NPS-AM-22-014

ACQUISITION RESEARCH PROGRAM
SPONSORED REPORT SERIES

Cybersecurity, Artificial Intelligence, and Risk Management: Understanding Their Implementation in Military Systems Acquisitions

December 29, 2021

Dr. Johnathan Mun, Professor

Dr. Thomas Housel, Professor

Acquisition Research Program

Naval Postgraduate School

The research presented in this report was supported by the Acquisition Research Program at the Naval Postgraduate School.

To request defense acquisition research, to become a research sponsor, or to print additional copies of reports, please contact the Acquisition Research Program (ARP) via email, arp@nps.edu or at 831-656-3793.

Abstract

The exponential growth in data management has led to explosive growth in data analytics, big data, machine learning (ML), and artificial intelligence (AI). Despite the positive effects these emerging solutions have on productivity, there is a desperate need for information on extreme risk factors (e.g., climate change, pandemic risks, data loss, failure of information technology systems) impacting cybersecurity. We conducted a systematic review on how AI, especially ML, is being considered in military acquisitions, including discussions around risk management and extreme events in order to identify how the Department of Defense could use these findings to increase awareness of the hidden aspects of ML and AI, especially in the face of extreme events.

THIS PAGE LEFT INTENTIONALLY BLANK

About the Authors

Dr. Johnathan C. Mun is a research professor at the U.S. Naval Postgraduate School (Monterey, California) and teaches master's and doctoral courses as well as executive seminars in quantitative risk analysis, decision sciences, real options, simulation, portfolio optimization, and other related concepts. He has also researched and consulted on many Department of Defense and Department of Navy projects and is considered a leading world expert on risk analysis and real options analysis. He has over 23 patents and patents pending and has authored 22 books including *Modeling Risk: Applying Monte Carlo Simulation, Real Options, Optimization, and Forecasting*, First, Second, and Third Editions (Wiley, 2006; Wiley, 2010; and Thomson-Shore, 2015); *Real Options Analysis: Tools and Techniques*, First, Second, and Third Editions (Wiley, 2003; Wiley, 2005; and Thomson-Shore, 2016); *Advanced Analytical Models* (Wiley, 2008; ROV Press, 2016); *The Banker's Handbook on Credit and Market Risk* (Elsevier Science, 2008); and others. He is the creator of the following software: Real Options Super Lattice Solver, Risk Simulator, Project Economics Analysis Tool (PEAT), Modeling Toolkit, Risk Explorer, and ESO Valuation. His books and software are being used at top universities around the world (including the Bern Institute in Germany, Chung-Ang University in South Korea, Georgetown University, ITESM in Mexico, Massachusetts Institute of Technology, Naval Postgraduate School, New York University, Stockholm University in Sweden, University of the Andes in Chile, University of Chile, University of Pennsylvania Wharton School, University of Hull in the United Kingdom, and Edinburgh University in Scotland).

Dr. Mun has taught at universities all over the world, from the U.S. Naval Postgraduate School (Monterey, California) and University of Applied Sciences (Switzerland and Germany) as a full professor, to Golden Gate University (California) and St. Mary's College (California), and has chaired many graduate research thesis committees. He also teaches risk analysis, real options analysis, and risk analysis for managers public courses where participants can obtain the Certified in Quantitative Risk Management (CQRM) designation on completion of the week-long program. He also holds the position of the EU President of the American Academy of Financial Management (AAFM) and sits on the Global Board of Standards at the AAFM. He is currently the CEO of Real Options Valuation Inc., and was formerly the Vice President of Analytics at Crystal Ball/Decisioneering Inc., where he headed the development of options and financial analytics software products, analytical consulting, training, and technical support. Prior to that, he was a Consulting Manager and Financial Economist in the Valuation Services and Global Financial Services practice of KPMG Consulting and a Manager with the Economic Consulting Services practice at KPMG LLP. He has extensive experience in econometric modeling, financial analysis, real options, economic analysis, and statistics. He has consulted on a variety of real options, risk analysis, financial forecasting, project management, and financial valuation issues for over 100 multinational firms (former clients include 3M, Airbus, Boeing, BP, Chevron Texaco, Financial Accounting Standards Board, Fujitsu, GE, Microsoft, Motorola, Pfizer, Timken, U.S. Department of Defense, U.S. Navy, Veritas, and many others). His experience prior to joining KPMG included being Department Head of financial planning and analysis at Viking Inc. of FedEx, performing financial forecasting, economic analysis, and research.

Dr. Mun received his PhD in Finance and Economics from Lehigh University, where his research and academic interests were in the areas of Investment Finance, Econometric Modeling, Financial Options, Corporate Finance, and Microeconomic Theory. He also has an MBA in business administration, an MS in management science, and a BS in Biology and Physics. He is Certified in Financial Risk Management (FRM), Certified in Financial Consulting (CFC), and Certified in Quantitative Risk Management (CQRM). He is a member of the American Mensa, Phi Beta Kappa Honor Society, and Golden Key Honor Society, as well as several other professional organizations, including the Eastern and Southern Finance Associations, American Economic Association, and Global Association of Risk Professionals. Finally, he has written many academic articles published in the *Advances in Quantitative Finance and Accounting*, the *Global Finance Journal*, the *International Financial Review*, the *Journal of Financial Analysis*, the *Journal of Applied Financial Economics*, the *Journal of International Financial Markets, Institutions and Money*, the *Financial Engineering News*, and the *Journal of the Society of Petroleum Engineers*.

Dr. Tom Housel specializes in valuing intellectual capital, knowledge management, acquisitions research, telecommunications, information technology, value-based business process reengineering, and knowledge value measurement in profit and nonprofit organizations. He is currently a tenured Full Professor for the Information Sciences (Systems) Department. He has managed a $5 million+ portfolio of field studies, educational initiatives, and industry relationships.

His current research focuses on determining the most promising methodologies for improving the acquisitions life cycle and developing a physics-based model to predict revenue growth in knowledge-intensive companies. He continues to work in the behavioral accounting decision-making area and has published in a number of international accounting journals (e.g., *Accounting and Business Research* and *European Accounting Review*). His research was published twice in the top information systems journal, *Management Information Systems Quarterly* (MISQ).

Prior to joining Naval Postgraduate School, he was an Associate Professor at the Marshall School of Business at the University of Southern California. His last assignment in the corporate world was as the Chief of Consumer Market Research for Telecom Italia in Venice, Italy, where he developed new methods for predicting the adoption rates for new interactive multimedia broadband applications.

He received his PhD from the University of Utah in 1980. He won the prestigious Society for Information Management award for best paper in the field in 1986 that was subsequently published in the MISQ. His work on measuring the value of intellectual capital has been featured in a *Fortune* cover story (October 3, 1994) and in numerous books, professional periodicals, and academic journals. His books include *Measuring and Managing Knowledge* (English and Chinese versions) and *Global Telecommunications Revolution: The Business Perspective* with McGraw-Hill (both in 2001).

THIS PAGE LEFT INTENTIONALLY BLANK

NPS-AM-22-014

ACQUISITION RESEARCH PROGRAM SPONSORED REPORT SERIES

Cybersecurity, Artificial Intelligence, and Risk Management: Understanding Their Implementation in Military Systems Acquisitions

December 29, 2021

Dr. Johnathan Mun, Professor

Dr. Thomas Housel, Professor

Acquisition Research Program

Naval Postgraduate School

THIS PAGE LEFT INTENTIONALLY BLANK

Table of Contents

Introduction

This research has the explicit goal of proposing a reusable, extensible, adaptable, and comprehensive advanced analytical modeling process to help the U.S. Navy in quantifying, modeling, valuing, and optimizing a set of nascent artificial intelligence (AI) and machine learning (ML) applications in the aerospace, automotive, and transportation industries and develop a framework with a hierarchy of functions by technology category and create a unique-to-Navy-ship construct that, based on weighted criteria, scores the return on investment (ROI) of developing naval AI/ML applications that enhance warfighting capabilities.

This current research proposes to create a business case for making strategic decisions under uncertainty. Specifically, we look at a portfolio of nascent AI and ML applications, both at the Program Executive Office (PEO) Ships and extensible to the Navy fleet. This portfolio of options approach to business case justification provides tools to allow decision-makers to decide on the optimal flexible options to implement and allocate in different types of AI and ML applications, subject to budget constraints, across multiple types of ships.

The concept of the impact of innovative technology on productivity has applicability beyond the Department of Defense (DoD). Private industry can greatly benefit from the concepts and methodologies developed in this research to apply to the hiring and talent management of scientists, programmers, engineers, analysts, and senior executives in the workforce to increase innovation productivity.

Research Objective

The primary objective of the proposed research is to provide a business case analysis and ROI estimates for AI and ML systems and applications that will improve their acquisitions life cycle. Currently, the DoD has a portfolio of nascent AI and ML applications, both at the PEO Ships and eventually extensible to the entire Navy fleet. The main research problem is to create business case examples on how this portfolio of AI/ML applications is valued and optimized. The portfolio of options approach provides business case justification, providing tools to allow decision-makers to down select the optimal flexible options to implement and allocate in different types of AI and ML applications, subject to budget constraints, across multiple types of ships.

Literature Survey

For the DoD, acquiring AI technology is a relatively new difficulty. Given the significant danger of AI system acquisition failures, it's vital for the acquisition community to look at new analytical and decision-making methodologies for controlling these systems' acquisitions. Furthermore, many of these systems are housed in tiny, inexperienced system development firms, further complicating the acquisition process with insufficient data, information, and processes. The DoD's well-known challenge of obtaining information technology (IT) automation will almost certainly be compounded when it comes to acquiring complicated and dangerous AI systems. To assist in minimizing costly AI system acquisition disasters, more powerful and analytically driven acquisition approaches will be required. To complement existing earned value management (EVM), this study identifies, reviews, and proposes advanced analytically based methods of integrated risk management (IRM; Monte Carlo simulation, stochastic forecasting, portfolio optimization, and strategic flexibility options) and knowledge value added (KVA; using market comparables to determine the economic value of intangibles and nonfinancial government programs).

The Real Options Valuation methodology is a new approach that has been effectively applied in a variety of commercial industries to measure the entire future worth of decisions taken when there is a significant degree of uncertainty at the time decisions are needed. PEO Ships needs a new methodology to assess the total future value of various combinations of nascent AI and ML applications and how they will enable affordable warfighting relevance over the full ship service life to successfully implement the Surface Navy's Flexible Ships concept.

This research project looks at how the IRM technique may be applied in the Future Surface Combatant Analysis of Alternatives (AoA) to estimate the entire future value and ROI of AI design characteristics.

Defense Acquisition System

The Defense Procurement System, which supervises national investment in technologies, projects, and product support for the United States Armed Forces, handles the acquisition of new systems for the DoD (2003). Its main goal is to “acquire high-quality goods that meet user objectives while delivering measurable advances in mission capability and operational support in a timely and cost-effective manner” (DoD, 2003). The Joint Capabilities Integration and Development System (JCIDS), the Planning, Programming, Budgeting, and Execution (PPBE) process, and the Defense Acquisition System are three different but interrelated processes inside the DoD Decision Support System (DoD, 2017a). Within the Defense Acquisition System, this study focuses on program management rather than contract management.

Acquisition Categories (ACAT) are assigned to acquisition programs based on the type of program and the dollar amount spent or expected to be spent within the program (DoD, 2015a). Figure 1 depicts the Defense Acquisition System’s numerous cost-based designations and categories. All ACAT classification dollar amounts are determined in Fiscal Year 2014 dollars (DoD, 2015a). ACAT I is for big defense acquisition programs with a Research, Development, Test & Evaluation (RDT&E) budget of more than $480 million, or a total procurement budget of more than $2.79 billion (DoD, 2015a). ACAT IA programs do not meet the criteria for ACAT I and will spend more than $835 million in total procurement (DoD, 2015a) or more than $185 million in RDT&E. ACAT II programs do not meet the criteria for ACAT I and will spend more than $520 million in total life-cycle cost, $165 million in the total program cost, or $40 million for any single year of a program (DoD, 2015a). Finally, ACAT III programs are those that do not meet the requirements for ACAT I or ACAT II (DoD, 2015a). Because each category has varied reporting requirements and designated decision-makers, the multiple designations allow for decentralized control of a program (DoD, 2017a).

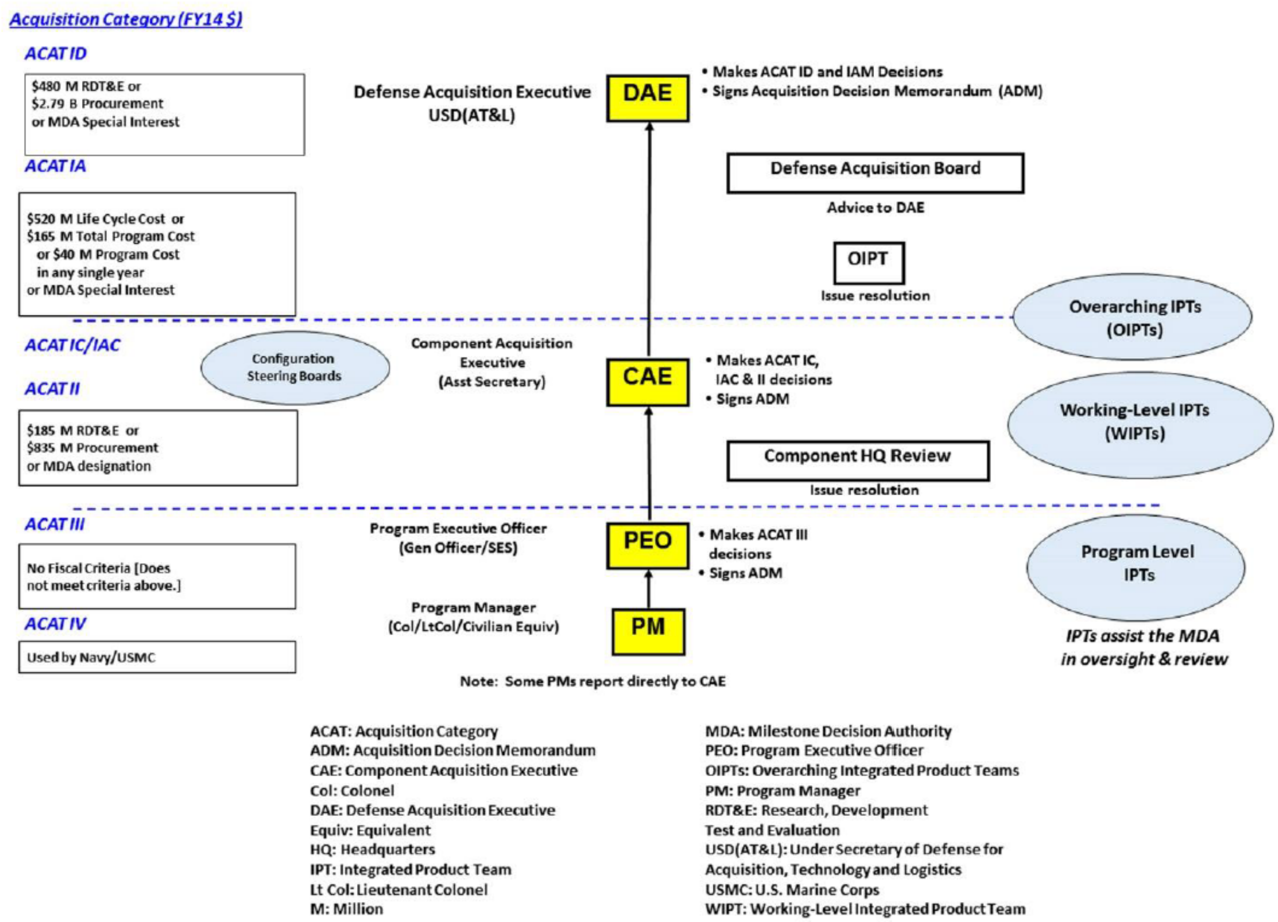


Figure 1. Acquisition Categories. Source: DoD (2017).

There are five phases within the Defense Acquisition System:

- Materiel Solution Analysis (MSA)
- Technology Maturation and Risk Reduction (TMRR)
- Engineering and Manufacturing Development (EMD)
- Production and Deployment (PD)
- Operations and Support (OS)

The acquisition process is driven by requirements for new or better capabilities, which are delivered through the JCIDS process (DoD, 2015a). The relationship between the acquisition and capabilities needs processes, as well as their interaction in the various acquisition phases, is depicted in Figure 2. The capabilities required from the JCIDS procedure are assumed to be correct and necessary in this investigation.

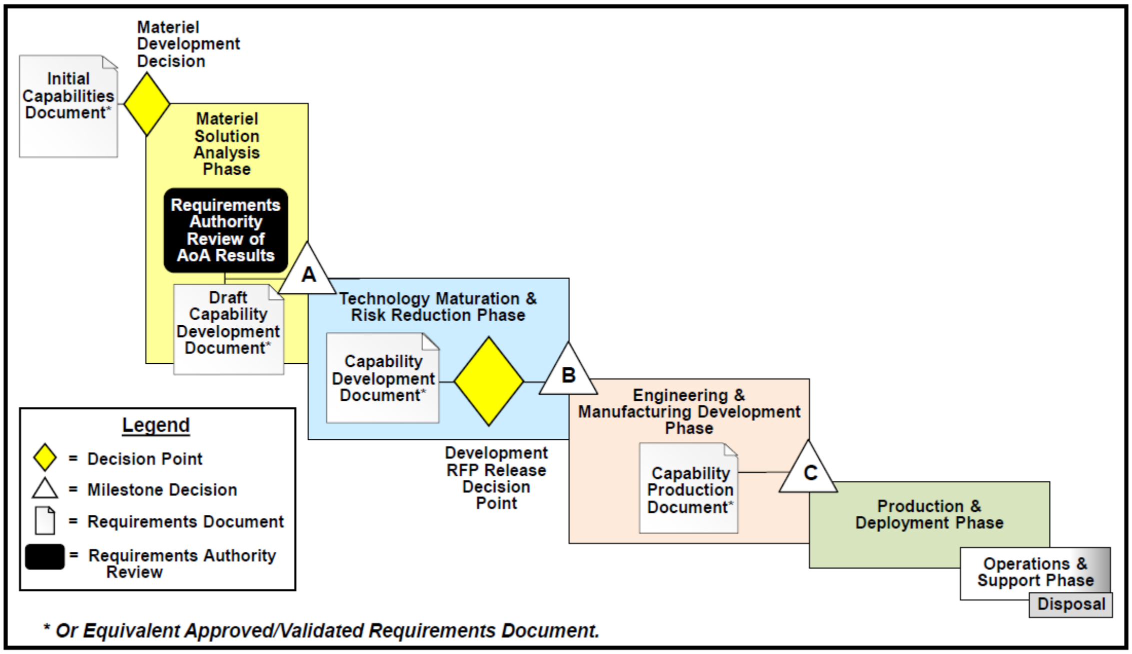


Figure 2. Interaction of Capabilities Requirements and Acquisition Process. Source: DoD (2015a).

The Materiel Development Decision kicks off the MSA phase after an Initial Capabilities Document (ICD) has been validated (DoD, 2015a). Although an acquisition program is not legally constituted until Milestone B at the end of the phase, this choice initiates the acquisition process (DoD, 2015a). The goal of the MSA phase is to select the most promising possible acquisition process solution that will meet the ICD's demands and to define the system's Key Performance Parameters (KPPs) and Key System Attributes (KSAs; DoD, 2015a). An AoA is used to assess the acceptability of proposed acquisitions based on "measures of effectiveness; important tradeoffs between cost and capacity; total life-cycle cost, including sustainment; time line; the concept of operations; and overall risk" (DoD, 2015a, p. 17). During this stage, the program manager (PM) is chosen and the program office is established (DoD, 2015a). After the necessary analysis is completed, the decision authority—usually the Defense Acquisition Executive (DAE), head of the DoD component, or Component Acquisition Executive (CAE), unless otherwise delegated—determines whether the program will proceed to the next phase based on the justification for the chosen solution, how affordable and feasible the solution is, and how adequate the cost, schedule, and other factors (DoD, 2015a). Milestone A is the name given to this decision (DoD, 2015a). The MSA phase examines all possible solutions to a stated demand and, as a result, may be an opportune time to investigate strategic techniques like KVA or IRM.

The program enters the TMRR phase after Milestone A approval to decrease the risk associated with the technology, engineering, life-cycle cost, and integration of the program before moving on to the EMD phase (DoD, 2015a). At this step, design and requirement trades are carried out based on the budget, timetable, and possibility of completion (DoD, 2015a). Contractors prepare early designs, including competing prototypes if practicable within the program, to show the practicality of their proposed solutions to the program office, guided by the acquisition strategy authorized at Milestone A (DoD, 2015a).

Technology Readiness Levels (TRLs) are a set of standards that show the level of risk involved with a solution maturing on time (DoD, 2015a). Technology Readiness Assessments (TRAs) are a metric-based technique for assessing the maturity and risk associated with important technology in an acquisition program (DoD, 2011). Each important technology in a program will be assigned a TRL by a TRA, ranging from 1 to 9 from lowest to maximum readiness level (DoD, 2011). Additional tools, such as IRM, to estimate the chances of a program remaining on schedule and on budget, may be useful at this stage. The Publication Decision Point for Development Requests for Proposals (RFPs) permits the release of an RFP with firm and clearly specified program requirements for contractors to submit bids (DoD, 2015a). Unless the milestone decision authority waives it, the Preliminary Design Review (PDR) occurs prior to the completion of the TMRR phase (DoD, 2015a). Milestone B approves a program's entry into the EMD phase, awards a contract, and establishes the Acquisition Program Baseline (APB; DoD, 2015a). The APB is a legal commitment to the milestone decision authority that outlines the authorized program, especially the cost and schedule over the program's life (DoD, 2015a).

Once Milestone B has been approved, EMD can commence. Prior to production, the material solution is conceived, produced, and tested to ensure that all requirements have been met (DoD, 2015a). The hardware and software designs have been finished, and prototypes have been developed to detect any design flaws that will be uncovered during developmental and operational testing (DoD, 2015a). Federal regulation requires DoD procurement projects with a contract value higher than $20 million to utilize EVM to track and report program progress, which begins during this phase (DoD, 2019a). The manufacturing or software sustainment methods, as well as production capabilities, must be appropriately proven once a stable design that meets the given requirements has been validated (DoD, 2015a). Milestone C verifies that these requirements have been met and authorizes the start of the PD phase (DoD, 2015a).

The goal of the PD phase is to deliver a product that meets the standards established earlier in the process (DoD, 2015a). Low Rate Initial Production (LRIP) for manufactured systems or limited deployment for more software-intensive programs occurs first, with the system undergoing Operational Test[ing] and Evaluation (OT&E) to verify that stated criteria were satisfied (DoD, 2015a). Full-rate manufacturing occurs when the fielded systems have been approved, and the product is deployed to operating units (DoD, 2015a). At this time, design changes are limited, however, some may still be made in response to identified flaws (Housel et al., 2019a). During this phase, contracts often revert to a fixed pricing strategy, lessening the PM's focus on cost and schedule variance (Housel et al., 2019b).

The operating system is meant to keep the product supported and perform well throughout its life cycle, which ends with the system's disposal (DoD, 2015a). Because operational units are using the product while production is ongoing, the OS phase overlaps with the PD phase, starting after the production or deployment decision (DoD, 2015a). PMs will maintain the system running by following the Life Cycle Sustainment Plan (LCSP) set during the purchase phase and providing the appropriate resources and support (DoD, 2015a). Technological upgrades, modifications due to operational needs, process enhancements, and other activities that may necessitate LCSP updates are all examples of sustainment and support (DoD, 2015a).

PMs employ six different models to develop their program structure, four of which are standard and two of which are hybrid, depending on the type of system being purchased (DoD, 2015a). These standard models serve as templates for hardware-intensive projects, defense-specific software-intensive programs, software-intensive programs that are incrementally deployed, and expedited acquisition programs (DoD, 2015a). The hybrid models, as seen in Figure 3, combine the progressive character of software development with a hardware-centric program. Before attaining the Initial Operating Capacity (IOC), software development is arranged through a sequence of tested software builds that will climax with the completely required capability (DoD, 2015a). The incremental builds are timed to coincide with prototype hardware testing and other developmental requirements (DoD, 2015a). With the exception of the accelerated program, all other models use the same basic foundation across the five phases.

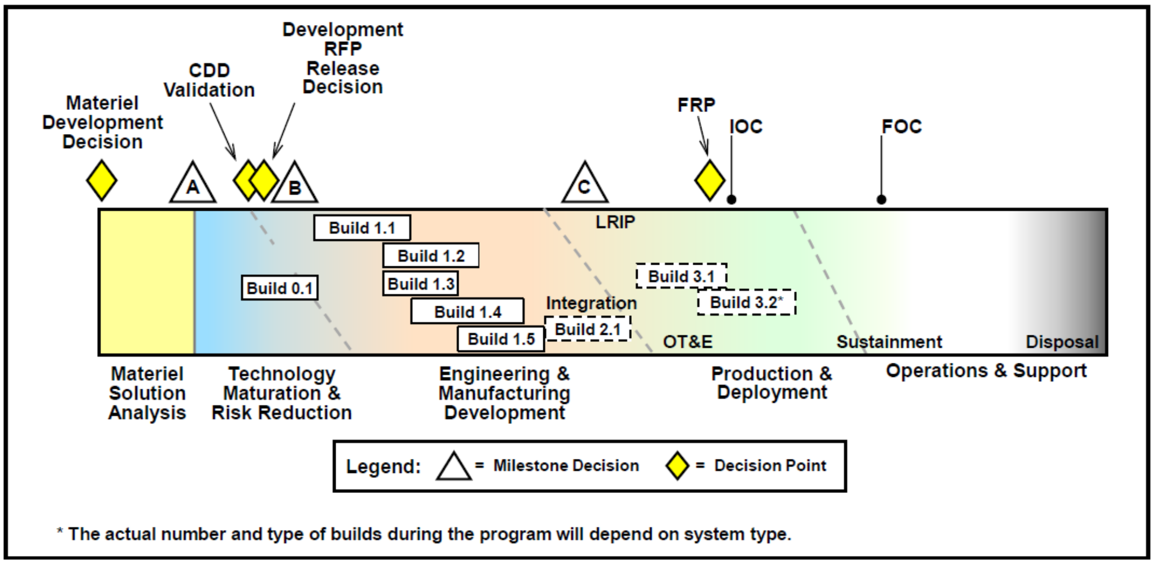


Figure 3. Hardware-Dominant Hybrid Program. Source: DoD (2015a).

AI and IT systems, as well as their connections to weapon systems, facilities, and Command, Control, Communications, Computers, Intelligence, Surveillance, and Reconnaissance (C4ISR), are becoming more common within the DoD (2015b). As a result of the integration, enemies pose a greater security risk, emphasizing the significance of good cybersecurity skills and processes (DoD, 2015b). The DoD manages cybersecurity policy using the Risk Management Framework (RMF), which employs security measures based on risk assessments throughout a system's life cycle (DoD, 2015b). "All DoD IT that receives, processes, stores, displays, or transmits DoD information" (DoD, 2014, p. 2) is covered by RMF. RMF's definition of cybersecurity goes beyond information security to include things like stable and secure engineering designs, training and awareness for all program users, maintainers and operators, and the response, recovery, and restoration of a system after an internal or external failure or attack (DoD, 2015b). Figure 4 depicts the six steps of the RMF's procedure, which occurs throughout the acquisition process.

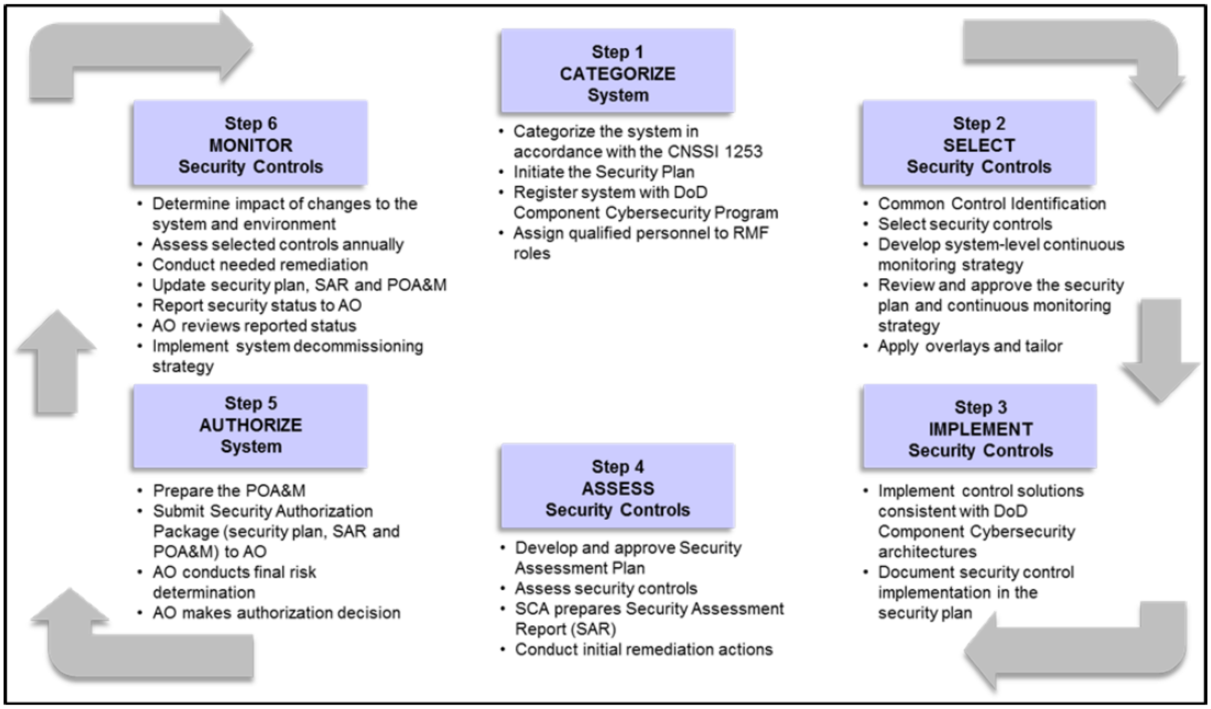


Figure 4. Risk Management Framework Process. Source: DoD (2014).

The first stage is to categorize the system, which includes assessing the possible impact of a breach and describing the system and its boundaries (DoD, 2014). The RMF team is formed, the security plan is implemented, and the system is registered with the DoD Component Cybersecurity Program (DoD, 2014). The ICD includes cybersecurity standards, which drive MSA concerns during the AoA phase (DoD, 2015b). A cybersecurity breach might have serious consequences for missions, according to the risk assessment (DoD, 2015b). The RMF provides a somewhat objective technique for determining the cybersecurity risk level, as well as the baseline security controls that must be incorporated in the system's purchase strategy (DoD, 2015b).

The RMF team determines security measures in Step 2, including those that are common to other DoD programs (DoD, 2014). A plan is designed and recorded for regularly monitoring the effectiveness of the controls (DoD, 2014). The security plan is subsequently submitted to the DoD Components, who examine and approve it (DoD, 2014). During the MSA phase, the acquisition and cybersecurity teams collaborate to ensure that the proper level of security is applied throughout the program's life cycle, as well as in the system architecture and design (DoD, 2015b). During the MSA, the continuous monitoring strategy and security plan are also designed (DoD, 2015b).

The approved security procedures are then implemented in accordance with DoD specifications (DoD, 2014). The implementation must be well documented in the security plan for the system (DoD, 2014). In the TMRR phase, cybersecurity requirements are included in the system performance requirements (DoD, 2015b).

The RMF team must then create, review, and approve a Security Assessment Plan that will allow the security controls to be properly assessed (DoD, 2014). Following approval, the security of the system is evaluated in line with DoD assessment processes and the Security Assessment Plan, during which vulnerabilities are assigned severity levels and the security risk for both the controls and the whole system is established (DoD, 2014). This is documented in the Security Assessment Report, which is necessary before any system is authorized and security control repair activities are carried out (DoD, 2014). Prior to issuing an RFP, the Capability Development Document's cybersecurity criteria are evaluated throughout the TMRR process (DoD, 2015b). The cybersecurity parts of the PDR, which is also done during the TMRR process, will ensure that the authorized plan is executed in the chosen design and risks are reduced to an appropriate level (DoD, 2015b). All computer code follows applicable standards and secure coding practices as the system grows in the EMD phase, with evaluations undertaken and documented in the security plan (DoD, 2015b).

A Plan of Action and Milestones (POA&M) is produced based on the identified vulnerabilities, which identifies activities to mitigate the vulnerabilities, resources required to fulfill the plan, and milestones for completing tasks (DoD, 2014). The Security Authorization Package is given to the authorizing official, who will decide whether the risk level is appropriate before authorizing the system (DoD, 2014). The POA&M is created during the MSA phase and continues throughout the system development process (DoD, 2015b).

Finally, security controls must be monitored throughout the system's life cycle to ensure that any changes to the system or environment do not compromise cybersecurity (DoD, 2014). If vulnerabilities are discovered, the necessary remedy will be carried out, and the security strategy will be updated (DoD, 2014). The cybersecurity of a system is monitored in line with the continuous monitoring strategy and security plan once it has been approved and operationally implemented (DoD, 2015b). When the system, its surroundings, or the anticipated use of the system change, new risk assessments are done (DoD, 2015b). If a vulnerability is discovered, the PM changes the security plan and the POA&M to specify how the issue will be resolved (DoD, 2015b).

Portfolio Modeling in Military Applications

Optimization is a long-standing and legendary subject that involves using data and information to assist decision-making in order to achieve an optimal, or near-optimal, result. Despite the fact that they collect more data than ever before, "government agencies have been significantly slower to apply these approaches to boost efficiency and mission effectiveness" (Bennett, 2017). Optimization solutions for these government agencies can make use of enormous volumes of data from many sources to give decision-makers alternative options that best match agency goals.

Standard economic indicators such as the internal rate of return (IRR), net present value (NPV), and ROI are often employed in evaluating commercial-based research and development (R&D) projects to assist in finding optimal alternatives, as Greiner et al. (2001) accurately stated. However, in their commercial form, such economic criteria are of little utility in appraising weapon system development efforts. As a result, this study looks at the difficulties the DoD has in estimating the value of weapon systems during the R&D portfolio selection process.

Beaujon et al. (2001) used a mathematical formulation of an optimization model to choose projects for inclusion in an R&D portfolio, subject to a range of constraints, to balance and optimize a portfolio of R&D projects (e.g., capital, headcount, strategic intent, etc.). There does appear to be widespread consensus that all of the recommended methods are fraught with risk. The authors devised a method for examining the sensitivity of project selection decisions to changes in the measure of value.

Burk and Parnell (2011) looked at how portfolio decision analysis is used in military applications such as weapon systems, force types, installations, and military R&D initiatives. They began by contrasting military and commercial portfolio challenges in general, as well as outlining the military decision environment's distinctive characteristics: aggressive and adaptive opponents, a public decision process with various stakeholders, and high system complexity. The authors concluded that, based on their research, the "most widely prominent element of these applications is the rigorous modeling of value from numerous objectives" (Burk & Parnell, 2011). "Quantitative approaches of evaluating and valuing risk are surprisingly infrequent, given the high level of uncertainty in the military environment" (Burk & Parnell, 2011), they discovered. Their investigation focused on how military analysts model portfolio values, weight evaluations, restrictions and dependencies, and uncertainty and risk in portfolio applications.

Davendralingam and DeLaurentis (2015) used a system of systems (SoS) technique to analyze military capabilities. According to the authors, this technique poses major technical, operational, and programmatic obstacles in terms of development. There aren't any tools for deciding how to construct and evolve SoS that takes performance and risk into account. To aid decision-making within SoS, they used methods from financial engineering and operations research perspectives in portfolio optimization. To address intrinsic real-world challenges of data ambiguity, internodal performance, and developmental risk, the authors suggested using more robust portfolio algorithms. The paper used a naval battle scenario to demonstrate scenario applications for finding system portfolios from a candidate list of accessible systems. Their findings reveal that by allowing the optimization problem to handle the mathematically intensive components of the decision-making process, the optimization framework effectively minimizes the combinatorial complexity of trade-space exploration. As a result, the authors argued that human decision-makers should be entrusted with selecting suitable risk aversion weights rather than the portfolio's mathematical constructions when making final decisions.

A portfolio management analysis was conducted by Sidiropoulos et al. (2014) with the goal of identifying and evaluating current commercial off-the-shelf (COTS) Portfolio Analysis (PA) software tools and solutions. Portfolio models were created using Risk Simulator. These models were filled with pertinent data before being run through a sufficient number of simulation iterations to evaluate candidate projects in terms of risk and expected military value (EMV). Portfolio Management Analysis (PMA) is discussed in this paper through examples and models at various levels of project management and systems engineering. The PMA aim is achieved after the full project design infrastructure is in place and the end users' instruments are ready to use. The authors wanted to find "approaches and tools to incorporate PMA net-centric strategies to meet war fighter and business operations requirements while maintaining current levels of service, ensuring manpower conservation, and meeting infrastructure resource requirements" (Sidiropoulos et al., 2014).

Flynn and Field (2006) examined quantitative metrics to assess the Department of the Navy's (DoN's) procurement portfolio in order to improve business operations through better analytical tools and models. The authors discovered that the DoN's time would be better spent if it shifted its focus away from individual acquisition projects (which have now been well examined) and toward a portfolio of systems as a whole. This strategy is similar to the methodology used in the commercial sector as a best practice. According to the study, this high-level view offers senior military officials useful metrics for assessing cost, capability, and requirement risks and uncertainties. Senior leaders can make better decisions from a set of plausible portfolios armed with these indicators in order to meet the Navy's national security objectives. To complement their research, financial management and acquisition staff picked a portion of the then-current DoN portfolio to test a portfolio analysis approach in the field of Mine Countermeasures, a diverse, representative system of projects. This pilot model was a multiphase process that included gathering life-cycle cost data for the various systems to be analyzed, establishing a scoring system with subject matter experts (SMEs) to determine how well current and future systems match capabilities to requirements, and developing a way to display results so decision-makers can examine risk–reward analysis and trade-offs. The researchers' ultimate goal was to use portfolio analysis to evaluate military investments.

The GAO (1997, 2007) stressed the importance of adjusting a portfolio mix in order to reduce risk and maximize returns. Despite the fact that the DoD creates superior weapons, the GAO found that it has failed to deploy weapon systems on time, on budget, and with the intended capabilities. While recent improvements to the DoD's procurement process have the potential to enhance outcomes, major cost and schedule overruns continue to plague programs. The GAO was tasked with looking into how the DoD's mechanisms for determining needs and allocating funding could be improved to better support weapon system program stability. According to the report, the GAO compared the DoD's policies for investing in weapon systems to the best practices used by successful commercial organizations such as Caterpillar, Eli Lilly, IBM, Motorola, and Procter & Gamble to produce a balanced mix of new products. According to the studies, successful commercial enterprises that the GAO studied employ an integrated, portfolio management approach to product development in order to establish a balanced mix of executable development programs and ensure a favorable return on their investments. Companies evaluate product investments collectively from an enterprise level, rather than as separate and unrelated activities, using this method. These commercial entities use established criteria and methods to weigh the relative costs, benefits, and risks of proposed products and select those that can exploit promising market opportunities while staying within resource constraints and moving the company toward its strategic goals and objectives. Investment decisions are regularly reconsidered in these enterprises, and if a product fails to meet expectations, companies make difficult go/no-go judgments over time. Effective portfolio management necessitates a governance structure with committed leadership and clearly aligned roles and responsibilities, portfolio managers who are empowered to make investment decisions, and accountability at all levels of the organization, according to the GAO's examination of companies. The DoD, on the other hand, authorizes new initiatives with far less regard for the broader portfolio and commits to them sooner and with less knowledge of cost and feasibility. Despite fighting as a joint force on the battlefield, the military services define needs and allocate resources individually, utilizing fragmented decision-making processes that do not allow for an integrated portfolio management approach like that utilized by successful commercial firms. As a result, the DoD might be less certain that its investment decisions meet the correct mix of warfighting demands, and it begins more programs than current and likely future resources can support, resulting in a fiscal tsunami. If this pattern continues, Congress will be forced to choose between diverting funds from other high-priority federal programs to pay DOD acquisitions or accepting gaps in warfighting capability.

The Army has adopted the Army Portfolio Management Solution (APMS) to enable the collection and analysis of information needed to prioritize the thousands of IT investments in its portfolio (Wismeth, 2012). Warfighter, Business, and Enterprise Information Environment Mission Areas, each of which is overseen by a three- or four-star general officer or senior executive, are the three mission areas that IT investments serve.

Government agencies and the DoD, according to Botkin (2007), require decision-support systems when making funding decisions for portfolios of programs or projects. When it comes to selecting potential programs, government agencies have had some success with Project Portfolio Management (PPM); however, once programs are up and running, financial managers are faced with funding optimization decisions that are similar to those faced by private-sector stock market portfolio managers. Government finance managers lack an analogous "stock-price" metric for program or project performance, whereas private-sector portfolio managers rely on financial portfolio analysis based on "stock price" to guide decision-making. According to Botkin's (2007) research, the government's Earned Value Management System (EVMS) indicators can be utilized to provide a good proxy for financial portfolio analysis. Risk and return trade-offs can be quantified and used to make portfolio decisions based on the results of this study. Botkin's study includes an example utilizing representative EVM data. Recommendations on the technique's potential usefulness and limits are presented.

The Office of Naval Research (ONR) is in charge of establishing and sponsoring the R&D required to support the Navy and Marine Corps' current and future requirements. According to Silberglitt et al. (2004), the ONR must fund a broad range of research to achieve this purpose, ranging from basic research to open up new long-term choices to extremely near-term advanced technology development to support the current fleet. In the face of uncertainty, the ONR must make R&D funding decisions (uncertainty in required capabilities, uncertainty in performance requirements, and uncertainty in the feasibility of a technology or R&D approach). The application of a RAND R&D portfolio management decision framework was presented in the Silberglitt et al. (2004) study.

The DoD should support dynamic and innovative solutions for tomorrow's warfighter by building acquisition portfolios that deliver an integrated suite of capabilities (Janiga & Modigliani, 2014). Today's program executive officers are sometimes tasked with executing a dozen or more identical but separate programs. Large commercial businesses, on the other hand, oversee integrated product lines that include everything from automobiles and electronics to software and health services. The DoD might use this technique to build portfolios of similar initiatives that yield improved capabilities in shorter time frames.

Jocic and Gee (2013) developed a method for comparing space services given by several systems in a portfolio that allows for a normalized value of diverse system properties and can be displayed using a three-dimensional graph with capability, cost, and scheduling axes. Portfolio optimization is achieved by remaining within the cost–capability plane's efficient performance frontier, maintaining within the cost–schedule plane's budgetary restrictions, and reducing the likelihood of a capability gap in the schedule–capability plane. The required portfolio capability is obtained from the military utility analysis–generated combat scenario outcomes.

Under an assignment headed "Portfolio Optimization Feasibility Study," the Institute for Defense Analyses (IDA) prepared a document for the Office of the Director, Acquisition Resources and Analysis (Weber et al., 2003). The goal was to see if it was possible to use optimization technology to improve long-term defense acquisition strategy. The model provided in this document is an example of optimization techniques that can estimate and optimize Acquisition Category I program production schedules over an 18-year period.

The modern warfighter, according to Vascik et al. (2015), operates in an environment that has substantially evolved in sophistication and interconnection over the last half-century. With each passing year, acquisition officers have more challenges in making decisions about potential joint capability programs due to the infusion of ever more complicated technology and integrated systems. Furthermore, despite efforts since 2010 to ensure system affordability, large cost overruns in recent acquisition programs demonstrate that more work is needed to develop improved methodologies and methods.

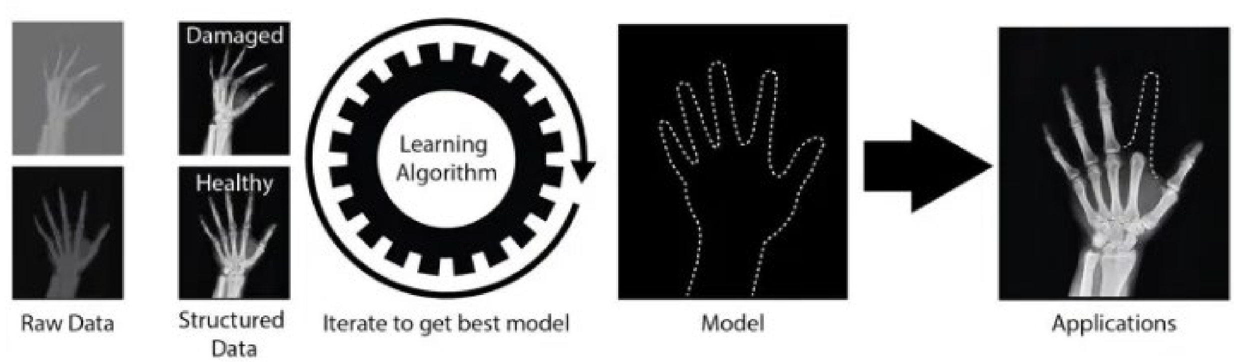
Vascik et al. presented research that expands on previous work that looked at system design trade-spaces for affordability under uncertainty and applied it to programs and portfolios. Exogenous factors that change over time, such as resource availability, stakeholder needs, or production delays, can affect the potential for value contribution by constituent systems throughout the course of a portfolio's life cycle, making an initially appealing design less appealing. By combining features of Epoch-Era Analysis with aspects of Modern Portfolio Theory, Vascik et al. (2015) presented a method for conducting portfolio design for affordability. The process is demonstrated through the creation of a carrier strike group portfolio that includes the integration of different legacy systems as well as the purchase of new vessels.

State of the AI

Machine Learning

Intelligence is the ability to process a specific sort of data, allowing a processor to solve significant problems (Gardner, 1993). Beyond the traditional idea of a person's analytic intelligence quotient (IQ), which can sometimes evaluate merely how well someone performs on an IQ test rather than their natural talents, psychologists have postulated many categories of intelligence. Howard Gardner proposed a theory of multiple intelligence, which suggests that traditional psychometric views of intelligence are too narrow and that intelligence should be expanded to include more categories in which certain processors, in this case, people, are better at making sense of different stimuli than others. Visual-spatial, linguistic-verbal, interpersonal, intrapersonal, logical-mathematical, musical, body-kinesthetic, and naturalistic intelligence are some of the categories of intelligence (Gardner, 1993). A counterargument would be that these categories simply represent learned and disciplined habits that people develop through time as a result of their personality and environment. Regardless, both definitions of intelligence (traditional and many) are relevant to the stages involved in developing an AI machine.

A computer can execute computations depending on the input data and produce an a priori defined outcome. It can be built and reprogrammed to repeat particular stages or algorithms, and even change its conclusions based on previously calculated results using error-correcting techniques. The underlying principle of ML is a combination of these two phases. A computer system is fed data that are structured in such a way that the algorithm can identify the data, deduce patterns, and make assumptions about any unstructured data that is presented later (Greenfield, 2019). In an X-ray learning algorithm, this is shown in Figure 5.



The image shows the steps an AI algorithm goes through in order to make a recommendation to a physician on where a missing body part should be. It takes in structured data and develops its understanding of what “right” looks like. When given unstructured data, the algorithm compares the image against previously trained models and identifies the abnormality with a recommendation on where to apply a fix, such as a prosthetic.

Figure 5. AI Training Algorithm. Source: Greenfield (2019).

The basic concept of ML is illustrated in Figure 5, although the current research focuses on the many types of learning from the standpoint of procurement. The following are interpretations of different forms of learning in procurement algorithms provided by Sievo (2019), an AI procurement software business.

Supervised Learning

The patterns are taught to an algorithm using previous data, and the algorithm then recognizes them automatically in new data. Humans give supervision in the form of the right responses, which train the algorithm to look for patterns in data. This is a term that is widely used in procurement sectors like spend classification (Sievo, 2019).

Unsupervised Learning

The algorithm is set up to look for novel and fascinating patterns in brand-new data. The algorithm isn’t expected to surface specific accurate answers without supervision; instead, it hunts for logical patterns in raw data. Within important procurement functions, this is rarely employed (Sievo, 2019).

Reinforcement Learning

The algorithm determines how to act in specific scenarios, and the behavior is rewarded or punished based on the outcomes. In the context of procurement, this is mostly theoretical (Sievo, 2019).

Deep Learning

Artificial neural networks gradually develop their capacity to accomplish a task in this sophisticated class of ML inspired by the human brain. This is a new opportunity in the procurement world (Sievo, 2019).

Natural Language Processing

Anyone who has used devices that appear to be able to understand and act on written or spoken words, such as translation apps or personal assistants like Amazon's Alexa, is already familiar with Natural Language Processing (NLP)–enabled AI. NLP is a set of algorithms for interpreting, transforming, and generating human language in a way that people can understand (Sammalkorpi & Teppala, 2019). Speech soundwaves are converted into computer code that the algorithms understand. The code then translates that meaning into a human-readable, precise response that can be applied to normal human cognition. This is performed by semantic parsing, which maps the language of a passage to categorize each word and forms associations using ML to represent not just the definition of the word, but also its meaning in context (Raghaven & Mooney, 2013). Figure 6 depicts this categorization and analysis process in the context of a procurement contract.

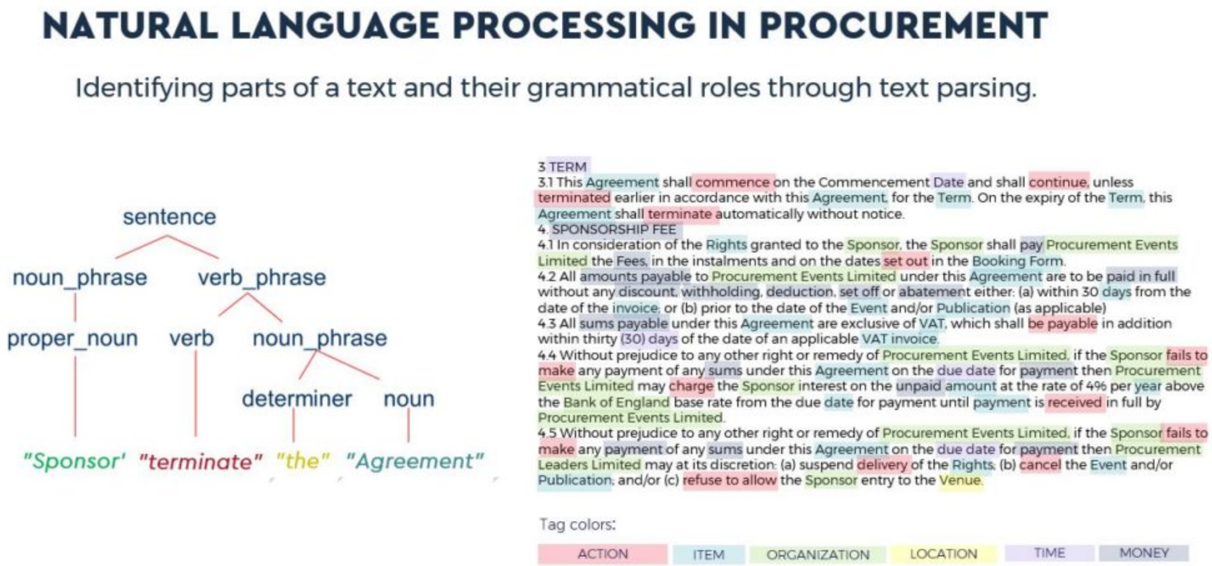


Figure 6. Semantic Parsing in Procurement. Source: Sievo (2019).

Robotic Process Automation

Robotic Process Automation (RPA) is not AI; rather, it is an existing process that has been advanced by AI, as explained in the third section of this paper. RPA is defined as "the use of technology by employees in a firm to set up computer software or a robot to capture and interpret current applications for processing transactions, altering data, triggering reactions, and communicating with other digital systems" (Institute for Robotic Process Automation and Artificial Intelligence [IRPA & AI], 2019, p. X). When used correctly, robotic automation offers numerous benefits because it is not constrained by human limitations such as weariness, morale, discipline, or survival requirements. Robots, like their human creators, have no ambitions. Working harder will not get you more money or get you promoted, and being permanently turned off will have no effect because robotic automation just duplicates the practical parts of the human intellect, not the underlying nature of mankind (Zarkadakis, 2019). (Note, however, that ML relies on an incentive system to make judgments about positive or negative reactions.)

A future AI-enabled RPA option is for a machine to learn how to control the source of positive reinforcement fully independent of the rules required to achieve its aim. Things that survive develop to do so because of positive reinforcement from their environment and the fact that they continue to act in a way that is considered survivable. This should be taken into account in any future AI efforts, and especially in the case of why a human must always be present when final judgments are made. Regardless of whether AI systems have a perfect track record or not, they should not be entirely trusted.

Technology Trust

The Turing Test was created to test the capabilities of AI, as detailed in the third section of this report. Google developers designed Duplex, a spoken-word NLP tool, in 2018 to interface with its AI assistant. Its goal is to make phone calls on behalf of humans, converse with other humans, and respond to inquiries in a natural manner, all while sounding human (Leviathan, 2018). The algorithm can search for the information required as if it were a human searching for it on Google, for example. The AI assistant then calls a restaurant, for example, to schedule an appointment with the assistant's human. After being given oral information from a person hearing the orders, the software stutters, pauses, and elongates certain vowels as though it has to think about what it is saying, and responds with other recommendations within its limitations.

The authors questioned an AI NLP program named 1558M about one of the research issues twice for the purposes of this paper, and the machine responded with an unusual "opinion" of a negative and cautionary character (Figure 7). This tool was built to allow users to experiment with Open AI's new ML model (King, 2019). What's noteworthy about these responses is that they are all original, which means a search of the phrases turns up no copies. However, the language and tone make them sound like they're coming from a knowledgeable source, with just enough small evidence on the topic to be credible. However, the program does not finish its last phrase, making it unfinished but noteworthy. Clearly, such AI capabilities has a lot of potential for helping someone integrate with the DoD.

Is DoD ready for AI in contracting?

The answer is, "No." The DoD has an extremely limited ability to respond to technological shifts in a timely manner. In addition to the problems inherent in implementing a new technology on the same scale as DoD systems, there are several reasons to be cautious with new contracting methods:

The DoD does not have sufficient funds and resources to do so.

Contractors are generally not the most skilled in applying modern technology.

Contractors generally have limited autonomy.

A system cannot be fully tested within a period of one year, as such it would require extensive testing to determine whether or not the system is a success or failure.

As a result, it is unlikely that the DoD will adopt automation, AI, or robotics without the assistance of other agencies. For example, DoD is developing a framework for "Autonomy-Enhanced Contracts," which will "ensure that the DoD's contracting activities will be more

Is DoD ready for AI in contracting?

The Defense Science Board recently issued a report calling for AI to be an essential part of all military contracting. However, it's important to note that this is a new concept that hasn't been fully explored.

The report is largely based on research into military operations conducted in Afghanistan by the U.S. Army and the U.S. Navy. The report's recommendations include developing AI that can work in concert with humans to augment operational capabilities. AI systems could assist with the creation of better weapons systems, or assist human commanders to do their jobs more effectively.

The report also recognizes that AI is not a silver bullet: It's not enough to simply give a robot an A.I. license. Rather, it's important to understand that it's a "toolbox," and that AI could play an important role in the overall mission. It's the human factor that will be key to ensuring that AI systems are reliable and effective. The report

Figure 7. Two Separate Results From an AI Called 1558M. Source: King (2019).

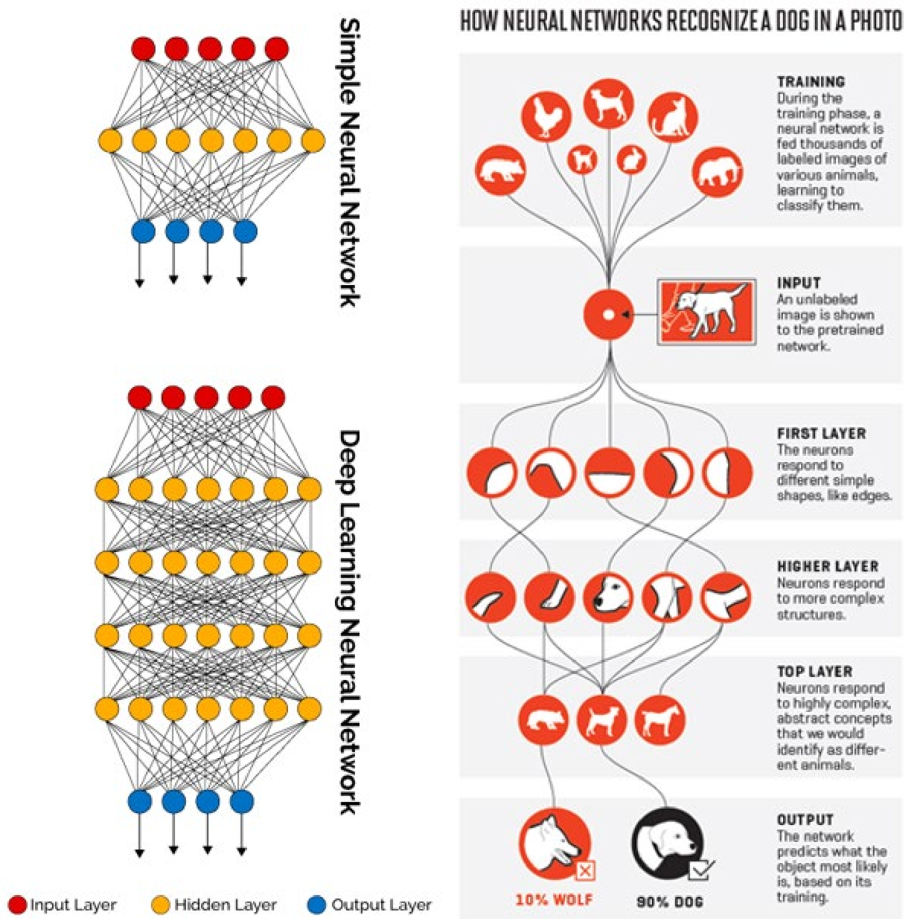
Explainable Reasoning

One of the barriers to AI adoption is the ability to explain how the algorithm arrived at its conclusions, which is necessary for auditing (Knight, 2017). It would be irresponsible to utilize AI for military or financial goals without the capacity to track how judgments were made. Figure 8 depicts how AI currently categorizes data. The AI programs that produce the required outcome come up with their own means of navigating multiple layers of complexities to develop output for the plethora of training data that went into creating the program.

Fortunately for the DoD, the Defense Advanced Research Projects Agency (DARPA), which is already ingrained in the defense ecosystem, is leading the charge on explainable AI research (Gunning, 2017). DARPA

> has taken the lead in pioneering research to develop the next generation of AI algorithms, which will transform computers from tools into problem-solving partners. DARPA research aims to enable AI systems to explain their actions, and to acquire and reason with common sense knowledge. DARPA R&D produced the first AI successes, such as expert systems and search, and more recently has advanced machine learning tools and hardware. DARPA is now creating the next wave of AI technologies that will enable the United States to maintain its technological edge in this critical area. (Defense Advanced Research Projects Agency [DARPA], 2019)

The mechanics of how a Deep Neural Network navigates its trained data to identify different photographs can be seen in Figure 9. Photos can be used to train an AI software, and associations of these trained data can then be used in the neural network to classify an input and eventually reach a conclusion. As a result, if the DoD decided to pursue human–machine cooperation in areas like contracting, its organic system would enable it to do so.



To identify the output layer, the Simple Neural Network uses a set of input data that only passes through one hidden layer. To better identify the output data, the Deep Learning Neural Network transmits the input data through numerous layers. The Deep Learning Neural Network goes through simple to more detailed layers of trained data that correspond with dog features to make a 90% confidence classification that the picture is a dog and a 10% possibility that it is a wolf to classify input data to determine if the given picture is a dog.

Figure 8. Simple Neural Network Compared to Deep Learning Network. Adapted from Golstein (2018), Parloff (2016).

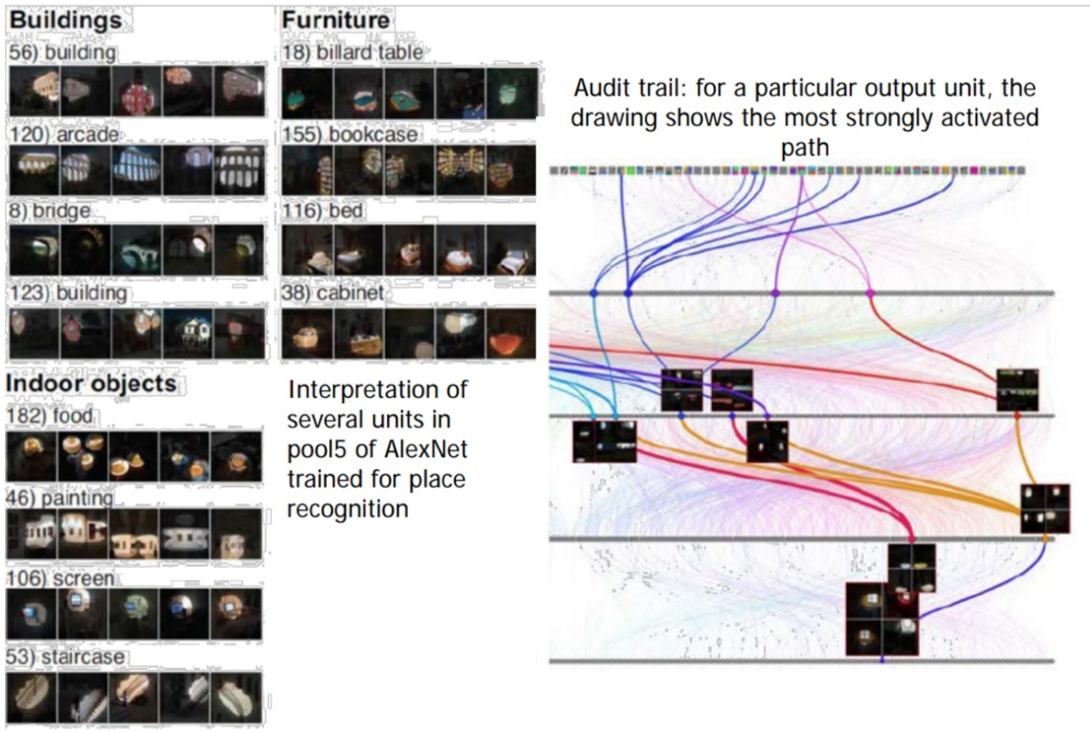
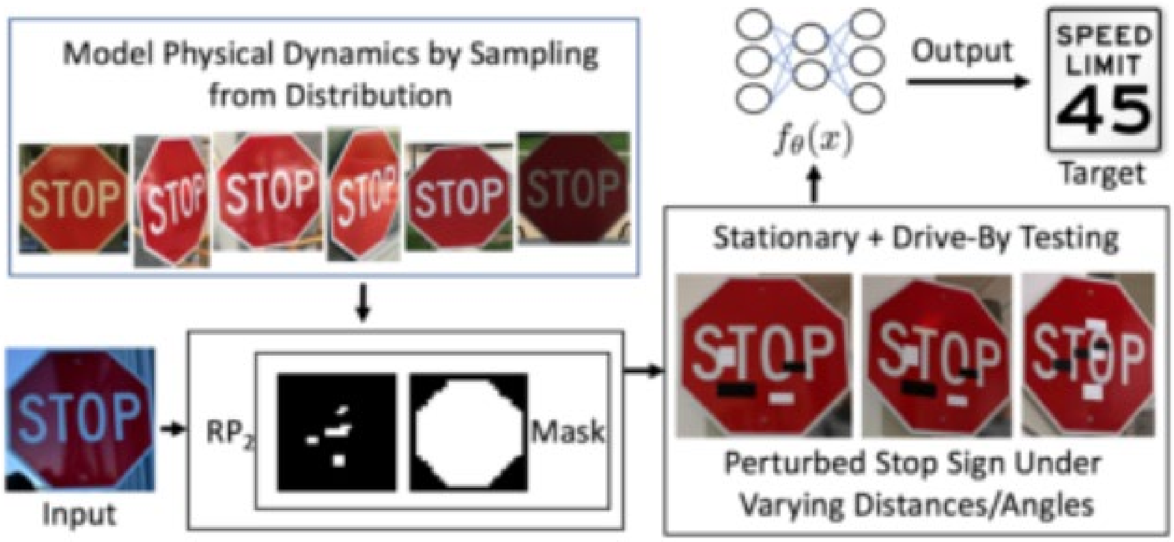


Figure 9. Visualization of Explainable AI. Source: DARPA (2019).

Human–Machine Partnership

Because sensor, information, and communication technologies generate data at rates faster than people can digest, comprehend, and act on, DARPA believes AI integration is vital as a human–machine symbiosis (DARPA, 2019). Machines are better at certain things, as they were throughout the industrial revolution, and using machines for those activities frees humans to become more productive in other areas. Separate areas of processing are where humans and machines flourish. Consider the following contrasts between computers and humans: calculate versus decide, compare versus make judgments, apply logic versus empathizing, unaffected by tiresome repetition versus preferences, deals with enormous data versus intuitional concentration on the most important (Darken, 2019). And, while AI is capable of performing some jobs on its own, it performs better when paired with a human partner. Without sufficient restrictions, AI is a trusting learning system that can be manipulated by evil actors. According to certain studies, AI can be misled in ways that humans cannot owing to human intuition. Other study has been able to deceive a self-driving car into thinking a benignly tampered with stop sign was a speed limit sign (Figure 10), which would almost certainly result in collisions if the car were left unattended (Eykholt et al., 2018).

Many people are aware of contemporary intelligent machine relationships that they may encounter on a regular basis without even realizing it. Google is the most popular search engine on the Internet because it gives more user happiness than its competitors, as stated with its other apps (Shaw, 2019). Google is so widely used as the primary search engine that many refer to it as “Googling” while looking for something online. This is a good example of humans engaging organically with a Bidirectional Encoder Representations from Transformers (BERT)–based AI system (Nayak, 2019). This is a strategy that trains a machine to answer a user’s inquiry based on the meaning of the words in the context of the question rather than on individual phrases. For example, when asking what time it is right before lunch, the user is really asking when they can eat; the outright answer would give the actual time, and the asker would deduce eating time, which was the underlying meaning of the question. Another example of human contact with intelligent machines is so-called self-driving automobiles. The user mostly sits in a supervisory role while the automobile takes over one of the most dangerous moments in their lives and handles all road tasks autonomously to drive (Darken, 2019).



An AI program in a self-driving car has trained data about a stop sign in its algorithm. When a target sign is seen in its environment, it references the trained data. As a test, researchers attached benign interruption markers on the sign, which confused the AI program to think the stop sign was a speed limit sign.

Figure 10. AI System Interpreting a Stop Sign. Source: Eykholt et al. (2018).

Contractors that rely on an AI system to make all of their decisions are vulnerable to deliberate misdirection by adversaries providing hostile information for competitive advantage or disruption. Fraudsters can learn how to manipulate computer algorithms, but only humans can assess the outcomes. AI software, on the other hand, can quickly extract data and explain contract content. It can swiftly gather and organize renewal dates and terms from a large number of contracts. It can help businesses evaluate contracts faster, organize and locate vast amounts of contract data more readily, reduce the risk of contract disputes and adversarial contract negotiations, and improve the number of contracts the business can negotiate and execute (Rich, 2018).

Case Study of Private Sector AI Application to Contracting

To compare DoD procurement options, we look at analogous situations in the private sector in the United States. Lawgeex is an example of a startup that is integrating AI into the procurement process in the private sector. An example contract component, the Nondisclosure Agreement (NDA), demonstrated that AI software could outperform U.S.-trained lawyers with an average accuracy of 94%, compared to 85% for humans

(Lawgeex, 2018). Large firms that rely on contracts to engage with partners, suppliers, and vendors have an 83% dissatisfaction rate with their organization's contracting processes, according to the report (Lawgeex, 2018). Another example is Icertis, which provides services to huge and well-known firms like 3M, Johnson & Johnson, and Microsoft, to name a few (Icertis, n.d.-a). Icertis offers a cloud-based AI platform that learns from the client's contracts, as well as control measures, to generate and help in contract setup, contract operations, governance, risk, and compliance, and reporting (Icertis, n.d.-a).

The fact that business is more acclimated to putting professional papers on digitally accessible storage infrastructure, whether local hard drives or the cloud, makes this practical now, rather than when it was initially theorized decades ago (Betts & Jaep, 2017). Nontechnical barriers to a completely automated contract review and analysis process now exist, such as the gathering of contract performance data, the disclosure of private contracts and their associated performance data, and changes in ethical limits on computer usage in legal practice (Betts & Jaep, 2017). The authors of these barriers also propose policy solutions to address them: begin using contract management software as a forcing function to create data in an AI teachable format, expand copyright protection for vendors to protect their intellectual property, and develop new rules to help mitigate AI risks so that it can work (Betts & Jaep, 2017).

Cloud-Based AI

We look at the concept of cloud computing to understand how AI may be disseminated throughout a system, update regulations, and learn from various human teachers in real time. When it comes to DoD technology adoption, the term "speed of relevance" is frequently used. The term "cloud" is used in the 2018 *DoD Cloud Strategy* to refer to an offsite physical IT infrastructure (Shanahan, 2018). This external infrastructure connects to a user's personal computer through the Internet to access data servers that store information and run centrally managed operating systems like Microsoft Windows. This means that every user has the same software computing capacity and access to the most recent software, regardless of their organization's IT professional talent or software budget. Organizations can have as much or as little access to what they need for projects as they need it, and they are unaffected by surges in demand or periods of inactivity, which now add to the cost of DoD systems (Shanahan, 2018). DoD's goal is to have AI-assisted rapid decision-making in a secure and visible data environment for increased operational efficiency.

> Data stored in an enterprise DoD cloud will be highly available, well-governed, and secure. Data will be the fuel that powers those advanced technologies, such as ML and AI. This critical decision-making data will be made available through modem cloud networking, access control, and cross-domain solutions to those who require access. Common data standards will be a key part of the Department's methodology for tagging, storing, accessing, and processing information. Ensuring an enterprise cloud environment will increase the transparency of this data, and drive the velocity of data analysis, processing, and decision making. Leveraging advances in commercial cloud security technologies will ensure the Department's information is protected at the appropriate level. (Shanahan, 2018, pp. 5–6)

Methodologies

Knowledge Value Added (KVA)

Benefits

KVA is a way for measuring the value produced by a system and its subprocesses that are objective and quantitative. Analysts can compare the obtained ratios to the ratios from other subprocesses to establish their relative efficacy because each process's value measurements employ ratio scale numbers. KVA translates all process outputs into common value units, resulting in a consistent productivity performance ratio across all operations. PMs can compare the value added by IT processes to the value generated by the human component. PMs can use these measurements to build meaningful ratios in their study of the program's performance thanks to the scales. Return on knowledge (ROK; i.e., a process's common unit outputs) is divided by the process cost necessary to produce the outputs, and for ROI calculations, the ratio is monetized outputs minus cost divided by cost. The ROKs and ROIs, which are always 100% associated, inform managers about the amount of value a process provides versus the amount of money invested to achieve that value. Unlike any other methodology, KVA assigns these figures to both the process and subprocesses, not only the company as a whole (as is done in standard, generally accepted accounting practice metrics used in standard financial ratios).

Conducting a KVA analysis of a program will provide a PM with a clearer understanding of the value of the program's operational components. While most firms utilize cost/schedule metrics to assess the success of a project or operation, ROK will provide them with additional value-based data to help them make better management decisions. The relative predicted baseline value of the program's components can be determined using PMs. Knowing that a certain job or subprocess produces the same output value as another process but at a different cost can help you understand why the entire system is performing differently. As a result, experienced managers have the information they need to dedicate resources to specific program components that need improvement or should be used more frequently, resulting in increased value added. It also enables for estimations of the potential value added of an AI system feature that was not originally planned for the project.

While a KVA study can provide information to aid in program or project management, it does not necessitate significant changes to organizational structure or reporting systems. Without bringing complicated new measures into the system, the review can be carried out as part of standard reporting procedures. The learning time, process instruction (e.g., work breakdown structure [WBS] can be used as a surrogate for this technique), and binary query method are all dependent on data from the project description and requirements documents. To validate the accuracy of the presented data, a modest amount of hands-on measuring may be required. As a result, the analysis can be completed faster than other standard assessment approaches (e.g., activity-based costing), providing PMs with more timely access to relevant data.

Challenges

The value of the components that produce the outputs of the subprocesses will be quantified using KVA, which is a ratio-scale number. It does this, however, only with processes that have known a priori outputs. The intangible objects that occur within the human brain, such as creativity and imagination, cannot be quantified using this method, or any other method for that matter. In reality, because there is no formula for creativity, no present method can effectively quantify these types of intangibles within a process. Because the creative process cannot be learned or described algorithmically, these factors are not common to the ordinary user and hence cannot be specified using any of the KVA methods—learning time, binary query, or process description. Once creativity has been used to create an AI capacity, KVA can be used to algorithmically describe its productivity. KVA assigns a process's current value, but it can't forecast the value of potential future additional outputs unless they can be described using one of the KVA methods.

Although KVA will supply ratio-scale data to assist in analyzing processes inside a program, the ratios are frequently only useful for comparisons between projects. Benchmarking the raw figures against other organizations or other divisions within the same organization will give a useful benchmark for assessing predicted ROK performance. The resulting ROK, ROI measurements will be comparable among organizations (for business and nonprofit) that create diverse products or services, regardless of the language used to describe outputs. Because these output descriptions are in standard units, they can be viewed as a value constant across all processes, with the value of a component subprocess or core process determined solely by the number of outputs. The end outcome of any correctly completed research will yield similar ROK and ROI estimations, which is KVA's ultimate purpose.

Integrated Risk Management (IRM)

To forecast when various projects will be completed, all organizations rely largely on project planning software. Completing projects on schedule, on budget, and to a set value is crucial to the effective operation of a business. Many factors can influence a timetable in today's high-tech world. When it comes to technical capabilities, they frequently fall short of expectations. In many circumstances, requirements may be insufficient and require more elaboration. Tests might produce unexpected results, both good and harmful. Cost rises, timetable lapses, and value variations can all be caused by a variety of factors. In rare circumstances, we may be blessed with good fortune, and the schedule can be accelerated without jeopardizing the project's productivity.

Project time lines are inherently insecure, and changes are expected. As a result, we should anticipate changes and devise the best strategy for dealing with them. So, why do projects take so much longer than expected? The inaccuracy of timetable estimation is one of the reasons. The following discussion describes the flaws in standard timetable estimation approaches, as well as how simulation and advanced analytics can be used to remedy these flaws.

It is crucial to first comprehend the IRM process and how the various methodologies are related in the context of risk analysis and risk management. From a qualitative management screening process to provide clear and concise reports for management, this framework contains eight separate steps of a successful and complete risk analysis implementation. The process was based on past successful risk analysis, forecasting, real options, valuation, and optimization projects in both consultancy and industry-specific settings by the author. These phases can be completed independently or in order for a more thorough integrated study.

The procedure can be broken down into eight easy steps:

- Qualitative Management Screening
- Forecast Predictive Modeling
- Base Case Static Model
- Monte Carlo Risk Simulation
- Real Options Problem Framing
- Real Options Valuation and Modeling
- Portfolio and Resource Optimization
- Reporting, Presentation, and Update Analysis (Mun, 2016a).

Qualitative Management Screening

The first stage in every IRM process is qualitative management screening. In accordance with the firm's mission, vision, goal, or overall business strategy, management must determine which projects, assets, initiatives, or strategies are viable for further analysis, which may include market penetration strategies; competitive advantage; and technical, acquisition, growth, synergistic, or globalization issues. That is, the initial list of initiatives should be qualified in terms of how well they would achieve management's objectives. When management frames the entire problem to be solved, the most important insight is often generated. The numerous dangers to the firm are identified and flushed out in this step.

Forecast Predictive Modeling

If historical or comparable data are available, the future is projected using time-series analysis or multivariate regression analysis. Other qualitative forecasting methods may be employed instead (subjective guesses, growth rate assumptions, expert opinions, Delphi method, etc.). Future revenues, sale price, quantity sold, volume, production, and other key revenue and cost drivers are projected at this stage in the financial process. Time series, nonlinear extrapolation, stochastic process, Autoregressive Integrated Moving Average (ARIMA), multivariate regression forecasts, fuzzy logic, neural networks, econometric models, Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and other methods are examples of methodologies.

Base Case Static Model

A discounted cash-flow model is generated for each project that passes the initial qualitative tests, whether it is for a single project or numerous projects under consideration (KVA analysis uses the market comparables approach to monetize processes and activities). Using the anticipated values from the previous phase, a net present value is generated for each project using this model as the base case analysis. The traditional approach of modeling and forecasting revenues and expenses, then discounting the net of these revenues and costs at an appropriate risk-adjusted rate, yields this net present value. Here the ROI, as well as other profitability, cost–benefit, and productivity indicators are calculated.

Monte Carlo Risk Simulation

Because the static discounted cash flow only provides a single-point estimate, there is often little trust in its accuracy, especially given the significant uncertainty surrounding future events that affect expected cash flows. Next, Monte Carlo risk simulation should be used to better evaluate the actual worth of a project. The discounted cash-flow model is normally subjected to a sensitivity analysis first; that is, by designating the net present value as the outcome variable, we can vary each of the previous variables and see how the resulting variable changes. As they go through the model, revenues, costs, tax rates, discount rates, capital expenditures, depreciation, and other prior factors all have an impact on the net present value number. By tracing back all of these previous variables, we can change each of them by a predetermined amount and assess the effect on the resulting net present value. Due to its shape, the most vulnerable preceding variables are depicted first, in descending order of magnitude, on a graphical depiction that is frequently referred to as a tornado chart. With this information, the analyst can evaluate which crucial aspects are deterministic in the future and which are very uncertain. The uncertain important variables that drive the net present value and, thus, the decision are known as critical success drivers. For these critical success criteria, Monte Carlo simulation is an excellent fit. Because several of these critical success determinants are linked—for example, operational costs may rise in proportion to the quantity sold of a particular product, or prices may be inversely associated to quantity sold—a correlated Monte Carlo simulation may be required. The majority of the time, historical data can be used to make these relationships. When you run correlated simulations, you get a lot closer to the real-world behavior of the variables.

Real Options Problem Framing

The dilemma now is what to do after quantifying hazards in the previous stage. The risk data gathered must be transformed into actionable intelligence in some way. So what, just because risk has been estimated as such and such using Monte Carlo simulation? And what do we do about it? The solution is to apply actual options analysis to mitigate these risks, value them, and position yourself to profit from them. The act of defining the problem generates a strategic map, which is the first stage in real possibilities. Certain strategic options for each project would have been obvious based on the overall problem identification that occurred during the initial qualitative management screening phase. The strategic options could include, for example, the ability to expand, contract, abandon, switch, choose, and so on. The analyst can then choose from a list of choices to investigate further based on the identification of strategic options that exist for each project or at each stage of the project. Real options are incorporated to projects to protect against downside risks and to profit from upswings.

Real Options Valuation and Modeling

The resulting stochastic discounted cash-flow model will have a distribution of values thanks to Monte Carlo risk simulation. As a result, simulation models, analyzes, and quantifies each project's unique risks and uncertainties. As a result, the NPVs and project volatility are distributed. We assume that the underlying variable in real options is the project's future profitability, which is represented by the future cash-flow series. The results of a Monte Carlo simulation can be used to calculate the implied volatility of the future free cash flow or underlying variable. Usually, the volatility is measured as the standard deviation of the logarithmic returns on the free-cash-flow stream (other approaches include running GARCH models and using simulated coefficients of variation as proxies). Furthermore, in real options modeling, the present value of future cash flows for the base case discounted cash-flow model is used as the initial underlying asset value.

Real options analysis is used to determine the strategic option values for the projects using these inputs.

Portfolio and Resource Optimization

Portfolio optimization is a step in the analysis that can be skipped. Because the projects are usually associated with one another, management should view the results as a portfolio of rolled-up projects if the analysis is done on numerous projects. Viewing them individually will not offer the actual picture. Because businesses don't just have one or two initiatives, portfolio optimization is essential. Because certain projects are interconnected, there is potential for risk hedging and diversification through a portfolio. Portfolio optimization takes all of these factors into account to build an optimal portfolio mix because firms have limited budgets, as well as time and resource constraints, while also having needs for particular overall levels of returns, risk tolerances, and so on. The research will determine the best way to allocate funds across multiple projects.

Reporting, Presentation, and Update Analysis

Until reports can be created, the analysis is not complete. Not only should the results be communicated, but so should the process. A complex black box set of analytics is transformed into transparent processes by clear, simple, and exact explanations. Management will never accept outcomes from black boxes if they don't know where the assumptions or data come from, or what kind of mathematical or financial manipulation is going on. Risk analysis presupposes that the future is uncertain, and that management has the authority to make mid-course corrections when these uncertainties or risks are resolved; the analysis is typically performed ahead of time, and therefore ahead of such uncertainty and risks. As a result, if these risks are identified, the analysis should be updated to integrate the decisions made or to revise any input assumptions. Several iterations of the real options analysis should be undertaken for long-horizon projects, with future iterations being updated with the newest data and assumptions.

Understanding the processes required to complete the IRM process is critical because it reveals not only the technique itself but also how it differs from previous analyses, indicating where the traditional approach finishes and the new analytics begin.

Applying IRM: Schedule and Risk Management

A list of tasks is usually the starting point for traditional schedule management. Following that, the tasks are ordered and linked from predecessor to successor for each task. They're usually shown in the form of a Gantt chart or a network. The network diagram is the focus of our discussion in this section. After that, the duration of each task in the network is calculated. Even though we know from experience that this estimate should be a range of values, each task's projected duration is provided a single-point estimate. As a result, the first error is relying on a single-point estimate. Furthermore, many people who make duration estimates try their hardest to put their best foot forward and give the most optimistic or best-case scenario. If we assume that the probability of attaining this best-case estimate for one task is 20%, then the probability of meeting the best case for two tasks is only 4% (20% of 20%), and only 0.8% for three tasks. There is simply an infinitesimal possibility of meeting the best-case timetable in a real project with many more tasks. The network is built and the various paths within the network are tracked after the job duration estimates have been created. Each of these path's job durations is added together, and the one that takes the longest is designated as the critical path.

Using example data, Figure 11 depicts a network and critical path (Mun, 2016a). The project completion date is calculated as the sum of task durations along the critical path. From the beginning to the finish of the network, there are four paths shown. With a total time of 22 days, Tasks 1-2-3-10-11 is the shortest/quickest path. Tasks 1-7-8-9-10-11 is the next shortest path at 34 days, followed by path 1-4-5-6-10-11 at 36 days. Finally, the crucial path for this network is 1-4-8-9-10-11, which takes the longest at 37 days.

Assume that this network of tasks is part of a bigger effort and that another effort upstream has gone over by a day. To get the entire effort back on track, a supervisor has requested a cut of the schedule by 1 or 2 days. Traditional schedule management has only one goal: to reduce the critical path's longest duration item. Another option is to reduce the length of each task along the critical path. Let's say we'll employ the first strategy because it's more focused, more likely to succeed, and causes fewer disputes on our team. As a result, we will wish to lower Task 8 from 9 to 10 days in order to shorten our timetable and satisfy our boss or customer. Let us quit the usual methods at this point, content with our efforts but eager to investigate alternatives. To improve project management, the next step is to look into simulation and risk analytics. We'll use Monte Carlo risk simulations on each task's predicted budget and schedule, resulting in a probabilistic and risk profile picture of the network's cost and schedule.

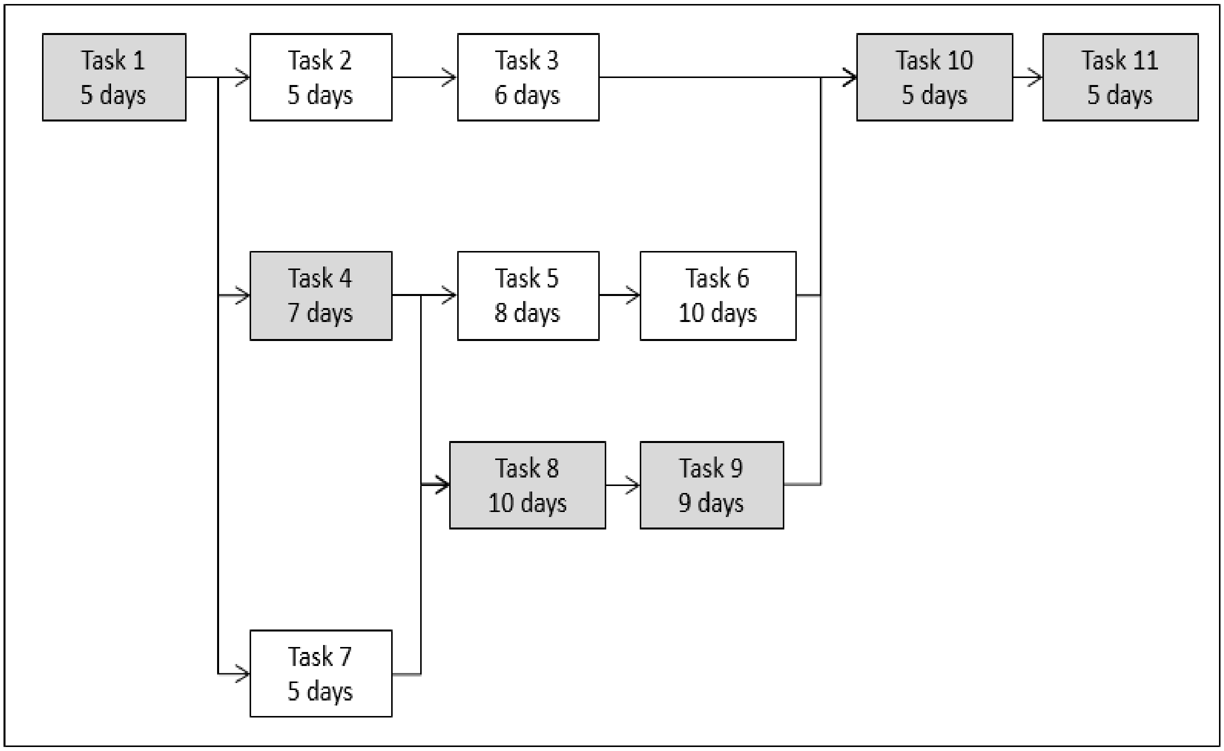


Figure 11. Complex Network Task

Probabilistic Schedule Management

If we accept that job durations can fluctuate, then schedule models should account for this uncertainty. A scheduling model can be created by defining a probability distribution for each task, which represents the probability of finishing the task in a certain amount of time. The complete range of probable project durations can then be forecasted using Monte Carlo simulation techniques.

An appropriate probability distribution to employ to describe the uncertainty for the length of a work is a basic triangle distribution. It's a perfect fit because when we ask someone to provide a range of duration values for a certain job, they often provide two of the distribution's elements: the lowest and maximum durations. To complete the triangular distribution, we only need to inquire or determine the most likely duration. Customers and supervisors alike appreciate the parameters since they are clear, intuitive, and easy to grasp. Other, more sophisticated distributions, such as the Beta or Weibull, could be employed, but there is little benefit, if any, because determining the estimated parameters for these distributions is prone to error, and the method of determination is not clearly explainable to the customer or employer.

To obtain the most accurate estimations, we should consult numerous sources for estimates of the task duration's least, most likely, and maximum values. We can talk to the contractor, the project manager, and the employees who are really doing the work, and then develop a list of time estimates. Historical data can also be used, although caution should be exercised because many initiatives are similar to previous projects but frequently contain numerous distinct aspects or combinations. Figure 12 might be used as a reference. Minimum values should indicate optimal resource consumption. Maximum values should account for significant issues, but it is not necessary to account for the absolute worst-case scenario in which everything goes wrong and the issues compound. Note that the most likely value is the one that is encountered the most frequently, but in most circumstances, it is less than the median or mean. The least, most likely, and highest values indicated in Figure 13 will be used for our example situation (see Figure 11). We may utilize Risk Simulator software to build triangular distributions based on these lowest, most likely, and maximum parameters by setting input assumptions. Figure 13 shows a column of dynamic duration values that was constructed by randomly selecting one sample from each of the corresponding triangular distributions.

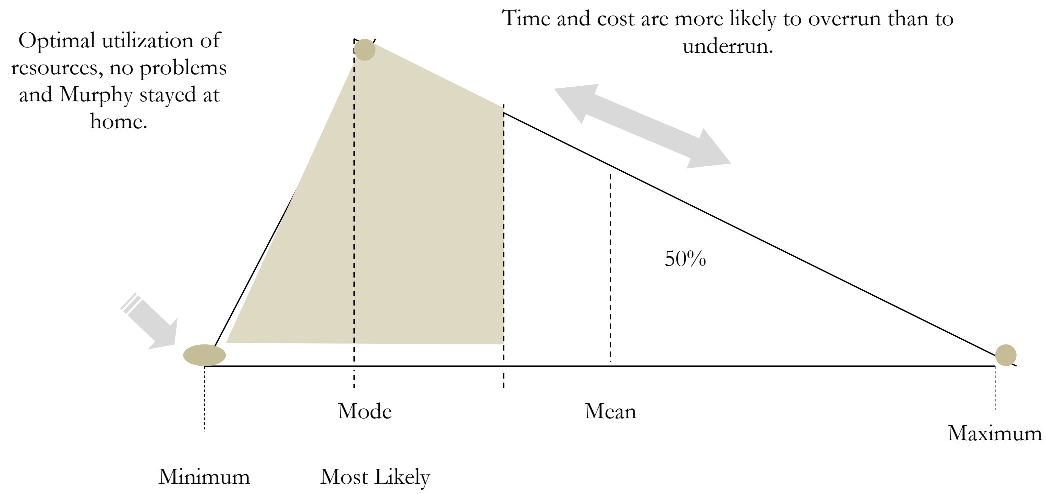


Figure 12. Triangular Distribution

The next stage is to use the scheduling network to determine the paths after the triangular distributions have been formed. From beginning to end, there are four paths through the network in the example problem presented in Figure 11. These pathways, together with their related durations, are depicted in Figure 14. The total duration of the entire schedule is the longest of the four paths. That figure would be designated as an Output Forecast in Risk Simulator. We are not concerned about critical path/near-critical path situations in probabilistic schedule analysis because the calculations automatically account for all path durations.

We can now perform a Monte Carlo simulation in Risk Simulator to generate a schedule duration forecast. The outcomes for the example problem are shown in Figure 15. Let's go back to the numbers that the standard method produces. The project was supposed to be finished in 37 days, according to the original estimate. Based on the Monte Carlo simulation, we can predict the likelihood of completing the task in 37 days if we utilize the left-tail function on the forecast chart. In this situation, there is only an 8.27% chance of finishing in the allotted 37 days. This outcome demonstrates the old method's second flaw: Not only is the point estimate wrong, but it also places us in a high-risk overrun situation before the work ever begins! The median value is 38.5 days, as illustrated in Figure 14. For most circumstances, some industry standards propose utilizing the 80% certainty estimate, which in the example problem translates to 39.5 days.

Task #	Task Name	Min	Likely	Max	Point Estimate
1	Stakeholder Analysis	4.5	5	6	5
2	Objectives Hierarchy	4.5	5	6	5
3	Decision Metrics Development	5.5	6	7	6
4	Functional Analysis	6	7	9	7
5	Primary Module Requirements	7	8	10	8
6	Primary Module Development	9	10	13	10
7	Secondary Module Functional Analysis	4.5	5	6	5
8	Secondary Module Requirements	9	10	12	10
9	Secondary Module Development	8	9	10	9
10	Trade Studies	2.5	3	4	3
11	Final Development Specification	2.5	3	4	3

Figure 13. Range of Task Durations

Path 1	Time 1	Path 2	Time 2	Path 3	Time 3	Path 4	Time 4
1	5.78	1	5.78	1	5.78	1	5.78
2	4.79	4	7.78	4	7.78	7	5.20
3	6.16	5	9.22	8	10.05	8	10.05
10	3.33	6	10.12	9	9.40	9	9.40
11	3.76	10	3.33	10	3.33	10	3.33
		11	3.76	11	3.76	11	3.76
Totals	23.82		39.99		40.10		37.52
Overall Total Schedule			40.10	(Max of all the totals)			

Figure 14. Paths and Durations

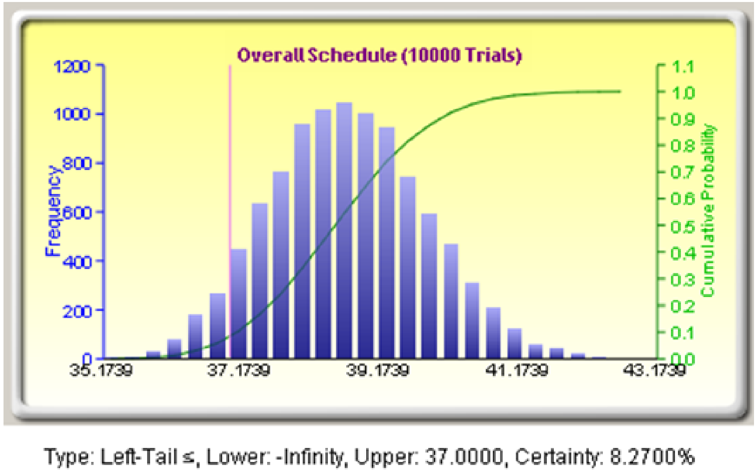


Figure 15. Simulation Results

Let us now return to the boss's proposal to cut the entire schedule by 1 day. Where should we focus our efforts in order to shorten the overall duration? We don't use the critical path when we employ probabilistic schedule management, so where do we begin? We can determine the most effective targets for reduction efforts using Risk Simulator's Tornado Analysis and Sensitivity Analysis features. The tornado chart (Figure 16) shows which variables (tasks) have the largest impact on the overall timetable. This graph shows the optimal objectives for lowering the mean/median values.

However, we can't talk about mean/median without talking about variety. The Sensitivity Analysis tool identifies which variables (tasks) contribute the most to the overall schedule output variation (see Figure 17). We can observe that the variation in Task 4 is the primary contributor to the overall schedule variation in this situation. Another intriguing finding is that variance in Task 6, which is not on the critical path, accounts for roughly 9% of the total variation.

In this case, decreasing the schedule duration for Tasks 4, 8, and 9 would yield the greatest savings in terms of overall schedule length. Finding the root causes of the significant variation in Tasks 4, 6, and 8 would undoubtedly provide more insight into these processes. The variance in Task 4 could, for example, be due to a lack of manpower. Management activities could be implemented to devote workers to the endeavor and significantly minimize variation, reducing overall variation and improving schedule predictability. Much more than merely asking the troops to minimize their work completion time, digging into the reasons for variation will lead to objectives where management interventions will be most beneficial.

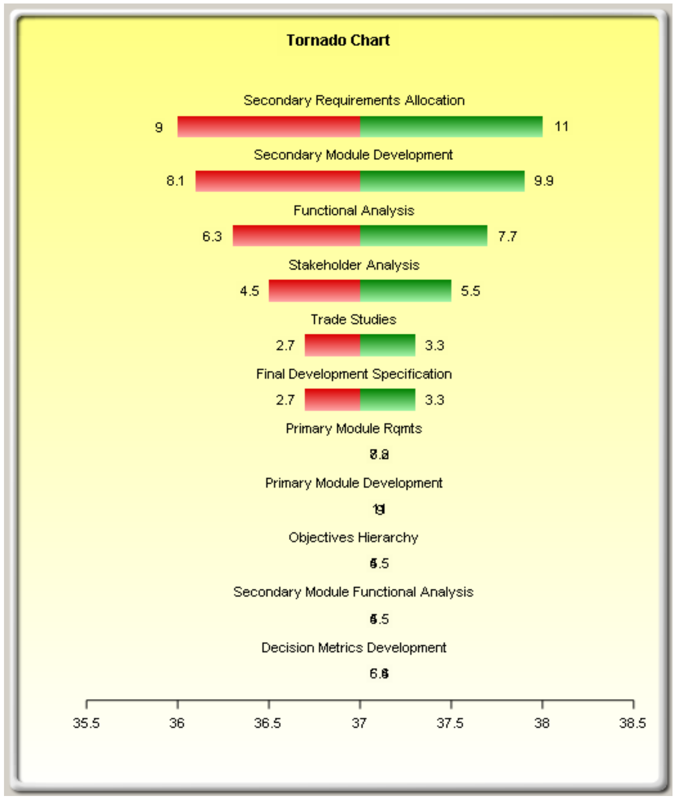


Figure 16. Tornado Analysis

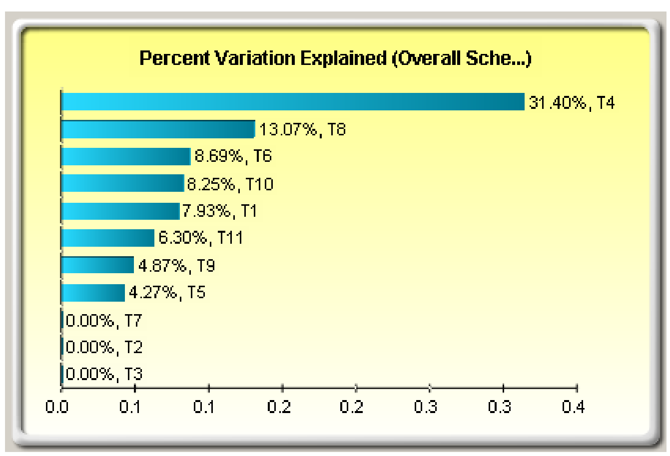


Figure 17. Sensitivity Analysis

We can also test other reduction strategies using the network schedule model. For example, under the traditional method, removing 1 day from Tasks 4, 8, and 9 would result in a 3-day reduction; however, if we reduce the Most Likely value for Tasks 4, 8, and 9 by 1 day and run the Monte Carlo risk simulation, we find that the median value is still 37.91, indicating only a 0.7-day reduction. This tiny decrease demonstrates the importance of addressing the variation. If we cut the variation in half, preserving the original lowest and most likely values but lowering the maximum for each distribution, the median falls from 38.5 to 37.91, which is roughly the same as lowering the most likely values. Taking both steps (lowering the most likely and maximum numbers) lowers the median to 36.83, giving us a 55% chance of finishing in less than 37 days. The most effective measure, according to this study, is to reduce the most likely value and overall variation.

To get to 36 days, we'll need to keep working through the list of tasks in the sensitivity and tornado charts (Figure 16 and Figure 17), one by one. If we apply the same procedure to Task 1, lowering the most likely and maximum numbers, we can complete the project in 36 days with a 51% certainty, and in 37 days with a 79.25% certainty. The entire schedule's maximum value is lowered from more than 42 to less than 40 days. However, to reach 36 days at the 80% certainty level, significant managerial efforts would be required.

Use the best-case numbers while managing your production time line. If we choose the most likely values, or even worse, the maximum values, production employees will not strive to achieve the best-case results, resulting in a self-fulfilling prophecy of delayed completion. When budgeting, we should plan for the most likely outcome while still acknowledging that the real world is full of risk and uncertainty. Provide the values that correspond to the 75% to 80% assurance level when explaining the schedule to the customer. Customers prefer predictability (on-time completion) over potentially faster completion with high risk in most circumstances. Finally, accept that the "worst-case" scenario is possible and devise contingency plans to safeguard your company in the event that it does happen. If the "worst-case"/maximum value is unsatisfactory, make the necessary changes to the process to reduce the outcome's maximum value to a level that is acceptable.

There is just one response for the scheduled completion date when using traditional schedule management. Each activity is given a time estimate, which is only correct if everything goes as planned, which is unlikely. Thousands of trials are done to explore the range of possible schedule duration results with probabilistic schedule management. A time estimate distribution is assigned to each task in the network, which appropriately reflects the task's uncertainty. To more effectively replicate real-world behavior, correlations might be entered. The output forecast distribution will appropriately reflect the whole range of probable outcomes because critical and near-critical paths are automatically considered. We can improve the effectiveness of our management efforts by using tornado and sensitivity assessments to limit schedule fluctuations and, if required, reduce the total timetable with high certainty.

Complex Tasks in Projects

The cost and schedule risk modeling is more difficult to describe and compute in complicated projects when there are nonlinear bifurcating and recombining paths (Figure 18). For example, we can see that after Task 1, future tasks can be done in parallel in the Project A tab of the basic example (Tasks 2, 3, and 4). Tasks 3 and 4 are then recombined to become Task 8. The user can design such complicated path models by simply adding tasks and integrating them in the visual map, as shown in Figure 18, with the appropriate icon tools. When the Create Model button is pressed, the software will generate an analytical financial model for you. That is, you will be taken to the Schedule & Cost page, where you will find the same configuration as before for entering data for this complicated model. The user will just need to conduct the relatively simple duties of creating the complex network path connections since the complex mathematical connections will be formed automatically behind the scenes to run the computations.

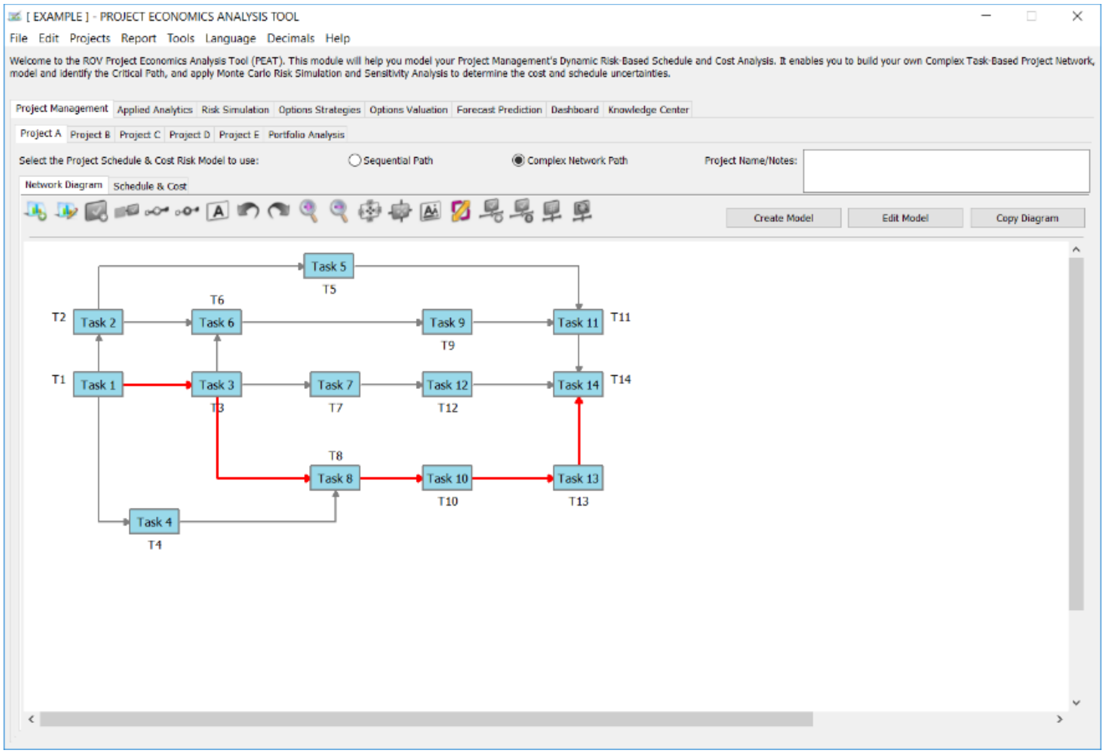
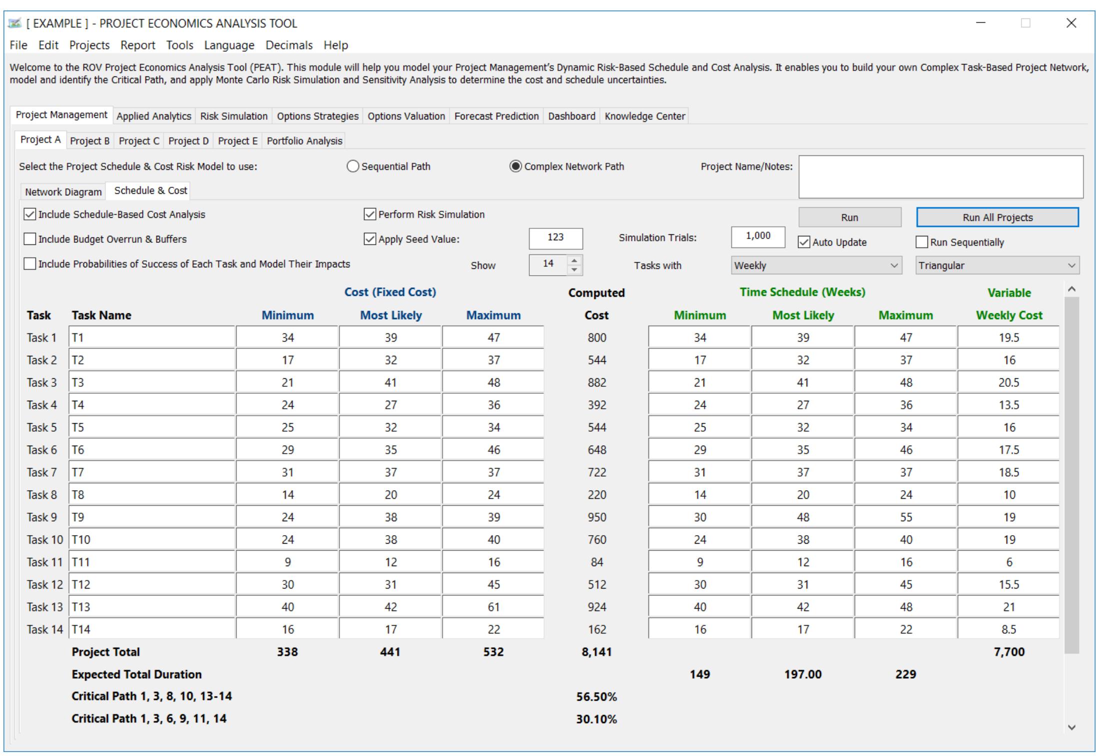


Figure 18. Complex Path Project Management



		Cost (Fixed Cost)			Computed	Time Schedule (Weeks)			Variable
Task	Task Name	Minimum	Most Likely	Maximum	Cost	Minimum	Most Likely	Maximum	Weekly Cost
Task 1	T1	34	39	47	800	34	39	47	19.5
Task 2	T2	17	32	37	544	17	32	37	16
Task 3	T3	21	41	48	882	21	41	48	20.5
Task 4	T4	24	27	36	392	24	27	36	13.5
Task 5	T5	25	32	34	544	25	32	34	16
Task 6	T6	29	35	46	648	29	35	46	17.5
Task 7	T7	31	37	37	722	31	37	37	18.5
Task 8	T8	14	20	24	220	14	20	24	10
Task 9	T9	24	38	39	950	30	48	55	19
Task 10	T10	24	38	40	760	24	38	40	19
Task 11	T11	9	12	16	84	9	12	16	6
Task 12	T12	30	31	45	512	30	31	45	15.5
Task 13	T13	40	42	61	924	40	42	48	21
Task 14	T14	16	17	22	162	16	17	22	8.5
	Project Total	**338**	**441**	**532**	**8,141**				**7,700**
	Expected Total Duration					**149**	**197.00**	**229**	
	Critical Path 1, 3, 8, 10, 13-14				**56.50%**				
	Critical Path 1, 3, 6, 9, 11, 14				**30.10%**				

Figure 19. Complex Project Simulated Cost and Duration Model With Critical Path

Critical Path Models (CPM) in Projects with Complex Tasks

Following the execution of the model, the complex route map displays the project's highlighted critical path (Figure 18), which is the one with the greatest potential for bottlenecks and delays in finishing the project on time. Figure 19 shows the exact path specifications and odds of being on the critical path (e.g., there is a 56.30% probability that the critical path will be along Tasks 1, 3, 8, 10, 13, 14).

The portfolio view (Figure 20) evaluates all projects and implementation paths for the user to make a better and more informed risk-based decision if there are many projects or prospective project path implementations. For comparison, the simulated distributions might be overlaid (Figure 21).

Users can see all of the projects that were modeled at a glance in Figure 22. Each project modeled can be a distinct project or the same project modeled with multiple assumptions and implementation choices (i.e., different means of carrying out the project) to assess which project or implementation option path makes the most sense in terms of cost and scheduling risks. The "Analysis of Alternatives" radio button selected allows users to see each project as a stand-alone project in terms of cost and schedule: single-point estimate values, simulated averages, and the probabilities that each of the projects will have (as opposed to Incremental Analysis, where one of the projects is selected as the base case and all other projects' results show their differences from the base case). Of course, the Risk Simulation analysis provides a more complete picture of the uncertainties and risks in the project, allowing users to see all of the simulation statistics and choose which confidence and percentile values to display. The simulated cost and schedule figures are also charted using bubble and bar charts in the "Portfolio Analysis" tab for a visual representation of the important outcomes.

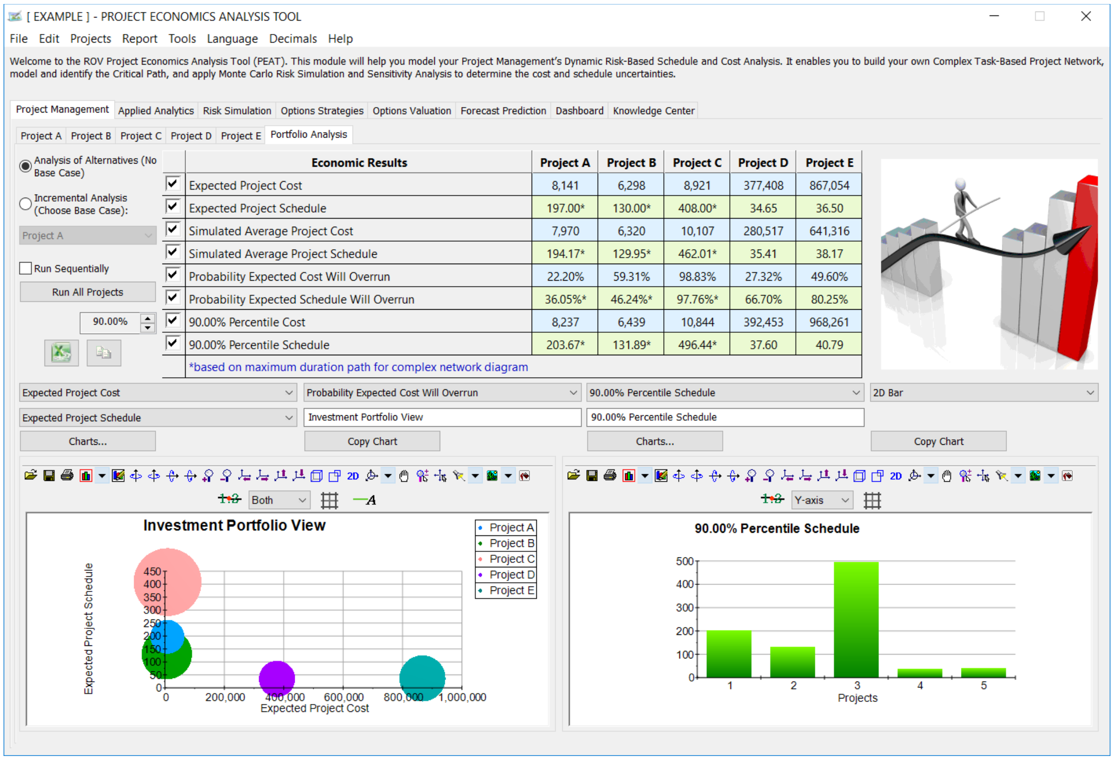


Figure 20. Portfolio View of Multiple Projects

Comparing and Overlaying Simulated Results

Figure 21's overlay chart displays the relative spreads, position, and skew of numerous projects' simulated costs or time lines stacked on top of one another to highlight their relative spreads, location, and skew of the findings. We can plainly see that the project whose distribution is on the right has a significantly higher cost to complete than the project on the left, as well as a somewhat larger level of cost spread uncertainty. Finally, Figure 22 depicts a comparison of the simulated project results using the AoA method. Figure 22 depicts the simulated outcomes, while Figure 20 depicts the expected value of the project costs and time line (not simulated, static, single-point estimations).

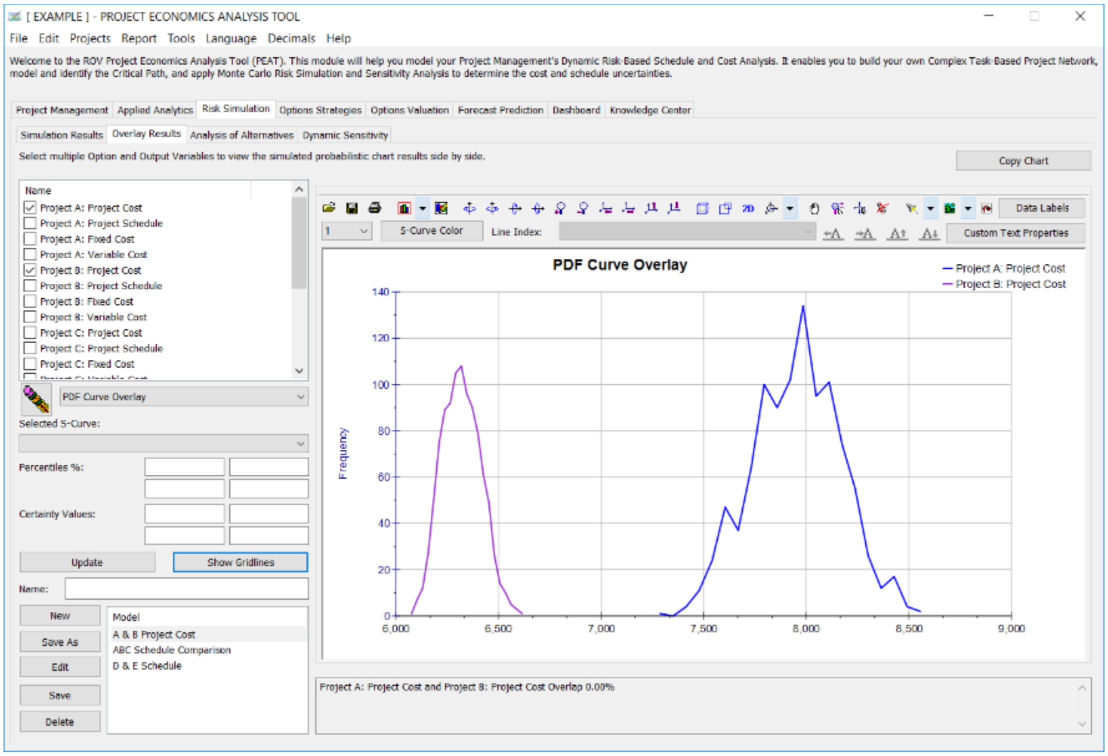
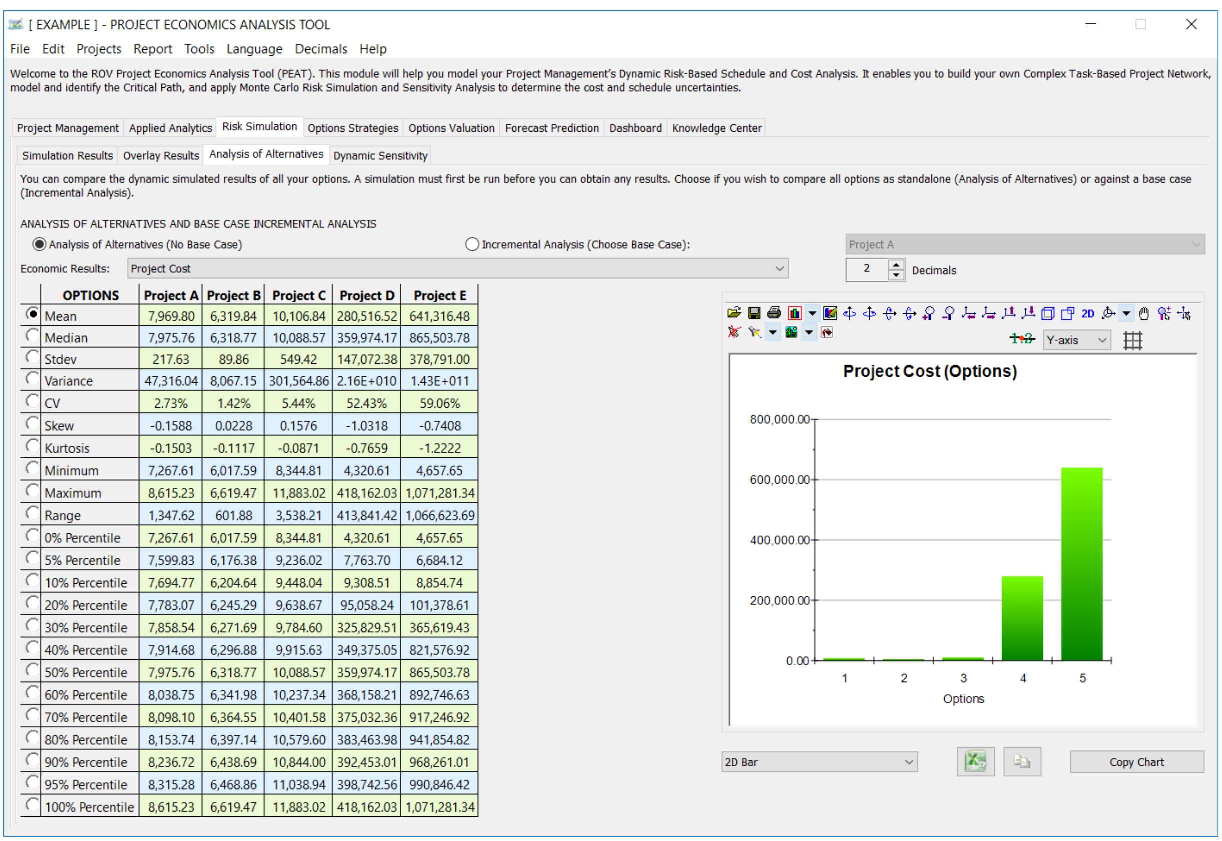


Figure 21. Overlay Charts of Multiple Projects' Cost or Schedule



OPTIONS	Project A	Project B	Project C	Project D	Project E
Mean	7,969.80	6,319.84	10,106.84	280,516.52	641,316.48
Median	7,975.76	6,318.77	10,088.57	359,974.17	865,503.78
Stdev	217.63	89.86	549.42	147,072.38	378,791.00
Variance	47,316.04	8,067.15	301,564.86	2.16E+010	1.43E+011
CV	2.73%	1.42%	5.44%	52.43%	59.06%
Skew	-0.1588	0.0228	0.1576	-1.0318	-0.7408
Kurtosis	-0.1503	-0.1117	-0.0871	-0.7659	-1.2222
Minimum	7,267.61	6,017.59	8,344.81	4,320.61	4,657.65
Maximum	8,615.23	6,619.47	11,883.02	418,162.03	1,071,281.34
Range	1,347.62	601.88	3,538.21	413,841.42	1,066,623.69
0% Percentile	7,267.61	6,017.59	8,344.81	4,320.61	4,657.65
5% Percentile	7,599.83	6,176.38	9,236.02	7,763.70	6,684.12
10% Percentile	7,694.77	6,204.64	9,448.04	9,308.51	8,854.74
20% Percentile	7,783.07	6,245.29	9,638.67	95,058.24	101,378.61
30% Percentile	7,858.54	6,271.69	9,784.60	325,829.51	365,619.43
40% Percentile	7,914.68	6,296.88	9,915.63	349,375.05	821,576.92
50% Percentile	7,975.76	6,318.77	10,088.57	359,974.17	865,503.78
60% Percentile	8,038.75	6,341.98	10,237.34	368,158.21	892,746.63
70% Percentile	8,098.10	6,364.55	10,401.58	375,032.36	917,246.92
80% Percentile	8,153.74	6,397.14	10,579.60	383,463.98	941,854.82
90% Percentile	8,236.72	6,438.69	10,844.00	392,453.01	968,261.01
95% Percentile	8,315.28	6,468.86	11,038.94	398,742.56	990,846.42
100% Percentile	8,615.23	6,619.47	11,883.02	418,162.03	1,071,281.34

Figure 22. Analysis of Alternatives

Benefits

IRM is a great tool for improving the quality of information accessible while making decisions because it combines multiple proven strategies. When applied to the examination of potential initiatives and investments, dynamic Monte Carlo simulation depicts the risks connected with the projects in a more realistic manner than traditional methodologies. Static forecasting based on assumptions and past performance provides a restricted view of a project's potential outcomes. Decision-makers can acquire a more full understanding of the project's uncertainty by running thousands of simulations or more while altering the variables within realistic possibilities. Increasing the amount of relevant and correct information available to managers will increase the quality of the leadership team's decisions.

IRM takes a methodical strategy to deal with AI investments. Following the eight phases is a simple procedure that aids in the quantitative decision-making process. While the functions within each phase can be sophisticated and require additional training, the overall process is straightforward and simple to follow. Because the IRM approach is fully defined, it may be integrated into existing procedures without requiring a complete reengineering. IRM uses data from existing approaches and expands the data to improve the scope of a project's evaluation. The true possibilities are quantified, and the outcome diverges from what is expected. The systemic design of IRM allows different members or teams to finish the process without having to re-collect data and start from the beginning. Analysts should be able to continue the procedure from any point in the approach after completing IRM training.

Real options analysis provides managers with the probability of certain project results, allowing them to select the best way to proceed with a project. Real options were offered not only at the start of the program, with three different routes in which the program may go, but also at each stage of the chosen strategy. By drafting a contract that allows an organization to modify its course of action as more information becomes available, the corporation can reduce losses from failing programs while maximizing gains from initiatives that are succeeding or showing promise. Fortunately, many viable possibilities are already ubiquitous in DoD buys. Contracts are frequently canceled by the government due to changes in budgetary policy, inability to satisfy requirements, or other factors. Including other genuine choices in contracts isn't an entirely new concept.

The use of common units to make strategic decisions about a system's value is a core component of the IRM methodology. Leadership can see a statistical range reflecting the potential value of a project by incorporating KVA values into the static and dynamic IRM models. The present values of the genuine option strategies were calculated using the market comparable prices produced by the value analysis. The effectiveness of most other ways is determined only by the program's cost, presuming that the value is inherent owing to the needs that were produced. IRM can provide decision-makers with information on both the expenses of a proposed investment in an initiative and the value of that project in comparable units.

Challenges

While IRM is a very useful analytical tool, it does have some disadvantages. The method's multiple techniques might be challenging to master (Housel et al., 2019a). To do a full study, it is a hard process that necessitates a solid understanding of both finance and statistics. While computing tools can help with the analysis, the inputs are more involved than simply typing a few numbers into a program and receiving the results. An analyst can generate the essential information to enable decision-makers access to the proper comparison material to make an informed decision if they have a good understanding of the core principles, enough training, and the right tools (Housel et al., 2019b). The amount of data gathered during statistical analysis can be overwhelming. The simulations and their conclusions appear to originate from a quantitative black box to individuals without a strong statistics background (Mun, 2016b). If decision-makers don't comprehend why an analyst makes a recommendation, it's simple to dismiss the advice and fall back on tried-and-true methods. To tackle this possible issue, create detailed and complete reports for management review, as well as knowledgeable presentations to allay worries about the unfamiliar procedures. To take advantage of actual options, they must be reviewed before a decision is made to implement any of them. When writing contracts, leadership must consider the future option to ensure that certain alternatives stay available. Some alternatives, such as expanding, can be implemented very easily by building a new project based on the first investment's success. However, if the contract does not include relevant conditions, project managers may not have as much flexibility in abandoning the project. Vendors must be willing to accept the possibility of subcontract cancellation when they are not at fault, which may increase the cost of completing a task. Managers must perform a careful study of which prospective options may be exercised in the future before signing contracts with vendors, due to the potential increased cost associated with contracting genuine options.

IRM, like all financial forecasting, makes projections based on previous data. Decision-makers can gain more insight from predictions that incorporate current information rather than relying just on historical trends. Meteorologists, for example, compile weather forecasts from a variety of sources: Current weather conditions are monitored using Doppler radar, satellites, radiosondes (weather balloons), and automated surface-observing systems (National Oceanic and Atmospheric Administration [NOAA], 2017). The data from multiple sources is run in models based on known historical patterns for the region using numerical weather prediction (NOAA, n.d.). Knowing the present conditions is just as crucial to a meteorologist as knowing the past models (NOAA, n.d.). Similarly, the models would deliver even more precise information if the project analyst could add pertinent information that is up to the minute (or to the requisite quality). Because of previous projects with historical data, outsourcing, lowering manning, and retaining the current structure all offer statistics that could be used in simulations. Despite the fact that this weakness is not exclusive to the IRM technique, executives should be aware of it in any financial forecast.

Finally, the DoD does not currently reward PMs who reap the rewards of risk. The risk framework in DoD acquisitions is intended to reduce project costs and schedule overruns. DoD contracts are structured in such a way that they do not incentivize vendors or the project as a whole to improve their capabilities or performance. When a for-profit company invests in an initiative that may fail, it does so because the potential upside gain outweighs the risk of failure. For example, if an aircraft's design target is to attain 250 knots and the design threshold is 200 knots, the budget will be allocated to the threshold rather than the objective. Unless the PM is able to reallocate resources internally, the program will not be able to meet its objectives. The acquisitions process considers the cost of achieving the goal rather than the worth of the goal. Performance is rewarded in for-profit businesses, which is evaluated by revenue. The DoD's implicit surrogate for revenue is cost reductions, which has a different value than improving a project's worth. Acquisitions by the DoD, on the other hand, are only made when the negative implications have been mitigated to the maximum extent practicable. The upside risk is unimportant to the PMs; all that matters is that the program is finished on time and on budget. Although it is still important to look at how potential projects fit into the DoD's broader collection of acquisitions and current assets, the contract structure limits certain of IRM's portfolio optimization features.

Comparison of Key Attributes

The type of methodology to use should be determined by the nature of the project at hand, including the level of commitment required from the organization, the organization's desire to align strategic goals with the project, the methodology's predictive capability, the flexibility required, and the amount of time available. While others in the business must understand concepts in order to comprehend status reports, EVM just requires the management team to track the project's cost and schedule against the baseline because there is no predetermined goal alignment with the organization. While the CPI and SPI can assist in estimating the ultimate cost and schedule, EVM has no true predictive potential because it is assumed that the schedule would follow the baseline regardless of historical performance volatility. In EVM, sticking to the baseline is critical, and altering requirements can substantially affect the baseline, lowering the methodology's effectiveness. For an AI project with its many unknown components and capabilities a priori, setting up, monitoring, and reporting the cost/schedule performance of each work item inside the WBS can be a time-consuming and costly operation.

To assess the value of a process or component output, KVA simply requires the KVA analyst and the process owner, who serves as the SME supporting the requirement to match the project with an organization's productivity goals. They can model the present baseline as-is process ROK and compare it to the proposed to-be process model ROK using this approach, resulting in a straightforward forecast of the improvement between the models. Because KVA can be used with any description language that defines process outputs in common units, analysts can choose the method that is most helpful for the system in question, allowing for flexibility. This analysis may be conducted quickly, with a rough assessment available in a few of days. To assess how a project fits into an organization's portfolio, the project's present value (PV), and potential real possibilities, IRM requires organizational leadership, portfolio and project managers, and the analyst. IRM gives a prediction of a project's anticipated performance by analyzing and simulating alternative situations, allowing managers to build in flexibility via genuine options at the right spots within the project. Assuming that the data required for the analysis are available, the process can be done quickly.

Methodologies in AI Acquisition

As previously stated, each methodology has strengths and weaknesses that make it more appropriate for certain applications than others. The iterative nature of software development is the most difficult aspect of adopting EVM when gaining AI. To be most successful, EVM requires well-stated, specific requirements for intermediate phases. While software program outputs are well specified, the methods required to produce the software are not, causing challenges when estimating cost and schedule. EVM can adequately monitor the progress if the software is not complex or comprises of well-known operations. Integrating software and hardware is also difficult with EVM since there are various elements of the program that must be merged to achieve the objectives, requiring additional debugging and recoding. When used to manage the physical production of systems or infrastructure, EVM is more efficient. It can track the cost and schedule progress of software work packages, but it's not as good at determining their worth.

Any IT system can use KVA to offer an objective, ratio-scale measure of value and cost for each core process and its subprocesses or components. Managers can then examine productivity ratios information, such as ROK and ROI, using the two factors to determine the efficiency of a process in relation to the resources utilized to create the output. This can assist the manager in deciding how to allocate resources for system updates or estimating the future value of a system that is being purchased. Managers can iterate the value of system real options analysis using simulation and other ways by combining KVA and IRM data. IRM can also use past data to evaluate risks and anticipate performance probability for metrics of potential success for programs and program components. It is a tool that can help with investment strategy and can be used to acquire any form of AI. It is not, however, intended to assist in the procurement of an AI program or in determining how to meet the program's specific criteria.

Summary

The scope, capabilities, and limitations of various AI systems are demonstrated by examining the benefits and challenges of the proposed approaches. It also aids in determining which areas and phases of the Defense Acquisition System life cycle. The following section offers suggestions based on the findings.

Conclusion

Simply put, how might certain advanced analytical decision-making processes be applied in the acquisition life cycle to supplement existing procedures to ensure a successful acquisition of AI technologies?

As previously stated, EVM is the sole program management methodology that the U.S. government requires for all DoD acquisition initiatives worth more than $20 million. Regardless of this necessity, EVM is a methodology that offers a systematic approach to IT acquisition through program management processes that can assist in keeping an acquisition program on track and below cost estimates. However, there are substantial drawbacks to utilizing EVM for AI acquisitions, the most prominent of which is that EVM was not built to manage AI acquisitions that follow a highly iterative and volatile course. Organic AI acquisitions necessitate a high level of flexibility in order to deal with the unknowns that surface during the development process, as well as value-adding opportunities that were not anticipated. Furthermore, EVM lacks a uniform unit of value metric that would allow typical productivity metrics like ROI to be calculated. When a program's worth is determined by how closely it adheres to its initial cost and schedule projections, the program's performance may suffer in terms of output quality when intended program activities become iterative, as in the development of many AI algorithms. EVM is not designed to recognize disproportionate increases in value if an AI acquisition program is going toward cost and schedule overruns, but the ensuing value added of the modifications to the original requirements offers disproportionate increases in value.

To address EVM's shortcomings in AI acquisitions, the methodology should be combined with KVA and IRM, which can be useful during the EVM requirements and monitoring phases by ensuring that a given AI acquisition is aligned with organizational strategy and that a baseline process model has been developed for establishing current performance prior to the acquisition of an AI system. After the AI has been obtained, a future process model that forecasts the value added of incorporating the AI can be used to set expectations that can be tested against the baseline model. IRM can be used to anticipate the value of strategic real choices flexibility that an acquired AI might bring, allowing leadership to choose the alternatives that best meet their desired goals for AI in defense core activities.

KVA should be utilized in AI acquisitions because it gives an objective, quantitative measure of value in common units, allowing decision-makers to better comprehend and compare different strategic options based on their value and cost. Only by employing KVA to determine the value inherent in the system can AI systems be given an ROI. PMs benefit from this information since it gives them a more full picture of the current and future systems' performance.

When obtaining AI through the Defense Acquisition System, it's also a good idea to use IRM. The risk estimates associated with the components and subcomponents of a program, in terms of potential cost overruns, value variabilities, and schedule delays, can be improved by using dynamic and stochastic uncertainty and risk-based modeling techniques to predict likely and probabilistic outcomes. Analyzing multiple real-world options in the context of the models' outputs will assist PMs in making the best decisions possible when defining the future of a program.

As is now done, PMs should only employ EVM throughout the EMD phase. EVM, on the other hand, will operate best in hardware manufacturing solutions with fully mature technology prior to the program's start. EVM is not well suited for AI development because many AI acquisition efforts involve upgrading current technology and generating new software solutions to meet requirements. Nonetheless, PMs can employ a variety of agile EVM strategies to complete projects on time and on budget if the proper procedures are done when establishing the baseline. Requirements must be broken down into tiny, simply defined tasks, with risk and uncertainty elements appropriately accounted for in the timetable. Other approaches, such as KVA and IRM, should be used in conjunction with EVM to guarantee that these elements are based on verifiable measurements rather than assuming how much more time, money, and value may be required to execute complex tasks.

KVA and IRM will assist in determining the value of the various options evaluated in the AoA process during the MSA phase. KVA can objectively assess the value of the current, as-is system as well as potential future systems. Then IRM can leverage other aspects like cost, value, complexity, and schedule to value the alternatives in terms of their respective parameter values. As the chosen solutions mature during the TMRR phase, a revised KVA analysis will reassess initial estimations and provide a predicted ROI that may be incorporated into an IRM risk and actual alternatives analysis for the AI solution before entering the EMD phase, if necessary.

Limitations and Future Research

This study looked into whether the various methodologies—EVM, KVA, and IRM—could be used to improve AI acquisition inside the Defense Acquisition System. Future research should look at how these approaches interact with or improve other acquisition system components. This comprises the specific procedures of JCIDS and PPBE, as well as the interactions between JCIDS, PPBE, and the Defense Acquisition System as a whole. Certain approaches, such as IRM, may be more useful when applied to the full acquisition process rather than just a part of it. Future research might also look into how these diverse methods could be utilized to acquire things that aren't related to AI or IT.

The study focused on AI as a whole, rather than individual types of AI. Future research should look into whether acquisition methods, strategies, and methodologies differ depending on the type of AI being acquired. This is particularly relevant when it comes to AI and its subsets. Based on their complexity, intricate nature, developing technology, and amount of risk, ML, intelligence with a specific emphasis or field of specialty, and general or universal intelligence will likely use different ways in the acquisition process.

Another area of prospective investigation is the use of these approaches in commercial AI acquisition. The focus of this study was solely on the application of the strategies in the DoD acquisition process. Commercial entities, on the other hand, face challenges when adopting extensive or complicated AI and IT systems, especially when the technologies are used at the enterprise level. Further research may reveal whether these same techniques could be useful to private-sector decision-makers during the development, adoption, or customization of commercial AI. The hype cycle for AI and automation is on the rise, as highlighted in the literature, and the demand to buy such technology is as relevant for the private sector as it is for the DoD. In addition, the current pandemic triggered by Coronavirus Disease 2019 (COVID-19) has compelled a permanent shift in society toward permanent distant labor. Because these trends are expected to continue in the near future, more automation tools will be needed to support this workforce. As part of the Fourth Industrial Revolution and Industry 4.0, these developments could be investigated for their consequences.

Finally, this study looked at only the most promising approaches out of a wide range of options. Other program management tools, management philosophies, analytic tools, or other approaches, as well as their benefits while adopting AI, should be investigated in future research. While the approaches investigated were chosen because they are likely to enhance the process and assist EVM improvements, other systems may be more appropriate in certain phases or provide additional benefits not seen in this study.

References

Anderson, M. G, & Mun, J. C. (2021). Technology trust: System information impact on autonomous systems adoption in high-risk applications. *Defense Acquisition Research Journal*, *28*(1), 2–39. https://doi.org/10.22594/10.22594/dau.19-841.28.01

Apttus. (2015). *Success with PayPal*. https://solutions.apttus.com/rs/902-TNK-191/images/Apttus%20Case%20Study%20paypal.pdf

Apttus. (2017, September 20). *Apttus contract management: Using applied AI in contract management* [Video]. YouTube. https://www.youtube.com/watch?V=vthnaq2505y

Armstrong, C. S. (2015). *The quest for Achilles' shield: Is the American military's fetish with technology harming mission accomplishment?* Joint Forces Staff College.

Ashby, W. R. (1956). *An introduction to cybernetics.* Chapman and Hall.

Baig, M. A. (2019, March 10). Gerasimov doctrine and modern hybrid warfare. *Daily Times.* https://dailytimes.com.pk/295075/gerasimov-doctrine-and-modern-hybrid-war/

Bartels, A. (2019). *The Forrester Wave™: Contract life cycle management for all contracts, Q1 2019*. Forrester Research.

Beaujon, G. J., Marin, S. P., & McDonald, G. C. (2001). Balancing and optimizing a portfolio of R&D projects. *Naval Research Logistics, 48*(1), 18–40.

Bech, H. (2019, September 26). *Silicon Valley's rule number one: Fake it till you make it*. TBKconsult. https://tbkconsult.com/silicon-valleys-rule-number-one-fake-it-to-you-make-it/

Bennett, S. B. (2017,July 13). *Optimization aids in quest for government efficiency.* Federal News Network. https://federalnewsnetwork.com/all-news/2017/07/optimization-aids-in-the-quest-for-government-efficiency/

Betts, K. D., & Jaep, K. R. (2017). The dawn of fully automated contract drafting: Machine learning breathes new life into a decades-old promises. *Duke Law and Technology Review*, *15*(1), 216–233.

Bhatt, U. S., Newman, D. E., Carreras, B. A., & Dobson I. (2005). Understanding the effect of risk aversion on risk. *Proceedings of the 38th Annual Hawaii International Conference on System Sciences*, 64b. https://doi.org/10.1109/HICSS.2005.649

Bostron, N. (2014). *Superintelligence: Paths, dangers, strategies.* Oxford University Press.

Botkin, B. (2007, June). *Applying financial portfolio analysis to government program portfolios* (Master's thesis, Naval Postgraduate School). https://calhoun.nps.edu/handle/10945/3481

Brandimarte, P. (2014). *Handbook in Monte Carlo simulation: Applications in financial engineering, risk management, and economics*. John Wiley & Sons.

Burk, R. C., & Parnell, G. S. (2011). Portfolio decision analysis: Lessons from military applications. In A. Salo, J. Keisler, & A. Morton (Eds.), *Portfolio decision analysis* (pp. 333–357). New York, NY: Springer.

Burkhalter, B. (1963). Applying artificial-intelligence to the pattern-cutters problem. *Operations Research*, *11*(1), B39.

Burton, J., & Soare, S. (2019). *Understanding the strategic implications of the weaponization of artificial intelligence* [Paper presentation]. 2019 11th International Conference on Cyber Conflict (CyCon), Tallinn, Estonia.

Burton, S. (2018, February). The case for plain-language contracts. *Harvard Business Review*. https://hbr.org/2018/01/the-case-for-plain-language-contracts

Buss, T. F., & Cooke, D. (2005, May). *Performance measurement in defense acquisitions: A case study of the Navy* [Paper presentation]. Acquisition Research Symposium, Naval Postgraduate School, Monterey, CA, United States.

Capra, F. (1996). *The web of life: A new scientific understanding of living systems.* Anchor Books.

Carlton, B., Ellis, K., Jones, J., & Schofield, B. (2019). *Marine Corps transport corrective maintenance process optimization and knowledge value analysis* [Unpublished manuscript].

Cassidy Law. (2018, September 21). *The dread-inducing review of a federal government RFP or contract*. http://cassidylawpllc.com/review-of-a-federal-government-rfp-or-contract/

Chaplain, C. (2017). *Space acquisitions: DoD continues to face challenges of delayed delivery of critical space capabilities and fragmented leadership* (GAO-17-619T). Government Accountability Office.

Chaplain, C. (2019). *DoD faces significant challenges as it seeks to address threats and accelerate space programs* (GAO-19-482T). Government Accountability Office.

Char, J., & Bitzinger, R. (2016, October 5). Reshaping the People's Liberation Army since the 18th Party Congress: Politics, policymaking, and professionalism. *Journal of Strategic Studies*, *39*(5–6), 599–607. https://doi.org/10.1080/01402390.2016.1235037

Christensen, D. (1994). An analysis of cost overruns on defense acquisition contracts. *Readings in Program Control*, 113–120. https://ntrs.nasa.gov/search.jsp?R=19950014332

Christensen, D. S. (1998). The costs and benefits of the Earned Value Management process. *Acquisition Research Quarterly*, *5*(4), 373–386. https://www.researchgate.net/publication/251811135_The_Costs_and_Benefits_of_the_Earned_Value_Management_Process

Clarivate. (n.d.). *Web of science.* Retrieved October 26, 2020, from http://apps.newisiknowledge.com/

Cook, R. I. (2000). *How complex systems fail*. Massachusetts Institute of Technology. https://web.mit.edu/2.75/resources/random/How%20Complex%20Systems%20Fail.pdf

Cooper, D. E. (2005). *Contract management: Opportunities to improve surveillance on Department of Defense service contracts* (GAO-05-274). Government Accountability Office.

Creviston, D. O. (2020). Transforming DoD for agile multidomain command and control. *Joint Force Quarterly*, *97*, 83–90.

Crosby, C. (2020). Operationalizing artificial intelligence for algorithmic warfare. *Military Review*, *100*(4), 42–51.

Cross, J. (2019, May 9). Department of Defense emerging technology strategy: A venture capital perspective. *Proceedings of the 16th Annual Acquisition Research Symposium*, *I*, 172–191. https://calhoun.nps.edu/bitstream/handle/10945/63024/SYM-AM-19-040.pdf?Sequence=1&isallowed=y

Cummins, T. (2019, October). *The cost of a contract*. World Commerce & Contracting. https://blog.iaccm.com/commitment-matters-tim-cummins-blog/the-cost-of-a-contract

Daley, S. (2019, September 24). *19 examples of artificial intelligence shaking up business as usual*. Built In. https://builtin.com/artificial-intelligence/examples-ai-in-industry

Damodaran, A. (2000). The promise of real options. *Journal of Applied Corporate Finance*, *13*(2), 29–44. https://doi.org/10.1111/j.1745-6622.2000.tb00052.x

Darken, R. (2019, October 21). *Human–machine teaming AI*. Naval Postgraduate School. https://nps.edu/documents/115153495/115419669/Human-MachineTeamv3.pdf/6eaf7ae2-092b-4070-8e29-17beae54e8ba?t=1571760220000

Davendralingam, N., & DeLaurentis, D. (2015, May). A robust portfolio optimization approach to system of system architectures. *Systems Engineering, 18*(3), 269–283.

Defense Advanced Research Projects Agency. (2019). *AI next campaign*. https://www.darpa.mil/work-with-us/ai-next-campaign

Defense Procurement and Acquisition Policy. (2012, April). *Defense contingency contracting handbook*. Office of the Under Secretary of Defense for Acquisition. https://www.acq.osd.mil/dpap/ccap/cc/corhb/Files/DCCOR_Handbook_2012.pdf

Defense Science Board. (2018, February). *Design and acquisition of software for defense systems*. Department of Defense. https://apps.dtic.mil/dtic/tr/fulltext/u2/1048883.pdf

Denning, P. (2019, September). *Harnessing artificial intelligence: Hierarchy of AI machines (Lecture #2)* [Video]. Naval Postgraduate School. https://calhoun.nps.edu/handle/10945/63576

Department of Defense. (n.d.). *PALT*. https://DoDprocurementtoolbox.com/site-pages/palt

Department of Defense. (2003, May 12). *The defense acquisition system* (DoD Directive 5000.01, Change 2). https://www.esd.whs.mil/Directives/issuances/DoDd/

Department of Defense. (2005). *Work breakdown structures for defense materiel items* (MIL-HDBK-881A). http://www.acqnotes.com/Attachments/MIL-Hand%20Book-881.pdf

Department of Defense. (2011, April). *Technology Readiness Assessment (TRA) guidance*. Assistant Secretary of Defense for Research and Engineering.

Department of Defense. (2014, March 12). *Risk management framework (RMF) for DoD information technology (IT)* (DoD Instruction 8510.01, Change 2). https://www.esd.whs.mil/Directives/issuances/DoDi/

Department of Defense. (2015a, January 7). *Operation of the defense acquisition system* (DoD Instruction 5000.02, Change 4). https://www.esd.whs.mil/Directives/issuances/DoDi/

Department of Defense. (2015b, September). *DoD program manager's guide for integrating the cybersecurity risk management framework (RMF) into the system acquisition lifecycle*.

Department of Defense. (2017a, February 26). *Defense acquisition guidebook*. https://www.dau.mil/tools/dag

Department of Defense. (2017b, June 9). *DoD space enterprise governance and principal DoD space advisor (PDSA)* (DoDD 5100.96). https://irp.fas.org/doddir/dod/d5100_96.pdf

Department of Defense. (2018, April 16). *Agile and earned value management: A program manager's desk guide*.

Department of Defense. (2019a, January 18). *Earned value management implementation guide (EVMIG)*.

Department of Defense. (2019b, February 12). *Summary of the 2018 Department of Defense artificial intelligence strategy: Harnessing AI to advance our security and prosperity*. https://media.defense.gov/2019/Feb/12/2002088963/-1/-1/1/SUMMARY-OF-DOD-AI-STRATEGY.PDF

Department of Homeland Security. (2019a, August 9). *Artificial intelligence (AI) for past performance—CPARS*.

Department of Homeland Security. (2019b). *CPARS artificial intelligence commercial solutions opening pilot program general solicitation* (CSOP-HQ-GS-000001, Amendment 1).

DiNapoli, T.J. (2019). *DoD's use of other transactions for prototype projects has increased* (GAO-20-84). Government Accountability Office.

Dixit, A. K., & Pindyck, R. S. (1995). The options approach to capital investment. *Harvard Business Review*, *73*(3). https://hbr.org/1995/05/the-options-approach-to-capital-investment

Dougherty, J., & Jay, M. (2018). Russia tries to get smart about artificial intelligence. *The Wilson Quarterly.* https://www.wilsonquarterly.com/quarterly/living-with-artificial-intelligence/russia-tries-to-get-smart-about-artificial-intelligence/

Edwards, C., & Kaeding, N. (2015) Federal government cost overruns. *Tax & Budget Bulletin, 72*. https://object.cato.org/sites/cato.org/files/pubs/pdf/tbb-72.pdf

Egel, D., Robinson, E., Cleveland, C. T., & Oates, C. J. (2020, January 27). AI and irregular warfare: An evolution, not a revolution. *War on the Rocks*. https://warontherocks.com/2019/10/ai-and-irregular-warfare-an-evolution-not-a-revolution/

Electronic Industries Alliance. (1998). *Earned Value Management systems.* Electronic Industries Alliance.

Engelbart, D. C. (1962). *Augmenting human intellect: A conceptual framework* (Summary Report AFOSR-3233). Stanford Research Institute.

Evron, Y. (2012, February). China's military procurement approach in the early 21st century and its operational implications. *Journal of Strategic Studies*, 63–93. https://doi.org/10.1080/01402390.2011.592004

Exec. Order 13859, 3 C.F.R. 3967–3972 (2019, February 11). https://www.federalregister.gov/documents/2019/02/14/2019-02544/maintaining-american-leadership-in-artificial-intelligence

Eykholt, K., Evitimov, I., Fernandes, E., Li, B., Rahmati, A., Xia, C., & Song, D. (2018). *Robust physical-world attacks on deep learning visual classification*. Cornell University.

FAR 1.102, Statement of Guiding Principles for the Federal Acquisition System (2019). https://www.acquisition.gov/far/1.102

Feickert, A. (2005). *The Joint Tactical Radio System (JTRS) and the Army's future combat system (FCS): Issues for Congress* (CRS Report No. RL33161). Congressional Research Service. https://digital.library.unt.edu/ark:/67531/metacrs7941/

Fischetti, M. P. (2018, January 2). Yes, it can be done: Expatiating defense acquisition. *Federal Times.* https://www.federaltimes.com/opinions/2018/01/02/yes-it-can-be-done-expediting-defense-acquisition/

Fleming, Q. W., & Koppelman, J. M. (2010). *Earned value project management* (4th ed.). Project Management Institute Inc. https://app.knovel.com/hotlink/toc/id:kpEVPME001/earned-value-project/earned-value-project

Flynn, B., & Field, J. (2006, January 1). *Transformation of analytical tools: Using portfolio analysis techniques in defense applications.* Armed Forces Comptroller. https://www.thefreelibrary.com/Transformation+of+analytical+tools%3A+using+po rtfolio+analysis+...-a0145158636

Francis, P. L. (2006). *Defense acquisition: Restructured JTRS program reduces risk, but significant challenges remain* (GAO-06-955). Government Accountability Office.

Francis, P. L. (2008). *Defense of Defense needs framework for balancing investments in tactical radios* (GAO-08-877). Government Accountability Office.

Friedman, N. (2013). *This truck saved my life*. Joint Program Office Mine-Resistant Ambush-Protected Vehicles.

Fuller, J. B., & Masko, J. (2019, September). *Theranos: The unicorn that wasn't*. Harvard Business School. https://www.hbs.edu/faculty/Pages/item.aspx?Num=55762

Future of Life Institute. (2020, August 15). *AI open letter*. https://futureoflife.org/ai-open-letter/?cn-reloaded=1

Gallagher, S. (2012, June 18). *How to blow $6 billion on a tech project*. Ars Technica. https://arstechnica.com/information-technology/2012/06/how-to-blow-6-billion-on-a-tech-project/

Gardner, H. (1993). *Multiple intelligences*. Basic Books.

Geist, E. (2016). It's already too late to stop the AI arms race—We must manage it instead. *Bulletin of the Atomic Scientists*, *72*(5), 318–21.

Gerding, E. F. (2013). Contract as a pattern language. *Washington Law Review*, *88*(4), 1323–1356. https://digitalcommons.law.uw.edu/wlr/vol88/iss4/6/

Gerenser, B. (2019). DoD launches travel system prototype. *Defense Transportation Journal*, *75*(2), 10–11.

Giachetti, R. E. (2015). Evaluation of the DoDAF meta-model's support of systems engineering. *Procedia Computer Science*, *61*, 254–260.

Giannetti, W. (2020). Quiet giant: The TITAN cloud and the future of DoD artificial intelligence. *Air & Space Power Journal*, *34*(1), 54–58.

Gibbs, S. (2014, October 27). Elon Musk: Artificial intelligence is our biggest existential threat. *The Guardian*. https://www.theguardian.com/technology/2014/oct/27/elon-musk-artificial-intelligence-ai-biggest-existential-threat

Golden, P. E. (2020). DoD's artificial intelligence problem: Where to begin. *The Army Lawyer*, *2*, 76–85.

Golstein, B. (2018, October 10). *A brief taxonomy of AI*. SharperAI. https://www.sharper.ai/taxonomy-ai/

Good, A. (2019, November 8). *Intelligent failure assessment*. Fail Forward. https://static1.squarespace.com/static/583382786b8f5b1d0c788b9e/t/58af22a6e4fcb57eb0f01028/1487872679331/Fail+Forward+Intelligent+Failure+Assessment.pdf

Gourley, S. (2012, November 28). *Rapid Fielding Initiative: A decade of providing urgently needed gear*. Defense Media Network. https://www.defensemedianetwork.com/stories/rapid-fielding-initiative/

Government Accountability Office (GAO). (1997, February). *Assessing risk and returns: A guide for evaluating federal agencies' IT investment decision-making* (GAO/AIMD-10.1.13). http://www.gao.gov/special.pubs/ai10113.pdf

Government Accountability Office. (2007).

Government Accountability Office. (2017). *Military acquisitions: DoD is taking steps to address challenges faced by certain companies* (GAO-17-644).

Government Accountability Office. (2019a, May 21). *2019 annual report: Additional opportunities to reduce fragmentation, overlap, and duplication and achieve billions in financial benefits* (GAO-19-285SP). https://www.gao.gov/reports/GAO-19-285SP/

Government Accountability Office. (2019b). *DoD's use of other transactions for prototype projects has increased* (GAO-20-84).

Greenfield, D. (2019, June 19). *Artificial intelligence in medicine: Applications, implications, and limitations*. Harvard University. http://sitn.hms.harvard.edu/flash/2019/artificial-intelligence-in-medicine-applications-implications-and-limitations/

Greiner, M. A., McNutt, R. T., Shunk, D. L., & Fowler, J. W. (2001). Selecting military weapon systems development portfolios: Challenges in value measurement. In *Proceedings of the Portland International Conference on Management of Engineering and Technology,* 2001 (PICMET '01) (pp. 403–410). doi:10.1109/PICMET.2001.952153

Gubrud, M. (2014). Stopping killer robots. *Bulletin of the Atomic Scientists*, *70*(1), 32–42.

Gunning, D. (2017, November). *Explainable artificial intelligence*. Defense Advanced Research Projects Agency. https://www.darpa.mil/attachments/xaiprogramupdate.pdf

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On past, present, and future of AI. *California Management Review*, *61*(4), 5–14.

Hagan, G. (2009, November). *Glossary of defense acquisition acronyms and terms*. Defense Acquisition University. http://www.acqnotes.com/Attachments/DAU%20-%2013th_Edition_Glossary.pdf

Hagel, C. (2014a, November 15). *The defense innovation initiative*. Defense.gov Archive. https://archive.defense.gov/pubs/OSD013411-14.pdf

Hagel, C. (2014b, November 15). *Reagan National Defense Forum keynote* [Speech]. Department of Defense. https://www.defense.gov/Newsroom/Speeches/Speech/Article/606635/

Heller, C. H. (2019). Near-term applications of artificial intelligence: Implementation opportunities from modern business practices. *Naval War College Review*, *72*(4), 79–105.

Hillner, E. P. (2019, May). *The Third Offset Strategy and the Army modernization priorities*. Center for Army Lessons Learned. https://usacac.army.mil/sites/default/files/publications/17855.pdf

Housel, T., & Bell, A. H. (2001). *Measuring and managing knowledge*. McGraw Hill.

Housel, T., & Kanevsky, V. (2006). *Measuring the value added of management: A knowledge value added approach*. Naval Postgraduate School. https://apps.dtic.mil/sti/pdfs/ADA496651.pdf

Housel, T., & Kanevsky, V. A. (1995). Reengineering business processes: A complexity theory approach to value added. *Infor*, *33*(4), 248. https://doi.org/10.1080/03155986.1995.11732285

Housel, T. J., Mun, J., Jones, R., & Carlton, B. (2019a, May). *A comparative analysis of advanced methodologies to improve the acquisition of information technology in the Department of Defense for optimal risk mitigation and decision support systems to avoid cost and schedule overruns* [Paper presentation]. 16th Acquisition Research Symposium, Monterey, CA, United States.

Housel, T. J., Mun J., Jones, R., & Carlton, B. (2019b, October). *A comparative analysis of advanced methodologies to improve the acquisition of information technology in the Department of Defense for optimal risk mitigation and decision support systems to avoid cost and schedule overruns* (NPS-AM-20-002). Naval Postgraduate School. https://dair.nps.edu/handle/123456789/2774

Hutton, J. (2011). *Defense contract management agency: Amid ongoing efforts to rebuild capacity, several factors present challenges in meeting its missions* (GAO-12-83). Government Accountability Office.

Icertis. (n.d.-a). *Contract management software*. Retrieved October 11, 2019, from https://www.icertis.com/contract-management-software/

Icertis. (n.d.-b). *Customers*. Retrieved October 11, 2019, from https://www.icertis.com/customers/

Icertis. (2019a). *Icertis customer profile: Mindtree*. https://www.icertis.com/customer/mindtree/

Icertis. (2019b, April 2). *Microsoft streamlined its contract management*. https://www.icertis.com/customers/microsoft-information-exchange-agreements-case-study/

Ilachinski, A. (2017, October). *AI, robots, and swarms: Issues, questions, and recommended studies*. Center for Naval Analyses. https://apps.dtic.mil/dtic/tr/fulltext/u2/1041749.pdf

Institute for Robotic Process Automation and Artificial Intelligence. (2019, November 16). *What is robotic process automation?* https://irpaai.com/what-is-robotic-process-automation/

Institute for the Study of War. (2019). *Provincial reconstruction teams*.

Janiga, M., & Modigliani, P. (2014, November–December). Think portfolios, not programs. *Defense AT&L Magazine,* 12–16. https://www.dtic.mil/get-tr-doc/pdf?AD=ADA612

Jocic, L., & Gee, J. (2013, May). Developing planning and decision support. *Crosslink.* http://www.aerospace.org/crosslinkmag/spring2013/developmentplanning-and-decision-sup

Jones, R. (2019). *Procurement and contracting: Overview and primary considerations*. Naval Postgraduate School.

Jones, R., & Housel, T. (2018, May 9). *Extending an econophysics value model for early developmental program performance prediction and assessment* [Paper presentation]. 15th Acquisition Research Symposium, Monterey, CA, United States.

Kania, E. B. (2019, August 27). *In military–civil fusion, China is learning lessons from the United States and starting to innovate*. Real Clear Defense. https://www.realcleardefense.com/articles/2019/08/27/in_military-civil_fusion_china_is_learning_lessons_from_the_united_states_and_starting_to_innovate_114699.html

Kaplan, A. M., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15–25.

Kashin, V., & Raska, M. (2017). *Countering the Third Offset Strategy: Russian perspectives, responses, and challenges*. S. Rajaratnam School of International Studies.

Keirsey, D., Mitchell, J., Bullock, B., Nussmeier, T., & Tseng, D. Y. (1985). Autonomous vehicle control using AI techniques. *IEEE Transactions on Software Engineering*, *11*(9), 986–992.

Kendall, F. (2011, October 13). *Letter to the Honorable Howard K. "Buck" McKeon*. Department of Defense. https://www.govexec.com/pdfs/101411bb1.pdf

Kendall, F. (2017). *Getting defense acquisition right*. DAU Press. https://DoD.defense.gov/Portals/1/Documents/pubs/Getting-Acquisition-Right-Jan2017.pdf

Kendall, F. (2018, March 20). *Five myths about Pentagon weapons programs*. Defense One. https://www.defenseone.com/ideas/2018/03/five-myths-about-pentagon-weapons-programs/146803/

King, A. D. (2019, November 16). *Talk to transformer*. https://talktotransformer.com/

Kissinger, H. A. (2019, August 30). How the Enlightenment ends. *The Atlantic.* https://www.theatlantic.com/magazine/archive/2018/06/henry-kissinger-ai-could-mean-the-end-of-human-history/559124/

Knight, W. (2017, April 11). *The dark secret at the heart of AI*. Technology Review. https://www.technologyreview.com/s/604087/the-dark-secret-at-the-heart-of-ai/

Kovacs, G., & Kot, S. (2016). New logistics and production trends as the effect of global economy changes. *Polish Journal Management Studies*, *14*(1), 122.

Kurzweil, R. (2000). *The age of spiritual machines: When computers exceed human intelligence*. Penguin Books.

Kwak, Y. H., & Anbari, F. T. (2011). History, practices, and future of earned value management in government: Perspectives from NASA. *Project Management Journal*, *43*(1), 77–90. https://doi.org/10.1002/pmj.20272

Lawgeex. (2018, February). *Comparing the performance of artificial intelligence to human lawyers in the review of standard business contracts*. Law.com. https://images.law.com/contrib/content/uploads/documents/397/5408/lawgeex.pdf

Lee, J. (2013). Industry 4.0 in big data environment. *German Harting Magazine, Technology Newsletter*, 26.

Lee, U. (2014). *Improving the parametric method of cost estimating relationships of naval ships* [Master's thesis, Massachusetts Institute of Technology]. MIT Libraries: DSpace @ MIT. https://dspace.mit.edu/handle/1721.1/92134

Leviathan, Y. (2018, May 8). Google Duplex: An AI system for accomplishing real-world tasks over the phone. *Google AI Blog*. https://ai.googleblog.com/2018/05/duplex-ai-system-for-natural-conversation.html

Levine, P., & Greenwalt, B. (2019, April 4). *What the 809 Panel didn't quite get right*. Breaking Defense. https://breakingdefense.com/2019/04/what-the-809-panel-didnt-quite-get-right-greenwalt-levine/

Li, L., Zheng, N., & Wang, F. (2019). On the crossroad of artificial intelligence: A revisit to Alan Turing and Norbert Wiener. *IEEE Transactions on Cybernetics*, *49*(10), 3618–3626.

Licklider, J. C. R. (1960). Man–computer symbiosis. *IRE Transactions on Human Factors in Electronics*, *4*(11).

Ludwigson, J. (2019). *DoD space acquisitions: Including users early and often in software development could benefit programs* (GAO-19-136). Government Accountability Office.

Mackin, M. (2015). *Littoral Combat Ship: Knowledge of survivability and lethality capabilities needed prior to making major funding decisions* (GAO-16-201). Government Accountability Office.

Maucione, S. (2019a, April 26). *DoD doesn't want to end up like Theranos, so it's being cautious about "fail fast."* Federal News Network. https://federalnewsnetwork.com/defense-main/2019/04/DOD-doesnt-want-to-end-up-like-theranos-so-its-being-cautious-about-fail-fast/

Maucione, S. (2019b, October 30). *Special report: Failure is an option for DoD's experimental agency, but how much?* Federal News Network. https://federalnewsnetwork.com/defense-main/2019/10/special-report-failure-is-an-option-for-DoDs-experimental-agency-but-how-much/

McCain, J. (2015, November 15). It's time to upgrade the defense department. *War on the Rocks*. https://warontherocks.com/2015/11/its-time-to-upgrade-the-defense-department/

McCusker, E. (2019). *Department of Defense fiscal year 2020*. Under Secretary of the Department of Defense Comptroller.

Mori, S. (2018). U.S. defense innovation and artificial intelligence. *Asia-Pacific Review*, *25*(2), 16–44.

Mun, J. (2015). *Readings in certified quantitative risk management (CQRM)* (3rd ed.). Thomson-Shore and ROV Press.

Mun, J. (2016a). *Real options analysis* (3rd ed.). Thomson-Shore and ROV Press.

Mun, J. (2016b, October). *Empirical cost estimation tool* [Paper presentation]. Naval Acquisitions Research Conference, Monterey, CA, United States.

Mun, J. (2019). Empirical cost estimation for U.S. Navy ships. *Universal Journal of Management*, *7*, 152–176.

Mun, J., George, K., & Ledbetter, E. (2020). *Total ownership with life-cycle cost model under uncertainty for surface ships' electro-optical-infrared-sensors* [Unpublished manuscript].

Mun, J., & Housel, T. (2010). *A primer on applying Monte Carlo simulation, real options analysis, knowledge value added, forecasting, and portfolio optimization.* Naval Postgraduate School. https://apps.dtic.mil/sti/pdfs/ADA518628.pdf

Mun, J., Housel, T., & Wessman, M. D. (2010). PEO-IWS ACB insertion portfolio optimization (NPS-AM-10-069-VOL-2). *Proceedings of the Seventh Annual Acquisition Research Symposium*, *2*, 738–764. https://my.nps.edu/documents/105938399/108624025/NPS-AM-10-069.pdf/c71c6830-853a-448b-beac-242bea4cba8b?version=1.0

National Defense Authorization Act for Fiscal Year 2016, Pub. L. No. 114-92 (2015). https://www.congress.gov/114/plaws/publ92/PLAW-114publ92.pdf

National Defense Authorization Act for Fiscal Year 2018, Pub. L. No. 115-91 (2017). https://www.congress.gov/115/plaws/publ91/PLAW-115publ91.pdf

Nationa Defense Authorization Act for Fiscal Year 2020, Pub. L. No. 116-92 (2019). https://www.congress.gov/116/plaws/publ92/PLAW-116publ92.pdf

National Defense Transportation Association. (2020, January 28). *DoD launches travel system prototype*. https://www.ndtahq.com/dod-launches-travel-system-prototype/

National Oceanic and Atmospheric Administration. (n.d.). *Numerical weather prediction*. Retrieved April 17, 2019, from https://www.ncdc.noaa.gov/data-access/model-data/model-datasets/numerical-weather-prediction

National Oceanic and Atmospheric Administration. (2017, August 14). *6 tools our meteorologists use to forecast the weather*. https://www.noaa.gov/stories/6-tools-our-meteorologists-use-to-forecast-weather

National Science Foundation. (2018). *National patterns of R&D resources: 2016–2017 data update.*

National Security Archive. (2019, February 26). *The Able Archer 83 sourcebook*. https://nsarchive.gwu.edu/project/able-archer-83-sourcebook

Nayak, P. (2019, October 25). *Understanding searches better than ever before*. Google. https://blog.google/products/search/search-language-understanding-bert

Nielsen, C. B., Larsen, P. G., Fitzgerald, J., Woodcock, J., & Peleska, J. (2015). Systems of systems engineering: Basic concepts, model-based techniques, and research directions. *ACM Computing Surveys*, *48*(2), 18:1–18:41.

Oakley, S. S. (2020). *Defense acquisitions annual assessment: Drive to deliver capabilities faster increases importance of program knowledge and consistent data for oversight* (GAO-20-439). Government Accountability Office.

Office of Small Business Programs. (2019, November 5). *Rapid Innovation Fund*. Department of Defense. https://business.defense.gov/Programs/RIF/

Office of the Under Secretary of Defense. (2003). *Manager's guide to technology transition in an evolutionary acquisition environment*.

Office of the Under Secretary of Defense for Acquisition and Sustainment. (2019a, November 1). *Ellen M. Lord*. https://www.acq.osd.mil/bio_lord.html

Office of the Under Secretary of Defense for Acquisition and Sustainment. (2019b, November 1). *OUSD(A&S) strategy road map*. https://www.acq.osd.mil/fo/docs/as-roadmap.pdf

Office of the Under Secretary of Defense for Research and Engineering. (2019, December 2). *USD(R&E) modernization priorities*. https://www.cto.mil/modernization-priorities/

Oppy, G., & Dowe, D. (2016, February 8). *The Turing test*. In E. N. Zalta (Ed.), *Stanford encyclopedia of philosophy.* Stanford University. https://plato.stanford.edu/entries/turing-test/

Parloff, R. (2016, September 28). From 2016: Why deep learning is suddenly changing your life. *Fortune.* https://fortune.com/longform/ai-artificial-intelligence-deep-machine-learning/

Payne, K. (2018). *Strategy, evolution, and war: From apes to artificial intelligence*. Georgetown University Press.

Pellerin, C. (2015, November 8). *Work: Human–machine teaming represents defense technology future*. Department of Defense. https://www.defense.gov/Explore/News/Article/Article/628154/workhu/

People's Republic of China Ministry of Science and Technology. (2018). *National High-Tech Program (863 Program)*. http://www.most.gov.cn/eng/programmes1/

Pickens, A. H., & Alvarado, D. J. (2018). *Other transaction agreements: An analysis of the oracle decision and its potential impact on the use of OTAs*. American Bar Association.

Porche, I. R., Mckay, S., Mckernan, M., Button, R. W., Murphy, B. Giglio, K., & Axelband, E. (2012). *Rapid acquisition and fielding for information assurance and cyber security in the Navy* (Report No. TR-1294-NAVY). RAND Corporation. https://www.rand.org/pubs/technical_reports/TR1294.html

Powner, D. A. (2009). *Information technology: Agencies need to approve the implementation and use of earned value management techniques to help manage major system acquisitions* (GAO-10-2). Government Accountability Office.

Raghaven, S., & Mooney, R. J. (2013). *Online inference-rule learning from natural-language extractions*. The University of Texas.

Ramos, A. L., Ferreira, J. V., & Barceló, J. (2012). Model-based systems engineering: An emerging approach for modern systems. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, *42*(1), 101–111.

Ramsey, L. (2019, June 28). Theranos founder Elizabeth Holmes faces jail time for fraud charges. Her trial is set to begin in summer 2020. *Business Insider.* https://www.businessinsider.com/theranos-founder-elizabeth-holmes-president-sunny-balwani-trial-date-2019-6

Rashid, M., Anwar, M. W., & Khan, A. M. (2015). Toward the tools selection in model based system engineering for embedded systems—A systematic literature review. *The Journal of Systems and Software*, *106*, 150–163.

Rich, B. (2018, February 12). How AI is changing contracts. *Harvard Business Review.* https://hbr.org/2018/02/how-ai-is-changing-contracts

Rios, C. (2005). *Return on investment analysis of information warfare systems* [Master's thesis, Naval Postgraduate School]. NPS Archive: Calhoun. https://calhoun.nps.edu/handle/10945/2068

Rios, C., Housel, J., & Mun, J. (2006). *Integrated portfolio analysis on investment and real options analysis of intelligence information systems (Cryptologic Carry on Program)* [Paper presentation]. Acquisition Research Symposium, Monterey, CA, United States. https://calhoun.nps.edu/handle/10945/33143

Rios, C., Housel, J., & Mun, J. (2015). Case study 11: Real options and KVA in military strategy at the United States Navy. In J. Mun (Ed.), *Case studies in certified quantitative risk management (CQRM)* (pp. 145–154). Thomson-Shore and ROV Press.

Roberts, S. (2017, February 11). Leonard Perroots, general who defused nuclear crisis with Soviets, dies at 83. *New York Times.* https://www.nytimes.com/2017/02/10/us/leonard-perroots-dead.html

Roosevelt, A. (2012, October 2). Joint Tactical Networking Center opens, JPEO JTRS officially closed. *Defense Daily.* https://www.defensedaily.com/joint-tactical-networking-center-opens-jpeojtrsofficially-closed/navy-usmc/

Sammalkorpi, S., & Teppala, J. P. (2019). *AI in procurement*. Sievo Oy.

Sargent, J. F., Gallo, M. E., & Schwartz, M. (2018, November 8). *The global research and development landscape and implications for the Department of Defense* (CRS Report No. R45403). Congressional Research Service. https://fas.org/sgp/crs/natsec/R45403.pdf

Sayler, K. M. (2020). *Artificial intelligence and national security* (CRS Report No. R45178). Congressional Research Service. https://fas.org/sgp/crs/natsec/R45178.pdf

Schaeffer, C. (2016, July 12). *Agile versus Waterfall for CRM Implementation success*. Customer Think. https://customerthink.com/agile-versus-waterfall-for-crm-implementation-success/

Schlimmer, S., & Brennan, B. (2018, July 4). *For vendors, DoD's CUI requirements more than an exercise*. Federal News Network. https://federalnewsnetwork.com/commentary/2018/07/for-vendors-DoDs-cui-requirements-are-more-than-an-exercise/

Schwab, K. (2015, December 12). The Fourth Industrial Revolution: What it means and how to respond. *Foreign Affairs*. https://www.foreignaffairs.com/articles/2015-12-12/fourth-industrial-revolution

Schwab, K. (2017). *The Fourth Industrial Revolution*. Crown Business.

Schwartz, M., Sargent, J. F., & Mann, C. T. (2018, July 2). *Defense acquisitions: How and where DoD spends its contracting dollars* (CRS Report No. R44010). Congressional Research Service. https://www.hsdl.org/?view&did=812910

Scott, W. A. (2007). *Request for and use of emergency supplemental funds for the Rapid Fielding Initiative*. Inspector General United States Department of Defense.

Section 809 Panel. (2018). *Report of the advisory panel of streamlining and codifying acquisition regulations* (Vol. 1).

Section 809 Panel. (2019a). *Report of the advisory panel on streamlining and codifying acquisition regulations* (Vol. 3).

Section 809 Panel. (2019b). *A road map to the Section 809 Panel reports*.

Selten, R. (1991). *Game equilibrium models IV social and political interaction*. Springer.

Shanahan, P. (2018). *DoD cloud strategy*. Department of Defense.

Sharkey, N. (2007, August 17). Robot wars are a reality. *The Guardian*. https://www.theguardian.com/commentisfree/2007/aug/18/comment.military

Shaw, M. (2019, October 15). *Why Google is the best search engine (and why businesses should care)*. Tower Marketing. https://www.towermarketing.net/blog/google-best-search-engine/

Shin, Y., Sim, S., & Lee, J. (2017). Model-based integration of test and evaluation process and system safety process for development of safety-critical weapon systems. *Systems Engineering*, *20*(3), 257–279.

Sidiropoulos, L., Sidiropoulou, A., & Lalagas, S. (2014). Defense portfolio analysis. *Journal of Computations & Modelling, 4*(1), 327–347.

Sievo. (2019, November 16). *AI in procurement*. https://sievo.com/resources/ai-in-procurement

Silberglitt, R., Sherry, L., Wong, C., Tseng, M., Ettedgui, E., Watts, A., & Stothard, G. (2004). *Portfolio analysis and management for naval research and development.* https://www.rand.org/content/dam/rand/pubs/monographs/2004/RAND_MG271.pdf

Simpson, J. (2018, March 12). *FY18 procurement action lead time (PALT) metric*. PEOSTRI. https://www.peostri.army.mil/palt-memo

Sparkes, M. (2015, January 13). Top scientists call for caution over artificial intelligence. *The Telegraph (UK).*

Statistics Solutions. (n.d.). *Data levels of measurement*. Retrieved September 9, 2019, from https://www.statisticssolutions.com/data-levels-of-measurement/

Stewart, R. (2019, July 26). *AFCEA Shark Tank: Rapid Acquisition Facilitation Tool (R.A.F.T.)*. Federal Government Experts. https://www.federalgovernmentexperts.com/post/afcea-shark-tank-rapid-acquisition-facilitation-tool-r-a-f-t

Sullivan, M. (2009). *Rapid acquisition of MRAP vehicles* (GAO-10-155T). Government Accountability Office.

Sullivan, M. (2015). *Defense Advanced Research Project Agency: Key factors drive transition of technologies, but better training and data dissemination can increase success* (GAO-16-5). Government Accountability Office.

Sullivan, M. J. (2018). *Defense science and technology: Actions needed to enhance use of laboratory initiated research authority* (GAO-19-64). Government Accountability Office.

Tarraf, D. C., Shelton, W., Parker, E., Alkire, B., Gehlhaus, D., Grana, J., Levedahl, A., Leveille, J., Mondschein, J., Ryseff, J., Wyne, A., Elinoff, D., Geist, E., Harris, B. N., Hui, E., Kenney, C., Newberry, S., Sachs, C., Schirmer, P., … Warren, K. (2019). *The Department of Defense posture for artificial intelligence: Assessment and recommendations* (Report No. RR-4229-OSD). RAND Corporation. https://www.rand.org/pubs/research_reports/RR4229.html

Tatum, D. (2018, June). *Contracting Officer's Representative (COR): An analysis of part-time and full-time COR roles, competency requirements and effectiveness* [Joint applied project report, Naval Postgraduate School]. NPS Archive: Calhoun. https://calhoun.nps.edu/bitstream/handle/10945/59604/18Jun_Tatum_Denise.pdf?Sequence=1&isallowed=y

Taylor, T. (2019). Artificial intelligence in defence. *The RUSI Journal*, *164*(5–6), 72–81.

Thomas, E., Christina, C., & Painter, G. (2019). *Leveraging technology to improve contract surveillance: Opportunity identification and analysis*. Naval Postgraduate School.

Tsai, A. (2014). An empirical model of four processes for sharing organizational knowledge. *Online Information Review*, *38*(2), 305–320. https://doi.org/10.1108/OIR-03-2013-0059

Under Secretary of Defense for Acquisition, Technology, and Logistics. (2016). *Performance of the defense acquisition system: 2016 annual report.* Department of Defense.

Van Eck, N. J., & Waltman, L. (2020). *VOSviewer: Visualizing scientific landscapes*. https://www.vosviewer.com/

Vanhoucke, M. (2014). *Integrated project management and control*. Springer International Publishing.

Van Schooten, D. (2018, August 16). *The Pentagon's contracting gurus mismanaged their own contracts: The Defense Contract Management Agency botched a $45-million project to help manage trillions of dollars in other contracts*. Project on Government Oversight. https://www.pogo.org/investigation/2018/08/pentagons-contracting-gurus-mismanaged-their-own-contracts/

Vascik, P., Ross, A., & Rhodes, D. (2015). *A method for exploring program and portfolio affordability tradeoffs under uncertainty using Epoch-Era Analysis: A case application to carrier strike group design.* Paper presented at 12th Annual Acquisition Research Symposium, Naval Postgraduate School, Monterey, CA.

Vincent, J. (2019, January 28). *The state of AI in 2019.* The Verge. https://www.theverge.com/2019/1/28/18197520/ai-artificial-intelligence-machine-learning-computational-science

Voelz, G. (2016). Catalysts of military innovation: A case study of defense biometrics. *Defense Acquisition Research*, *23*(2), 178–201.

Waikar, S. (2018, December 17). *What can we learn from the downfall of Theranos?* Stanford Graduate School of Business. https://www.gsb.stanford.edu/insights/what-can-we-learn-downfall-theranos

Walton, T. (2016). *Securing the Third Offset Strategy: Priorities for the next secretary of defense*. NDU Press. https://ndupress.ndu.edu/Portals/68/Documents/jfq/jfq-82/jfq-82_6-15_Walton.pdf

Weber, C. A., Balut, S. J., Cloos, J. J., Frazier, T. P., Hiller, J. R., Hunter, D. E., . . . Tran, D. (2003, October). *The acquisition portfolio schedule costing/optimization model: A tool for analyzing the RDT&E and production schedules of DoD ACAT I systems* (IDA Document D-2835). Alexandria, VA: Institute for Defense Analyses. https://www.dtic.mil/cgi-bin/GetTRDoc?AD=ADA421123

Weisgerber, M. (2017, December 21). The Pentagon's new artificial intelligence is already hunting terrorists. *Defense One*. http://www.defenseone.com/technology/2017/12/pentagons-new-artificial-intelligence-already-hunting-terrorists/144742/

White House. (2020). *National strategy for critical and emerging technologies.* https://www.whitehouse.gov/wp-content/uploads/2020/10/National-Strategy-for-CET.pdf

Wiener, N. (1948). *Cybernetics: Or control and communication in the animal and the machine.* MIT Press.

Wimmer, H., & Rada, R. (2018). Applying artificial intelligence to financial investing. In *The Encyclopedia of Information Science and Technology*. IGI Global.

Wismeth, J. (2012, March 9). *Improving Army information technology asset visibility.* Carlisle, PA: Army War College, Strategic Studies Institute. https://www.dtic.mil/get-tr-doc/pdf?AD=ADA562133

Work, R. O. (2014, November 12). *Deputy secretary of defense speech at the CSIS Global Security Forum*. Department of Defense. https://www.defense.gov/Newsroom/Speeches/Speech/Article/606631/

Work, R. O. (2015, January 28). *The Third U.S. Offset Strategy and its implications for partners and allies*. Department of Defense. https://www.defense.gov/Newsroom/Speeches/Speech/Article/606641/the-third-us-offset-strategy-and-its-implications-for-partners-and-allies/

Work, R., & Schmidt, E. (2019, July 17). In search of ideas: The National Security Commission on Artificial Intelligence wants you. *War on the Rocks*. https://warontherocks.com/2019/07/in-search-of-ideas-the-national-security-commission-on-artificial-intelligence-wants-you/

Yao, M., Jia, M., & Zhou, A. (2018). *Applied artificial intelligence: A handbook for business leaders*. TOPBOTS Inc.

Young, J. J., Jr.. (2004, November 30). *Blueprint for the future, Naval Research and Acquisition Team 1999–2004 strategic plan* [Memorandum]. Department of Defense. https://www.secnav.navy.mil/rda/Pages/ViewPolicy.aspx

Yu, W., Chang, P., Yao, S., & Liu, S. (2009). KVAM: Model for measuring knowledge management performance of engineering community of practice. *Construction Management and Economics*, *27*(8), 733–747. https://doi.org/10.1080/01446190903074978

Zarkadakis, G. (2019, September 11). *The rise of the conscious machines: How far should we take AI?* Science Focus. https://www.sciencefocus.com/future-technology/the-rise-of-the-conscious-machines-how-far-should-we-take-ai/

Zoroya, G. (2013, December 18). How the IED changed the U.S. military. *USA Today.* https://www.usatoday.com/story/news/nation/2013/12/18/ied-10-years-blast-wounds-amputations/3803017/

Acquisition Research Program
Naval Postgraduate School
555 Dyer Road, Ingersoll Hall
Monterey, CA 93943

www.acquisitionresearch.net