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IMPACT OF HUMAN CHARACTERISTICS IN BASIC UNDERWATER DEMOLITION/SEAL (BUD/S) TRAINING PERFORMANCE

by

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LIST OF ACRONYMS AND ABBREVIATIONS

AO	area of operation
BMI	body mass index
BTC	basic training command
BUD/S	Basic Underwater Demolition/SEAL
DARPA	Defense Advanced Research Projects Agency
ID	identification
IDTC	inter deployment training cycle
JTAC	Joint Terminal Attack Control
NSW	Naval Special Warfare
NSWAC	Naval Special Warfare Assessment Command
NSWO	Naval Special Warfare Orientation
NSWPREP	Naval Special Warfare Preparatory Course
O-Course	obstacle course
OLS	ordinary least squares
ORM	Operational Risk Management
PST	physical screening test
SEAL	Sea Air Land
SERE	Survival, Evasion, Resistance, Escape
SOCOM	United States Special Operations Command
SQT	SEAL Qualification Training
SWCC	Special Warfare Combatant Crewman
TGIT	task group integration training
TRADET	training detachment
ULT	unit level training

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I. INTRODUCTION

Reporting and clerical functions at Naval Special Warfare (NSW) Echelon IV commands are ripe for digitization, automation and optimization. While cost is a concern for prioritizing a more automated data system, there are potentially large benefits including the use of these data for prediction modelling. This study shows a framework for how to use "big data" in the context of SEAL training and how it can be used to identify performance success rates during BUD/S various types of training evolutions (e.g., two mile swim, four mile run). In addition, we highlight how long-term efficiencies could be gained from greater automation of data within the NSW system.

Naval Special Warfare Command requires its SEAL and Special Warfare Combatant Crewman (SWCC) operators to be mentally and physically capable to perform and succeed in every mission that is given to them. The trust and reputation in their ability to succeed is built on a historical foundation of carefully selected individuals with the right character and strength to meet the unwavering standard of a Navy SEAL. To maintain trust in the NSW community and preservation of its standards for entry into its ranks, every opportunity must be made to optimize its assessment and selection process.

Every individual who is accepted into the BUD/S program is unique. To be clear, there is no obvious way to determine if someone will pass or fail the training pipeline. Certain so-called mental "x-factors" that encompass a person's internal desire to succeed are immeasurable and will always produce outliers in a dataset. However, data collected on candidates prior to and during training can help produce statistical performance trendlines that encompass an ideal candidate.

This study utilizes a unique digitalized NSW dataset used in a prediction model framework. The Student Performance dataset focuses on performance metrics for all training evolutions conducted in BUD/S (e.g., two-mile swim, four-mile run). In addition to performance metrics, it also includes demographic information as well as other human body metrics (e.g., height, weight, gender, hand dominance) Moreover, the data set also captures a candidate's marital status (single, married, divorced) and whether they are enlisted or an officer.

For our prediction model, we use Ordinary Least Squares (OLS) in our regression analysis. The regression model uses the Student Performance dataset to predict whether an individual passes their evolution. For performance fails, the results show higher probabilities for fails to occur amongst females, Blacks, Hispanics, and enlisted SEALs. As for passing evolutions, we find that individuals who are taller, older, lighter (in terms of weight), males, married, White, and officers are more likely to pass their evolutions.

This study highlights how long-term efficiencies could be gained from greater automation of data through the use of simple software. Some data (such as those shown in this study) could provide long-term benefit if captured in a more persistent manner. As a final recommendation, we highly advocate the implementation of a more automated data/software collection system and the use of "big data" for NSW studies going forward in the near future.

The paper proceeds as follows. Chapter II provides institutional details for Naval Special Warfare training. Chapter III describes the datasets and variables. Chapter IV details the methodology used in our final analysis. Chapter V presents the results. Chapter VI concludes the study.

II. INSTITUTION DETAILS

A. NAVAL SPECIAL WARFARE TRAINING BACKGROUND

Navy SEAL training is dangerous, but for good reason. It is a dynamic training environment that is influenced by multiple human and environmental factors. Leveraging risk upfront is necessary to ensure a candidate is prepared and able to succeed as a future SEAL. Lowering standards to reduce risk is an unacceptable compromise. Although risk cannot be removed, it can be managed and mitigated to help ensure confidence in the training, instructors, and established standards. NSW's commitment to improving the assessment and selection process can be demonstrated by the recent development of the Naval Special Warfare Assessment Command (NSWAC) in August 2022.

According to Rear Adm. H.W. Howard, III, former commander, U.S. Naval Special Warfare Command, the purpose of the new command is to "build the sustainable architecture for diversified outreach, more rigorous pre-assessments for character, cognitive and leadership attributes across the Assessment and Selection pathway and implement the innovative initiatives that strengthen continuous assessment across the continuum of a Naval Special Warfare" (Perlman 2022). In its current form, Navy SEAL assessment, selection, and training is split into six stages.

(1) STAGE 1: Naval Special Warfare Preparatory Course

After completing bootcamp as an enlisted sailor or commissioning as an officer, the first training stage is Naval Special Warfare Preparatory Course (NSWPREP). NSWPREP is a five-week long course focused getting candidates physically prepared to begin Basic Underwater Demolition/SEAL (BUD/S) training. It also incorporates professional development, mental training, and other various academic topics of importance. Recently relocated to Coronado, CA, NSWPREP provides candidates the ability to train in the same environment as BUD/S. BUD/S training has taken place in Coronado, CA since 1971. Before moving to stage 2, NSWPREP candidates must pass all testing requirements.

(2) STAGE 2: Naval Special Warfare Orientation

Naval Special Warfare Orientation (NSWO) is a two-week training period designed to accustom students to the basic evolutions and tests that will be conducted in BUD/S. Areas of focus include running in the sand, open ocean swimming, obstacle course, and technical pool skills. Depending on a student's overall performance, to include run, swim, and obstacle course test scores, instructors will determine if a student moves to the first phase of BUD/S or is removed from the program.

(3) STAGE 3: First Phase

First Phase marks the beginning of BUD/S training. It is seven weeks long and designed to measure your physical ability, water competency, mental toughness, and capability to work as a team while under stress. Each week comprises multiple physical evolutions (Log PT, surf passage, ruck runs, etc.) and tests to measure and prepare you for the fourth week of training: Hell Week. Lasting five-and-a-half days, Hell Week tests each student's physical and mental fortitude. It is a major milestone in the training pipeline, responsible for the most attrition compared to any other evolution. Following Hell Week, the remaining members of the class will recover then conduct a final set of physical tests before moving on to Second Phase.

(4) STAGE 4: Second Phase

Like First Phase, Second Phase is seven weeks long. The primary focus of second phase is to teach students basic combat diving skills. The first portion of training is learning about open-circuit diving and displaying your ability to remain comfortable and in control underwater. The remaining time in Second Phase is spent utilizing closed circuit dive rigs. Students will spend multiple weeks learning and practicing underwater navigation and various other critical skillsets. After completing series of culminating dive tests, students will move back to the land for Third Phase.

(5) STAGE 5: Third Phase

The Third and final phase of BUD/S concentrates on the fundamentals of land warfare. Over the span of seven weeks, students will learn land navigation, marksmanship, demolitions, patrolling, and small unit tactics. Each component of training has its own testing requirements, designed to reflect your ability to learn, retain, and execute a complex skill. Physical standards are still maintained and tested throughout the phase in addition to all the other requirements. Upon completion of Third Phase, students have the necessary foundational tactics and skills required in the next stage of training.

(6) STAGE 6: SEAL Qualification Training

SEAL Qualification Training (SQT) is the final stage before joining a SEAL Team. SQT is 26-week course designed to build a student's tactical knowledge to a more advanced level required for a SEAL platoon. In SQT, students learn to operate in multiple environments to include the water, desert, and mountains. At the conclusion of SQT, students will undergo advanced static and freefall operations as well as Survival, Evasion, Resistance, and Escape (SERE) training. Upon receiving a Trident, a student will be assigned to a SEAL Team and prepare for the Inter Deployment Training Cycle (IDTC) (Naval Special Warfare 2022).

B. INTER DEPLOYMENT TRAINING CYCLE (IDTC)

The 18-month IDTC combined with a six-month overseas deployment completes a 24-month cycle which is the standard rotation of the SEAL Teams. This allows one SEAL Team per coast to deploy while the additional three teams man, train and equip for the next deployment. While this is the model of SEAL Team rotational deployment and training, frequent disruptions to the schedule may occur.

Traditionally, the first six months of IDTC are reserved for professional development. Commonly called PRODEV, this phase is reserved for enhancing individual qualifications for the enlisted SEALs and developing the platoon administration for the officers. During this phase most SEAL operators will attend qualification schools such as sniper, breaching, communications, range supervisor, advanced combat swimmer or Joint Terminal Attack Controller (JTAC), among others. These schools are run by a variety of commands and services and are often not NSW specific. This phase concludes with all SEALs returning to the platoon they will call their own for the next 18-months. Many times, the end of PRODEV marks the first time the SEAL platoon has all its members under one roof.

The second phase of IDTC is Unit Level Training (ULT). This phase is the most demanding phase in IDTC due to the frequent travel and continuous assessment from the instructor staff at the NSW Training Detachment (TRADET). The training cells are broken into the following categories: Assaults, Maritime/Mobility and Land Warfare. The duration of each block of training varies, some blocks are ten days while others can be up to 4 weeks. Often there is a quick turn-around between training blocks resulting in scant recovery time. The high training tempo during ULT combined with the increased physical training typically leads to the highest number of injuries when compared with other IDTC phases.

The final phase of IDTC is Task Group Integration Training (TGIT). The focus of this phase is to integrate with other support elements and train for the specific area of operation (AO) and mission set based on the upcoming deployment. This phase cumulates with a final battle problem where the team and platoon finish all final training requirements and become mission capable. Once IDTC is complete the priority shifts to logistical efforts to support the deployment.

C. HISTORICAL TRAINING ISSUES, MEDICAL STUDIES AND MITIGATION REPONSES

The study of adverse medical conditions related to BUD/S training is nothing new. In a 1991 study of SEAL trainees published in the *Clinical Journal of Sports Medicine*, Dr. Jerry Linenger and his team concluded, “Strenuous physical training results in a high incidence of medical conditions and musculoskeletal injury in trainees” (Linenger et al. 1993). This study found that combined medical conditions and musculoskeletal injuries occurred at a rate of 61.4 cases per 100 trainee-months at risk (Linenger et al.). More recent medical studies of BUD/s students have attempted to identify psychological and physiological predictors of resilience. A 2020 study by Andrew Ledford and his team concluded, “Both psychological and physiological resilience can be important predictors of persistence individually, but combining the measures provides a more holistic view to predict the success of an individual in this intensive training program” (Ledford et al. 2020).

The recent death of SEAL candidate Seaman Kyle Mullen during BUD/S in February 2022 has reignited the public discussion of safety during training (Mongilio 2022). Currently, Naval Special Warfare Basic Training (BTC) command employs a multitude of safety measures to reduce risk. A few examples are heat index tables denoted by a flag color, water/air temperature tables for surf immersion, instructor safety training, and operational risk management (ORM) papers. ORMs are risk templates designed to be applied to any training evolution. ORMs outline each individual risk and possible outcome associated with that risk, then apply a mitigating action to reduce the overall. The main goal of an ORM is to outline risk, not necessarily prevent it.

NSW BTC currently uses environmental data to assess risk but does not apply historical records to refine their risk assessment. Using past environmental parameters overlayed with individual/class performance/mishaps within a day/evolution trend analysis could potentially help expose potential patterns in historical data. This could allow instructors the ability to see a real time assessment of risk and make better-informed decisions within the training environment. Although environmental and medical variables were not assessed in this study, similar statistical methodology could be applied to these variables to gain insight into current and historical training issues and the affects they have performance.

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III. DATA

We applied individual level information from Naval Special Warfare Command as our primary data source for analysis. The Student Performance dataset focuses on performance metrics for all training evolutions conducted in BUD/S (e.g., two-mile swim, four-mile run). In addition to performance metrics, it also includes demographic information as well as other human body metrics (e.g., height, weight, gender, hand dominance) Moreover, the data set also captures a candidate's marital status (single, married, divorced) and whether they are enlisted or an officer. The combined dataset includes a total of 232,636 observations from the years 2016 to 2022 as shown in Table 1.[1]

The BUD/S Student Performance data is particularly analyzing individual human characteristics against evolution performance in BUD/S. It also provides a holistic view for every type of individual that go through the BUD/S program. Table 1 shows summary statistics for the Student Performance BUD/S dataset. Out of the 232,636 observations, the vast majority (84.5%) were categorized as White. Hispanics were the next largest group (7.4%) followed by "Other Race" (4.9%), Asian (1.2%), and Black (1.1%). The average age was 26.8 with a minimum of 17 years of age and a maximum of 41 years of age. The SEAL enlisted category included 86.2% of the observations. Single people are represented as 89.1% of the total, Married individuals are 10.6%, and Divorced or Unknown are only 0.2% of the total. The average height is 70.3 inches and the average weight is 179.0 pounds.

[1] We drop any observation less than 17 years of age, weight less than 100 pounds, and height less than 50 inches.

Table 1. BUD/S Summary Statistics

	Obs	Mean	Std. dev.	Min	Max
Age	232,636	26.88726	3.811172	17	41
Height	232,636	70.32258	2.581809	60	84
Weight	232,636	179.0104	18.45157	117	260
Male	232,636	0.9997808	0.0148047	0	1
Married	232,636	0.1062346	0.3081384	0	1
Single	232,636	0.8909283	0.3117298	0	1
Divorced or Unknown	232,636	0.0028371	0.0531885	0	1
White	232,636	0.8451486	0.3617637	0	1
Black	232,636	0.0106217	0.1025133	0	1
Asian	232,636	0.0124013	0.1106689	0	1
Hispanic	232,636	0.0735054	0.2609648	0	1
Indian	232,636	0.0049304	0.070044	0	1
Pacific Islander	232,636	0.0041997	0.064669	0	1
Other	232,636	0.0491927	0.2162707	0	1
Enlisted	232,636	0.8624117	0.3444681	0	1
Right Hand	232,636	0.5769528	0.4940438	0	1
Swim	232,636	0.2922377	0.4547919	0	1
Run	232,636	0.2284642	0.4198441	0	1
O course	232,636	0.2831204	0.4505154	0	1
Water Other	232,636	0.0486296	0.215093	0	1
Physical Screening Test	232,636	0.0313451	0.174249	0	1
Other Evolution Type	232,636	0.116203	0.3204689	0	1
Value Pass	232,636	0.8716966	0.3344281	0	1

Foreign National students and SWCC were removed from the original dataset because analysis solely focused on U.S. BUDs candidates. Males made up 99.98% of the observations. Data was recorded for only two female candidates, preventing further analysis due to the limited sample size.

We categorize the type of evolution into six categories. Swim is listed as the evolution for 29.2% of the observations, Next is, O-Course (or obstacle course) (28.3%). Next is, Run (22.8%), Other Evolution Type (11.6%), Water Other (4.9%), and Physical Screening Test (PST) (3.1%). Value Pass Evolution is our main outcome variable and shows 87.2% of the observations passing their evolution.

Multiple training evolutions were combined to form each variable. The Swim category includes 24 recorded evolution types comprised of 1NM, 1.5NM, 2NM, 3.5NM, 5.5NM and 35/50M underwater swim. The O-Course category includes all pass/fail o-course recorded evolutions. The Run category includes 14 recorded evolution types comprised of soft sand, test and training four-mile runs. Other Evolution Type category includes all other recorded BUD/S evolutions outside of the previous five categories. Examples of these evolutions include land navigation, open/closed circuit dives, and rifle/ pistol tests. The Water Other category includes drown-proofing, underwater knot tying and life-saving. The PST category includes all pass/fail recorded PSTs.

Both data sets were organized by student identification (ID) numbers. Each student ID number correlates to a data entry point on that individual, whether it was background or evolution data. Because of this collection method, a single student ID would have multiple data entry points, varying in size based on their time in the training pipeline. This is the reason why there is over 232,000 data entry points.

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IV. METHODOLOGY

For our prediction model, we use Ordinary Least Squares (OLS) in our regression analysis. The first regression model uses individual level data from Naval Special Warfare to predict evolution pass rates. This model is shown below:

$$\textit{Pass Evolution}_{iet} = \alpha + X'_{iet}\theta + \epsilon_{iet} \qquad (1)$$

The $\textit{Pass Evolution}_{iet}$ takes a value of one if individual *i* passes evolution *e* in time period *t* and zero otherwise. Seven different outcome variables are used in the analysis including Swim, Run, O-Course, Water Other, PST, Other Types, and Overall (*i.e.*, all evolution types). The vector X'_{iet} is a set of individual predictor variables including Current Age, Height, Weight, Male, Married, Divorced or Unknown, Black, Asian, Hispanic, Indian, Pacific Islander, Other Race, and Right Hand. The model also includes a constant term, α. Baseline variables omitted from the regressions are Single and White. Finally, ϵ_{iet} is an idiosyncratic error term.

We include a second regression model to more precisely analyze the predictive effects of the age distribution on evolution pass rates. This model is shown below:

$$\textit{Pass Evolution}_{iet} = \alpha + \beta_1 \textit{Age 18}_{iet} + \beta_2 \textit{Age 19}_{iet} + \beta_3 \textit{Age 20}_{iet} + \beta_4 \textit{Age 22}_{iet} + \beta_5 \textit{Age 23}_{iet} + \beta_6 \textit{Age 24}_{iet} + \beta_7 \textit{Age 25}_{iet} + \beta_8 \textit{Age 26}_{iet} + \beta_9 \textit{Age 27}_{iet} + \beta_{10} \textit{Age 28}_{iet} + \beta_{11} \textit{Age 29}_{iet} + \beta_{12} \textit{Age 30}_{iet} + \beta_{13} \textit{Age 31}_{iet} + \beta_{14} \textit{Age 32}_{iet} + \beta_{15} \textit{Age 33}_{iet} + \beta_{16} \textit{Age 34}_{iet} + X'_{iet}\theta + \epsilon_{iet} \qquad (2)$$

where $\textit{Pass Evolution}_{iet}$ takes a value of one if individual *i* passes evolution *e* in time period *t* and zero otherwise. For simplicity in this model, we focus solely on the Overall outcome variable as discussed previously. We restrict the sample to ages 18 to 34 years-old and use age 21 as the baseline age variable omitted from the analysis. This regression includes a series of age dummies (18, 19, 20, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, and 34 years old) to more specifically measure the predictive effects of these ages on evolution pass rates. The vector X'_{iet} includes the variables Height, Weight, Male, Married, Divorced or Unknown, Black, Asian, Hispanic, Indian, Pacific Islander, Other

Race, and Right Hand. The model also includes a constant term, α. Other baseline variables (besides the 21 years-old variable) omitted from the regression are Single and White. Finally, ϵ_{iet} is an idiosyncratic error term.

For our last model, we use a variation of Equations (1) and (2) which focuses more on age groupings instead of individual age dummies. This model is shown in Equation (3).

$$Pass\ Evolution_{iet} = \alpha + \beta_1 Age\ 25\text{–}30_{iet} + \beta_2 Age\ 31\text{–}34_{iet} + X'_{it}\theta + \epsilon_{iet} \qquad (3)$$

Where *Pass Evolution*$_{iet}$ takes a value of one if individual *i* passes evolution *e* in time period *t* and zero otherwise. Equation (3) is similar to Equation (2) since we focus solely on the Overall outcome variable in this analysis. Likewise, we restrict the sample to ages 18 to 34 years-old. Instead of individual age dummies, we include age grouping dummies in this model. The first age grouping is 25- to 30-year-olds and the second is 31- to 34-year-olds. The baseline age grouping is 18- to 24-year-olds. The vector X'_{iet} includes the variables Height, Weight, Male, Married, Divorced or Unknown, Black, Asian, Hispanic, Indian, Pacific Islander, Other Race, and Right Hand. The model also includes a constant term, α. Other baseline variables (besides the 18- to 24-year-old age grouping) omitted from the regression are Single and White. Finally, ϵ_{iet} is an idiosyncratic error term.

V. RESULTS

A. MAIN RESULTS

Table 2 shows the main results from Equation (1). Seven different outcome variables are utilized in the analysis including Swim, Run, O-Course, Water Other, PST, Other Types, and Overall. The Current Age coefficient fluctuates from a low of -0.0061777 in the Other Types column up to a high of 0.0056754 in the O-Course column. Four out of the seven coefficients for the Current Age variable are statistically significant at the 1% level. In the main results shown in the Overall column, the Current Age coefficient is statistically significant at the 1% level and has a point estimate of 0.0014543 indicating each additional year of age increases the overall evolution pass rate by 0.145%.

The Height coefficient in the Overall column in Table 2 is statistically significant at the 1% level and shows a point estimate of 0.0029537. This indicates that each additional inch in height increases the overall evolution pass rate by 0.295%. The Weight coefficient in the Overall column is statistically significant at the 1% level and has a point estimate of -0.0002719. This indicates that each additional pound of weight predicts a decrease in the evolution pass rate by 0.027%. Therefore, a lower body mass index (BMI) should have higher predictive pass rates for individuals in NSW.

We find little predictive effect from the Male coefficient in Table 2. This is hardly surprising since only two females were listed in the original dataset. The lower number of females makes it hard to get precise results for that coefficient and likely led to the large confidence intervals making the results statistically insignificant. On the other hand, the Married coefficient in the Overall results is statistically significant at the 1% level and shows a point estimate of 0.0119732. This indicates that married individuals pass evolutions at a rate of 1.197% higher than single individuals, *ceteris paribus*. Furthermore, the Divorced or Unknown category has lower pass rates in comparison single individual

Table 2. Predictors of Evolution Pass Rates

	Swim	Run	O-Course	Water Other	PST	Other Types	Overall
Current Age	0.002783***	-0.0003688	0.0056754***	-0.0012999	-0.0005638	-0.0061777***	0.0014543***
	(0.0003538)	(0.00043)	(0.0003487)	(0.0011472)	(0.0003573)	(0.0008894)	(0.0002122)
Height	0.0005273	0.0068842***	0.0038586***	0.0057805***	0.0003478	-0.0045213***	0.0029537***
	(0.0006313)	(0.0007639)	(0.0006113)	(0.0019406)	(0.0005573)	(0.0016439)	(0.0003809)
Weight	0.0007032***	-0.0013033***	-0.0009153***	-0.0004497*	0.0000226	0.0020212***	-0.0002719***
	(0.0000897)	(0.000108)	(0.000087)	(0.0002712)	(0.0000818)	(0.0002245)	(0.0000538)
Male	-0.1301052*	0.1197701	0.185379**	-0.0705686	-0.0067831	-0.0743937	-0.0089773
	(0.080944)	(0.1081269)	(0.0806392)	(0.3827574)	(0.0266133)	(0.230775)	(0.0469659)
Married	0.0065392*	0.0140906***	0.0136627***	0.0031657	0.0065799*	0.016229*	0.0119732***
	(0.0038534)	(0.0046439)	(0.0037096)	(0.011711)	(0.003626)	(0.0096827)	(0.0023116)
Divorced or Unknown	-0.0484251**	-0.0304688	-0.0314024	0.1124957*	0.0093281	0.041888	-0.029384**
	(0.0228681)	(0.0272701)	(0.0222736)	(0.0638853)	(0.0266335)	(0.0414404)	(0.0130806)
Black	-0.0734492***	-0.0129976	-0.0552066***	-0.1667527***	-0.0327565***	-0.1201672***	-0.0525413***
	(0.0113328)	(0.0136499)	(0.0107203)	(0.0355902)	(0.0074793)	(0.0316947)	(0.0067592)
Asian	0.0001907	-0.015517	-0.0549362***	0.0026399	0.0078132	0.0097175	-0.0105965*
	(0.0104213)	(0.0126324)	(0.0097446)	(0.0356485)	(0.007781)	(0.0298636)	(0.0062752)
Hispanic	-0.0139404***	0.0078102	-0.0104683**	-0.0158362	-0.0014406	0.0064058	-0.0028012
	(0.0044798)	(0.0055034)	(0.0043866)	(0.0134964)	(0.0033621)	(0.0113513)	(0.0026963)
Indian	-0.0604643***	-0.0093136	-0.012231	0.0084817	-0.0219909	-0.0118635	-0.0247477**
	(0.0167034)	(0.0201421)	(0.015905)	(0.0501912)	(0.0143293)	(0.0392169)	(0.0098915)
Pacific Islander	-0.0098203	0.0013442	0.0260023	-0.0985693**	0.0086776	0.0073436	0.0030068
	(0.0175086)	(0.0225813)	(0.0184215)	(0.0485438)	(0.0114184)	(0.0440197)	(0.0107244)
Other Race	-0.0235976***	0.0166837***	0.0000723	-0.0024067	-0.0003137	-0.0125369	-0.0058708*
	(0.0053917)	(0.0064329)	(0.0052495)	(0.0156852)	(0.0051548)	(0.0128316)	(0.0032152)
Enlisted	-0.041479***	-0.0610055***	-0.0805253***	-0.0373995***	-0.007901**	-0.0788196***	-0.0541732***
	(0.0034491)	(0.0040608)	(0.0033398)	(0.011054)	(0.0037343)	(0.0075545)	(0.0020379)
Right Hand	0.001933	0.0730564***	-0.0068017***	0.0454665***	0.0009281	0.0380096***	0.008378***
	(0.0026362)	(0.003136)	(0.0025376)	(0.0081588)	(0.0034028)	(0.006609)	(0.0015739)
Constant	0.8274405***	0.5316862***	0.532538***	0.6091786	0.9906086***	0.9173357***	0.7245233***
	(0.0889551)	(0.1167795)	(0.0880957)	(0.3984578)	(0.0418337)	(0.2493719)	(0.0519405)

Table notes:

***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

Standard errors are in parentheses.

$Pass_{iet}$ = 1 if the service member i passes evolution e in time period t and = 0 otherwise.

Baseline variables include Single and White.

N = 232,636

The different race coefficients (Black, Asian, Hispanic, Indian, Pacific Islander, and Other Race) displayed in Table 2 show a mixed picture for predictive effects. The Black coefficients are negative across the board and range in value from a low of -0.1667525 to a high of -0.0129976 with six of the seven coefficients being statistically significant at the 1% level. The Overall point estimate for Black is -0.0525413 indicating Blacks have a 5.25% lower pass rate for evolutions in comparison to Whites, *ceteris paribus*. Probably the most striking feature for the Black coefficients is the extreme drop-in pass rates related to water evolutions. For example, the point estimate for Black in the Swim evolution column is -0.0734492 and Water Other is -0.1667527. Therefore, Blacks pass swim evolutions at a rate 7.34% lower than Whites and Water Other evolutions at rate 16.68% lower than Whites, *ceteris paribus*.

The Asian and Indian coefficients were the only other race variables in the Overall column in Table 2 that were negative and statistically significant. The Asian coefficient was -0.0105965 and statistically significant at the 10% level. The Indian coefficient was -0.0247477 and statistically significant at the 5% level. The other race variables in the Overall column, Hispanic and Pacific Islander were both statistically insignificant at the standard levels.

The Enlisted personnel coefficient in Table 2 was negative across the board and ranges in value from a low of -0.0805253 to a high of -0.0007901. All seven of the Enlisted race coefficients were statistically significant at the 1% level. The Overall column shows a point estimate of -0.0541732 for enlisted personnel indicating enlisted personnel have evolution pass rates that are 5.42% lower than officers, *ceteris paribus*. The Right-Hand coefficient is positive in six of the seven columns and statistically significant in five of the seven columns. The point estimate for Right Hand in the Overall column is 0.008378 indicating right-handed individuals have slightly higher pass rates (by out 0.838% on average).

Table 3 displays regression results from Equation (2). As discussed previously, these results are utilized to analyze the predictive effects of the age distribution more precisely on evolution pass rates. The 21-year-old age group is the comparison group for the table. We find statistically insignificant results for the 18- and 22-year-old age groups.

Table 3. Age Summary

Age	Overall
18	0.0141492
	(0.0131768)
19	0.0188775***
	(0.0067336)
20	0.0106816**
	(0.0053957)
22	0.0031204
	(0.0047457)
23	0.0219234***
	(0.0043203)
24	0.0189345***
	(0.0041787)
25	0.0085006**
	(0.0039668)
26	0.0131764***
	(0.0039861)
27	0.0224043***
	(0.0040174)
28	0.02852***
	(0.0041285)
29	0.0216607***
	(0.0042229)
30	0.014468***
	(0.0042533)
31	0.0282976***
	(0.0044919)
32	0.0220054***
	(0.0047796)
33	0.0361645***
	(0.0053969)
34	0.0338042***
	(0.0062909)
Constant	0.7488339***
	(0.051912)

Notes: ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.
Standard errors are in parentheses.
$Pass_{iet}$ = 1 if the service member *i* passes evolution *e* in time period *t* and = 0 otherwise.
Baseline age is 21 years old.
Control variables in the regression include Height, Weight, Gender, Married, Divorced or Unknown, Black, Asian, Indian, Pacific Islander, Other Race, Enlisted, and Right Hand.
Sample restricted to ages 18–34.
N = 227,034

The results in Table 3 generally track those in Table 2 and suggest better pass rates for older individuals, *ceteris paribus*. The main statistically significant jump in Table 3 occurs at the 23- and 24-age groups (in comparison to the 21-year-old baseline comparison group). The Overall point estimate for 23-year-olds is 0.0219234 and for 24-year-olds it is 0.0189345. Therefore, evolution pass rates for 23-year-olds are 2.19% higher and 24-year-olds are 1.89% higher, respectively, in comparison to 21-year-olds, *ceteris paribus*. The dummy variables for the ages 25 through 34 range are all positive and statistically significant at the 1% level indicating higher ages (in comparison to 21-year-olds) are associated with higher evolution pass rates, *ceteris paribus*.

Table 4 displays the results from Equation (3). As a reminder, this table focuses more closely on wider age groupings to provide another metric to use to estimate the predictive effects of age on evolution pass rates. Other variables as shown in Equation (3) are included to show the comprehensive picture for their predictive effects.

Table 4. Age Bin Summary

	Overall
Height	0.0026844***
	(0.0003869)
Weight	-0.0002183***
	(0.0000545)
Male	-0.0104249
	(0.0470143)
Married	0.01386***
	(0.0023766)
Divorced or Unknown	-0.0294553**
	(0.0130948)
Black	-0.0448217***
	(0.0070614)
Asian	-0.0138708**
	(0.006391)
Hispanic	-0.0034202
	(0.0027217)
Indian	-0.0257022***
	(0.0099408)
Pacific Islander	0.001929
	(0.0107355)
Other Race	-0.006568**
	(0.0032481)
Enlisted	-0.0556395***
	(0.0020779)
Right Hand	0.0079343***
	(0.0015438)
Age 25–30	0.0038068**
	(0.0017272)
Age 31–34	0.0139278***
	(0.0024589)
Constant	0.771221***
	(0.0517852)

Notes: ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.
Standard errors are in parentheses.
$Pass_{iet}$ = 1 if the service member *i* passes evolution *e* in time period *t* and = 0 otherwise.
Baseline variables include Single, White, and Age Bin 18–24.
Sample restricted to ages 18–34.
N = 227,034

The point estimate in Table 4 for the Age 25–30 coefficient is 0.0038068 and statistically significant at the 5% level. As a comparison, the Age 31–34 Age point estimate is 0.0139278 and statistically significant at the 1% level. The point estimates indicate the older age bins have evolution pass rates that are between 0.3% and 1.39% higher in comparison to the 18–24 Age bin, *ceteris paribus*. This is in line with the other tables that show older individuals tend to have higher pass rates in comparison to the younger cohorts.

The other variables in Table 4 largely track the results from the previous tables. Higher pass rates are found with taller individuals and lower pass rates are found with individuals that weigh more, *ceteris paribus*. The Male coefficient is once again found to be statistically insignificant at the conventional levels. Married individuals have higher pass rates (1.39%), and divorced or unknown individuals have lower pass rates (-2.95%) in comparison to single individuals, respectively.

As for the race variables in Table 4, the results show lower pass rates for Blacks (-4.48%), Asians (-1.39%), Indians (-2.57%), and the Other Race category (-0.66%) in comparison to Whites. Of note, the coefficients for Hispanic and Pacific Islander were both statistically insignificant at the conventional levels. Enlisted personnel have lower pass rates (-5.56%) in comparison to officers. Finally, we find higher pass rates (0.793%) for right-handed individuals in comparison to left-handed or unknown individuals.

B. DISCUSSION AND FUTURE RESEARCH

The main results show a pattern of higher pass rates associated with more mature individuals in Naval Special Warfare. There are several ways to measure maturity, but in this study, we find older and married individuals clearly have higher pass rates, *ceteris paribus*. The same is true for the officers in the data. Does this mean NSW should only target mature candidates for its training programs? That is unclear. On the one hand, targeting more mature recruits will raise pass rates and likely cut down on training costs. On the other hand, such a policy may hinder the development of younger recruits who may bring different talents (not included in this dataset) to the force.

The other predictor variables tend to show proxies (such as weight) for physically fit personnel having higher evolution pass rates. This is not surprising and new recruits should be advised about the importance of being physically fit *before* they begin their training (if they have not made fitness a priority already). One oddball variable, Right Hand, indicates that right-handed individuals tend to have higher pass rates. It is not apparent why this is the case in the data. That said, it may be useful to investigate why this is occurring and if anything can be done to improve pass rates for those who are not right-handed.

The low pass rates amongst the minority population (Black, Asian, Indian, and Other Race) are concerning and deserves a closer look by NSW Command. In particular, the Black population has one the lowest pass rate in the data, *ceteris paribus*. The data indicate Black personnel have a 5.25% lower probability of passing evolutions in comparison to White individuals. The main problem appears to be that Black candidates tend to struggle in the evolutions that involve water activities. For example, Blacks have lower pass rates in the Swim evolution category (-7.34%) and in the Water Other category (-16.68%) in comparison to Whites, *ceteris paribus*. We highly recommend that NSW investigate why this might be the case and make corrections if needed.

In addition to the possible future research topics highlighted above, we believe there are other areas that could use additional attention. We believe it would be useful to expand this dataset to include other subfactors such as environmental factors (water quality, air quality, water temp), injuries (or suicides and other death types), other special operation forces such as those in the Army, Marines, Air Force, and Coast Guard, and special forces operators in allied countries. Specific data that could be useful for analysis that was missing from the NSW datasets includes geographic information on where the candidate was born and raised, athletic background, additional health metrics (such as Body Mass Index (BMI)) and additional family background information (such as single parent and number of siblings).

Although not the focus of this study, we are aware of some ongoing initiatives within the NSW community that could assist with data management such as the heath data collected from wearable devices backed by the Defense Advanced Research Project

Agency (DARPA) and the U.S. Special Operations Command (SOCOM) partnership with the human performance optimization software company SMARTABASE.

Data collection and management will never be perfect, but it can be optimized by connecting the streams of data we already have with approved management tools. Furthermore, we believe future qualitative research (through surveys) on similar topics might be useful to provide insights about *why* we are seeing some of these trends and how to correct any issues during training for NSW operators.

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VI. CONCLUSION

This study uses restricted data from Naval Special Warfare Command to predict evolution pass rates for operators during NSW training cycles. The dataset we utilize includes over 232,000 observations with detailed demographic information (age, gender, marital status, and race, amongst other factors) for individuals going through the NSW training regimen. In addition, it provides seven different types of evolutions (Swim, Run, O-Course, Water Other, PST, Other Types, and Overall) to provide context for where individuals are most likely to pass or fail the evolutions during their training schedule.

For our prediction model, we use Ordinary Least Squares (OLS) in our regression analysis. Our main findings indicate higher pass rates for more mature individuals (e.g., older, married, and officer status). Furthermore, we find higher pass rates for individuals who are taller, lighter (in terms of weight), and right-handed personnel. Lower pass rates are found among minorities (Blacks, Asians, Indians, and Other Races). The Black population had high fail rates in the evolutions that involve water activities.

We advise future research to focus on the reasons for these outcomes among the minority population as well as other special forces operators in the United States and her allies. Qualitative research through standard survey methods in the future would be useful in answering why trends are occurring. In addition, we advocate expanding the current data work presented here with additional subfactors including environmental factors and outcomes related to injuries and extreme outcomes such as training deaths or suicides.

This study is just one example of how long-term efficiencies could be gained from greater automation of data through the use of simple software. Some data (such as those shown in this study) could provide long-term benefit if captured in a more persistent manner. We highly advocate the implementation of a more automated data/ software collection system and the use of "big data" for NSW studies going forward in the near future. Moving forward, NSW/SOCOM should optimize their current methods of collecting data on students while in the training pipeline. Currently, multiple Excel spreadsheets are used to record and track individual background, performance, and health data. While Excel works, it is susceptible to human error and creates a labor-intensive analyzation process. Implementing a purpose-built software/application program designed to provide a holistic profile on each individual candidate will decrease man hours spent on data collection/analytics and increase NSW/SOCOM’s ability to interpret and action data results.

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