4 but at lower values than for factor 2, while ASVAB Category 3a (asvab_cat3a) has a high negative loading. I interpret non-cognitive factor 4 as capturing the residual of factor 2, as an index of enlisted Marines with a relatively lower aptitude for superior performance.

Large values for non-cognitive factor 5 represent enlisted Marines that require drug waivers in order to enlist in the Marine Corps, as indicators for drug waivers (dg_waiver) had a high positive loading. On the other hand, other waivers (other_waiver) had a high negative loading on non-cognitive factor 5. I interpret non-cognitive factor 5 as an index of enlisted Marines that lack self-control and willingly violate drug laws.

Non-cognitive factor 6 is the final factor and large values for this factor represent enlisted Marines that score in the highest tier on the ASVAB, as the indicator for ASVAB Category 1 (asvab_cat1) had high positive loading on this factor. ASVAB Category 2 (asvab_cat2) and ASVAB Category 3a (asvab_cat3a) had negative loadings for non-cognitive factor 6, while AFQT score (afqt_scr_qy) also loaded positive for this factor. I interpret non-cognitive factor 6 as an index of enlisted Marines with the highest aptitude for superior performance.

3. Performance Factors

The third factor analysis is executed on performance variables collected throughout an enlistee's military career. Table 4 contains the descriptive statistics for the performance variables. The average service proficiency and conduct marks for enlistees in this sample are 4.4/4.3. The CFT and physical fitness test (PFT) scores can range from 0 to 300. The mean score for the CFT and the PFT in this sample are 290.9 and 267.2, respectively. This section contains descriptive statistics on the enlistees' level of qualification in the MCMAP. The MCMAP qualification levels from lowest to highest are tan, gray, green, brown, and black. Marines are encouraged to progress to higher levels within the MCMAP. Furthermore, this section contains descriptive statistics on rifle and pistol qualifications. For rifle qualification, 83.7 percent of the sample is qualified as an expert. Enlisted Marines below the rank of E6 are not required to qualify using a pistol unless it is required by their respective MOS. 38.5 percent of the sample had a pistol qualification listed in their record. Of those with a pistol qualification, 50.8 percent qualified as an expert.

Table 4. Performance Descriptive Statistics

	Observations	Mean	Standard Deviation	Min	Max
<u>Performance Metrics</u>					
Average Proficiency Marks (Service)	179733	4.400	0.133	3	5
Average Conduct Marks (Service)	179733	4.394	0.134	1	5
Combat Fitness Test Score	179733	290.918	12.706	145	300
Physical Fitness Test Score	179733	267.199	22.837	0	300
Marksmanship Waiver	56876	0.622	0.485	0	1
Marksmanship Score	56876	276.016	30.075	1	340

	Observations	Mean	Standard Deviation	Min	Max
Performance Metrics					
MCMAP - Unqualified	179733	0.362	0.481	0	1
MCMAP - Tan Belt	179733	0.998	0.043	0	1
MCMAP - Gray Belt	179733	0.827	0.378	0	1
MCMAP - Green Belt	179733	0.586	0.493	0	1
MCMAP - Brown Belt	179733	0.277	0.448	0	1
MCMAP - Black Belt	179733	0.125	0.331	0	1
Rifle Expert	179733	0.837	0.369	0	1
Rifle Marksman	179733	0.207	0.405	0	1
Rifle Sharpshooter	179733	0.633	0.482	0	1
Rifle Unqualified	179733	0.083	0.276	0	1
Pistol Expert	69206	0.508	0.500	0	1
Pistol Marksman	69206	0.305	0.461	0	1
Pistol Sharpshooter	69206	0.471	0.499	0	1
Pistol Unqualified	69206	0.011	0.104	0	1
Separated - Voluntarily	179733	0.212	0.408	0	1
Separated - Misconduct	179733	0.000	0.002	0	1
Separated - Fraudulent Enlistment	179733	0.000	0.012	0	1
Separated - Poor Performance	179733	0.000	0.015	0	1
Separated - Medical/Physical	179733	0.000	0.017	0	1
Separated - Other Reasons	179733	0.003	0.055	0	1
Good Conduct Medal	179733	1.000	0.015	0	1

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6
proficienc~e	-0.1227	0.2408	0.4153		0.1128	
ma_unquali~d		-0.1159	-0.3141			
ma_tan						
ma_gray		0.2098	0.1811		0.5316	
ma_green	-0.1247	0.4474	0.1771		0.5315	
ma_brown	-0.1382	0.7338	0.1261		0.1722	
ma_black	-0.1356	0.6641	0.1122			
rexpert	-0.1457		0.1489	-0.3633	0.1099	
rmarksman				0.5378		
rsharps				0.1397		0.1019
runqual				0.4850		
pexpert	-0.6062					-0.3408
pmarksman	-0.4296					0.5185
psharps	-0.5675					-0.1047
punqual						
cbt_fitnes~y	-0.1005	0.1343	0.6590		0.1024	
phys_fit_s~y	-0.1096	0.1791	0.6126		0.1001	
miss_pexpert	1.0019					
miss_pmark~n	1.0019					
miss_psharps	1.0019					
miss_punqual	1.0019					

(blanks represent abs(loading)<.1)

Figure 7. Performance Factor Loadings

Using both the scree plot and the criterion of 90 percent again, the first three performance factors are retained. These factors account for 86.4 percent of the cumulative variance in performance data. Figure 7 lists the loadings for the performance factors. Large values for performance factor 1 represent enlisted Marines that have missing marksmanship qualification data. In addition, rifle expert (rexpert), MCMAP green belt (ma_green), MCMAP brown belt (ma_brown), MCMAP black belt (ma_black), and average proficiency marks in service (proficiency_average_service) all load negative on this factor. I interpret performance factor 1 as an index of enlisted Marines with the low performance potential on mandatory physical qualifications.

Performance factor 2 is the opposite of performance factor 1 as large values for performance factor 2 represent enlisted Marines that have qualified at higher MCMAP levels, as indicators for MCMAP green belt (ma_green), MCMAP brown belt (ma_brown), and MCMAP black belt (ma_black) have high positive loadings on this factor. The indicators for average proficiency marks in service (proficiency_average_service), MCMAP gray belt (ma_gray), CFT score (cbt_fitness_scr_qy) and PFT score (phys_fitness_scr_qy) also have low positive loadings on this factor, while MCMAP unqualified (ma_unqualified) loads negative on this factor. I interpret performance factor 2 as an index of enlisted Marines with the potential for superior performance on mandatory physical qualifications.

Lastly, large values for performance factor 3 represent enlisted Marines that have achieve superior performance on the PFT and CFT, as the indicators for PFT score (phys_fitness_scr_qy) and CFT score (cbt_fitness_scr_qy) have high positive loadings on this factor. Performance factor 3 accounts for the remaining 13.7 percent of the cumulative variance in the performance data and is associated with superior performance on the PFT and CFT. Rifle expert (rexpert), MCMAP green belt (ma_green), MCMAP brown belt (ma_brown), MCMAP black belt (ma_black), and average proficiency marks in service (proficiency_average_service) all have low positive loadings on this factor, while MCMAP unqualified (ma_unqualified) has a negative loading on this factor. I also interpret performance factor 3 as an index of enlisted Marines with the potential for superior physical fitness.

B. CROSS-VALIDATION LASSO

The Commandant of the Marine Corps (1997) in All Marine Corps Activities 360/97 explains that Marines with proficiency and conduct marks of 4.5 to 4.8 are considered to be excellent Marines and Marines with marks of 4.9 to 5.0 are considered to be outstanding Marines. For the purpose of this analysis, gold-standard Marines are defined as those Marines with average in service proficiency and conduct marks of 4.5/4.5. Using that definition of gold-standard for the dependent variable, the cross-validation lasso retained a total of 20 variables. In addition to the demographic variables of single, male, Hispanic-Latino, non-Hispanic Black, Asian, and other race, cross-validation lasso determined that the three education factors, six non-cognitive factors, three performance factors, and good conduct medal (GCM) should be retained. The cross-validation lasso is 83.12 percent accurate in the training set and 83.13 percent accurate in the validation set. Overall, cross-validation lasso has the highest accuracy in predicting gold-standard Marines compared to the other algorithms described in the Data and Methodology chapter.

C. LOGISTIC REGRESSION FOR PREDICTING THE GOLD-STANDARD

The following equation represents the logistic regression used to predict which enlistees would be identified as gold-standard Marines:

$$P(GS = 1|x) = \frac{e^z}{1 + e^z}$$

where

$z = b_0 + b_1$ALTERNATIVE EDUC + b_2 BA-NOT ADULT EDUC + b_3 BA-HOME SCHOOL + b_4 NO WAIVER + b_5 MODERATE APTITUDE + b_6 LEARNING ABILITY + b_7 LOWER APTITUDE + b_8 DRUG WAIVERS + b_9HIGH APTITUDE + b_{10} LOWER PERFORMANCE POTENTIAL + b_{11} HIGHER PERFORMANCE POTENTIAL + b_{12}SUPERIOR PHYSICAL FITNESS + b_{13}GCM + b_{14} SINGLE + b_{15} MALE + b_{16}WHITE + b_{17}BLACK + b_{18}HISPANIC-LATINO + b_{19}ASIAN + b_{20}OTHER RACE

Table 5 contains the marginal effects of the multivariate logistic regression model above. The marginal effects are interpreted as the probability that an enlistee will be a gold-standard Marine given a one-unit change in the respective variable, holding all else constant. The challenge with this interpretation is that it is highly unlikely that a given enlistee will only have a single change in a single variable.

Table 5. Logistic Regression Results for Predicting Gold-Standard Marines

	(1)
	Marginal Effects
Outcome = High Performance	
Alternative Educ	0.0037****
	(0.0008)
BA, not adult/alternative educ	0.0122****
	(0.0014)
BA, home schooled educ	0.0113****
	(0.0013)
No Waivers	-0.0013*
	(0.0007)
Moderate Aptitude	0.0218****
	(0.0008)
Learning Ability	0.0065****
	(0.0007)
Lower Aptitude	0.0060****
	(0.0007)
Drug Waivers	-0.0035****
	(0.0007)
High Aptitude	0.0141****
	(0.0007)
Lower Performance Potential	-0.0379****
	(0.0007)
Higher Performance Potential	0.0697****
	(0.0008)
Superior Physical Fitness	0.2757****
	(0.0018)
Good Conduct Medal (d)	0.0735***
	(0.0229)
Single (d)	-0.0937****
	(0.0090)
Male (d)	-0.1280****
	(0.0041)
White (d)	0.0114**
	(0.0052)
Black (d)	0.0147**
	(0.0060)
Hispanic/Latino (d)	0.0141**
	(0.0055)
Asian (d)	0.0454****
	(0.0087)
Other Race (d)	0.0434****
	(0.0089)
Observations	179733

Marginal effects; Standard errors in parentheses
(d) for discrete change of dummy variable from 0 to 1
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, **** $p < .001$

It is not surprising to see that the education factors can all be used to predict enlistees that are likely to be gold-standard Marines. We already understand that enlistees that possess the minimum education requirements to enter service have a significant advantage at being able to effectively serve within the Marine Corps. Education factor 2 and 3 do confirm previous hypothesis that higher education credentials are correlated with superior performance. Furthermore, education factor 1 shows that those enlistees with an alternative adult diploma are predicted to have a slight increase in likelihood of being a gold-standard Marine. This is useful insight to the Marine Corps given that it traditionally focuses on those enlistees that are considered to be high quality due to their possession of a traditional high school diploma.

The bottom line is that the Marine Corps can only pull so much predictive information from education factors. The non-cognitive factors, on the other hand, provide additional predictive insight, like what is gained from the TAPAS. Non-cognitive factors 1 and 5 indicate that enlistees with lifestyle waivers and drug waivers are predicted to have a lower likelihood of becoming gold-standard Marines. Lifestyle waivers in this research refers to waivers for age, dependents, prior service, medical or physical requirements, enlistment from alien/hostile countries, and other reasons. These two factors indicate that the underlying personality traits, such as non-delinquency or responsibility, may be lacking in these individuals and the Marine Corps can use this information on waivers to make future enlistment decisions.

Similarly, the remaining non-cognitive factors provide additional predictive insight that is not provided by education factors alone. Three of the remaining non-cognitive factors address an enlistee's aptitude for performance, while the last non-cognitive factor addresses an enlistees' learning ability. For example, non-cognitive factor 2 can be used by the Marine Corps to identify enlistees that have an increased likelihood of being gold-standard Marines due to their moderate aptitude for higher performance. Using this information to further refine how the Marine Corps identifies and recruits enlistees has the potential to reap significant benefits in terms of performance.

The notable interpretations for the performance factors are that performance factors 2 and 3 have the most significant impact on predicting which enlistees will be gold-standard Marines. Consider the example of performance factor 3 which describes superior performance on the PFT and CFT. Holding all other factors constant, an enlistee that achieve superior physical performance on fitness tests is predicted to have a much higher likelihood of becoming a gold-standard Marine. A one-unit change in the factor analytic index for the combined PFT and CFT performance increases the probability of gold-standard by 0.28. Similarly, holding all other factors constant, an enlistee that earns higher belts in MCMAP is predicted to have a higher likelihood of becoming a gold-standard Marine. While at first glance, both interpretations may seem overly simplified, that is not the case. For example, consider the case of a single, male enlistee that earns higher belts in MCMAP. Due to the decrease in likelihood of being a gold-standard Marine due to being single and male, this hypothetical Marine would not necessarily stand out as a gold-standard Marine simply because he earned a higher belt in MCMAP.

In the end, the final interpretation that I will highlight is on the use of the GCM to predict which enlistees will be gold-standard Marines. This variable can be interpreted as an enlistee with a GCM is predicted to have an increased likelihood of being a gold-standard Marine. The challenge with this interpretation is that Marines earn a GCM for every three consecutive years of good conduct in the Marine Corps. This means that a Marine will have received their first GCM near the end of their first term when the Marine Corps should have already identified them as being a gold-standard Marine. I use GCM in this predictive analysis as a proxy for personality traits such as conscientiousness, agreeableness, and emotional stability that could have been indicated by facet scores on the TAPAS.

D. LOGISTIC REGRESSION FOR PREDICTING GENERALISTS AND SPECIALISTS

The logistic regressions for predicting which enlisted Marines will become generalists and which will become specialists are discussed below. Appendix C contains the MOSs that were grouped together to define which Marines are generalists versus specialists. More traditional MOSs, such as infantry, and general support occupations are grouped under generalists, while more technical occupations are grouped under specialists.

These groupings are subjective, and cases can be made to shift specific occupations between the groupings.

The following equation represents the logistic regression used to predict which enlistees would be identified as generalists. It should be noted that the logistic regression for predicting which enlistees will be identified as specialists is identical, with the exception that the outcome variable generalists (G) is changed to specialists (S):

$$P(G = 1|x) = \frac{e^z}{1 + e^z}$$

where

$z = b_0 + b_1$ALTERNATIVE EDUC + b_2 BA-NOT ADULT EDUC + b_3 BA-HOME SCHOOL + b_4 NO WAIVER + b_5 MODERATE APTITUDE + b_6 LEARNING ABILITY + b_7 LOWER APTITUDE + b_8 DRUG WAIVERS + b_9HIGH APTITUDE + b_{10} LOWER PERFORMANCE POTENTIAL + b_{11} HIGHER PERFORMANCE POTENTIAL + b_{12}SUPERIOR PHYSICAL FITNESS + b_{13}GCM + b_{14} SINGLE + b_{15} MALE + b_{16}WHITE + b_{17}BLACK + b_{18}HISPANIC-LATINO + b_{19}ASIAN + b_{20}OTHER RACE

Tables 6 contain the marginal effects of the multivariate logistic regression model for predicting which enlisted Marines will become generalists. Of note, to get the values for the specialists model, all you need to do is change the sign for coefficient. The marginal effects are interpreted as the probability that an enlistee will be a generalist Marine, or a specialist Marine, given a one-unit change in the respective variable, holding all else constant. Like the challenges discussed with the interpretation of the marginal effects of the logistic regression for predicting which enlisted Marines will become gold-standard Marines, it is highly unlikely that a given enlistee will only have a single change in a single variable at a given time.

Table 6. Logistic Regression Results for Predicting Generalist Marines

	(1)
	Marginal Effects
Outcome = Generalist	
Alternative Educ	0.0073**** (5.30)
BA, not adult/alternative educ	0.0013 (0.61)
BA, home schooled educ	-0.0028 (-1.29)
No Waivers	0.0124**** (9.99)
Moderate Aptitude	-0.1372**** (-104.82)
Learning Ability	-0.0803**** (-56.00)
Lower Aptitude	-0.0113**** (-9.33)
Drug Waivers	0.0297**** (23.75)
High Aptitude	-0.0284**** (-21.83)
Lower Performance Potential	-0.0442**** (-35.56)
Higher Performance Potential	-0.0048*** (-3.02)
Superior Physical Fitness	0.0192**** (11.60)
Single (d)	0.0654**** (6.07)
Male (d)	0.0050 (1.11)
White (d)	-0.0442**** (-4.55)
Black (d)	-0.0212** (-2.11)
Hispanic/Latino (d)	-0.0456**** (-4.76)
Asian (d)	-0.0616**** (-5.07)
Other Race (d)	-0.0611**** (-4.80)
Good Conduct Medal (d)	-0.2906**** (-4.60)
Observations	179733

Marginal effects; *t* statistics in parentheses
(d) for discrete change of dummy variable from 0 to 1
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$, $^{****}p < .001$

When it comes to predicting which enlisted Marines will become generalists, the interpretations are slightly more complicated than those in previous results. For example, first consider the use of the education factors to predict which enlisted Marines will become generalists. Only education factor 1, which was previously interpreted to be an index for enlisted Marines who possess education credentials that are non-traditional/alternative, can be used to predict which enlisted Marines have a higher likelihood of becoming generalists. While this may initially seem like a weakness of this analysis, it sheds light on the fact that the Marine Corps should consider moving away from previous policies that focus on recruiting heavily from the pool of applicants that have traditional high school diplomas.

Because the Marine Corps has very little information about the future performance potential of enlistees when they first join, the interpretations of the non-cognitive factors provide some useful insights. First, non-cognitive factors 1 and 5, indices of enlisted Marines that required no lifestyle waivers but drug waivers in order to enlist, can be used to predict those enlisted Marines that have a higher likelihood of becoming a generalist. Secondly, the remaining non-cognitive factors can all be used to predict which enlisted Marines have a lower likelihood of becoming a generalist. For example, non-cognitive factor 2, which is the index of enlisted Marines with a moderate aptitude for superior performance, are predicted to have a lower likelihood of becoming a generalists.

The last notable interpretation for the generalists model is that performance factor 3, which is the index of enlisted Marines with the potential for superior physical fitness, can be used to predict which enlisted Marines have an increased likelihood of becoming generalists. On the other hand, performance factors 1 and 2 which were indices of Marines with lower and higher performance potential on mandatory physical qualifications, can be used to predict which enlisted Marines have a lower likelihood of becoming generalists. This indicates that enlisted Marines that are more well-rounded, to include higher fitness scores on the PFT and CFT, have a higher likelihood of being a generalist.

The above interpretations are only for the generalists model. The interpretations for the specialists model are very similar. Without going into the specifics of each set of factors again, the following is a brief example from the specialists model. In the specialist model, education factor 1, which is the index for enlisted Marines who possess education credentials that are non-traditional/alternative, are predicted to have a lower likelihood of becoming a specialist. Similarly, non-cognitive factors 2, 3, 4, and 6 can be used to predict which enlisted Marines are more likely to become specialists. This indicates that Marines that have higher aptitude for superior performance and learning ability have an increased likelihood of becoming a specialist in the Marine Corps.

E. SUMMARY

Despite not receiving the desired data on TAPAS in the TFDW data set, factor analysis enabled me to develop proxy factors, all of which were ultimately retained during the cross-validation lasso. In the first multivariate logistic model, the proxy factors and various demographic variables are predictive of whether an enlisted Marine would be a gold-standard Marine. Furthermore, several of the same proxy factors and demographic variables are also predictive of whether an enlisted Marine would be a generalist or a specialist. The bottom line or so-what of this analysis is further highlighted in the following chapter.

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VI. CONCLUSIONS AND RECOMMENDATIONS

A. CONCLUSIONS

This research achieved its primary and secondary goals of providing the Marine Corps with evidence that it is possible to predict which enlisted Marines will become gold-standard Marines and which enlisted Marines are more likely to become generalists or specialists based on variables that are observable at the time of enlistment and over the course of their first term stored in TFDW. This research fills in a small gap in the current knowledge on which factors can be used to predict future performance; however, it highlights areas where the DOD and Marine Corps can change policies or invest additional resources to identify and retain the required talent and skills necessary to meet future manpower requirements. At a minimum, this research confirms and reinforces the fact that the DOD and Marine Corps should continue to invest in the use of a combination of cognitive and non-cognitive tests to screen and select enlistees.

1. Predicting Gold-Standard Marines

The predictive model developed in this research can be used to predict whether an enlisted Marine will be a gold-standard Marine during their first-term. Given that this model is generated using proxy variables for education-, cognitive and non-cognitive-, and performance-related factors, it is imperative that the DOD and Marine Corps confirm the predictive nature of similar models using combined ASVAB and TAPAS data prior to making any program or policies decisions. The bottom line is that all indications are that the Marine Corps can make decisions grounded in a more well-developed data set that paints a more holistic picture of an enlisted Marine than is currently provided from simple demographic and aptitude variables.

2. Predicting Generalists and Specialists

Similar to the predictive model for gold-standard Marines, the predictive model that is targeted towards range of skills enables the Marine Corps to predict whether an enlisted Marine will be a generalist or a specialist. Consistent with the broader academic literature discussed in this research, the empirical analysis indicates that there is a possible tradeoff between recruiting generalists and recruiting high performance Marines. It is strongly recommended that the Marine Corps further refine how it defines a generalist and a specialist. Once this refinement is completed, the Marine Corps can reevaluate the accuracy of this model in predicting whether an enlisted Marine will be a generalist or a specialist. Furthermore, refining how generalists and specialists are defined will support the Marine Corps' ability to make accurate manpower decisions based on the tradeoff between the desired range of skills and the future performance potential of the enlisted Marines.

3. Valuation of Variables and Factors

One of the most interesting insights from this research are the indications of how the Marine Corps may under or overvalue certain education credentials and aptitude metrics. For example, the factor analysis and predictive models indicate that Marines that possess adult/alternative diplomas are predicted to be gold-standard Marines and generalists. Traditionally, the DOD and Marine Corps have focused heavily on recruiting Marines with high school diplomas and have undervalued Marines with alternate diplomas.

Similarly, the Marine Corps has historically required waivers for drug use and lifestyle factors. This research indicates that individuals with waivers are predicted to have a lower likelihood of being a gold-standard Marine, but a higher likelihood of being a generalist. If the CMC is focused on building a Marine Corps that is comprised of more generalists that can solve a variety of problems in a chaotic operating environment, the Marine Corps may need to change how it values enlisted Marines with waivers. The major take-away from this research is that if the Marine Corps is going to move away from the industrial era models, the values given to the metrics used to make decisions must also be reevaluated as the models change.

B. RECOMMENDATIONS FOR FUTURE RESEARCH

1. Predicting Gold-Standard Performance Earlier or Later in a Marine's Career

While the Marine Corps has traditionally focused on analyzing attrition at earlier points in a Marine's career, this research highlights the potential to identify superior performance at the conclusion of a Marine's first term. Expanding this research earlier or later in a Marine's career will equip Marine Corps leadership with additional information from which leaders can make informed decisions. For example, if the Marine Corps expands this research to examine the ability to predict superior performance in later terms, it may provide insights into which Marines should be afforded additional education and EPME opportunities. This will support the CMC's goals of developing an older and more educated operating force.

2. TAPAS and Other Non-Cognitive Data

This research relies on proxy variables that are generated from available personnel data, given that TFDW did not contain sufficient TAPAS data. A data set of the same size that contains TAPAS composite and individual TAPAS facet scores would support future research that is focused on using a combination of cognitive and non-cognitive metrics to predict various outcomes, such as attrition, superior performance, or misconduct. With an increase in TAPAS data, the Marine Corps must also clearly define how the TAPAS composite and facet scores should be interpreted in order to enable researchers to identify specific personality traits that may demand more scrutiny and analysis. The bottom line is that the DOD and Marine Corps have not made many great strides in adding to the traditional data sets or variables that will support predicting and identifying specific Marines that are targets for recruiting and retention.

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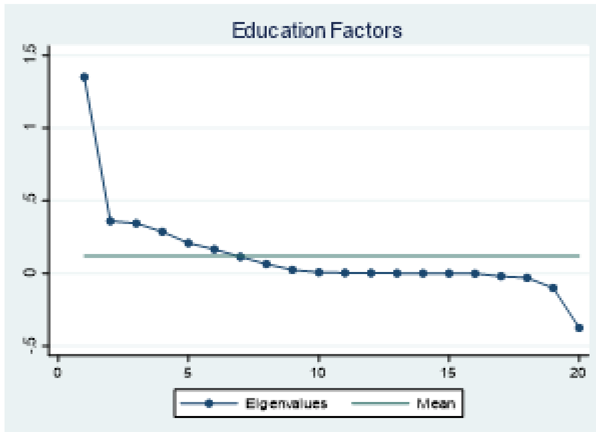
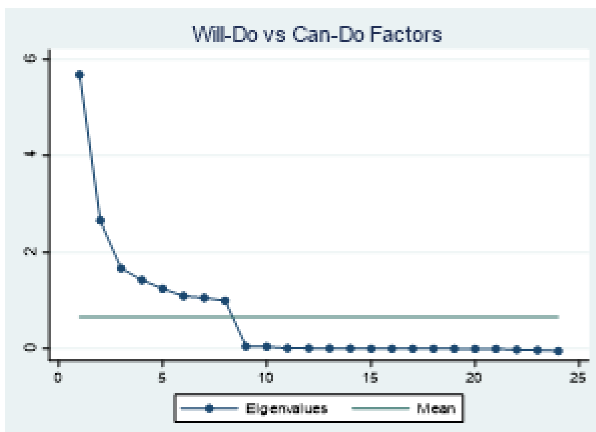
APPENDIX A. VARIABLES AND DESCRIPTIONS

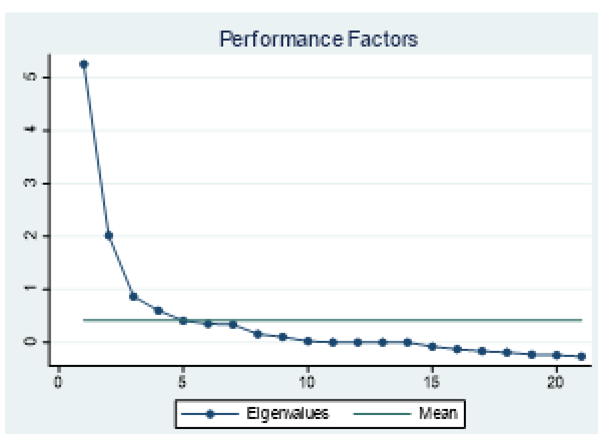
Stata Variable Name	Stata Label
educ_cert1	Less Than High School (HS) Diploma
educ_cert5	Other Non-Traditional HS Credential
educ_cert7	Distance Learning Diploma
educ_cert8	Non-HS Graduate with One Semester of College
educ_cert9	Current HS Student and Not a Senior
educ_certB	Adult/Alternative Diploma
educ_certC	Occupational Program Certificate
educ_certD	Associates Degree
educ_certE	GED
educ_certF	Exit Exam Failure
educ_certG	Professional Nursing Diploma
educ_certH	Homeschool Diploma
educ_certJ	HS Certificate of Attendance
educ_certK	Bachelor’s Degree
educ_certL	HS Diploma
educ_certM	Currently Enrolled Other Than HS Diploma
educ_certN	Master’s Degree
educ_certR	Post Master’s Degree
educ_certS	Current HS Senior
educ_certU	Doctorate Degree
educ_certW	First Professional Degree
educ_certX	National Guard Youth Challenge Program w/ GED
educ_certY	No Education Credential
educ_certZ	Unknown Education Credential
grad	Graduated
single	Single
male	Male
nHWhite	Non-Hispanic White
nHBlack	Non-Hispanic Black
asian	Asian
other	Other Race
asvab_cat1	ASVAB AFQT Category 1
asvab_cat2	ASVAB AFQT Category 2
asvab_cat3a	ASVAB AFQT Category 3a
asvab_cat3b	ASVAB AFQT Category 3b
asvab_cat4a	ASVAB AFQT Category 4a
asvab_cat4b	ASVAB AFQT Category 4b
asvab_cat4c	ASVAB AFQT Category 4c
asvab_cat5	ASVAB AFQT Category 5

dlab	Defense Language Aptitude Battery Score
mos	Primary Military Occupational Specialty
ist_crunches	Initial Strength Test (IST) - Crunches
ist_run	IST - Run
ist_hang	IST - Flexed Arm Hang
ist_pull_ups	IST - Pull Ups
mq_waiver	Mental Qualification Waiver
lv_waiver	Law Violation Waiver
drug_waiver	Drug Waiver
meduc_waiver	Minimum Education Waiver
other_waiver	Other Waiver
proficiency_average_service	Average Proficiency Marks for Service
conduct_average_service	Average Conduct Marks for Service
gcm	Good Conduct Medal
cbt_fitness_score_qy	Combat Fitness Test Score
phys_fitness_score_qy	Physical Fitness Test Score
ma_unqualifed	Martial Arts - Unqualified
ma_tan	Martial Arts - Tan Belt
ma_gray	Martial Arts - Gray Belt
ma_green	Martial Arts - Green Belt
ma_brown	Martial Arts - Brown Belt
ma_black	Martial Arts - Black Belt
rexpert	Rifle Qualification - Expert
rmarksman	Rifle Qualification - Marksman
rsharps	Rifle Qualification - Sharpshooter
runqual	Rifle Qualification - Unqualified
pexpert	Pistol Qualification - Expert
pmarksman	Pistol Qualification - Marksman
psharps	Pistol Qualification - Sharpshooter
punqual	Pistol Qualification - Unqualified
educ1	Education Factor 1
educ2	Education Factor 2
educ3	Education Factor 3
noncog1	Non-Cognitive Factor 1
noncog2	Non-Cognitive Factor 2
noncog3	Non-Cognitive Factor 3
noncog4	Non-Cognitive Factor 4
noncog5	Non-Cognitive Factor 5
noncog6	Non-Cognitive Factor 6
perf1	Performance Factor 1
perf2	Performance Factor 2
perf3	Performance Factor 3

APPENDIX B. SCREE PLOTS







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APPENDIX C. MOS GROUPINGS

Generalist MOSs	MOS Description
01XX	Personnel and Administration
03XX	Infantry
04XX	Logistics
08XX	Field Artillery
18XX	Amphibious Assault Vehicle
30XX	Supply Administration & Operations
31XX	Distribution Management
33XX	Food Service
35XX	Motor Transport Career
41XX	Morale Welfare & Recreation
57XX	Chemical, Biological, Radiological and Nuclear Defense
58XX	Military Police & Corrections
66XX	Aviation Logistics
80XX	Miscellaneous Requirements MOS
81XX	Miscellaneous Requirements MOS
84XX	Miscellaneous Requirements MOS
89XX	Miscellaneous Requirements MOS
99XX	Miscellaneous Requirements MOS

Specialist MOSs	MOS Description
02XX	Intelligence
05XX	Marine Air-Ground Task Force Plans
06XX	Communications
09XX	Training
11XX	Utilities
13XX	Engineer, Construction, Facilities & Equipment
21XX	Ground Ordnance Maintenance
23XX	Ammunition and Explosive Ordnance Disposal
26XX	Signals Intelligence/Ground Electronic Warfare
27XX	Linguist
28XX	Ground Electronics Maintenance
34XX	Financial Management
44XX	Legal Services
45XX	Communication Strategy
55XX	Music
59XX	Electronics Maintenance
60XX	Aircraft Maintenance

61XX	Aircraft Maintenance
62XX	Aircraft Maintenance
63XX	Avionics
64XX	Avionics
65XX	Aviation Ordnance
68XX	Meteorology & Oceanography
70XX	Airfield Services
72XX	Air Control/Air Support/Anti-Air Warfare/Air Traffic Control
73XX	Navigation Officer/Enlisted Flight Crews

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