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Acquiring Artificial Intelligence Systems: Development Challenges, Implementation Risks, and Cost/Benefits Opportunities

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Acquiring Artificial Intelligence Systems: Development Challenges, Implementation Risks, and Cost/Benefits Opportunities[1]

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Abstract

The acquisition of artificial intelligence (AI) systems is a relatively new challenge for the U.S. Department of Defense (DoD). Given the potential for high-risk failures of AI system acquisitions, it is critical for the acquisition community to examine new analytical and decision-making approaches to managing the acquisition of these systems in addition to the existing approaches (i.e., Earned Value Management). In addition, many of these systems reside in small start-up or relatively immature system development companies, further clouding the acquisition process due to their unique business processes when compared to the large defense contractors. This can lead

[1] This ARP Conference Paper is an updated and abridged version of the full ARP Report NPS-PM-21-014, which is available at https://dair.nps.edu/handle/123456789/4313

to limited access to data, information, and processes that are required in the standard DoD acquisition approach. The well-known recurring problems in acquiring information technology automation within the DoD will likely be exacerbated in acquiring complex and risky AI systems. Therefore, more robust, agile, and analytically driven acquisition methodologies will be required to help avoid costly disasters in acquiring AI systems. This research provides a set of analytical tools for acquiring organically developed AI systems through a comparison and contrast of the proposed methodologies that will demonstrate when and how each method can be applied to improve the acquisitions life cycle for AI systems.

Introduction

This report seeks to address the emerging field that falls under the umbrella term "Artificial Intelligence" or AI, and the Defense Acquisition System (DAS) that is not designed to develop and procure such state-of-the-art, rapidly evolving AI technologies. Thus, the research examines the challenges of acquiring an AI-based system within the typical acquisitions framework in business and in the Department of Defense (DoD) by conducting an analysis on a set of recommended quantitative tools for use in analyzing the processes in the acquisition of organically developed DoD AI systems. Thus, this research introduces tried and true quantitative methods (EVM, KVA, IRM) for their application to the DoD Acquisition of AI systems. Therefore, this research proposes the re-examination of acquisition methods, strategies, and methodologies based on the category of AI being acquired.

Acquisitions of AI systems is a relatively new challenge for the DoD. Given the high risk of failure for such system acquisitions, it is critical that the acquisition community examines potential new approaches to help manage the AI acquisition life cycle. The well-documented recurring problems in acquiring information technology within the DoD will likely be exacerbated in acquiring these leading edge, complex, and risky systems. The identification, review, and recommendation for the optimal use of new acquisition methodologies, to supplement or replace existing methodologies, should help avoid costly disasters in AI system acquisitions. In addition, the use of these methodologies should also create a more flexible acquisition scheme that allows for incorporation of unanticipated, value added components of future AI systems. Please note that this conference paper is an abridged version of the research conducted by Housel et al. (2020). For a more thorough discussion, see the full report of this research that provides a robust literature review, more detailed explanations, as well as the step-by-step process for each of the three methodologies please see the full report.[2]

AI has been in use in various commercial and governmental domains to address a variety of decision support problems. However, existing DoD acquisition frameworks may not be adequate to address the unique nature of AI systems life-cycle investments. AI systems are qualitatively different than standard automation systems that focus on routine, repeatable tasks. To develop acquisition frameworks for AI systems, it is first necessary to examine how AI systems will be used to support, or supplant, decision-makers. The purpose of this research project is to provide a set of quantitative and analytically robust decision-making methodologies for acquiring AI systems that address the inadequacies of the current standard investment acquisition life-cycle framework.

To better understand the potential contributions of this research, it is important to recognize the recent drive towards using innovation in improving Defense Acquisition outcomes. During the Cold War, the United States and particularly the Department of Defense enjoyed a position of prominence in the realm of military technological development. Therefore, the use of

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the common Defense Acquisition System allowed the DoD to develop, test, and field large-scale weapons systems through a slow, labor intensive development process. However, the rapid growth of technological developments has diminished the DoD's technological advantage over many of the United States' near peer global competitors. As a result of the current challenges, the DoD launched several key initiatives such as "Better Buying Power 3.0," which is "aimed at accelerating acquisition reform and incentivizing innovation within government," as well as the Defense Innovation Initiative, and the "Third Offset Strategy" (Voelz, 2016, p. 180).

The underlying premise behind these recent efforts is that the traditional methods of acquisition are less than optimal in achieving the desired outcomes in DoD weapons and business systems. Therefore, the goal of implementing innovation in the DoD acquisition process has been designed to provide the means of achieving these better acquisition outcomes. Some of the key attributes in the recent initiatives include adopting best practices in DoD labs (Sullivan, 2018) and increasing the use of rapid development cycles through prototyping (DiNapoli, 2019). In addition, the DoD also seeks to take advantage of the commercial sector's rapid development of innovative technologies by partnering with the commercial development of dual use technology—technology that has application for both the private and defense sectors (Kendall, 2017; Voelz, 2016). It is this urgent context that provides a push for innovation in the DoD acquisition processes and provided the impetus for the current research study.

The underlying challenge is best understood through a discussion of programmatic risk management requires a foundational understanding of the effect of risk on human behavior. Primarily, this is the effect of risk on the PM and other program leaders. The goal is to gauge how these principal acquisition professionals respond to risk and their aversion to risk with regard to acquisitions decision-making in terms of cost, schedule, and performance. Bhatt et al. (2005) note that a fundamental understanding of risk management addresses the question, "How much risk is acceptable?" (p. 64). As noted by Housel et al. (2019), "A recurring issue at the U.S. Department of Defense (DoD) is that acquisitions of information technology (IT) have been fraught with schedule and cost overruns. The problem is the risk and project management tools the DoD currently use inadequately address the fiscal and temporal overruns (p. 3)." This premise is supported by numerous studies on DoD acquisitions, particularly those that involve complex IT systems. A prime example that illustrates this issue is the multitude of reports on the development of space and satellite systems (Chaplain, 2017, 2019; Ludwigson, 2019). The issue of concern is that PMs and other managers of DoD acquisitions, particularly in the case of advancing cutting-edge technological systems, are increasingly becoming either overly risk tolerant or increasingly risk adverse.

Thus, the motivation to be risk averse promotes a cautious culture among the DoD Acquisition community. As the DoD continues to develop systems that are increasingly complex, the risk tolerance of PMs and other Acquisition leaders is diminished in direct proportion to their inability to meet the program requirements for cost, schedule, and performance. It follows that the result of this is an organizational culture in the DoD Acquisition community that is unwilling to assume risk. In addition, there is tremendous pressure to push unrealistic schedule and cost goals and results in unforced errors in the acquisition program's baseline. As a result of these unintended consequences, programs are most often more expensive, late, and/or not able to perform to the standards specified.

Research and Problem Statement

The current problem at the DoD is that the complexity and speed of decision-making is increasing exponentially with the advent of intelligent systems that support or that actually make decisions in time-critical, high-impact problem spaces. The current process management and control tools that a program manager (PM) might use to support acquisitions do not provide adequate warning of, or provide sufficient information about the root causes of, fiscal budgetary overruns and time schedule delays. This is a problem because PMs are, as a result, unable to respond to issues in a timely manner, delaying the delivery of promised capabilities to the services. Additionally, the money and resources spent in excess of the original budget could be used in other acquisition programs. To better understand the possible causes and solutions to the AI acquisition problem, this study will examine the strengths and weaknesses of three performance and project management methodologies.

These methodologies, Earned Value Management (EVM), Knowledge Value Added (KVA), and Integrated Risk Management (IRM), are used to strategically and tactically plan, monitor in real time, measure, and preemptively forecast the value and progress of AI acquisitions. A review of these recommended project analysis and control methodologies will offer insights into the strengths and weaknesses each approach could offer acquisition professionals within the general phases of the Defense Acquisition System. This research offers potential solutions to improve early warnings of cost and schedule overruns, and value opportunities foregone in the acquisition process. As such, this research focuses on the review of these methodologies and their applications to the acquisition process of AI systems.

Research Objective

The current research examines the challenges of acquiring an AI-based system within the common acquisitions framework in business and in the DoD. The primary objective of the current research is to evaluate three quantitative analysis tools for improving the acquisition of organically developed DoD AI systems. A comparison and contrast of the proposed methodologies will identify when and how each method can be applied to improve the acquisitions life cycle for AI systems.

Research Questions

The questions examined in this research are as follows:

1. How should each proposed methodology be used throughout the AI systems acquisition life cycle?
2. Will the combination of methodologies reduce the risks associated with acquiring an organically developed AI system?
3. When should the methodologies be used in the acquisition life cycle to ensure successful acquisition of AI systems?
4. What are the risks inherent in following a 5000 series acquisition framework when acquiring an organically developed AI system?

Technical Approaches and Outcomes of the Research

This research provides an in-depth review of each of the three methodologies (IRM, KVA, and EVM). While each acquisition project is unique, all must pass a series of common hurdles to succeed. A successful AI acquisition approach requires the support of methodologies that are designed to identify and value system options and forecast the future value of systems while assessing and mitigating investment risks. The dominant methodology for managing DoD acquisitions that exceed $20 million is EVM. The current structure of EVM may be enhanced with the addition of the IRM and KVA methodologies due to the unique needs of an AI system acquisition. This research examines how these three methodologies might be incorporated within an acquisition life-cycle framework assessing the benefits and risks of this potential extension of the standard framework. These methodologies have been used extensively in the past in acquisition research performed for the Acquisition Research Program (ARP) at the Naval Postgraduate School (NPS). This current study will build on the key learnings from this prior research to enhance the acquisition life-cycle framework with a focus on the unique characteristics of AI system acquisitions. The anticipated outcome of this research will be a set of guidelines for how and when to use the three methodologies to improve the potential success of acquisition of AI within the acquisition's life cycle. The history of organic complex information technology (IT) has been characterized by cost and schedule overruns creating havoc for acquisition professionals as well as system designers and future users who expect to receive valuable new capabilities (Housel et al., 2019; Oakley, 2020). The DoD's standard 5000 series acquisition life cycle will provide the context for reviewing the ways the methodologies can be used to enhance the acquisition life-cycle approach in managing the acquisition of AI systems.

Artificial Intelligence (AI)

This next section will briefly discuss Artificial intelligence (AI) in context of its current impact in the Defense Acquisition System through a discussion on how the three Acquisition methodologies (EVM, KVA, and IRM) can be utilized to assess an AI program based on its stage in the Acquisition life cycle. AI does not refer to a specific system. It is a broad nomenclature for a collection of related inorganic computer science methods used to simulate human intelligence. The term AI typically conjures up the general concept of machine learning, which is a type of AI where a computer system is programmed to identify and categorize external real-world stimuli via a "learning" process. The DoD's AI strategy defines AI as "the ability of machines to perform tasks that normally require human intelligence—for example, recognizing patters, learning from experience, drawing conclusions, making predictions, or taking action—whether digitally or as the smart software behind autonomous physical systems" (DoD, 2019). This capability of enhanced automation is of great interest to the DoD as potential future near-peer adversaries such as Russia and China, are investing heavily in this field for military purposes (DoD, 2019).

The Growth of AI Literature from Inception to Industry 4.0

Utilizing the Web of Science comprehensive academic search engine, the researchers found 316,009 scholarly publications, including 188,275 academic journal articles on the topic of AI. The period of these AI publications covers the entire timeline from the inception of term "artificial intelligence" in the early 1960s until present day. Using Van Eck and Waltman's (2020) VOSviewer tool for visualizing scientific landscapes, the researchers created a network map that showed the illustrates how AI ("intelligence" in the diagram) relates to other key topics. A visualization of the major key terms in AI research is depicted below in Figure 1.

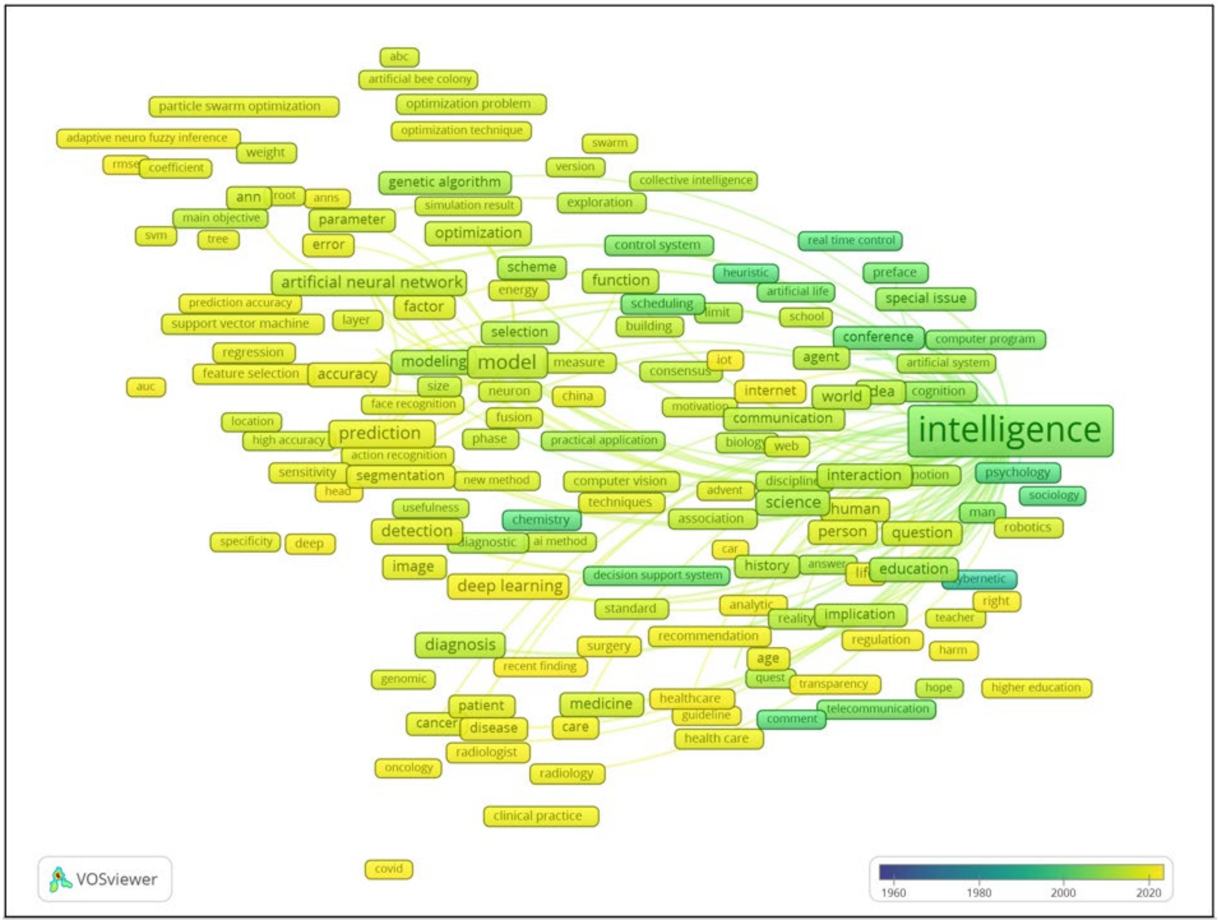


Figure 1. The Key Topics in AI from 1960 to Present Day

Figure 1 depicts how AI relates to numerous terms that have more than 50 publications related to AI since it branched out of cybernetics in the 1960s. As Figure 1 depicts, AI topics have branched out of the general computer science and automation fields into other fields such as healthcare, as noted in medical terms in Figure 1. As the timeline illustrated in Figure 1, much of the expansion in AI topics has occurred in the past two decades. A major cause of the recent interest in AI in the past decade is the phenomenon known as “The Fourth Industrial Revolution” or “Industry 4.0” (Lee, 2013; Schwab, 2015). In noting how steam power impacted the agrarian society in the First Industrial Revolution, the assembly line in the Second Industrial Revolution, the computers in the Third Industrial Revolution, Schwab (2015) argues that society is on the cusp of a “technological revolution that will fundamentally alter the way we live, work, and relate to one another.” Schwab (2017) and his colleagues at the 2011 Hanover Conference on Technology made the case that impact of this new revolution is quite extensive,

> We have yet to grasp fully the speed and breadth of this new revolution. Consider the unlimited possibilities of having billions of people connected by mobile devices, giving rise to unprecedented processing power, storage capabilities, and knowledge access. Or think about the staggering confluence of emerging technology breakthroughs … such as artificial intelligence. (p. 9)

While much of this research focuses on the DoD Acquisition of AI, the tools this research proposes for the project management in developing and procure AI (KVA and IRM) have a broader application.

AI in National Security and Defense Applications

As the capabilities of AI has expanded in the Fourth Industrial Revolution, there has been a growing concern that the international arena, particularly the three Great Powers of the United States, China, and Russia, may already be in the throes of an "AI Arms Race" (Geist, 2016). One of prevalent fears among scholars in the age of expanding AI, is the risk of developing "autonomous weapons" that can no longer be controlled (Geist, 2016). In essence, by developing AI weapon systems, humanity may be sowing the seeds of its own destruction. As former Secretary of State Kissinger noted on the rise of AI:

> The scientific world is impelled to explore the technical possibilities of its achievements, and the technological world is preoccupied with commercial vistas of fabulous scale. The incentive of both these worlds is to push the limits of discoveries rather than to comprehend them. And governance, insofar as it deals with the subject, is more likely to investigate AI's applications for security and intelligence than to explore the transformation of the human condition that it has begun to produce. (Kissinger, 2019)

Kissinger's (2019) words strike at the heart of the growing mistrust of this new technology that has exploded with the recent rise of Big Data and more powerful computing. This fear may also grow as AI can potentially dominate international relations with a new race to develop and weaponize AI (Geist, 2016).

AI and The DoD's Third Offset Strategy

The discussion will now shift towards the DoD's recent drive towards AI. As the potential capabilities of AI became more evident, then Secretary of Defense Chuck Hagel (2014) launched the "Third Offset Strategy." The DoD's Third Offset Strategy hearkens back to the "First Offset" launched by President Eisenhower where the United States developed its strategic arms to reduce the need for standing conventional forces during the early Cold War and the "Second Offset" where after the Vietnam War, the DoD, through programs such as DARPA, increased the capabilities of its conventional forces to counter the Warsaw Pact (Hillner, 2019). Then Deputy Secretary Work noted that it is the challenges of the current geopolitical environment, artificial intelligence can help reinstate the U.S. previous technological overmatch, "Learning machines are an example of technology that can help turn AI and autonomy into an offset advantage" (Pellerin, 2015). It was the Third Offset Strategy that pushed for subsets initiatives such as the Defense Innovation Initiative and Frank Kendall's (2017), then Under Secretary of Defense for Acquisition, Technology and Logistics, "Better Buying Power 3.0" which were focused on bringing back the competitive edge that the U.S. military once had over its geopolitical competitors.

The theme that arises from the Third Offset, Defense Innovation Initiative, and Better Buying Power 3.0 is that the Defense Acquisition System is unable to meet the requirements of fielding software intensive systems such as AI systems. Kendall (2017) discussed this problem by illustrating the challenging that PMs with software intensive systems such as AI face due to the extensive cycle of developing, testing, fielding "several builds of software in various stages of maturity" simultaneously while dealing with the organizational bureaucracy that slows the PM down (p. 50).

DoD Acquisition of New Software-Intensive Technology

The fielding of new and advanced technologies such as AI is a challenge for the DoD and all federal government. The current methodologies have proven unsuccessful in meeting the task of providing the requirements to the warfighter to face the challenges of the modern battlefield (Kendall, 2017). However, with the release of recent strategic changes such as implementing innovation practices and advanced prototyping, the DoD may prove up to the task of fielding the materiel and equipment to support the Department and the Services (Kendall, 2017; Voelz, 2016). Some of the practices that have proven success is the adopting best practices in DoD labs and increasing the use of rapid development cycles through prototyping (DiNapoli, 2019; Sullivan, 2018).

A recent case study on the two-decade process of developing biometrics for the use in the Services provides the lessons learned on comes to acquisition of new and advanced technology. According to Voelz (2016), "The case study of biometrics demonstrates that effective military innovation can only occur through an integrated approach that takes into account the interdependent elements of technology development, acquisition planning, doctrinal design, and warfighting strategy" (p. 180). While not exactly the same, the lessons learned of adapting biometrics in the Services is an example of how the DoD can adopt AI throughout the department. This is because a key attribute that biometric systems and AI systems share are that they are both heavily software intensive development process.

Earned Value Management

EVM provides cost and schedule metrics to track performance in accordance with an acquisition project plan. EVM is required for large DoD acquisition programs that use incentive contracts valued at or greater than $20 million (DoD, 2015a). EVM methodology uses a WBS to try to ensure that an acquisition project is on schedule and within the estimated cost for each work package. It is used to measure work progress and any deficiencies using cost and schedule metrics that also can be used to measure program performance trend analysis with a focus on identifying any budget and schedule deviations from plan. However, the analysis is done after each process or stage in the WBS. In other words, the actual cost and time spent to execute a particular phase is compared against the initially projected budgeted plan.

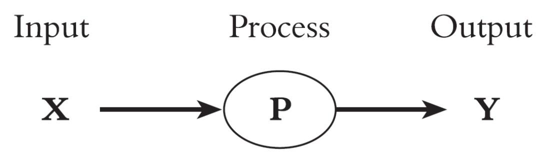
Given the propensity of IT and AI acquisitions to be over budget and behind schedule, EVM metrics help PMs identify and attempt to avoid overruns and schedule deviations. Recognized plan deficiencies can help program managers identify waste and chokepoints that require immediate correction. When deficiencies in cost or schedule occur, EVM analysis can be used to reforecast the budget and schedule with the focus of providing PMs with up-to-date accurate performance information. EVM analysis uses schedule and cost estimates to find the Planned Value (PV) of a given acquisition project. Cumulative PV provides the total value that should be achieved by a specified date. The specific label for PV within the DoD acquisitions community is Budgeted Cost for Work Scheduled (BCWS). Actual Cost (AC) is the accumulated accrued costs of labor and materials at any point in time during a project. The label for AC within the DoD acquisitions community is Actual Cost of Work Performed (ACWP). Earned Value (EV) measures the progress for a given plan. The DoD acquisitions label for EV is Budgeted Cost of Work Performed (BCWP).

In sum, EVM exists to provide an assessment of the actual physical work a project has completed compared to a baseline plan (Fleming & Koppelman, 2010). EVM integrates the actual cost spent on the project to date with the work that has been performed on the project, allowing managers to compare the progress of the project with their planned budget and schedule (Fleming & Koppelman, 2010). It provides managers the ability to compare cost performance with work completion rather than simply cost performance and planned cost, as is done in traditional cost management (Fleming & Koppelman, 2010). When properly employed, EVM provides a reliable prediction of the total cost and schedule requirements for a project through three distinct dimensions: the planned value, earned value, and actual cost (Fleming & Koppelman, 2010). It is important to note the term *value* in EVM does not have the same meaning as in other methodologies, such as KVA. Within the context of EVM, *value* is defined as the work accomplished towards completion of the project. There is no reference to the quality of the completed work or additional (or missing) benefits the work might provide to a system. The value is assumed because the specifications were defined in the project requirements. EVM has proven to be a reliable system to manage cost and schedule performance for manufacturing in both defense and commercial industries. However, as systems become more complicated and information technology (IT) and AI gain a more prominent place within even traditional manufacturing projects, EVM may need additional information from additional methodologies to improve its capabilities. Better incorporating the strategic guidance associated with a program, the value gained from subcomponents and subprocesses, the risk associated with developing subcomponents of a system, and incrementally improving a process may help improve the Defense Acquisition System as a whole.

Knowledge Value Added

KVA is an empirical model that focuses on the practical application and implementation of knowledge management (Tsai, 2014). Originally developed to assist in business process reengineering, KVA creates an objective, quantifiable method to measure the value of a process or service (Housel & Kanevsky, 1995). Typical financial approaches to business process reengineering use the dollar amount of a final product to determine the value of an object, failing to account for the knowledge required in the various subprocesses involved in making the product (Housel & Kanevsky, 1995). In its essence, KVA performs a single function: describing all process outputs in common units. KVA accounts for the value of all components, processes, and support systems necessary to complete a task or create a product or service by describing all outputs in common units. It allows managers to compare the efficiency of the various steps across all processes within a common value reference point.

Value has a different meaning in KVA than it does in other methodologies, such as EVM or IRM. KVA bases its definition of *value* on complexity theory and views organizational processes by their ability to change their input (raw material, information, energy, etc.) into common units of output, as shown in Figure 2 (Housel & Kanevsky, 1995). Per Figure 2, process P changes the input in some manner, creating a different product or service at the output, adding value to the system based on the number of common unit changes from input to output (Housel & Kanevsky, 1995). If process P did not change input X, then output Y is the same as input X, indicating no value was added by the system (Housel & Kanevsky, 1995). While the change from X to Y may be minute or large depending on the process, KVA converts all changes into common units, and these changes indicate the amount of value added by process P to produce the final product. The value generated through the process is proportional to the change in the state from X to Y, denoting the amount of knowledge required to make the changes (Yu et al., 2009). Thus, the contribution to a process is equivalent to the sum of all knowledge necessary to produce a product and/or interpret meaning from an input (Housel & Kanevsky, 2006). This is true for all processes within a system, from production to service to management.



P(X) = Y

Fundamental assumptions:

1. If X = Y no value has been added.
2. “value” $\propto$ “change”
3. “change” can be measured by the amount of knowledge required to make the change.

So “value” $\propto$ “change” $\propto$ “amount of knowledge required to make the change”

Figure 2. Value Added Process (Housel & Bell, 2001, p. 94)

The KVA methodology is best completed by following the seven-step process shown in Figure 3. Practitioners can use several methods to describe the units of change, such as tasks, Haye knowledge points, Shannon bits, units of knowledge, and so on (Housel & Bell, 2001). For ease of measurement, three measures are typically used within KVA to estimate the embedded knowledge within a process (Housel & Bell, 2001). Learning time, column two in Figure 3, measures the length of time it takes an average user to learn a process and correctly complete it (Housel & Bell, 2001). Process description, column three, is the number of process instructions used to transform the given input into the desired output (Housel & Bell, 2001). Each instruction must require an approximately equal amount of knowledge to complete a task (Housel & Bell, 2001). The binary query method uses the number of binary questions (i.e., bits) necessary to accomplish the process, roughly equivalent to the lines of code within a computer program (Housel & Bell, 2001). However, any measure that satisfies the basic concepts of KVA can be used to create a common-units measure (Housel & Bell, 2001).

Steps	Learning time	Process description	Binary query method
1.	Identify core process and its subprocesses.		
2.	Establish common units to measure learning time.	Describe the products in terms of the instructions required to reproduce them and select unit of process description.	Create a set of binary yes/no questions such that all possible outputs are represented as a sequence of yes/no answers.
3.	Calculate learning time to execute each subprocess.	Calculate number of process instructions pertaining to each subprocess.	Calculate length of sequence of yes/no answers for each subprocess.
4.	Designate sampling time period long enough to capture a representative sample of the core process's final product/service output.		
5.	Multiply the learning time for each subprocess by the number of times the subprocess executes during sample period.	Multiply the number of process instructions used to describe each subprocess by the number of times the subprocess executes during sample period.	Multiply the length of the yes/no string for each subprocess by the number of times this subprocess executes during sample period.
6.	Allocate revenue to subprocesses in proportion to the quantities generated by step 5 and calculate costs for each subprocess.		
7.	Calculate ROK, and interpret the results.		

Figure 3. The KVA Approach (Housel & Bell, 2001)

KVA identifies the actual cost and value of an organization's assets (human and technological), standard functional areas, or core processes. KVA identifies every process required to produce an output, and the historical costs of those processes, the unit costs, and unit values of products, processes, functions, or services can be measured. By describing all process and subprocesses (down to the detailed level of WBS) outputs in common units, the methodology also permits market-comparable data to be generated; this ability is particularly important for nonprofits like the military and government organizations. When market comparables from industry are used, value is quantified in two key productivity metrics: Return on Knowledge (ROK) and Return on Investment (ROI). Following these steps yields a defensible estimate of the productivity (i.e., ROK, ROI) of a given process or set of subprocesses. These estimates can then be used to track progress in an EVM framework in terms of cost, schedule, and importantly, the value produced. The KVA estimates can also be used to track the volatility of a set of processes and this metric can be used in the IRM processes that forecast future value from, for example, an AI system.

KVA is potentially useful tool for inclusion in the Defense Acquisition System. Since the DoD is not a for-profit company, it does not have revenue to judge the effectiveness of its programs in a monetized form. Instead, it relies on various metrics and evaluations that are not comparable from system to system. If the DoD implements the KVA methodology more widely, PMs may have a more objective measure to compare various technological solutions to fulfill evolving requirements. Understanding the value that a system or process provides in direct comparison with the value of other systems, whether they are similar or unrelated processes, could provide beneficial information in the decision-making, budgeting, and planning processes.

Integrated Risk Management

IRM is a system developed by Dr. Johnathan Mun designed to provide management the ability to analyze risk associated with the development of a new project or initiative. IRM combines several commonly accepted analytical procedures, such as predictive modeling, Monte Carlo simulation, real options analysis, and portfolio optimization, into a single, comprehensive methodology. The methodology uses existing techniques and metrics such as discounted cash flow, return on investment (ROI), and other metrics within the analytical processes to improve the traditional manner of evaluating potential projects within a company or the DoD. In contrast to the other methodologies, IRM focuses on the risk involved with a decision. It seeks to mitigate negative effects from risk while maximizing rewards from potential outcomes. At its core, IRM is a technique to provide managers the best analytic information available to use during the real options process. Figure 4 illustrates the comprehensive IRM process.

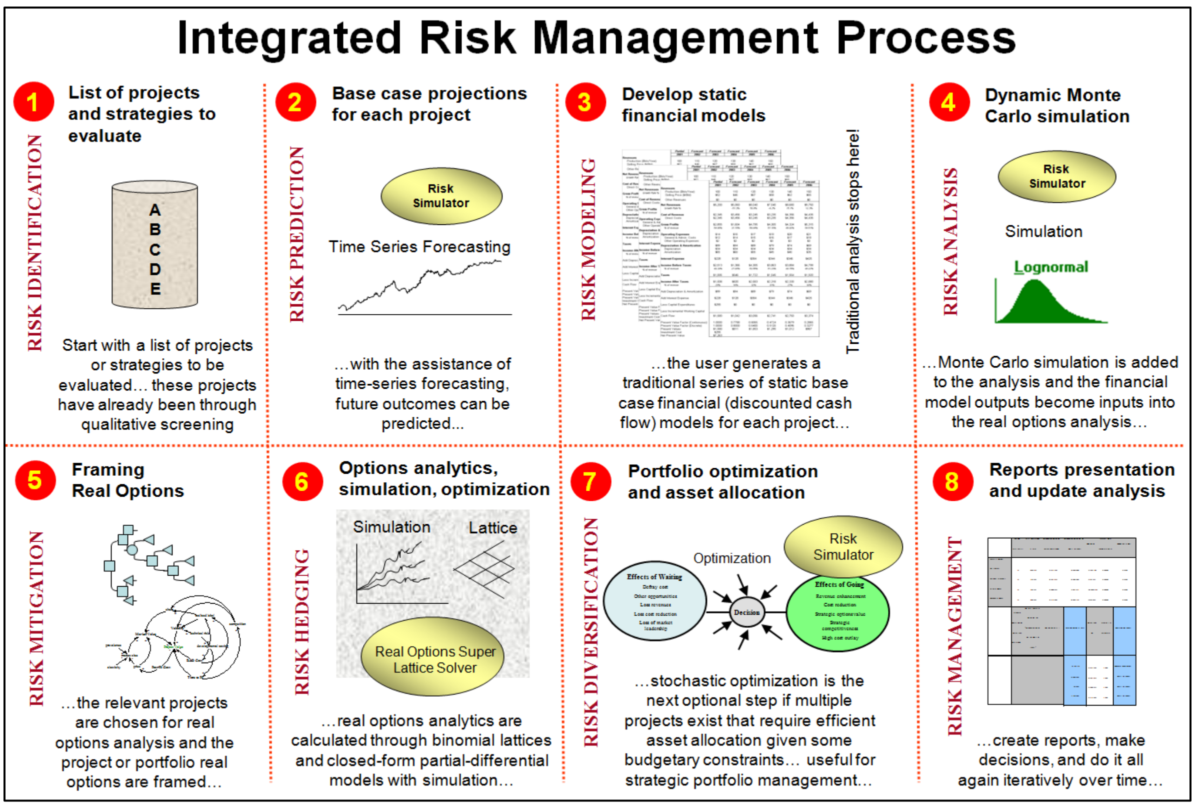


Figure 4. Integrated Risk Management Process (Mun & Housel, 2010)

As depicted in Figure 4, there are eight steps within the IRM methodology:

1. Qualitative management screening
2. Forecast predictive modeling
3. Base case static modeling
4. Monte Carlo risk simulation
5. Real options problem framing
6. Real options valuation and modeling
7. Portfolio and resource optimization
8. Reporting, presenting, and updating analysis

While each of the individual steps provides value to a project manager, incorporating all of them in a contiguous approach will allow decision-makers the most effective use of the IRM process.

IRM is a comprehensive methodology that is a forward-looking risk-based decision support system incorporating various methods such as Monte Carlo Risk Simulation, Stochastic Forecasting, Portfolio Optimization, Strategic Flexibility Options, and Economic Business Case Modeling. Economic business cases using standard financial cash flows and cost estimates, as well as non-economic variables such as expected military value, strategic value, and other domain-specific subject matter expert (SME) metrics (e.g., Innovation Index, Conversion Capability, Ability to Meet Future Threats, Force Structure, Modernization and Technical Sophistication, Combat Readiness, Sustainability, Future Readiness to Meet Threats) can be incorporated (Mun, 2016). These metrics can provide robust forecasts as well as mitigating risk via simulations that account for program uncertainties. The tools set also uses modeling to determine potential program benefits compared to program costs (e.g., return on investment for innovation or return on sustainability). Capital investment and acquisition decisions within AI program investment portfolios can then be made based on the resulting rigorous quantitative analysis (considering budgetary, manpower, and schedule constraints). Projects can be broken down into their detailed work breakout structure (WBS) and tasks, where these tasks can be combined in complex systems dynamic structures or implementation paths. The cost and schedule elements for each task can be modeled and risk-simulated within the system to estimate the resulting total cost and schedule risk of a given AI acquisition program. Portfolio management is often integrated with IRM methods to provide a more holistic view in terms of acquisitions of IT and AI acquisition programs.

The IRM methodology is a systematic technique to determine the best possible projects to pursue based on the statistical likelihood of their success. Using historical knowledge of defense acquisition programs and AI systems in both the government and commercial realms could improve the budgeting and scheduling processes. Determining the likely range of outcomes through dynamic statistical modeling may improve the program's performance. By better understanding the risk associated with various components, a more appropriate schedule and budget could be developed. IRM may also help determine which real options should be included in acquisition contracts. A high-risk program may need more options, such as the options to abandon, delay, or expand, based on its actual performance. Finally, IRM could prove useful in portfolio management, helping decision-makers determine which programs to initiate when viewing the portfolio of other programs in progress and used operationally.

Acquisition Life Cycle & AI

Housel et al. (2019) noted that the DoD 5000 series Acquisition Life Cycle (see Figure 5) can be aligned to the generic technology investment life cycle. As depicted in Figure 6, while terminology differs between the DoD 5000 and generic technology life cycle phases, the sequence of activities in these respective life cycles are congruent.

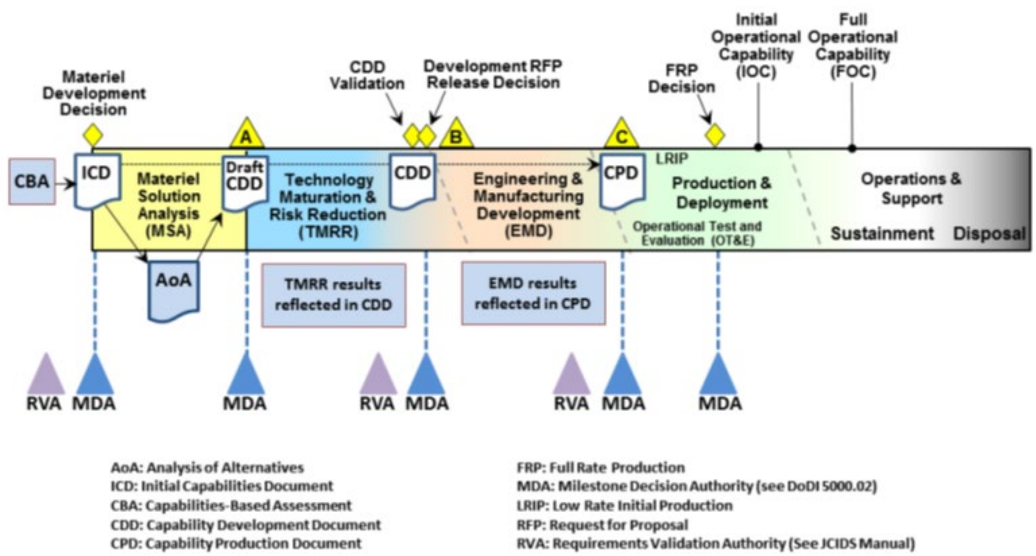


Figure 5. The 5000 Series Acquisition Life Cycle (DoD, 2017)

Pre-Materiel Solutions Analysis	Materiel Solutions Analysis	Technology Maturation and Risk Reduction	Engineering and Manufacturing Development	Production and Deployment	Operations and Support
-Strategic goal alignment -Pre-investment	Pre-Investment	Pre-investment	Implementation	Implementation	Post-implementation

Figure 6. Aligning the Generic and 5000 Series Life Cycles (Housel et al., 2019)

Housel et al. (2019) noted that the acquisition methodologies, to include EVM, KVA, IRM, and others may be used "concert," however, "certain tools are more appropriate for a particular phase than others" (p. 48). Thus, the PM and should "use the tools appropriately in that they provide more information for a complex environment" (Housel et al., 2019, p. 48). Therefore, during the beginning of the life cycle such as the Pre-Materiel Solution Analysis, the Materiel Solution Analysis (MSA), or the Technology Maturation and Risk Reduction (TMRR) phases, methodologies that such as IRM and KVA may be of more use to the PM as they provide quantitative value metrics such as a common unit assessment of the technology and risk, as opposed to EVM that only measures cost. Meanwhile, during the main implementation phases of Engineering and Manufacturing Development (EMD) and Production and Development (PD), all three metrics—EVM, KVA, and IRM—can provide useful data to assess the program. However, during the post-implementation or Operations and Support (OS) phase, KVA is more likely to provide useful data over EVM.

Comparison of Acquisition Methodologies in AI Development

In a recent Congressional Research Service (CRS) on AI it was noted that "standing DoD processes—including those related to standards of safety and performance, acquisitions, and intellectual property and data rights—present another challenge to the integration of military AI" (Sayler, 2020, p. 16). As discussed earlier in the report, the difficulty of traditional Acquisition methods in relation to emerging technology such as AI is the speed the development and deployment of these technologies often outpaces the Defense Acquisition System. When compared to the commercial sector, the DoD process for developing and fielding its AI systems has a mismatch between when compared to the timelines for its requirements. This is likely because there is a stark contrast with “the pace of commercial innovation and the DoD’s acquisition process” (Ilachinski, 2017, p. 1). This is because it takes an average of 91 months, or 7 and a half years, to go from the Analysis of Alternatives (AoA) to the Initial Operational Capability (IOC; Ilachinski, 2017). The Defense Science Board (2018) found the DoD’s timeline for fielding systems is multiple times longer than the commercial sector which uses an iterative process to field AI systems in approximately 6 months. As noted in the RAND Report that assessed the DoD’s posture for AI:

> Our starting point at the onset of our study was the DoD model of technology development, procurement, fielding, and sustainment, giving rise to two dimensions of posture assessment related to technologies: advancement and adoption. However, as we carried out our study, it became clear that this model is not valid for AI, owing to the spiral nature of AI technology development. (Tarraf et al., 2019, p. 51)

Because of the challenges of procuring and fielding AI systems, the CRS Report reached the conclusion that the “DoD may need to continue to adjust its acquisitions process to account for rapidly evolving technologies such as AI (Sayler, 2020, p. 17). Similarly, the RAND Report also noted that the DoD should utilize and adapt acquisition approaches that are “appropriate for the technology” (Tarraf et al., 2019).

One method that the DoD can adjust or adapt its acquisition process and/or approach is to adapt and utilize the Acquisition methodologies based on the complexity of the development. As noted by Ilachinski (2017) and the Defense Science Board (2018), AI systems development processes tend to be iterative in their approach. Thus, the need for rapid development and prototyping is likely to be utilized more than in traditional Acquisition Life Cycles (Tarraf et al., 2019). However, despite being iterative in nature, the techniques recommend by Housel et al. (2019) of using EVM, KVA, IRM, or a combination of using various methodologies in concert can also be applied to the Acquisition of AI systems as shown in Table 1.

Table 1. Selection of Acquisition Methodologies Based on Complexity of Development

Complexity of Development	EVM	KVA	IRM	
Mature Technologies	X	X		
Iterative Development		X	X	
Complex AI Systems		X	X	X
Non-Complex AI Systems	X	X		

Note. Iterative Development is for AI systems that are either prototypes or have rapid generational development cycles (i.e., versions).

For the mature technologies and/or non-complex AI systems, because there is typically less risk in these life cycles, the PM can follow the normal of the EVM methodologies to monitor the progress of the development. However, the PM can also choose to utilize KVA to assess the AI systems with its common unit of value.

Comparison of Key Attributes

Choosing a methodology should depend on the nature of the project under consideration, specifically, the commitment needed from the organization, the organization’s desire to align strategic goals with the project, the predictive capability of the methodology, the flexibility required, and the time available. While others in the organization need to understand the concepts to comprehend status reports, EVM only needs the management team to track the cost and schedule of the project compared to the baseline as there is no determined goal alignment with the organization. While the CPI and SPI can help estimate the final cost and schedule, there is no true predictive ability associated with EVM since the assumption is that the schedule will proceed according to the baseline, regardless of previous performance volatility. Adherence to the baseline is essential in EVM, and changing requirements can drastically alter a baseline, reducing the effectiveness of the methodology. Setting up, monitoring, and reporting the cost/schedule performance of each work package within the WBS can be a time-consuming and expensive task for an AI project with its many unknowable components and capabilities a priori.

KVA needs only the KVA analyst and the process owner, as the SME, to determine the value of a process or component output, supporting the need to align the project with an organization's productivity goals. Using this analysis, they can model the current baseline as-is process ROK and compare it with the proposed to-be process model ROK, thus offering a simple prediction of the improvement between the models. Since KVA can be used with any language of description that defines the process outputs in common units, analysts can choose whichever method is most beneficial for the particular system in question, providing flexibility. This analysis can be completed quickly, potentially providing a rough-cut assessment within a few days.

IRM requires the organizational leadership, portfolio and project managers, and the analyst to determine how a project fits within an organization's portfolio, the present value (PV) of the project, and potential real options. By analyzing and simulating various scenarios, IRM provides a prediction of a project's likely performance, which allows managers to build in flexibility via real options at the appropriate locations within the project. Assuming the data necessary for the analysis is available, the process can be completed in a relatively quick manner.

Methodologies in AI Acquisition

As previously discussed, the methodologies all have strengths and weaknesses, making them more suitable in certain applications than others. The biggest challenge in using EVM when acquiring AI is the iterative nature of software development. EVM needs clearly stated, detailed requirements for intermediate steps to be most effective. While the outputs of software programs are defined well, the steps required to build the software are not, leading to problems when developing cost and schedule estimates. If the software is not complex or consists of known processes, EVM can sufficiently monitor the progress. Integrating software and hardware is also complicated with EVM since there are numerous pieces of the program that must be combined to meet the goals, resulting in additional debugging and recoding. EVM is more efficient when used to manage the physical creation of systems or infrastructure. It can monitor the cost/schedule progress of software work packages but is not as useful at estimating the value of those programs.

KVA can provide an objective, ratio-scale measure of value and cost for each core process and its subprocesses or components within any IS system. Using the two parameters, managers can then analyze productivity ratios information, such as ROK and ROI, to determine the efficiency of a process compared to the resources used to achieve the output. This can help the manager decide how to use resources to update systems or estimate the future value of a system being acquired. Combining the KVA results with IRM allows managers to iterate the value of system real options analysis through simulation and other techniques. IRM can also quantify risks and forecast performance probabilities for measures of the potential success for programs and components of programs using historical data. It is a tool to assist with the investment strategy, making it useful when acquiring all types of AI. However, it is not designed to help manage the actual acquisition of an AI program or determine how to meet its detailed requirements.

Examining the benefits and challenges of the proposed methodologies demonstrates the scope, capabilities, and limitations of various AI systems. It also helps inform in which areas and phases of the Defense Acquisition System life cycle it may be appropriate to include the methodologies or components of the methodologies within the system. The main research question of this study was, simply, how can certain advanced analytical decision-making methodologies be used in the acquisition life cycle to complement existing methods to ensure a successful acquisition of AI technologies?

As discussed, EVM remains the only program management methodology required by the U.S. government for all DoD acquisition programs with a contract value exceeding $20 million. Regardless of this requirement, EVM is a methodology that provides a structured approach to the acquisition of IT via program management processes that can help ensure an acquisition program stays on schedule and within budgeted cost estimates. However, there are significant limitations when using EVM for AI acquisitions, the major weakness being that it was not designed for managing AI acquisitions that follow a very iterative and highly volatile pathway. Organic AI acquisitions require a high level of flexibility to deal with the unknowns that arise during the development process as well as value adding possibilities not in the original plan. In addition, EVM does not provide a common unit of value metric to enable standard productivity metrics, such as ROI. When value is inferred by how consistent a program is with original baseline cost and schedule estimates, the performance of the program may be sacrificed in terms of the quality of the outputs when planned program activities become iterative, as in the development of many AI programs. If an AI acquisition program is trending toward cost and schedule overruns, but the resulting value added of the modifications to the original requirements provides disproportionate increases in value, EVM is not designed to recognize this increase in value.

To remedy these shortcomings of EVM in AI acquisitions, the methodology should be combined with KVA and IRM, which can be useful during the requirements and monitoring phases of EVM 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 before acquisition of an AI system. A future process model that estimates the value added of the incorporation of the AI can also set expectations that can be measured against the baseline model after the AI has been acquired. IRM can be used to forecast the value of strategic real options flexibility that an acquired AI may provide so that leadership can select the options that best fit their desired goals for the AI in defense core processes.

Because it provides an objective, quantifiable measure of value in common units, KVA should also be used in AI acquisitions to allow decision-makers to better understand and compare different strategic options based on their value and the cost. Obtaining a return on investment of AI systems can only be done when using KVA to determine the value embedded in the system. This information provides insight to PMs as well as a more complete perspective regarding the performance of both the current and the to-be systems.

Likewise, using IRM is recommended when acquiring AI through the Defense Acquisition System. Applying dynamic and stochastic uncertainty and risk-based modeling techniques to predict likely and probabilistic outcomes can improve the risk estimates associated with the components and subcomponents of a program, in terms of their potential cost overruns, value variabilities, and schedule delays. Analyzing various real options within the context of the models' outputs will help PMs make the most advantageous choices when determining a program's future.

PMs should use EVM only in the Engineering and Manufacturing Development (EMD) phase, as is currently done. That said, EVM will work best in hardware manufacturing solutions with technology that is fully mature prior to the program starting. Since many AI acquisition programs consist of advancing the current technology and developing new software solutions to meet requirements, EVM is not perfectly suited for AI development. Nevertheless, PMs can use various agile EVM techniques to complete projects on cost/schedule baselines provided the appropriate steps are taken when establishing the baseline. Requirements must be broken into small, easily definable tasks with suitable risk and uncertainty factors accounted for within the schedule. Other methodologies, such as KVA and IRM, should be used with EVM to ensure these factors are based on defendable metrics rather than simply guessing how much additional time, money, and value may be necessary to complete complex tasks.

During the Materiel Solution Analysis (MSA) phase, KVA and IRM will help determine the value of the different options considered in the analysis of alternative (AoA) process. KVA can objectively measure the value of the current, as-is system and the potential to-be systems under consideration. Then IRM can use additional factors to value the alternatives in terms of their relative parameter values such as cost, value, complexity, timeline. As the chosen solutions mature during the Technology Maturation and Risk Reduction (TMRR) phase, an updated KVA analysis will reassess initial estimates and provide a projected ROI that can be incorporated in an IRM risk and real options analysis for the AI solution prior to entering the EMD phase as appropriate.

Limitations and Future Research

This research examined whether the various methodologies—EVM, KVA, and IRM—could be used within the Defense Acquisition System to improve the acquisition of AI. Future research should examine how these methodologies may interact with or improve other components of the acquisition system. This includes the Joint Capabilities Integration and Development System (JCIDS) and Planning, Programming, Budgeting, and Execution (PPBE) components as individual processes and the interaction of JCIDS, PPBE, and the Defense Acquisition System as a whole. Certain methodologies, specifically IRM, may be more beneficial when used throughout the entire acquisition process instead of within a portion of the system. Additionally, future research could examine how these different methods may be used in the acquisition of products outside the AI or IT realm.

The research conducted looked at AI as a whole and not specific types of AI. Future studies should examine if acquisition methods, strategies, and methodologies should change based on the category of AI being acquired. This is of specific interest when considering artificial intelligence and its subsets. Machine learning, intelligence with a specific focus or field of expertise, and general or universal intelligence would likely have different methods used in the acquisition process based on their complexity, complicated nature, undeveloped technology, and level of risk.

The applicability of these methodologies within commercial acquisition of AI is another area of potential research. This research focused exclusively on the application of the respective techniques within the DoD acquisition process. However, commercial entities also struggle when acquiring complex or complicated AI and IT systems, particularly when the systems operate at the enterprise level. Further research may indicate if these same methodologies could provide value to decision-makers in the private sector during the creation, adoption, or customization of commercial AI. As noted earlier, the hype cycle for AI and automation is on the rise and the demand to procure such technologies is as relevant for the commercial sector as it is for the DoD. Furthermore, the recent pandemic caused by the Coronavirus Disease 2019 (COVID-19) has forced a permanent shift in society towards an increased trend towards a permanent remote workforce. As these trends are likely to continue in the foreseeable future, an increased in automation tools will be required to support this workforce. These trends could be explored for their implications as part of the Fourth Industrial Revolution and Industry 4.0.

Finally, this research only examined the most promising methodologies out of numerous different possibilities. Future research could examine other program management tools, management philosophies, analytic tools, or other methodologies and their benefit when acquiring AI. While the examined methodologies were chosen because they would likely benefit the process and support improvements in EVM, other systems may be more appropriate in certain phases or may offer additional benefits not seen in this research.

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