Johnathan Mun

The Department of Defense (DoD) sends a large number of officers to various military universities to obtain graduate degrees, perform academic research, and acquire the technical skills and nontechnical competencies highly valued in their respective billets. The cost of sending an officer to a 1.5- to 2-year program for a master’s degree or doctorate may be upwards of $250,000–$500,000 per officer, plus the costs associated with temporary duty away from their billets for 3–4 years. The question is whether the benefits of such education and research are indeed greater than the cost incurred by the DoD. The proposed methodologies in this article apply theoretical constructs by using a systems approach to utilization; convolution methods to determine the frequency and quantity of use; and an analytical framework, empirical impact analysis, and work life-cycle approach.
The research also includes an examination of three short case studies that deal with the value of military research: (1) a return on investment (ROI) case study on the Naval Postgraduate School Acquisition Research Program (NPS ARP); (2) an ROI case study on the ROI of NPS education; and (3) an ROI case study on Defense Acquisition University. The research findings indicate a statistically significant positive impact on the retention of graduating officers, lower attendance cost, and greater DoD control of the courses covered. Finally, the author concludes that the ROI of a training initiative might be intrinsic, unmeasurable, and subjective, rather than simple applications of specific knowledge or learned skill sets on the job.

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The U.S. Navy is cutting its higher education funding according to the fiscal 2022 budget request released on May 28, 2021, which includes cuts in the U.S. Naval Academy (USNA), Naval Postgraduate School (NPS), and Naval War College (NWC) (Correll, 2021).

This research attempts to shed some light on the value propositions and return on investment (ROI) of military education and research. Education and research are inextricably linked in that both aspects contribute to the value of the Warfighter of the future. The intangible value of military education is significant in developing leadership skills; critical, creative, and strategic thinking skills; and quick tactical decision-making skills for junior and senior officers. In particular, as opposed to civilian universities, a military-oriented curriculum taught by faculty members with military-based academic and research backgrounds or knowledge allows the flow of institutional knowledge and expertise down to the students. And the strategic, tactical, and innovative changes and challenges of the future require continuous education of our joint forces to maintain a competitive advantage over our nation’s current and future adversaries.

**Background**

The value of education and research has always been a simple concept to understand but one that is fairly difficult to measure. We can generally agree that higher education adds significant value to the individual, both in terms of future economic returns through better and higher paying jobs, and in terms of incalculable and intangible values such as the deepening of one’s knowledge and perspective and the enrichment of one’s experience of the world. The literature is filled with descriptions of qualitative social benefits of higher education. However, the complete ROI for education is difficult to quantify economically and mathematically. And determining the value of highly specialized education such as military graduate education and research makes the value problem even more complex.

**Education and research are inextricably linked in that both aspects contribute to the value of the Warfighter of the future.**

The various U.S. military services send a large number of their mid-level officers (mostly O-3 and O-4 levels) to graduate programs to obtain graduate and advanced degrees as well as technical skills and nontechnical
competencies highly valued in their respective billets. Sending an officer to a 1.5- to 2-year graduate program costs upwards of $250,000 plus the opportunity cost of lost services (Ausink et al., 2016). A doctoral program costs upwards of $500,000 per officer, plus the respective soft opportunity costs of temporary duty away from their billets for 3–4 years (Department of the Navy, 2018). The question is whether the benefits of such education are indeed greater than the cost incurred by the U.S. Department of Defense (DoD). The current research looks at various novel ways to value the monetary ROI of these military education and research activities in sponsored DoD institutions.

The DoD Acquisition Workforce Development Fund (DAWDF) was created to provide “funds for the recruitment, training, and retention of acquisition personnel” (Ausink et al., 2016, p. ix). The purpose of the DAWDF is to “ensure the DoD Acquisition Workforce has the capacity, in both personnel and skills, to properly perform its mission; provide appropriate oversight of contractor performance; [and] ensure that DOD receives the best value for the expenditure of public resources” (Ausink et al., 2016, p. 1).

As mentioned, the value of education and research has always been a simple concept to understand but fairly difficult to measure, where higher education has value in terms of tangible economic and intangible values such as in-depth perspective and experience of the world. “The U.S. Navy invests over $3.3B across the FYDP [Future Years Defense Program] at NPS, NWC, and civilian schools” (Department of the Navy, 2018, p. 356); and in the past, the ROI in sending officers to such in-residence, on-campus education programs has been measured, to some degree, by retention or years of service beyond the education. The assumption is that these officers will apply the knowledge and skills learned in their respective billets or positions. Retaining our top warfighting talent and broadening their skill sets with the strategic and critical thinking attributes honed by
these educational programs help build an officer corps that would be more capable of executing the DoD’s strategy and enhancing our national security posture. Our future requires leaders who possess both the knowledge and the moral capacity to decide and act, and education is the key (Department of the Navy, 2018). Indeed, a 21st-century education for our military forces is vital to national security, and the Navy must change its evaluation and promotion system to value education (Kroger, 2019).

**Research Motivation**

Considering the importance of education and its associated costs, related research indicated that “the overall benefits in terms of ROI to the Navy from graduate education can be measured, given certain assumptions” (Kamarck et al., 2010, p. xv). But the report continues with a highly simplistic set of assumptions to generate said ROI. While most of the report analyzes the political landscape, military policies, and guidance on education, it includes only one paragraph explaining the potential benefits of an officer with a graduate degree. Using generalized and highly subjective, rough, order-magnitude estimates, it notes that “ROI can only be justified with an officer’s long-continued service and reutilization post-education” (Kamarck et al., 2010). This indicates that even a detailed study performed by one of the world’s most prestigious think tanks falls short of determining an adequately robust ROI measure for military education. Such prior research reinforces the fact that ROI determination in military education is not an easy undertaking. Therefore, this current research will not evaluate the efficacy of the political status or policy deliberations but will focus on a singular goal: determining a set of potentially viable methodologies and techniques from which a robust ROI for military education and research can be ultimately determined. Computing the actual ROI requires a longer research project, necessitating the collection of actual data from current and former graduate students, and their current billets and performance, and hence falls outside the scope of the present research.
Research Objective and Problem Statement

The DoD’s investment in education must be “fiscally disciplined focusing on the tenants [sic] of Warfighting First, Operate Forward, and Be Ready” (Department of the Navy, 2018, p. 120). Education resources need to be aligned with the highest priorities and ROI. The current research examines the challenges of determining the ROI of military education. The primary objective of the research is to provide a set of recommendations and methodologies, as well as additional insights and examples of how some of these methods can be applied.

Research Questions

The questions examined in this research follow:

1. How can ROI be defined and calculated within the realms of military education and research?
2. What is the ROI of military education and research within DoD-sponsored institutions such as the Naval Postgraduate School (NPS), U.S. Naval Academy (USNA), Naval War College (NWC), and Defense Acquisition University (DAU)?

Our future requires leaders who possess both the knowledge and the moral capacity to decide and act, and education is the key.

Technical Approaches and Outcomes of the Research

Various technical approaches are proposed in this research to extract the valuation of an ROI for military education and research. Three main areas are (a) theoretical constructs, where various underlying theories in economics, finance, mathematics, data sciences, artificial intelligence methods, and decision sciences are brought to bear; (b) integrated risk management, where advanced Monte Carlo simulation of the life cycle of value-added benefits of education are run, and portfolio optimizations are executed to determine the ROI and benefit of military education; and (c) knowledge value-added, where intangible and noneconomic values can be
monetized to generate quantifiable values to determine educational ROI. All three groups of methods are utilized in the case studies presented in this article.

Because they are very difficult to quantify and convert to a numerical ROI, this research dispenses with the detailed discussions of the soft benefits of graduate education (good judgment, better perception, risk management skills, common sense, presentation skills, leadership skills, etc.). Therefore, this current research focuses on more tangible skills that can be valued and modeled into an ROI measure.

**Theoretical Constructs**

Various theoretical approaches are examined in this research, from the Systems Approach with Utilization Metrics, Frequency-Quantity of Use, and Analytical Framework Approach to an Empirical Impact and Work Life-Cycle Approach. These methods will be combined with data science, artificial intelligence, and decision analytics approaches, such as Integrated Risk Management and Knowledge Value-Added, to determine the ROI of military education.

**Integrated Risk Management (IRM)**

IRM is a comprehensive methodology that is a forward-looking, risk-based decision support system incorporating various techniques such as Monte Carlo risk simulation, stochastic forecasting, portfolio optimization, strategic flexibility options, and economic business case modeling. Economic business cases using standard financial cash flows and cost estimates, as well as noneconomic variables such as Expected Military Value, Strategic Value, and other domain-specific Subject Matter Expert (SME) metrics (e.g., Innovation Index, Conversion Capability, Ability to Meet Future Threats, Force Structure, Modernization and Technical Sophistication, Combat Readiness, Sustainability, Future Readiness to Meet Threats) can be incorporated (Mun, 2016a). These metrics can be forecasted as well as risk simulated to account for their uncertainties and modeled to determine their return-to-education cost (e.g., ROI for
innovation or return on sustainability). Capital investment and acquisition decisions within education portfolios can then be tentatively made, subject to any budgetary, billet requirement, and knowledge capability constraints. Portfolio management is often integrated with IRM methods to provide a more holistic view in terms of educational programs.

**Knowledge Value-Added (KVA)**

KVA identifies the actual cost and value of an organization’s assets (human, educational, and technological), standard functional areas, or core processes. It identifies every process required to produce an output and the historical costs of those processes; the unit costs and unit values of products, processes, functions, or services can then be measured. By describing processes in common units, the methodology also permits market-comparable data to be generated. This ability is particularly important for nonprofits like the military and government organizations. Value is quantified using productivity metrics: return on knowledge (ROK) and return on knowledge investment (ROKI).

**Research Configuration**

The research configuration described in this section begins with a literature survey on the state of the art, identifying the challenges in computing ROI in the military in general, military education, and military research. Following the survey is a detailed description of the proposed theoretical constructs used in the research (systems approach, frequency and use, analytical framework, empirical impact, work life cycle, and intrinsic-intangible value), KVA, and IRM (Monte Carlo simulation, strategic real options, portfolio optimization). Next are the proposed theoretical constructs: (a) an ROI case study on the NPS Acquisition Research Program (ARP); (b) an ROI case study on the ROI of NPS education; and (c) an ROI case study on the DAU. A summary of the key conclusions follows the case studies.

**Literature Survey**

In general, businesses have to question the value of their training and educational investments, as well as balance them against other investment opportunities that are more cut-and-dried. For instance, invest in a certain machine, and it generates a higher production output that can be measured; in turn, it generates additional revenue against the original investment. In such situations, ROI on the machine can be computed easily by performing a cost-benefit analysis. However, when evaluating the value added by education, the math becomes more complicated, if not intractable.
Challenges in Computing ROI in the Military

A decision maker’s primary responsibility is to decide which investment alternatives provide the greatest return with the least risk of loss. In civilian organizations, numerous methods and models assist with these decisions (Mun, 2016b), but in military and government agencies, these methods often fall short because typical governmental and military investments do not provide for a monetary return. Instead, they provide “intangible returns such as national defense, public safety, goodwill, and other public goods that are difficult, but not impossible, to quantify” (MacLeod & Dinwoodie, 2015, p. 328).

Various economic models for calculating ROI exist, and most require only a few basic inputs such as costs, benefits, time horizon, and risks. The “benefit of calculating ROI of government investments is to save costs over other alternatives” (MacLeod & Dinwoodie, 2015, p. 328), but scholarly research into assessing the ROI of complete military systems is lacking or, at least at the time of writing, insufficient and unsatisfying. In MacLeod and Dinwoodie’s (2015) article, they present “a method that efficiently compares equipment options using a composite index that generates a normalized measure of performance return. By objectively assessing the equipment’s ROI, leaders can eliminate low-value and inefficient programs, ultimately saving U.S. taxpayer dollars” (p. 328).

For fully funded education, the Service must pay not only the cost of the education but the pay and allowances allocated for education associated with an officer’s billet.

ROI in Military Education

The DoD sends its officers to graduate-level institutions each year to obtain advanced degrees, primarily to fill positions in their Services where duties require the knowledge and skills gained in graduate school. Furthermore, the benefits of a graduate education extend beyond the specific assignment for which the officer was educated, applying to subsequent assignments as well. For fully funded education, the Service must pay not only the cost of the education but the pay and allowances allocated for education associated with an officer’s billet. The Service also assumes the opportunity cost of the officer’s services while away on temporary duty, and that same officer will also have to forgo any experience that might have been gained while in school. Evaluating the qualitative effects of a graduate
education poses several challenges. DoD educational policy suggests broader and more extensive use of graduate education than simply filling billets that have been determined to require it (Kamarck et al., 2010). The question, therefore, is whether the benefit gained from a graduate military education is worth the high cost.

**ROI in Research**

University research in the United States is world-class, and to continue such leadership requires major funding. Public and private sectors have risen to meet that financial need through increased support of university research. However, with this increased investment, greater accountability is needed. Bessette (2003) recommends that public funding agencies complete the following actions:

- Quantify and tabulate research outputs such that economic impacts are reported as a percent return on investment or ROI. With this model, multiple stakeholders can evaluate divergent research technologies using a measurement that is familiar to scientists, business leaders, elected officials, and the public. (p. 355)

Trewyn (2001) points out that

- Public research universities face many challenges..., not the least of which involves documenting the value-added outcomes that derive from the teaching, research, and public service missions of the institution. Governing boards, accrediting bodies, funding agencies, state legislators, taxpayers, and the American citizenry in general want to know. (p. 71)

In fact, investment bankers and stockbrokers should not be the sole individuals interested in ROI; a university’s prospective students and parents want to know what sort of ROI can be obtained from the education program. However, estimating the ROI in scientific research proves to be elusive and difficult. According to Grant and Buxton (2018), valuing benefits in monetary terms is required because the time between investment and return is typically long. In addition, international research collaboration can make it difficult to attribute returns to national investments, where any ROI computations will require large amounts of data over long periods of time. But the problem is,

- A massive amount of intellectual capital gets created every day from $150 billion in annual research funding allocated to federal laboratories and universities in the United States. Unfortunately, most of that intellectual capital never makes it to the market and does not generate any return on investment. (Nag, 2018, para. 1)
Methodology—Proposed Theoretical Constructs

This section examines the following theoretical approaches:

- the *Systems Approach with Utilization Metrics*, where the ROI can be determined using production outputs
- the *Frequency and Quantity-of-Use Approach*, which looks at both the frequency and quantity of learned knowledge used to determine the value of the knowledge learned
- an *analytical framework approach* that is used if cross-sectional data can be gathered
- the *Empirical Impact Approach*, used to determine if, indeed, statistically significant added value exists in post-training compared to situations without any training
- the *Work Life-Cycle Approach*, which can be used to determine the life-cycle valuation of education

These methods will be combined into a single robust set of methods with modern data science and decision analytics approaches such as *IRM* and *KVA*, as discussed in more detail in the sections that follow, to simulate and triangulate the ROI of military education.

**Systems Approach with Utilization Metrics**

The standard utility model originally proposed by Schmidt et al. (1982) can be adapted to a more modern systems approach with the utilization model specified as:

\[ \delta U = N[(\Phi_T - \Phi_{UT})\Omega\sigma - C] \]  

(1)

where \( \delta U \) is the net monetary value of training; \( N \) is the number of trained individuals; \( \Phi \) is the output generated by trained, \( T \), and untrained, \( UT \), individuals; \( \Omega \) is the duration of the training; \( C \) is the cost of the training;
and $\sigma$ is the standard deviation of the performance output of the untrained group. Therefore,

$$ROI = \frac{\delta U}{C} \times 100\%$$

**Frequency and Quantity-of-Use Approach**

To quantify the value of the knowledge learned, this approach applies the frequency and quantity of learned knowledge used. The approach assumes a certain frequency that a specific type of learned knowledge is triggered or used and is further assumed to have a discrete Poisson distribution. Next, the quantity or amount of the learned knowledge that is used (this can be converted into monetary value or some other economic value or kept simply as an index of output or output ratios such as those computed using the KVA methodology discussed previously) and can be distributed from among a group of continuous distributions (e.g., Fréchet, Gamma, etc.). Specifically, let $X$, $Y$, and $Z$ be real-valued random variables whereby $X$ and $Y$ are independently distributed with no correlations. Further, we define $F_X$, $F_Y$, and $F_Z$ as their corresponding cumulative distribution functions (CDFs), and $f_X$, $f_Y$, $f_Z$ as their corresponding probability density functions (PDFs). Next, we assume that $X$ is a random variable denoting the frequency that a certain type of learned knowledge is triggered or used and is further assumed to have a discrete Poisson distribution. $Y$ is a random variable denoting the quantity or amount of the learned knowledge that is used (this can be converted into monetary value or some other economic value or kept simply as an index of output or output ratios such as those computed using the KVA methodology) and can be distributed from among a group of continuous distributions (e.g., Fréchet, Gamma, Log Logistic, Lognormal, Pareto, Weibull, etc.). Therefore, $Frequency \times Quantity$ equals the **Total Unit Quantified**, which we define as $Z$, where $Z = X \times Y$ (Mun, 2016a).

Then the Total Usage formula yields:

$$F_Z(t) = P(Z < t) = \sum_k P(XY < t | X = k) \times P(X = k)$$

$$F_Z(t) = P(Z < t) = \sum_k P(kY < t) \times P(X = k)$$

where the term with $X = 0$ is treated separately:

$$F_Z(t) = P(0 < t | X = 0) \times P(X = 0) + \sum_{k=0} P(Y < t \frac{1}{k}) \times P(X = k)$$

$$F_Z(t) = \sum_{k=0} f_Y(t) \frac{1}{k} + P(X = 0)$$

(2)
The next step is the selection of the number of summands in Equation 2. As previously assumed, $f_X(k) = P(X = k)$ is a Poisson distribution where $P(X = k) = \frac{\lambda^k e^{-\lambda}}{k!}$ and the rate of convergence in the series depends solely on the rate of convergence to 0 of $\frac{\lambda^k}{k!}$ and not on $t$, whereas the second multiplier $P(Y < \frac{t}{k}) \leq 1!$. Therefore, for all values of $t$ and an arbitrary $\delta > 0$, there is a value of $n$ such that:

$$\sum_{k=n}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!} < \delta$$  (3)

In our case, $\delta$ can be set, for example, to 1/1000. Thus, instead of solving the quantile equation for $t_p$ with an infinite series, on the left-hand side of the equation, we have:

$$F_Z(t) = P(Z < \eta) = \sum_k \frac{\lambda^k e^{-\lambda}}{k!} = p$$  (4)

We can then solve the equation:

$$F_Z(t, n) = \sum_{k=n}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!} F_Y\left(\frac{t}{k}\right) = p$$  (5)

with only $n$ summands.

For example, if we choose $p = 0.95$, $\delta = 1/1000$ and $n$ such that Equation 3 takes place, then the solution $t_p(n)$ of Equation 4 is such that:

$$|F_Z(t_p(n)) - F_Z(t_p(n), \eta)| < \frac{1}{1000}$$  (6)

In other words, a quantile found from Equation 5 is almost the true value, with a resulting error precision in the probability of less than 0.1%.

The only outstanding issue that remains is to find an estimate for $n$ given any level of $\delta$. We have:

$$\sum_{k=n}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!} F_Y\left(\frac{t}{k}\right) < e^{-\sum_{k=n}^{\infty} \frac{\lambda^k}{k!}}$$  (7)
The exponential series \( R_n(\lambda) = \sum_{k=n}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!} \) in Equation 7 is bounded by \( \frac{\lambda^{n+1} e^{-\lambda}}{(n+1)!} \) by applying Taylor’s Expansion Theorem, with the remainder of the function left for higher exponential function expansions. By substituting the upper bound for \( R_n(\lambda) \) in Equation 7, we have:

\[
\sum_{k=n}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!} F_Y\left(\frac{t}{k}\right) < \frac{\lambda^{n+1}}{(n+1)!}\]

Now we need to find the lower bound in \( n \) for the solution of the inequality:

\[
\frac{\lambda^{n+1}}{(n+1)!} < \delta
\]

Consider the following two cases:

If \( \lambda \leq 1 \), then \( \frac{\lambda^{n+1}}{(n+1)!} \leq \frac{1}{(n+1)!} \leq (n+1)^{(n+1)} e^n \). Consequently, we can solve the inequality \( (n+1)^{(n+1)} e^n < \delta \). Since \( n^n \) grows quickly, we can simply take \( n > -\ln \delta \).

For example, for \( \delta = \frac{1}{1000} \), it is sufficient to set \( n=7 \) to satisfy Equation 9.

If \( \lambda > 1 \), then, in this case, using the same bounds for the factorial, we can choose \( n \) such that:

\[
(n+1)(\ln(n+1) - \ln \lambda - 1) > -\ln \delta - 1
\]

To make the second multiplier greater than 1, we will need to choose \( n > e^{2\ln \lambda - 1} \).

**Approximation to the solution of the equation \( F_Z(t) = p \) for a quantile value**

From the previous considerations, we found that instead of solving \( F_Z(t) = p \) for \( t \), we can solve \( F_Z(t,n) = \sum_{k=n}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!} F_Y\left(\frac{t}{k}\right) = p \) with \( n \) set at the level indicated above. The value for \( t_p \) resulting from such a substitution will satisfy the inequality \( |F_Z(t_p(n)) - F_Z(t_p(n),n)| < \delta \).

**Solution of the equation \( F_Z(t,n) = p \) given \( n \) and \( \delta \)**

By moving \( t \) to the left one unit at a time, we can find the first occurrence of the event \( t = a \) such that \( F_Z(a,n) \leq p \). Similarly, moving \( t \) to the right, we can find \( b \) such that \( F_Z(b,n) \geq p \). Now we can use a simple Bisection Method or other search algorithms to find the optimal solution to \( F_Z(t,n) = p \).
Analytical Framework Approach

An analytical framework approach is used if cross-sectional data can be gathered—specifically, data on measurable outputs such as those in a standard economic production function. Nonlinear regression and generalized linear models can be run, assuming continuous data variables, and Logit/Probit/Tobit models can be run on discrete and truncated limited dependent variables (Mun, 2021).

Production function

\[ Y = f(\epsilon, \tau, \phi, \theta, \omega, \ldots, \epsilon) \]  

(11)

where \( Y \) is the measurable production output, \( \epsilon \) is the education and training investment amount, \( \tau \) is the technology supporting said production, \( \phi \) is the capital investment, \( \theta \) is the organizational design structure, \( \omega \) is the environmental impacts, and \( \epsilon \) is the forecast error in the model. Therefore, we can determine \( \frac{\partial Y}{\partial \epsilon} \), and this will represent the expected change in the average value of production with respect to each unitary change in educational investment after accounting for all the other variables. In other words, this is the net effect of educational contribution to overall outcomes.

Performing some partial differentials, we obtain:

\[
\frac{\partial Y}{\partial \epsilon} = \frac{\partial f}{\partial \epsilon} \frac{\partial \tau}{\partial \epsilon} + \frac{\partial f}{\partial \phi} \frac{\partial \phi}{\partial \epsilon} + \frac{\partial f}{\partial \theta} \frac{\partial \theta}{\partial \epsilon} + \frac{\partial f}{\partial \omega} \frac{\partial \omega}{\partial \epsilon}
\]  

(12)

A nonlinear regression can be run on Equation 12, assuming continuous data variables, or Logit, Probit, and Tobit models can be run on discrete and truncated limited dependent variables (Mun, 2016b).

Empirical Impact Approach

The Empirical Impact Approach can be used to determine if, indeed, a statistically significant added value exists in post-training compared to situations without any training (Mun, 2021). Multivariate, unequal variance, general linear models can be applied. If the standard deviations of these two sample datasets (with and without the requisite training and education) are
still unknown but assumed to be different, combining them into a single pooled estimate as done previously would be inappropriate (Mun, 2016a). Therefore, the sample standard deviations ($s$) will be used independently to estimate the population standard deviations ($\sigma$). Nonetheless, normality of the underlying dataset is assumed, although this assumption becomes less important with larger datasets. The two-sample unequal variance $t$-test would be needed, and its specifications are described in Equation 13:

$$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{\sqrt{s_1^2/n_1 + s_2^2/n_2}}$$

and

$$df = \frac{(s_1^2/s_1^2)^2}{n_1 - 1} + \frac{(s_2^2/s_2^2)^2}{n_2 - 1}$$

Equation 13

$H_0: \mu_1 = \mu_2$, that is, the two samples’ means are statistically similar.

In addition, if the collected data are limited and categorical or ordinal in nature, or if there are significant biases in the data, we can apply the Kruskal–Wallis (KW) test, which is an extension of the Wilcoxon Signed-Rank test by comparing more than two independent samples. The corresponding parametric test is the One-Way Analysis of Variance (ANOVA), but unlike the ANOVA, the KW does not require that the dataset be randomly sampled from normally distributed populations with equal variances. The KW test is a two-tailed hypothesis test where the null hypothesis is such that the population medians of each treatment are statistically identical to the rest of the group; that is, no effect is evident among the different treatment groups. Similar to the ANOVA method, the KW tests the following hypothesis:

$$H_0: m_1 = m_2 = ... = m_k \text{ for } i = 1 \text{ to } k$$

(population medians are identical)

The method starts off with $k$ variables to be tested. For each variable, the data are ranked from smallest to largest, with the smallest value receiving the rank of 1, and all tied ranks are assigned their average values. Then, all the ranks are summed for each variable, yielding a list of summed ranks $\Sigma(R1), \Sigma(R2), ..., \Sigma(RK)$. Then, the $H$ statistic is computed using:

$$H = \frac{12}{N(N+1)} \left[ \frac{(\Sigma R_1)^2}{n_1} + \frac{(\Sigma R_2)^2}{n_2} + ... + \frac{(\Sigma R_k)^2}{n_k} \right] - 3(N+1)$$

Equation 14

The calculated $H$ is compared to critical $H$ values computed using a chi-square distribution with degrees of freedom $df = k - 1$.

**Work Life-Cycle Approach**

Finally, the Work Life-Cycle Approach can be used to determine the life-cycle valuation of education. According to Kamarck et al. (2010), several past studies of individuals with privately funded education such as an MBA
or other technical master’s degree show that they earn an average rate of return of at least 46% more than a bachelor’s degree in a 2008 study, and the ROI ranges between 27% to 36% for an MBA.

However, the application of a similar methodology might not work well within the DoD because the U.S. military’s human resource environment is such that it is a closed internal and hierarchical structure. For instance, an officer’s pay is based on his or her rank and years of service, regardless of educational background. It can be argued that higher education may result in higher efficiency and productivity, thereby increasing the speed of promotions, but these are fairly difficult to quantify. An alternate approach might be to consider the years of service beyond the time the education was received. This amounts to the value of retention—in other words, how much the military can save in costs by having a higher retention and reutilization rate than by having to train a new officer to replace a billet due to attrition. Using comparables, traditional financial metrics can be applied to determine the ROI. The Work Life-Cycle Approach model might look something like:

$$\text{ROI} = \frac{\Psi [f(h, \tau, o) + \delta P_t(V_t)] - C_0}{C_0}$$

where $\Psi$ is the years of service; $C_0$ is the cost of education; $\delta P_t$ is the change in productivity due to the new knowledge gained (with a nonlinear depreciation over time); $V_t$ is the salary and overhead cost of the billet; $\tau$ is the learning curve measured in time to train a new officer to adequately replace the outgoing officer; and $o$ is the opportunity cost of lower retention rate or cost of attrition. With the proper experimental approach, these variables can be adequately measured to provide a robust ROI measure.

As a matter of comparison, for privately funded educational programs, one can much more easily model the ROI where we can use a traditional NPV to determine the ROI such as:

$$\text{NPV} = \sum_{i=1}^{k+i} [S_i \pi_t - S_0 \pi_0] e^{-rt} - \sum_{i=1}^{j} C_i e^{-rt}$$

$$\text{ROI} = \frac{\sum_{i=1}^{k+i} [S_i \pi_t - S_0 \pi_0] e^{-rt} - \sum_{i=1}^{j} C_i e^{-rt}}{\sum_{i=1}^{j} C_i e^{-rt}}$$

where $S_i$ is the salary with the education; $S_0$ is the presumably lower salary without the requisite education; $\pi$ is the inflationary and natural growth rate of the salary over the time period $t$, each with a different acceleration slope for educated $e$ and uneducated $0$ rates; $r$ is the reinvestment rate or
opportunity cost of the cost of education $C_t$ that changes over time, over the course of the education $j$; and the analysis is performed on the life cycle of the individual’s working life, starting from the current age $n$ to the retirement age $k$ (the age of natural attrition, retirement age, or the average age of leaving the employment market). These inputs can be Monte Carlo risk-simulated using the IRM Approach.

Creative thinking, leadership, strategic thought, and quick tactical decision-making skills can be honed through education, especially when taught by a faculty with military-based academic and research backgrounds.

Intrinsic and Intangible Value Propositions

Intangible and intrinsic value exists in both military education and research but cannot be readily quantified in standard ROI calculations. In nonmilitary college education in the private sector, higher education brings with it various intangible added value, such as value to society (Blagg & Blom, 2018) through diversification and innovation of the nation’s economy, encourages graduates to be more civic-minded, increases wages and lowers crime rate, increases tax receipts of the country, increases productivity and output, lowers expenditures on policing due to lower crime, and lowers dependencies on social welfare programs. However, the intangible value of military education is different. The military is a closed vertical society. A survey of past naval students at NPS, NWC, and USNA indicated that approximately 96% agreed that formal education was extremely useful or very useful in their naval careers. The study found that military personnel have more positive perceptions of their institutions than civilian personnel.

We can certainly conclude that the intangible value of military education is significant in developing leadership and critical thinking skills for junior as well as senior officers. The military-oriented curriculum taught by faculty members with former military experience or knowledge allows the flow of institutional knowledge down to the students. Although these intangible and qualitative aspects of military education are significant, this current research focuses on the more quantitative measure of ROI. Nonetheless, creative thinking, leadership, strategic thought, and quick
tactical decision-making skills can be honed through education, especially when taught by a faculty with military-based academic and research backgrounds. And the strategic, tactical, and innovative changes and challenges of the future require continuous education of our joint forces to maintain a competitive advantage over our current and future adversaries.

**Knowledge Value-Added**

KVA is an objective, quantifiable method for measuring the value associated with a system and the subprocesses within the system. The value measurements of each process are ratio-scale numbers, allowing analysts to compare them with the values from other subprocesses to determine their relative effectiveness. Productivity ratios such as ROK—the output of a process divided by the process cost—can be adapted for use in KVA. The ROKs and ROIs, which are always 100% correlated, give managers information about the amount of value a process generates compared to the amount of money spent to create the value.

**Integrated Risk Management**

IRM is a system developed by the author and designed to provide management with the ability to analyze the risk associated with the development of projects or initiatives. It combines several commonly accepted analytical procedures—such as predictive modeling with Monte Carlo simulation, real options analysis, and portfolio optimization—into a single, comprehensive methodology. The methodology uses existing techniques and metrics such as discounted cash flow, ROI, and other metrics within the analytical processes to improve the traditional manner of evaluating potential projects within a company or in an organization like the DoD. In contrast to the other methodologies, IRM focuses on the risk involved with a decision. It seeks to mitigate negative effects from risk while maximizing rewards from potential outcomes. At its core, IRM is a technique to provide decision makers with the best analytic information available to use during the real options process. All of these methods can be combined in various ways to create a robust set of methodologies to determine the true ROI of military education and research.
Case Study: NPS Acquisition Research Program

The DoD Acquisition Workforce Development Fund was created to provide “funds for the recruitment, training, and retention of acquisition personnel of DOD” (Ausink et al., 2016, p. 1). The purpose of the DAWDF is “to ensure the DoD Acquisition Workforce has the capacity, in both personnel and skills, to properly perform its mission; provide appropriate oversight of contractor performance; [and] ensure that DOD receives the best value for the expenditure of public resources” (Ausink et al., 2016, p. 1). Within this context, NPS graduate students have been collaborators in multiple research opportunities in the NPS ARP and can now bring these analytical skills to the acquisition workforce (AWF).

The NPS ARP should be seen as a research and development (R&D) organization that generates innovations from research that may take years to bear fruit. ARP research is focused on possible scenarios that might add value, reduce cost, provide savings, add capabilities, and provide value-added insights that will make acquisition processes more productive and efficient. It should also be recognized that typical R&D organizations yield a small number of breakthrough products and services, and ARP research output should be viewed the same way. ARP research studies provide estimates of the future increases in the ROI of technologies to support core U.S. Navy processes such as shipbuilding and ship maintenance. Many DoD leaders see ROI as a measure of cost savings, often without reference to the value created by an asset, intellectual capital, or other forms of value production. In a nonprofit or governmental organization, an ROI ratio requires a revenue surrogate in common units, and establishing such units is what KVA does. In the following summaries of the ROI on ship maintenance and shipbuilding.
core processes, the Housel and Mun ARP studies used market comparables to establish an estimate of the price per common unit of output of core processes to provide a monetized revenue surrogate. The cost of doing this kind of research, performed by SMEs and professionals at NPS, compared to the cost of doing such studies by a comparable consulting company (e.g., McKinsey) would likely be at least three times as much due to the steep learning curve by non-SMEs (Ford et al., 2017; Housel et al., 2015; Majchrzak et al., 2017).

Research-based ROI

Naval research and education are not separate tasks but tend to coexist alongside the innovation engines of the country. Several ARP studies provided estimates of the potential ROI increases in Navy ship maintenance and shipbuilding core processes. The following tables summarize the results of the ship maintenance and shipbuilding ROI increase estimates from incorporating three technologies into core processes. Table 1 shows that the detailed design and outfitting phases of shipbuilding benefit the most from the use of the technologies and that the sea trials and postshakedown maintenance benefit the least. Even if several orders of magnitude off, the ROI would still yield a highly significant percentage. We would maintain that the ARP research’s contribution to this specific project (even with a highly conservative estimate that it is worth 1/1000 of ROI) is above 240%.³

| TABLE 1. ROI PROJECTIONS FOR SHIPBUILDING USING PLM, 3DP, AND 3D LST TECHNOLOGIES |
|-----------------------------|---------------------|---------------------|---------------------|---------------------|
| Item | Process or Phase | As-Is ROI | To-Be ROI | Change in ROI | Automation Tools |
| 1 | Concept Design | -2% | 94% | 96% | AM, PLM |
| 2 | Detailed Design | 561% | 1826% | 1265% | AM, PLM |
| 3 | Preconstruction Planning | 218% | 244% | 25% | PLM |
| 4 | Block Fabrication | -67% | -31% | 36% | 3DLS, AM, PLM |
| 5 | Block Assembly and Outfitting | -17% | 116% | 133% | 3DLS, AM, PLM |
| 6 | Keel Laying and Block Erection | -63% | 1% | 64% | 3DLS, AM, PLM |
| 7 | Predelivery Outfitting | 505% | 1270% | 764% | 3DLS, AM, PLM |
| 8 | System Testing | 280% | 582% | 301% | 3DLS, PLM |
| 9 | Sea Trials | 1018% | 961% | -57% | PLM |
| 10 | Postdelivery Outfitting | 476% | 1243% | 767% | 3DLS, AM, PLM |
| 11 | Postdelivery Tests | 239% | 282% | 42% | PLM |
| 12 | Postshakedown Maintenance | 221% | 201% | -20% | PLM |
| Totals | 135% | 464% | 329% |

Note. 3DLS = 3D Laser Scanning; 3DP = 3D Printing; 3DLS = 3D Landing Ship, Tank; AM = Aviation Structural Mechanics; PLM = Precision Landing Mode.
Table 2 shows research on a Make or Buy analysis of the impacts of whether the Navy should execute 3D printing operations, 3D laser scanning technology, and collaborative product life-cycle management on ship maintenance and modernization cost savings that had ROI of the common unit of output (high-, medium-, or low-complexity parts) ranging from 103% to 1,120% in ROI per year per ship, averaging at 600%. These ROI values can be multiplied by a factor of 100 over the next 10 years when more ships implement the recommendations. Again, we would maintain that the ARP research’s contribution to this specific project is above 600%. Even if the ARP study cost savings estimates were off by several orders of magnitude, they would well have been large enough to justify the overall investments in the ARP research studies.

Table 3. A Standard PWC or McKinsey Research Program Cost

<table>
<thead>
<tr>
<th></th>
<th>Hourly (2022 Levels)</th>
<th>% Utilization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Partner</td>
<td>$800</td>
<td>2%</td>
</tr>
<tr>
<td>Manager</td>
<td>$600</td>
<td>5%</td>
</tr>
<tr>
<td>Senior Consultant</td>
<td>$500</td>
<td>10%</td>
</tr>
<tr>
<td>Analyst</td>
<td>$400</td>
<td>15%</td>
</tr>
<tr>
<td><strong>Total Cost</strong></td>
<td><strong>$312,000</strong></td>
<td></td>
</tr>
</tbody>
</table>

*Note.* PWC = PricewaterhouseCoopers.
Worst-Case Scenario ROI

Next, we can show the absolute worst-case scenario ROI in Table 3 and Figure 1. The annual ARP cost is $1.7 million, with 15 research projects on average. If done similarly by a third-party consulting company such as PricewaterhouseCoopers or McKinsey, the research usually runs around $250,000–$350,000 over the course of 1 year. For instance, the standard research takes 12 months, and a standard project requires a partner, manager, and, at the very least, a senior consultant and analyst. Even with the assumption that only 2% to 15% of their hours are used for the project, the average cost is $312,000 per research project. Table 3 illustrates the computations.

A risk-based Monte Carlo simulation of 100,000 trials was run, and we see from Figure 1 that the average ROI, even in the worst-case scenario, is **120.5%**, with a 100% probability that the ROI of the ARP program returns a positive value. In other words, assuming that we separate and put aside for the moment the actual and significant value of the actionable intelligence from the research programs and focus solely on the cost savings of the research, we generate a value of $3.75 million for the investment of $1.7 million for research and operating expenses. This creates an ROI of **120.5%** in this worst-case scenario (the 95% confidence interval has the ROI between 105% and 136%).
Value of Knowledge and ROI

The ARP researchers use graduate students to assist in their work. These MS, MBA, and PhD students are active-duty Navy and Marine officers who will return to their commands armed with valuable hands-on practical research knowledge and experience that are second to none. We quantify these knowledge value-added learnings from the ARP research they have conducted and monetize them using the KVA approach, as seen in Table 4. The ROI on a single ARP research program is calculated to be 253%.

<table>
<thead>
<tr>
<th>TABLE 4. VALUE OF KNOWLEDGE</th>
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</thead>
<tbody>
<tr>
<td>Experiential Graduate ARP Research</td>
</tr>
<tr>
<td>Number of Days per Year</td>
</tr>
<tr>
<td>Normalized Total Knowledge Units</td>
</tr>
<tr>
<td>Accumulated Knowledge Used</td>
</tr>
<tr>
<td>Hours/Day Used</td>
</tr>
<tr>
<td>Units of Knowledge Used/Day</td>
</tr>
<tr>
<td>Total Knowledge Units</td>
</tr>
<tr>
<td>Consultant Annual Salary</td>
</tr>
<tr>
<td>Comp Price Per Unit of Knowledge</td>
</tr>
<tr>
<td>Daily Value</td>
</tr>
<tr>
<td>Value/Year Per Student</td>
</tr>
<tr>
<td>Average Students Exposed</td>
</tr>
<tr>
<td>Valuation for Each Category</td>
</tr>
<tr>
<td>Total Valuation of Knowledge</td>
</tr>
<tr>
<td>ARP Total Cost (Research Only)</td>
</tr>
<tr>
<td>ROI of ARP in Knowledge Terms</td>
</tr>
</tbody>
</table>

The calculations assume that the graduate students will populate the future AWF. We also assume that the acquisition case studies that have been developed from ARP research and are used to teach a wide variety of acquisition, business, public policy, and information science classes provide important lessons that translate into future acquisition workforce knowledge. We have normalized the knowledge into common units of learning time and assumed that the graduate students would apply their acquisition knowledge to acquisition challenges and opportunities for adding value to the core acquisition processes. Those students who attend the annual Acquisition Symposium are also likely to pick up some valuable key lessons that they can then apply to future acquisition decision-making situations. The opportunities to obtain acquisition
knowledge in these three learning contexts are summarized in Table 4. These estimates are very conservative and represent 1 year of learning opportunities. The central assumption in this analysis, as in most educational value analyses, is that the students will be able to apply their knowledge once they leave NPS. As it is put to use, it will generate value for the acquisition workforce.

In summary, we can quantify that the ARP’s ROI, based on an annual investment of $1.7 million, will range from the absolute worst case of 121% to an average of 240–600% for each specific program (Table 5). The KVA method pegs the ROI at 253%. Therefore, using standard industry best practices, we conclude the average conservative ROI for the entire ARP program to be around 304% for the approximate annual $1.7 million total investment for research and operating expenses. These ROI estimates should be seen as the minimum value because a significant intangible value exists when we run research programs with uniformed graduate students and when we hold the annual Acquisition Symposium.

<table>
<thead>
<tr>
<th>TABLE 5. SUMMARY ROI FOR MILITARY RESEARCH AND DEVELOPMENT</th>
</tr>
</thead>
<tbody>
<tr>
<td>ROI for Military Research and Development (e.g., ARP)</td>
</tr>
<tr>
<td>Minimal Worst-Case ROI</td>
</tr>
<tr>
<td>Most Likely ROI</td>
</tr>
<tr>
<td>Range of ROI Depending on Program</td>
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</tbody>
</table>

**Case Study: The Value and ROI of NPS**

**Strategic and Intangible Value**

In this section, we look at NPS as an analytical case study of ROI on military education. It is at the forefront of providing specialized graduate, postgraduate, and certificate-level programs supporting U.S. national security policies and priorities, including counterterrorism, homeland security, and security cooperation. While the Navy has the option to send its officers to private and public universities, an analysis of alternatives shows that in doing so, the Navy would sacrifice its agility and responsiveness and potentially even incur a higher cost. In fact, according to the *NPS Value Book*, “[cost] comparisons are being made erroneously between civilian universities market price (tuition) and NPS full costs. Tuition covers 15–25% of public and 25–30% of private universities’ full cost ... Analysis has shown NPS to be average to below average in total costs” (Naval Postgraduate School, 2012a, p. 16). The higher cost of external
civilian universities, the lack of direct application to the military, and the loss of control by the Navy or DoD over the curriculum show that civilian universities cannot meet the Navy’s long-term needs for military education.

The cost-effectiveness of an NPS education was previously reported in the Memorandum for the Deputy Chief of Naval Operations (Gates et al., 1998). Specifically, it stated that if NPS and civilian programs differ in duration (e.g., 18 versus 28 months), any cost comparison must include the students’ salaries and benefits. The Department of the Navy’s Director, Assessment Division, estimated that the annual cost of salary, benefits, and housing per NPS-resident officer totaled $63,300, as compared to approximately $72,300 per officer student at other comparable civilian institutions. Higher civilian costs exist because most NPS officers live in base housing (Gates et al., 1998).

NPS was rated as high by the Base Realignment and Closure (BRAC) Technical Joint Cross Service Group (TJCSG) when over 146 technical facilities were examined to determine their value to defense Research, Development, Test and Evaluation (RDT&E; Department of Defense, 2005). The report identified the most important 13 technical areas in developing military strength, then evaluated each technical facility over three functional areas: research, development and acquisition, and test and evaluation.

While the Navy has the option to send its officers to private and public universities, an analysis of alternatives shows that in doing so, the Navy would sacrifice its agility and responsiveness and potentially even incur a higher cost.

Naval maritime supremacy requires a Navy-oriented focus to meet the technical and professional challenges of the 21st century and beyond. The U.S. Navy requires focus on naval professional development by meeting the requirements of technological innovation and knowledge quality control. For the Navy, undergraduate, graduate, and professional military education is an investment, and, like any investment, its returns need to be evaluated.4

**Tactical and Tangible Quantitative ROI for NPS**

In order to quantitatively measure a robust ROI for NPS educational programs, the quantifiable benefits and costs are first obtained and analyzed, and later invoked in a life-cycle cost-benefit model with simulation. ROI is commonly a monetary or economic metric. This means
we can determine ROI only based on the main tangible monetary benefits of an NPS education, such as the lower tuition costs and higher retention rate of NPS graduates. The retention rates modeling uses the Analytical Framework Approach, whereas the life-cycle cost-benefit modeling uses the Work Life-Cycle Approach previously examined. The life-cycle model used a modification of the Systems Approach with Utilization Metrics combined with the Frequency and Quantity-of-Use Approach. This was complemented with IRM methods in applying Monte Carlo simulation. The following subsections break down the methods into quantized analytical chunks.

**NPS Graduates Show Higher Retention Rates in the Navy**

Cohort data from the 1987 through 1995 graduating classes (Naval Postgraduate School, 2012b) show that 2 years after graduation, the retention rates are relatively high for NPS MS and PhD graduates, non-NPS civilian MS-level graduates, and non-NPS civilian BS-level graduates, ranging from 99.31% to 95.78% on average. *This high rate of retention in the first few years is to be expected as officers sent to graduate programs typically are required to “pay back” their education costs with guaranteed service for several years.* In comparison, at 17–22 years postgraduation, the NPS graduates showed a 55.42% DoD retention compared to 46.23% for non-NPS MS graduate programs and 13.07% for other non-NPS BS undergraduate programs. The total sample sizes for the data aggregation were 3,254 for NPS, 2,255 from other graduate programs, and 24,344 from other undergraduate programs.

An analysis of the cross-sectional retention bands for the three groups indicates a smooth laminar flow across all cohorts with respect to 2- and 4-year retention rates. More disturbance seems to be around the 10-year milestone, especially for the undergraduate degree holders, and less so for the NPS graduates. The highest volatility appears in the undergraduate degree holders’ cross-section starting from the 10-year through the 15-year and 20-year milestones. A time-series analysis indicates sharp 10-year declines in retention. The drop is most precipitous for undergraduate degree holders. The analysis also shows a significant difference between the BS and
MS NPS graduates and a smaller but visually distinct difference between non-NPS MS and NPS graduates.

The average rates across these various cohorts in time reveal differences among all groups, and these differences are tested statistically using parametric ANOVA for single factor multiple treatments and confirmed with a nonparametric KW test. The null hypotheses tested were that, for each retention milestone, no statistically significant difference was evident among all three groups of graduates when comparing all groups at once. While both the ANOVA and KW tests can identify whether any differences surfaced among the three groups tested, they do not identify where the differences come from. Hence, further analyses using the one-tailed paired parametric t-test of two independent variables with unequal variances were run on every combination of the three groups, and the results were confirmed using the nonparametric two-variable Wilcoxon signed-rank test. The parametric tests were applied because we have large sample sizes, as noted previously, for example, up to 24,344 graduates in all the cohorts for the non-NPS undergraduate programs. This allows us to take advantage of the law of large numbers and the central limit theorem, justifying the use of parametric tests. The nonparametric tests were also applied because the averages were used, and the larger sample sizes were reduced to a smaller subset, where the underlying normality assumption may or may not be violated. In addition, the natural truncation of percentages (i.e., 0% to 100%) calls for the use of nonparametric methods.

The test results indicate that with an alpha significance level set at $\alpha = 0.05$, the one-tailed directional tests (the null hypothesis tested was that no difference exists in retention rates, versus the alternative hypothesis that the NPS graduates had higher retention rates than the non-NPS graduate degree holders, and greater than the non-NPS undergraduate degree holders) that in almost all cases, NPS graduates have statistically significantly higher retention rates than all non-NPS graduates. The only area showing nonsignificance is the 20-year average retention rates between NPS graduates and non-NPS graduate degree holders. This might be due to the authorized strength limitations imposed by Congress on the number of flag and general officers (Authorized Strength, 2012).
Retention Rates Are Fairly Predictable and Expected

Now that we have statistically established that NPS graduates tend to have a higher retention rate than non-NPS graduates, the question is whether this trend is predictable. Predictability is key for the DoD in terms of anticipating force readiness levels for the future, and having a more stable group of qualified Naval officers 10, 15, or 20 years out, which allows for the fleet to plan for future-readiness and future-capability levels.

A time-series indexed set of linear and nonlinear econometric models was tested, starting with simple linear and nonlinear functional forms. The coefficients of determination ranged from 77.4% to 99.6% predictive power, with adequate error measurements (Akaike, Bayes Schwarz, and Hannan–Quinn criteria). Using these models, the retention rates were forecasted and compared against the actual rates, and the forecast errors were generated. The mean absolute percentage error (MAPE) of predictions was computed, and the median of these errors fluctuates between 0.01% and 3.34%, which corresponds to a median forecast error of between ±0.11% and ±4.42%, as measured by the mean absolute deviation (MAD).

Further modeling is required as, although the initial error rates are well within reasonable bounds, we wish to see if more advanced functional forms can be used to predict these retention rates more accurately. The more exhaustive econometric functional forms tested included the standard linear and nonlinear models, followed by quadratic, log-linear, logistic, linear log, double log, reciprocal, and log-reciprocal models.

Using the best models for each group of graduates, the retention rates were again modeled and compared against the actuals to determine their viability and prediction errors. The results showed that using more complex functional forms provided higher efficacy levels and lower errors. Using these best prediction models, we can now run a more comprehensive life-cycle cost model.
ROI Analysis Using Cost and Benefit Life-Cycle Analysis of Alternatives

Based on the two preceding subsections, we know that NPS graduates have a higher retention rate (after the requisite “payback years,” a student has to stay in the Service in return for the funded education) compared to non-NPS graduates (both graduate and undergraduate degree recipients), and we have shown that we can adequately predict these retention rates. Next, using these two main sources of information, we build a 20-year cost-benefit life-cycle model of a potential NPS student and future graduate and model this officer’s tenure with the Navy, compared against the prospect of not having a graduate degree or obtaining said degree at a nonmilitary university. The cost of training a new replacement officer is the cost savings or benefits, compared to the educational cost investment required at NPS.

As mentioned, according to the NPS Value Book, “analysis has shown NPS to be average to below average in total costs” (Naval Postgraduate School, 2012a, p. 16). NPS continuously calculates various cost-per-student measures for naval and reimbursable students (NPS, personal communication, January 9, 2020). The NPS education cost model identifies and incorporates all costs at NPS associated with providing the academic/graduate education program. The model includes all direct costs of graduate, for-credit education as well as NPS overhead cost associated with the education. However, it excludes all direct costs of sponsored research activities; direct costs of executive or professional nondegree education at NPS; and the relevant allocated share of NPS general, administrative, and business overhead costs associated with NPS noneducation operations such as sponsored research.5

Predictability is key for the DoD in terms of anticipating force readiness levels for the future, and having a more stable group of qualified Naval officers 10, 15, or 20 years out, which allows for the fleet to plan for future-readiness and future-capability levels.

For this research, we obtained the tuition costs for some comparable private universities (tuition and required cost only, excluding housing and books) and the U.S. Treasury spot rates. We applied a nonlinear cubic spline interpolation to generate the annualized future rates. These rates were used as the cash flow’s discount rate factor to obtain the net
present value of benefits and compare them with the up-front, 2-year educational cost.

A 20-year life-cycle cash flow was created using the forecasted retention rates, costs of comparable private universities, the U.S. Treasury rates, and the cost of sending a graduate student to NPS. Other expenses such as books, room and board, the officer’s salary, and miscellaneous reimbursable expenses were excluded because regardless of where the Navy sends its officers, these costs would still be borne. In this research, the key consideration is the apples-to-apples relative comparison of tuition and required costs of sending a junior officer either to NPS or a non-NPS private university to obtain a graduate degree. The absolute valuation of total costs is irrelevant.

We know that NPS graduates have a higher retention rate (after the requisite “payback years,” a student has to stay in the Service in return for the funded education) compared to non-NPS graduates (both graduate and undergraduate degree recipients), and we have shown that we can adequately predict these retention rates.

Probability distributions were set up on the cost of a private graduate degree; the NPS equivalent cost; the educational and NPS cost inflation rates; the forecasted retention rates; and the cost of training, replacement, and retention of a new officer to take the place of one who is leaving. Whenever possible, distribution-fitting routines (e.g., Kolmogorov–Smirnov) were run on existing data, or theoretical metrics such as forecast standard errors were used in the simulation procedure. Simulation modeling was run using 1,000,000 trials for each input, and the relevant Monte Carlo-simulated NPV and ROI were computed. Simulation was required because every scenario and assumption is uncertain but fluctuates within reasonable bounds. For instance, the student may decide among various alternative civilian universities (tuition costs are bounded) and may have a higher or lower attrition rate (forecast errors are bounded). Costs of education at NPS and civilian institutions can also change, but, again, within reasonable values. Therefore, using simulation methods, we can incorporate all possible outcomes in a million scenarios of each assumption. For example, an officer might decide on NPS
vs. MIT; stay for 12 years postgraduation; happen to enroll in the 2 years when interest rates are the highest, but the tuition rates were depressed due to low enrollment and budget cuts; or is a Navy SEAL, thereby requiring a higher replacement cost due to the specialized training requirements.

We performed an analysis of alternatives’ ROI differential when the DoD sends a junior officer to NPS for a graduate master’s degree compared to sending the same officer to a private university for a similar master’s degree. Due to the higher retention rates and lower costs of students who attend and graduate from NPS, the results of our analysis show that the expected ROI is 673%, with a 90% confidence interval of the ROI between 541% and 821%, after accounting for all the uncertainties in the input parameters and assumptions. In other words, we can safely say that 95% of the time, given all the uncertainties and fluctuations in comparable costs and retention rates, sending an officer to NPS as compared to a private civilian graduate school will yield an additional 541% in ROI or a 6.41 return-to-cost ratio. Hence, for every $1 spent on an NPS education, the DoD obtains a benefit or return of $6.41 (the net benefit is $5.41 or 541%).

This falls within the reasonable boundaries obtained for the ROI for naval acquisition research programs, as described previously.

Similarly, we performed an analysis of alternatives’ ROI differential when the DoD sends a junior officer to NPS for a graduate master’s degree compared to not sending the officer at all. This situation assumes that the officer has the requisite undergraduate bachelor’s degree and stays at that education level. Due to the higher retention rates of NPS graduates at the DoD, we ascertained that the expected ROI is 469%, with a 90% confidence interval of the ROI between 361% and 590%, after accounting for all the uncertainties in the input parameters and assumptions. In other words, we can safely say that 95% of the time, given all the uncertainties and fluctuations in NPS costs and changes in retention rates over time, sending an officer to NPS as compared to the status quo will yield an additional 361% in ROI or a 4.61 return-to-cost ratio. Hence, for every $1 spent on an NPS education, the DoD obtains a benefit or return of $4.61 (the net benefit is $3.61 or 361%).
Finally, we performed an analysis of alternatives’ ROI differential when the DoD sends a junior officer to a non-NPS civilian university for a graduate master’s degree compared to not sending the officer at all. This scenario again assumes that the officer has the requisite undergraduate bachelor’s degree and stays at that education level. Due to the higher retention rates of graduates, the results show that the expected ROI is 403%, with a 90% confidence interval of the ROI between 289% and 550%, after accounting for all the uncertainties in the input parameters and assumptions. In other words, we can safely say that 95% of the time, given all the uncertainties and fluctuations in civilian graduate education costs and changes in retention rates over time, sending an officer to any non-NPS graduate program will yield an additional 289% in ROI or a 3.89 return-to-cost ratio. Hence, for every $1 spent on non-NPS graduate education, the DoD obtains a benefit or return of $3.89 (the net benefit is $2.89 or 289%).

From the point of view of the DoD, for every dollar invested in NPS education, the benefits return anywhere between 5.69 and 7.73 times the investment (Table 6), but these ROI values are simply the tip of the iceberg, as the intangible value of a military graduate institution to the DoD is incalculable.

Results Summary
In summary, we can conclude that NPS graduates show a statistically significantly higher retention rate in the U.S. Navy. As expected, retention rates decline over time, but the decline is fairly predictable; and the rate of decline is statistically significantly less for NPS graduates than non-NPS graduate and undergraduate degree holders. More complex econometric models with different functional forms such as logistic, log-linear, and log quadratic models, were used to generate reasonable retention rates. These forecasts were then used to build life-cycle cost models and simulation models to determine the lifetime ROI for NPS students from the point of view of a DoD investment.

We see that not only does NPS provide significant intangible value to its students and the DoD as a whole, but it also provides quantifiable economic ROI. We see that from the point of view of the DoD, for every dollar invested
in NPS education, the benefits return anywhere between 5.69 and 7.73 times the investment (Table 6), but these ROI values are simply the tip of the iceberg, as the intangible value of a military graduate institution to the DoD is incalculable.

**TABLE 6. SUMMARY ROI FOR RESEARCH AND EDUCATION**

<table>
<thead>
<tr>
<th>ROI for Military Education (e.g., NPS)</th>
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<tbody>
<tr>
<td>Delta ROI: NPS vs. Civilian Master’s Program (Expected Value)</td>
<td>673.00%</td>
</tr>
<tr>
<td>Delta ROI: NPS vs. Civilian Master’s Program (90% Confidence Interval)</td>
<td>541%-821%</td>
</tr>
</tbody>
</table>

For every $1 spent on NPS, the benefit gained is $7.73 on average

| ROI: NPS Master’s Program vs. Status Quo Bachelor’s Degree (Expected Value) | 469.00% |
| ROI: NPS Master’s Program vs. Status Quo Bachelor’s Degree (90% Confidence Interval) | 361%-590% |

For every $1 spent on NPS, the benefit gained is $5.69 on average

| ROI: Civilian Master’s Program vs. Status Quo Bachelor’s Degree (Expected Value) | 403.00% |
| ROI: Civilian Master’s Program vs. Status Quo Bachelor’s Degree (90% Confidence Interval) | 289%-550% |

For every $1 spent on any graduate degree, the benefit gained is $5.03 on average

The simulated ROI’s probability distributions for the three scenarios show that the NPS versus civilian MS program has the highest ROI (averaging and peaking at 673%) because the lower cost at NPS and resulting higher retention rates make it the most profitable. The NPS versus undergraduate status quo without attending any graduate programs (averaging and peaking at 469%) scenario reveals that, because the entire NPS cost is incurred, the ROI is lower than the differential cost for NPS versus civilian MS. Finally, the lowest comparable ROI, which is still significant (averaging and peaking at 403%), is achieved when an officer attends a civilian MS program as opposed to not attending any graduate studies at all. Hence, in summary, we see that graduate education for naval officers provides a significant return on the government’s investment, and that NPS provides the best economic ROI, above and beyond all the qualitative and intangible values previously discussed.

These ROI values are comparable to the examples provided in the Work Life-Cycle Approach of a civilian MBA and MS graduate of 318% and the 304% average ROI from military research programs, both described earlier. The higher ROI for NPS also results from the lower cost of education and longer retention rates of its graduates.
Case Study: The Value and ROI of DAU

In this section, we present a brief case study of the value of DAU educational programs. DAU is a best-in-class corporate university for the Defense Acquisition Workforce, with online courses as well as live sessions. Its mission is to provide a global learning environment to develop qualified acquisition, requirements, and contingency professionals who deliver and sustain effective and affordable warfighting capabilities (see http://www.dau.edu). As such, it is a critical part of the DoD-sponsored acquisition education.

During FY2017–2018, DAU sent out surveys to tens of thousands of its course participants. These are standard end-of-course surveys taken immediately after the completion of a course as well as postcourse assessments that are sent as a follow-up several months later. In addition, surveys to the participants’ supervisors were also submitted several months after the conclusion of the course. DAU uses a commercial web-based evaluation application, where some questions require a percentage response versus others requiring a 7-point Likert scale response (i.e., 1 for strongly disagree to 7 for strongly agree), to compare the survey results with other training organizations. Each year, tens to hundreds of thousands of DAU anonymous surveys are received and compared with millions of others in the database.

Of the 145 supervisors surveyed, over 95% of the respondents would value DAU education highly, with a Likert scale of 4 or higher.

The surveys contain standard educational questions, including the setup of the course, the facility, quality of graded materials, quality of the faculty, and length or pace of the course. Out of the two dozen or so questions, we were able to cull the necessary data for the most relevant questions that pertain to the value of DAU’s programs. Of special interest is the supervisor’s survey question on their view of the course’s ROI. Of the 145 supervisors surveyed, over 95% of the respondents would value DAU education highly, with a Likert scale of 4 or higher.

Survey Modeling and Analysis Results

The survey results were subjected to multiple analytical models to see what critical information can be gained from these surveys. An Inter-Class Correlation for Inter-Rater Reliability Test as well as the Guttman’s Lambda
and Internal Consistency and Reliability Test were employed to determine whether the survey responses were statistically valid, trustworthy, reliable, and replicable. In addition, econometric modeling and multivariate tests were run. Some artificial intelligence algorithms, such as machine learning, were also applied to identify any patterns that might exist in the data (see Appendix).

Conclusions from the Point of View of Supervisors

The main conclusions of the DAU postcourse and follow-up surveys from the point of view (POV) of supervisors are as follow:

• The survey responses reflect statistical consistency and reliability. This means that for the 145 supervisors who sent their employees for training, their responses exhibited statistical reliability. We conclude that the responses to the survey are valid and trustworthy, rather than being completed haphazardly and without any biases. Therefore, conclusions drawn based on the survey data are statistically valid.

• We find statistical significance indicating that, on average, supervisors view that the ROI is statistically significantly greater than zero (mid-point of a Likert scale).

• Organizations value the ROI to an employee’s personal career growth as being the same as the ROI to the entire organization.

• Organizations view the ROI of a training initiative to the organization as going beyond its sole impact on an employee’s job performance.

• Organizations view the ROI of a training initiative to an individual employee as greater than its sole impact on an employee’s job performance. This might mean that the value of training is not entirely quantifiable or immediately actionable and that some value might be intrinsic, unmeasurable, and subjective.

• Organizations view the ROI to the organization as being more than a simple summation of actual enumerable skills or new knowledge learned. In addition, organizations perceive ROI as being more than applications of specific knowledge or skill sets on the job.

• Organizations see value if the training helped improve an employee’s performance and enabled the employee to apply the knowledge and skills successfully, but only if it is also worthwhile to the employee’s own career development based on specific goals and expectations set prior to the training.
course. Each of these criteria by itself does not necessarily contribute to the perceived ROI, but only when they are combined holistically.

- Using distributional fitting, we see that the probability distribution of the estimated improvement percentage as a direct result of a training course (VAR12) shows, on average, a 50.7% increase in productivity, with three-quarters of the supervisors surveyed saying that productivity improvements were at least 32%.

Conclusions from the Point of View of Students

The main conclusions of the DAU postcourse and follow-up surveys from the POV of the students follow:

- For the 16,157 students who responded to the surveys, the responses as a whole exhibited statistical reliability as well as statistical consistency, indicating that no biases were evidenced in the data. We can conclude that the responses to the survey are valid and trustworthy, rather than being completed haphazardly. Therefore, conclusions drawn based on the survey data are statistically valid.

- The student’s view at the end of the course in terms of the usefulness of the course material presented is materially and significantly different after spending time on the job.

- The student’s view at the end of the course in terms of the amount of new knowledge learned that might apply to their job is materially and significantly different after spending time on the job.

- The student’s view at the end of the course in terms of the amount of work time requiring the use of the new knowledge learned is materially and significantly different after spending time on the job.

- A statistically significant improvement in the student’s work abilities is evident as a direct result of the training received.
• A statistically significant increase is evident in the ability to apply the knowledge and skills learned in class.

• A statistically significant amount of new knowledge is learned in class.

• At a future follow-up session, a former student’s estimate of how much work improvement was a direct result of the training course depended on experience during the follow-up session and was not completely known immediately after the course ended.

• About three-quarters of the students surveyed believed that their productivity increased at least 20% after taking the course. We also see that the students’ POV (Gumbel distribution) is more conservative than the supervisors’ POV (normal distribution), but with a similar shape and scale.

Return on Investment Analysis

Finally, an analysis of the ROI is performed on the DAU courses. The conclusion is that the average ROI from the POV of the students and supervisors/organizations is between 411% and 477%, and the probability that, on average, any given course taken at DAU has at least 87% and 93% probabilities that the ROI is positive, from the POV of the student and the supervisor/organization, respectively.

Conclusions

As the basis for reorienting education, the Department of the Navy (2018), through the Education for Seapower report, recommended the following strategic vision:

The Naval Education Enterprise must produce leaders of character, integrity, and intelligence steeped not only in the art of war, the profession of arms, and the history and traditions of the Naval service, but also in a broader understanding of the technical and strategic complexities of the Cognitive Age, vital to assuring success in war, peace, and grey zone conflict; officer and enlisted leaders of every rank who think critically, communicate clearly, and are imbued with a bias for decisive and ethical action. (p. 14)

As such, the motivation for the main research question was whether military education and research have any value to the Department of the Navy and DoD in general, and, if so, how would one compute its ROI? We consider the fact that the drive for lifelong education in naval officers is a personal
but also an institutional responsibility. Education is vital for the strategic viability and long-term lethality of our warfighting forces and country.

We can conclude that the intangible value of military education is significant in developing leadership and critical thinking skills for junior as well as senior officers. The military-oriented curriculum taught by faculty members with former military experience or knowledge allows the flow of institutional knowledge down to the students. Although these intangible and qualitative aspects of military education are significant, this current research focuses on the more quantitative measure of ROI.

We can conclude that the intangible value of military education is significant in developing leadership and critical thinking skills for junior as well as senior officers. The military-oriented curriculum taught by faculty members with former military experience or knowledge allows the flow of institutional knowledge down to the students.

Using NPS as a case study, we can further conclude that NPS graduates show statistically significantly higher retention rates in the U.S. Navy. Further, we can conclude that, as expected, retention rates decline over time, but the decline is fairly predictable, and the rate of decline is statistically significantly less for NPS graduates than non-NPS graduate degree holders and undergraduate degree holders. More complex econometric models with different functional forms such as logistic, log-linear, and log quadratic models were used to generate reasonable retention rates. These forecasts were then used to build life-cycle cost models and simulation models to determine the lifetime ROI for NPS students from the point of view of a DoD investment. Finally, machine learning algorithms in artificial intelligence were also applied for pattern recognition purposes.

The following are the main conclusions of the study:

- DoD-sponsored military education graduates tend to stay longer in the military, beyond their required payback years, which means their knowledge and capabilities are exploited for longer and the DoD needs to recruit and train fewer people in the long run.
DoD-sponsored military education is less expensive than external universities, on average, while providing specific military education needed by the Services.

DoD research performed at military universities is less expensive and more military-relevant than using private consultants.

Table 7 recapitulates the critical results from the research.

### TABLE 7. SUMMARY ROI FOR RESEARCH AND EDUCATION

<table>
<thead>
<tr>
<th></th>
<th>Minimal Worst-Case ROI</th>
<th>Most Likely ROI</th>
<th>Range of ROI Depending on Program</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ROI for Military Research and Development (e.g., ARP)</strong></td>
<td>121.00%</td>
<td>304.00%</td>
<td>240%-600%</td>
</tr>
<tr>
<td><strong>ROI for Military Education (e.g., NPS)</strong></td>
<td>673.00%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Delta ROI: NPS vs. Civilian Master's Program (Expected Value)</td>
<td>541%-821%</td>
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<td>For every $1 spent on any graduate degree, the benefit gained is $5.03 on average</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>ROI for Short or Specialized Military Courses (e.g., DAU)</strong></td>
<td>411%-477%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>For every $1 spent on DAU, the benefit gained is $5.77 on average</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global Average ROI (ARP, NPS, DAU): 485%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In an earlier discussion, we saw that the ROI for military-based research has significant qualitative intangible worth as well as quantitative economic ROI. In summary, we can quantify that the ARP’s ROI, based on an annual investment of $1.7 million, will range from the absolute worst case of 121% to an average of 240%-600% for each specific program. The KVA method pegs the ROI at 253%. Therefore, using standard industry best practices, we conclude the average conservative ROI for the entire ARP program to be approximately 304%.
Previously, the analysis was extended to look at the ROI of NPS. We see that from the point of view of the DoD, for every dollar invested in NPS education, the benefits return anywhere between 5.7 and 7.7 times the investment, which represents expected ROIs between 469% and 673% (Table 7). These ROI values are minuscule in comparison to the holistic, intangible, and qualitative value of a military graduate university to the DoD.

Using the DAU data, we determine that the ROI of military education in the defense acquisition world is between 411% and 477%, and the probability that on average any given course taken at DAU has at least 87% and 93% probabilities that the ROI is positive. The global average for DoD education on average provides the government with an ROI of approximately 485%.

In conclusion, training only prepares the Warfighter to deal with the known factors of war (e.g., the importance of good marksmanship), but education prepares Warfighters to deal with the unknown factors (e.g., effective decision-making in risk-fraught, rapidly changing circumstances). Well-educated Warfighters create significant added value and make up lethal and effective combat-ready units for the future.

**Limitations and Recommendations for Future Research**

This research examined and created various theoretical constructs and empirical methods to generate ROI for military education and research. The current research both proposed these methodologies and used available data to simulate cash-flow life-cycle models. The recommended next steps of the research would be to obtain long-term data from current and previous students via survey instruments, interviews, and work performance data, and other requisite information that flows out of this data collection process. The data with higher fidelity can then be reprocessed through the methodologies described.
References


Endnotes

1 Knowledge Value-Added
   KVA includes the following seven-step method (Housel & Kanevsky, 2007):
   - Identify functional areas and core processes along with their subprocesses. It is quite useful to have at least two process- or functional-area SMEs to ensure reliable estimates.
   - Establish common units and levels of aggregation of the process output to measure learning time. Other common-unit measures of output can also be used, such as tasks, computer code, or process instructions that may be contained in existing documentation as long as they are calibrated to a common level of complexity using learning times.
   - Calculate the learning time (i.e., knowledge surrogate) required to execute each process or functional area.
   - Designate a sampling time period long enough to capture a representative sample of the core processes or functional area’s aggregated output.
   - Multiply the learning time for each process by the number of times the process executes during the sample period.
   - Calculate the cost to execute knowledge (e.g., learning time or process instructions) by the resource used to produce the outputs (i.e., people, technology) to determine process costs.
   - Calculate ROK and ROKI.

2 Integrated Risk Management and Real Options Analysis
   Real-life conditions are fraught with uncertainty and risks. Understanding the knowledge inherent in, and accounting for, the effects of these uncertainties is crucial to successful management. When uncertainty becomes resolved through the passage of time, actions, and events, decision makers can make the appropriate midcourse corrections by applying the knowledge gained and making decisions along flexible strategies. Strategic Real Options is a discipline that incorporates this learning model and permits the decision maker to take advantage of the full range of options, whereas traditional analyses that neglect this strategic flexibility will grossly undervalue certain capabilities, projects, and strategies (Mun, 2016b).

   The real options approach is part of the IRM process, an eight-step, quantitative, software-based modeling approach for the objective quantification of risk (such as cost, schedule, and technical). The approach can be applied to program management; resource portfolio allocation; return on investment to the military (maximizing expected military value and objective value quantification of nonrevenue government projects); analysis of alternatives or strategic flexibility options; capability analysis; prediction modeling; and general decision analytics (Mun, 2016a). The method supports project and capability selection among hundreds of alternatives constrained by fixed budgets and tight schedules to maximize capability and readiness at the lowest cost possible. This methodology is particularly amenable to resource reallocation and has been taught and applied by the author for the past 15 years at over 100 multinational corporations and encompassing over 50 projects at the DoD. The authors’ books and methodology are now used and taught at more than 100 universities globally.
How much is a platform technology really worth when its initial costs are high and it is delivered with lower than desired initial capabilities, but with the potential for significant flexibility for future add-ons? Should the government build or buy a new untested technology? Is running a proof of concept a better strategy than executing large-scale acquisitions immediately? How is a Warfighter’s capability extended with flexible weapon systems? Is a modular open architecture really worth the added costs?

The Strategic Real Options approach helps answer these questions and more, by estimating the value of military capability in a common and objective way across various alternatives and expressing the ROI of each option. These ROI estimates across the portfolio of alternatives provide the inputs necessary to predict the value of various options for accomplishing the recently stated Secretary of Defense reallocation goals. IRM incorporates risks, budget constraints, reallocation options, and total ownership costs in recommending a defensible path forward. This approach identifies risky projects and programs while projecting immediate and future cost savings, total life-cycle costs, flexibility alternatives, critical success factors, and portfolio optimization, while controlling for cost overruns and schedule delays. It provides an optimized portfolio of capability options while maintaining the value of strategic flexibility. The IRM approach incorporates multiple Nobel-prize winning and well-established theories and applications in corporate finance, investments, economics, statistics, mathematics, and decision sciences into a comprehensive and flexible process that is defensible, replicable, scalable, and extensible to all areas of the DoD (Mun, 2016b).

Using valuation best practices in industry, we perform ROI analysis on the ARP program from various points of view to determine the final ROI:

- Some research provides significant ROI if the processes, recommendations, and actionable intelligence are executed. The ARP research will take minimal credit for the potential ROI (i.e., 1/1000 of the ROI savings) and attribute it to the ARP research.
- We look at the worst-case scenario, where even if the research results are not implemented, cost savings are still realized. This approach will generate the absolute minimal baseline of what the ARP ROI should be.
- In addition, graduate students (MS, MBA, PhD candidates) participate in the research, as well as attend symposiums. Students find value in the knowledge and experience gained, and we will capture these intangibles using Knowledge Value-Added methodologies to monetize and determine the knowledge-based ROI.
- Intangible and intrinsic value exists above and beyond any standard ROI calculations. These include the interactions of sponsors with researchers, graduate students, faculty, and program executive offices and commands with researchers; the live interactions of participants at the annual symposiums; and the knowledge dissemination.

Cost comparison analysis of a degree earned from NPS and a similar degree earned from a comparable civilian university was performed. While the degrees may
be similar on the outside and just as challenging in their pursuit, civilian degrees
certainly do not have the same tailored, defense-centric, militarily career-enhancing
curriculum provided by NPS. This is a flaw inherent in any direct one-to-one cost
comparison. Curricular requirements at NPS include Educational Skill Requirements
(ESRs) dictated by the Secretary of the Navy that are intended to broaden the
military student’s educational experience. NPS provides Joint Professional Military
Education (JPME) coursework from Navy War College faculty in order that officers
satisfy their academic degree and joint military requirements within a single tour.
Additional coursework is also required to ensure the student appreciates the military
relevance of the academic subject material, thereby enabling immediate application
upon rejoining the operational force. Similar courses are not available at civilian
universities and represent a hidden, but necessary, cost in NPS’ budget (Mauz &
Gates, 2000).

5 The NPS Value Book

In summary, the NPS cost model is broken into three points of view:

• Annual Cost-per-Student: This measure relates education costs to the
effective number of full-time students on board. Higher or lower student
credit loads are not reflected. In 2019, the NPS Cost-per-student full-time
equivalence was approximately $40,000.

• Annual Normalized Cost-per-Student Full-Time Equivalent (SFTE): The
NPS education model provides more education and more credit hours
to students than comparable civilian universities, anywhere from 50% to
100% more. Assuming an average load increase of 75%, we can normalize
NPS Cost/SFTE for comparison with standard student programs at other
civilian universities. For 2019, the normalized Cost/SFTE was $34,000. NPS
believes that this normalized Cost/SFTE is a more valid measure for cost
comparisons.

• Annual Naval Normalized Cost/SFTE: This is a determination of cost
per student, but only for Navy Direct-Funded students. In 2019, Naval
Normalized Cost/SFTE was $42,000.

6 Life-Cycle Cost Model Assumptions

A life-cycle cost model with Monte Carlo simulation was created with the
following input assumptions:

• Graduate education tuition costs for nine comparable civilian public
universities were obtained. The simulation assumes a triangular distribution.

• An annualized private education inflation rate ranging from 2.0% to 3.5%
was simulated, based on the Common-fund Higher Education Price Index
(HEPI).

• The relevant 1-year to 20-year U.S. Treasury rates from the U.S. Department
of Treasury were used, and a nonlinear cubic spline interpolation was
applied to determine the annualized forward rates. These are used as the
government discount rates in the life-cycle model.

• NPS education cost used was triangulated among $34,000, $40,000, and
$42,000 per year, based on the internal NPS cost model.

• NPS cost was accreted between 1.5% to 2.5% per year, based on normalized
annual budgetary increases.
• The cost to train, retain, and replace a naval officer between the O-4 and O-6 levels was simulated to be between $250,000 and $500,000, depending on the billet, with a most likely cost of $350,000.

• A 20-year life-cycle model was used, and 1,000,000 simulation trials were run in the model for the uncertain assumptions in this list.

7 Assumptions in the DAU ROI Analysis
Several assumptions are made to enable the ROI analysis, namely:

• We used DAU’s own annual report to determine that there are over 152,557 students taking online courses and 44,326 graduates from resident courses in FY2019 (Defense Acquisition University, 2020).

• The FY2020 Congressional Budget request was for $163 million, which covers all operating costs of DAU, including any requisite travel expenses for its students, faculty salaries, operations and maintenance of its facilities, and other expenses.

• The average cost per student, averaged across online and resident programs, is between $900 and $4,500. The lower end applies to online courses versus resident courses at the upper end of the range, as well as varying depending on the course type and course level.

• Based on the survey of over 16,157 students, they attended 171 different courses, and the allocation of these course levels (100-, 200-, 300-, and 400-level courses) is unequally distributed among O-1 to O-6 officers (we excluded special seminars for flag officers), with the predominant number of students at the O-3 to O-5 levels, spread across multiple 100- and 200-level courses.

• Using the O-1 to O-6 pay scales (source: http://www.federalpay.org), and assuming that the faculty members are between GS-12 and GS-15 levels, a Monte Carlo risk simulation was run to determine the cost of education for an average course.

• Similarly, probability distributional and curve-fitting routines were run on the perceived enhanced efficiency and effectiveness at doing one’s job, as determined from the 6-month follow-up surveys. Using these distributions, Monte Carlo risk simulations were run to determine the potential ROI.
Appendix

Survey Modeling and Statistical Results

The survey results were subjected to multiple analytical models to see what critical information can be concluded from these surveys. An Inter-Class Correlation for Inter-Rater Reliability Test as well as the Guttman's Lambda and Internal Consistency and Reliability Test were employed to determine whether the survey responses were statistically valid, trustworthy, reliable, and replicable. In addition, econometric modeling and multivariate tests were run. Some artificial intelligence algorithms, such as machine learning, were also applied to identify any patterns that might exist in the data.

Analytical Results from Survey of Supervisors

Inter-Class Correlation for Inter-Rater Reliability Test

VAR1; VAR3; VAR7; VAR8; VAR12
Inter-Class Correlation: 0.66
Spearman-Brown Correction: 0.96
Inter-Rater Reliability: 0.0000

VAR2; VAR4; VAR5; VAR6; VAR9; VAR10; VAR11; VAR13
Inter-Class Correlation: 0.63
Spearman-Brown Correction: 0.96
Inter-Rater Reliability p Value: 0.0000

One Variable T-Test for Means

VAR4, Two-Tailed p Value: 0.0000

Analysis of Variance (One Way ANOVA with Multiple Treatments)

VAR1; VAR3; VAR7; VAR8; VAR12
ANOVA p Value: 0.0000

VAR2; VAR4; VAR5; VAR6; VAR9; VAR10; VAR11; VAR13
ANOVA p Value: 0.0000

Nonparametric Kruskal–Wallis Test

VAR1; VAR3; VAR7; VAR8; VAR12
Kruskal Wallis p Value: 0.0001

VAR2; VAR4; VAR5; VAR6; VAR9; VAR10; VAR11; VAR13
Kruskal Wallis p Value: 0.0001

Two-Variable (T) Independent Equal Variance

VAR4; VAR9 p Value Two Tailed: 0.8021
VAR4; VAR2 p Value Two Tailed: 0.0058
VAR2; VAR9 p Value Two Tailed: 0.0022
VAR4; VAR11 p Value Two Tailed: 0.9592
VAR4; VAR13 p Value Two Tailed: 0.2287

Nonparametric Mann–Whitney Test

VAR4; VAR9 p Value Two Tailed: 0.9264
VAR4; VAR2 p Value Two Tailed: 0.0043
VAR2; VAR9 p Value Two Tailed: 0.0028
Basic Econometrics and Regression

Model Inputs: VAR4 vs. LN(VAR2); VAR6; VAR9; VAR13

- Multiple R: 0.94580
- R-Square: 0.89454
- Adjusted R-Square: 0.89152
- Standard Error: 0.39582
- Observations: 145

<table>
<thead>
<tr>
<th>Coef</th>
<th>Std. Error</th>
<th>T-stat</th>
<th>p value</th>
<th>Lower 5%</th>
<th>Upper 95%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
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<td>0.19891</td>
<td>-1.13507</td>
<td>-0.61902</td>
<td>0.16748</td>
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<td>0.19318</td>
<td>3.93730</td>
<td>0.00013</td>
<td>0.37867</td>
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<td>VAR6</td>
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<td>5.09750</td>
<td>0.00000</td>
<td>0.13587</td>
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<tr>
<td>VAR9</td>
<td>0.83622</td>
<td>0.04443</td>
<td>18.82177</td>
<td>0.00000</td>
<td>0.74838</td>
</tr>
<tr>
<td>VAR13</td>
<td>-0.22733</td>
<td>0.06006</td>
<td>-3.78502</td>
<td>-0.34608</td>
<td>-0.10859</td>
</tr>
</tbody>
</table>

ANOVA
- Degrees of Freedom (DF): 4, 140, 144
- Sum of Squares (SS): 186.04, 21.93, 207.97
- Mean Square (MS): 46.51, 0.16
- F-Statistic: 296.86391
- p Value: 0.0000

Distributional Fitting: Continuous (Anderson–Darling)

- Rank MAPE % AD Distribution
  1. 13.47% 0.1976 Normal
  2. 15.37% 0.2108 Logistic
  3. 16.68% 0.3170 GumbelMax
  4. 27.51% 0.2899 GumbelMin

Best Fit Rank: 1
Fit Name: Normal
Anderson-Darling Statistic: 0.197647
MAPE: 0.134716
Mean: 0.506852
Sigma: 0.277159

Actual to Theoretical Four Moments:
- Mean: 0.512414, 0.264282, 0.028672, -0.771227
- Sigma: 0.506852, 0.277159, 0.000000, 0.000000

Analytical Results from Survey of Students

Inter-Class Correlation for Inter-Rater Reliability Test
- VAR1; VAR2; VAR3; VAR4; VAR5; VAR6; VAR7
  Inter-Class Correlation: 0.33
  Spearman-Brown Correction: 0.93
  Inter-Rater Reliability: 0.0000

- VAR1; VAR3; VAR5; VAR7
  Inter-Class Correlation: 0.74
  Spearman-Brown Correction: 0.93
  Inter-Rater Reliability p Value: 0.0000
VAR2; VAR4; VAR6  
Inter-Class Correlation: 0.84  
Spearman-Brown Correction: 0.96  
Inter-Rater Reliability $p$ Value: 0.0000

VAR8; VAR9  
Inter-Class Correlation: 0.02  
Spearman-Brown Correction: 0.04  
Inter-Rater Reliability $p$ Value: 0.0032

**Analysis of Variance (One Way ANOVA with Multiple Treatments)**  
VAR1; VAR2; VAR3; VAR4; VAR5; VAR6; VAR7  
ANOVA $p$ Value: 0.0000

**Nonparametric Kruskal–Wallis Test**  
VAR1; VAR2; VAR3; VAR4; VAR5; VAR6; VAR7  
Kruskal Wallis $p$ Value: 0.0000

**Two-Variable (T) Independent Equal Variance**  
VAR1; VAR2  
$p$ Value Two-Tailed: 0.0000  
VAR3; VAR4  
$p$ Value Two-Tailed: 0.0000  
VAR5; VAR6  
$p$ Value Two-Tailed: 0.0000

**Nonparametric Mann–Whitney Test**  
VAR1; VAR2  
$p$ Value Two-Tailed: 0.0000  
VAR3; VAR4  
$p$ Value Two-Tailed: 0.0000  
VAR5; VAR6  
$p$ Value Two-Tailed: 0.0000

**Basic Econometrics and Stepwise Regression**  
ARRANGEMENT: Y<->X3;X7;X1;X5  
Regression Results  
OVERALL FIT  
Multiple R 0.75271  
Maximum Log-Likelihood 3753.34608  
R-Square 0.56658  
Akaike Info Criterion (AIC) -0.46393  
Adj R-Square 0.56647  
Bayes Schwarz Criterion (BSC) -0.45964  
Standard Error 0.19180  
Hannan-Quinn Criterion (HQC) -0.46251  
Observations 16142  

<table>
<thead>
<tr>
<th>Coef</th>
<th>Std. Error</th>
<th>T-stat</th>
<th>$p$ value</th>
<th>Lower 5%</th>
<th>Upper 95%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.01274</td>
<td>0.00614</td>
<td>-2.07418</td>
<td>0.03808</td>
<td>-0.02479</td>
</tr>
<tr>
<td>VAR3</td>
<td>0.37981</td>
<td>0.01040</td>
<td>36.50831</td>
<td>0.00000</td>
<td>0.35942</td>
</tr>
<tr>
<td>VAR8</td>
<td>0.02617</td>
<td>0.00132</td>
<td>19.87973</td>
<td>0.00000</td>
<td>0.02359</td>
</tr>
<tr>
<td>VAR1</td>
<td>0.25276</td>
<td>0.01001</td>
<td>25.24347</td>
<td>0.00000</td>
<td>0.23314</td>
</tr>
<tr>
<td>VAR5</td>
<td>0.05341</td>
<td>0.00968</td>
<td>5.51641</td>
<td>0.00000</td>
<td>0.03443</td>
</tr>
</tbody>
</table>

**ANOVA**  
DF | SS | MS | $F$ | $p$ Value |
---|----|----|----|-----------|
Regression | 4 | 776.01 | 194.00 | 5273.63619 | 0.00000 |
Residual | 16137 | 593.63 | 0.04 | |
Total | 16141 | 1369.64 | | |

Defense ARJ, July 2022, Vol. 29 No. 3 : 192–245
Hypothesis Test
Critical F-statistic (99% confidence with DFR1 and DFR2): 3.320336
Critical F-statistic (95% confidence with DFR1 and DFR2): 2.372483
Critical F-statistic (90% confidence with DFR1 and DFR2): 1.945208

Random Forest Supervised Data Mining
The Classification and Regression Trees (CART) model generates branches and subgroups of the categorical dependent variable (e.g., low-, medium-, high-retention, or low-, medium-, and high-satisfaction levels) using characteristic independent variables (officer rank, level of experience, number of years at an institution, education level pursued, etc.). CART is typically used for data mining and constitutes a supervised machine learning approach in artificial intelligence. This is a classification approach when the dependent variable is categorical, and the tree is used to determine the class or group within which a target testing variable is most likely to fall. The data are split into branches along a tree, and each branch split will be determined using Gini coefficients (information loss measures) based on the questions asked along the way. The final structure looks like a tree with its many branches. Additional splitting and stopping rules are applied along the way, and the terminal branches will provide predictions of the target testing variable. In the random forest approach, bootstraps of CART regression trees are run multiple times with different combinations of data points and variables to develop a consensus forecast of group assignments. Using a single set of training variables, the data and variables are bootstrapped and resampled. Each resampling will be run in the CART or regression tree model, and the consensus categorization results will be generated (Mun, 2021).

Bagging with 100 iterations and base learner with Cross-validation

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation coefficient</td>
<td>0.8659</td>
</tr>
<tr>
<td>Mean absolute error</td>
<td>0.0923</td>
</tr>
<tr>
<td>Root mean squared error</td>
<td>0.1470</td>
</tr>
<tr>
<td>Relative absolute error</td>
<td>37.356%</td>
</tr>
<tr>
<td>Root relative squared error</td>
<td>50.091%</td>
</tr>
<tr>
<td>Total Number of Instances</td>
<td>16,142</td>
</tr>
</tbody>
</table>

K-Means Clustering
A K-Means Clustering with Gaussian Mix model applies Naïve Bayes and likelihood estimations and are considered as unsupervised artificial intelligence machine learning algorithms. These approaches are applied to recognize patterns in data, learning from experience as more data is applied to the algorithm, drawing conclusions, and making predictions in terms of where certain groups of student characteristics (officer rank, level of experience, number of years at an institution, education level pursued, etc.) can be clustered or grouped together with the highest probability (Mun, 2021). This approach helps us to identify the types of students and their characteristics that are most likely to succeed at a certain metric (e.g., highest retention, best productivity levels, etc.).

Number of iterations: 19
Within cluster sum of squared errors: 8084.545176982922
Initial starting points (random):
Cluster 0: 1,0.8,1,0.7,0.5,0.6,0.5,7,7
Cluster 1: 0.1,0.1,0.1,0.1,0.1,0.1,0.1,5,6
Missing values globally replaced with mean/mode
Final cluster centroids:

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Full Data</th>
<th>0</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(16142.0)</td>
<td>(8044.0)</td>
<td>(8098.0)</td>
</tr>
<tr>
<td>VAR1</td>
<td>0.4754</td>
<td>0.7143</td>
<td>0.2382</td>
</tr>
<tr>
<td>VAR2</td>
<td>0.5071</td>
<td>0.5019</td>
<td>0.5123</td>
</tr>
<tr>
<td>VAR3</td>
<td>0.4385</td>
<td>0.6783</td>
<td>0.2003</td>
</tr>
<tr>
<td>VAR4</td>
<td>0.4941</td>
<td>0.4882</td>
<td>0.5000</td>
</tr>
<tr>
<td>VAR5</td>
<td>0.4060</td>
<td>0.6141</td>
<td>0.1994</td>
</tr>
<tr>
<td>VAR6</td>
<td>0.4555</td>
<td>0.4495</td>
<td>0.4616</td>
</tr>
<tr>
<td>VAR7</td>
<td>0.4398</td>
<td>0.6393</td>
<td>0.2416</td>
</tr>
<tr>
<td>VAR8</td>
<td>5.5050</td>
<td>6.2471</td>
<td>4.7678</td>
</tr>
<tr>
<td>VAR9</td>
<td>5.6808</td>
<td>5.6875</td>
<td>5.6742</td>
</tr>
</tbody>
</table>

**Artificial Intelligence Multi-Layered Perceptron**
Classifier model (full training set)

Linear Node 0

<table>
<thead>
<tr>
<th>Inputs</th>
<th>Weights</th>
</tr>
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<tbody>
<tr>
<td>Threshold</td>
<td>0.06925846705171</td>
</tr>
<tr>
<td>Node 1</td>
<td>-0.9353491867299</td>
</tr>
<tr>
<td>Node 2</td>
<td>1.00459405724956</td>
</tr>
<tr>
<td>Node 3</td>
<td>1.5804835885907</td>
</tr>
<tr>
<td>Node 4</td>
<td>-0.8778430933414</td>
</tr>
</tbody>
</table>

**Distributional Fitting: Continuous (Anderson–Darling)**

<table>
<thead>
<tr>
<th>Rank</th>
<th>MAPE %</th>
<th>AD</th>
<th>Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>45.80%</td>
<td>0.2826</td>
<td>GumbelMax</td>
</tr>
<tr>
<td>2</td>
<td>46.98%</td>
<td>0.4680</td>
<td>Fréchet</td>
</tr>
<tr>
<td>3</td>
<td>53.94%</td>
<td>0.2703</td>
<td>Normal</td>
</tr>
<tr>
<td>4</td>
<td>57.65%</td>
<td>0.2782</td>
<td>Logistic</td>
</tr>
<tr>
<td>5</td>
<td>88.72%</td>
<td>0.3492</td>
<td>GumbelMin</td>
</tr>
<tr>
<td>6</td>
<td>289.64%</td>
<td>0.7048</td>
<td>TDist</td>
</tr>
<tr>
<td>7</td>
<td>447.11%</td>
<td>1.0000</td>
<td>Standard Normal</td>
</tr>
<tr>
<td>8</td>
<td>477.33%</td>
<td>1.0758</td>
<td>Weibull3</td>
</tr>
<tr>
<td>9</td>
<td>551.54%</td>
<td>0.4355</td>
<td>Exponential2</td>
</tr>
<tr>
<td>10</td>
<td>2710.10%</td>
<td>N/A</td>
<td>Uniform</td>
</tr>
</tbody>
</table>

Best Fit Rank: 1
Fit Name: GumbelMax
Alpha: 0.290457
Anderson-Darling Statistic: 0.282634
Beta: 0.276531
MAPE: 0.458042
Actual to Theoretical Four Moments:
0.439753 0.291298 0.234879 -0.931816
0.450074 0.354664 1.139547 2.400000
Author Biography

Dr. Johnathan Mun

is Professor of Research at the Naval Postgraduate School and is a specialist in advanced decision analytics, quantitative risk modeling, strategic flexibility real options, predictive modeling, and portfolio optimization. He has authored 32 books; holds 22 patents and patents pending; has created over a dozen software applications in advanced decision analytics; and has written over 100 technical notes, journal articles, and white papers. He is currently the CEO of Real Options Valuation, Inc., and his prior positions include vice president of Analytics at Oracle/Crystal Ball and a senior manager at KPMG Consulting. Dr. Mun holds a PhD in Finance and Economics from Lehigh University, an MBA and MS from Southeastern University, and a BS in Physics and Biology from the University of Miami.

(E-mail address: jcmun@nps.edu)