technologies

Article

Get Real Get Better: A Framework for Developing Agile Program Management in the U.S. Navy Supported by the Application of Advanced Data Analytics and AI

Jonathan Haase [1], Peter B. Walker [2,*], Olivia Berardi [3] and Waldemar Karwowski [4,*]

[1] NAVSEA PEO USC, PMS 408, Expeditionary Warfare Office, Washington, DC 20376, USA; jonjhaase@gmail.com
[2] PEO USC, PMS 408–Expeditionary Medicine, 1333 Isaac Hull Ave., Washington Navy Yard, DC 20376, USA
[3] Cydecor, Inc., 251 18th St. S Ste 550, Arlington, VI 22202, USA; olivia.l.berardi.ctr@us.navy.mil
[4] Department of Industrial Engineering and Management Systems, University of Central Florida, Orlando, FL 32816, USA
* Correspondence: peter.b.walker.mil@health.mil (P.B.W.); wkar@ucf.edu (W.K.)

Abstract: This paper discusses the "*Get Real Get Better*" (GRGB) approach to implementing agile program management in the U.S. Navy, supported by advanced data analytics and artificial intelligence (AI). GRGB was designed as a set of foundational principles to advance Navy culture and support its core values. This article identifies a need for a more informed and efficient approach to program management by highlighting the benefits of implementing comprehensive data analytics that leverage recent advances in cloud computing and machine learning. The Jupiter enclave within Advana implemented by the U.S. Navy, is also discussed. The presented approach represents a practical framework that cultivates a "*Get Real Get Better*" mindset for implementing agile program management in the U.S. Navy.

Keywords: program management; data analytics; machine learning; artificial intelligence; agile development

Citation: Haase, J.; Walker, P.B.; Berardi, O.; Karwowski, W. Get Real Get Better: A Framework for Developing Agile Program Management in the U.S. Navy Supported by the Application of Advanced Data Analytics and AI. *Technologies* **2023**, *11*, 165. https://doi.org/10.3390/technologies11060165

Academic Editors: Mohammed Mahmoud and Pedro Antonio Gutiérrez

Received: 26 August 2023
Revised: 12 November 2023
Accepted: 13 November 2023
Published: 20 November 2023

1. Introduction

Rapid advances in business applications of data analytics (DA) and artificial intelligence (AI) have great potential to transform and disrupt the current program-management capabilities and practices [1–3]. Many recently published studies have demonstrated the benefits of the effective implementation and integration of data analytics and AI in project management (see, for example, [4,5]). While most of these studies focused primarily on project management, Santos and de Carvalho [6] discussed the benefits of scaling agile project management to large projects. This paper introduces the requirements for leveraging data analytics and AI to enhance program management in the U.S. Navy environment.

In a fast-evolving world, the United States Navy military consistently strives to stay ahead by ensuring the efficient execution of complex programs while continuing to meet mission-critical objectives. To meet these continuing and changing demands, the Navy's Chief of Naval Operations established the foundations for a program known as *Get Real Get Better* (GRGB) in 2021. GRGB was designed as a set of foundational principles to advance Navy culture and support its core values. "Get Real" focuses on self-assessment and transparency. To stay ahead of its near-peer competition, the Navy needs to be continually self-aware and provide continued assessment regarding its performance. Similarly, "Get Better" attempts to utilize this self-assessment and commit to improvement. Here, the focus is on achieving the highest standards of performance.

This paper discusses the *Get Real Get Better* (GRGB) approach for developing agile program management in the U.S. Navy. Currently, the Navy seeks to apply advanced data analytics and artificial intelligence (AI) to transform program management by identifying and fixing the root causes of its current challenges. At its core, the proposed GRGB framework leverages data-driven decision making (Get Real) to build program management performance (PMP) and evaluation criteria to cultivate an environment of program management performance improvement (Get Better).

2. Background: Project and Program Management

2.1. Agile Project Management

The agile approach to project management has been extensively used within the software development sector and manufacturing settings due to the industry's dynamics and the need for rapid adaptation to unforeseen changes in business environments [7,8]. However, current agile project management is still limited by the absence of advanced analytical methods allowing for automated prediction, estimation, planning, resource and risk management, and decision-making in general [5]. For example, Cabrero-Daniel [9] conducted an extensive literature review and longitudinal meta-analysis of the retrieved studies, focusing on integrating artificial intelligence with agile software development methodologies and the role of artificial intelligence and its future applications within agile software development with a focus on continuous integration and delivery. Furthermore, Auth et al. [10] proposed a conceptual framework to speed up the potential applications of artificial intelligence in the project management area.

2.2. AI-Supported Agile Project Management

Many recent studies have pointed out that modern management faces the challenge created by potentially disruptive AI applications across entire organizations and their business processes [1,5], including, among others, organization-specific AI use cases [11], software engineering [12], healthcare [13], and medicine [14]. Most recently, Odeh [15] argued that project managers should take full advantage of AI to transform traditional project management processes to meet stakeholders' needs and deliver the desired project outcome. Furthermore, Bento et al. [16], based on a systematic literature review, pointed out that the field of project management still needs to fully embrace the benefits of AI technology, and more research and development is required in this direction.

As discussed by Dam et al. [17], the rapid developments in the field of artificial intelligence (AI) can transform the current practices in agile project management (APM) by accelerating productivity and increasing project success rates. Such a transformation can be achieved by assisting project managers through AI-based automation of repetitive and high-volume tasks, improving project analytics for estimation and risk prediction, and enabling AI-supported actionable decision-making. The most recent systematic literature review by Taboada et al. [18] concluded that AI and machine learning (ML) could be very useful in the management of IT and construction projects by enabling significant improvements in project planning [19], scheduling [20], cost and quality [21], forecasting [22], risk management [23], and decision-making competences [24–26].

2.3. Human–AI Collaboration in Project Management

According to Abedin et al. [27], AI systems are currently being implanted into various information systems, including medical diagnostics, health, layout design, human resources, arts, entertainment, financial/credit scoring, and autonomous vehicles. Shang et al. [28] suggested that AI technologies are underutilized in project management due to limited support from top management, the absence of organizational readiness, the high cost of AI implementation and maintenance, and the shortage of personnel trained in AI. Furthermore, a questionnaire study by Fridgeirsson et al. [29] suggested that the respondents did not consider artificial intelligence as a technology that could support the required human cognitive skills and leadership abilities. However, as pointed out by Puranam [30], effective human–AI collaborative decision making should be considered as a problem in organization design based on two different criteria, i.e., (1) specialization, where humans and AI systems perform tasks that they are best at, and (2) multiple learning configurations, which consider the ways that humans and AI systems may "learn together" and use the most relevant knowledge for collaboration.

Some recent studies have shown the success of human–AI teamwork [31] with hybrid decision making, where the individual strengths of the humans and the AI systems allow the optimization of the joint decision outcomes. Such collaborative efforts, where the human–AI team outperforms the individual agents acting separately, are also called hybrid intelligence [32,33]. Examples of such effective human–AI collaboration include knowledge work [34], data annotation [35], medical diagnosis [36], mental health [37], and computationally informed mission planning [38]. Furthermore, the new developments in the theory of organizational decision-making [39] also suggest effective ways in which the decisions of organizational members can be combined with AI-based decisions for successful human-AI teaming and collaboration in the project management area. Finally, it should be noted that, according to Smolensky et al. [40], the recent developments in neurocompositional computing [41] will allow us to overcome the limitations of current computing paradigms and enable building AI systems that exhibit a high level of cognitive abilities, which are required for the realization of AI-powered project management applications.

2.4. Program Management in the U.S. Navy

This paper describes a practical framework for developing agile program management in the U.S. Navy. It should be noted that most of the published literature on the applications of advanced data analytics and AI focuses on project management rather than program management. However, as pointed out by many studies [42–46], there are significant differences between project and program management. Notably, Lycett et al. [42] noted that program management is not just a scaled-up version of project management and that the "one size fits all" approach to program management is inappropriate in the dynamic business environment. They also pointed out that while project management is inward-focused and task-oriented, program management is strategy-focused and represents a wider organizational view. In that context, program management links the gap between project delivery and the organization's strategic planning [43]. For example, program management in the information technology sector should continually change to uphold effective alignment with organizational strategies and react to the external environment as needed to preserve its relevance [44]. On the other hand, managing specific projects in a given program requires making decisions to align them with the program goals.

Pellegrinelli [45] also contended that it is important to distinguish project management from program management, including the related concepts, approaches, and techniques relevant to each discipline. Concerning the role of managers, Walenta [46] outlined some key differences between project managers and program managers by noting that (1) project managers are inward-oriented, while program managers are focused on the outside environment; (2) the competencies of successful project managers significantly differ from the competencies of successful program managers; and (3) project managers do not possess the required knowledge and skills for program management. Furthermore, de Groth [47] noted that project-oriented organizations use program management to cope with learning challenges across teams at different organizational levels. To integrate the above concepts, Thiry [48] proposed a unified model for learning performance program management that combines value management with project management.

3. Data-Driven Organizations

3.1. The Power of Data-Driven Decision-Making

There are several recent studies on the benefits of data-driven decision-making, defined as the process of using data to inform decision-making and validate courses of action [7–9]. Stobierski [10] outlined the advantages of data-driven decision-making, arguing that data analytics can improve project management outcomes. From a program management perspective, data-driven decision-making could take many forms. For example, a program office might use spending plans to estimate obligations and expenditure rates. These estimates might then be used to make fiscal decisions regarding where to spend money in future years and how to break down procurement versus research expenditures or develop new contracts for execution. The important notion is that the data can drive the decision-making process and positively impact organizational performance. Indeed, as access to data and the ability to process these data in a more parallel manner become more accessible, it will become even easier for organizations to adopt a data-driven decision framework.

Data collection and analysis are key to the US Navy's "*Get Better, Get Real*" strategy. Specifically, the collection of authoritative data drives confidence in the decisions that are being made to drive programmatic change. Not only do the data help to baseline where certain program constraints exist, but they also provide traceability with respect to how changes may impact the organization. Data also reduces the need for intuitive decision-making, eliminating the influence of personal bias. By leveraging authoritative data, a program office can fully commit to a particular strategy by having confidence that this approach will have specific impacts in a particular area.

3.2. Becoming a Data-Driven Organization

Organizations seeking to become more data-driven need to foster a data-driven culture [7–10]. This requires the adoption of a mindset that values the insights and use of authoritative data. Program managers at the Navy can curate this by developing a culture of "data awareness" by encouraging behaviors that seek to leverage data to drive performance change. Program managers should also seek to eliminate barriers to accessing authoritative data as much as possible. As program offices seek to make this transition from an intuitive to a data-driven culture, there are several steps that can be taken to ensure this happens in a manner that facilitates programmatic success. These steps include the following:

Establish an Authoritative Data Lake: Create a centralized database to store and manage all project-related data, ensuring easy access for program managers (PMs) and other stakeholders. While there is a need to identify authoritative data sources, the data oftentimes may not exist or do not exist in the form that is needed for appropriate analyses. In this case, program managers should seek ways to develop new data pipelines that would allow for the collection of new and meaningful data;

Develop Data Collection Standards: One potential pitfall for organizations hoping to adopt a data-driven mindset is the inconsistency in which data are collected and reported. To avoid this, program managers should seek to implement uniform data collection standards across different departments, programs, and projects, making it easier to compare and analyze data. Developing data dictionaries or metadata repositories is critical here. A data dictionary is defined as a centralized repository of information about data, such as its meaning, relationships to other data, origin, usage, and format. By posting this information in an easily accessible location and ensuring the dictionary is available to users across all levels of the organization, the program office can ensure that data are being used in a reliable and consistent fashion. This also ensures that conclusions drawn from the use of those data are consistent and explainable to users;

Invest in Data Management Tools: The adoption of a data-driven culture begins with the consistent use of data management tools. Program managers should equip themselves and their professionals with data management tools, including machine learning and statistical modeling techniques, to enable them to derive valuable insights from the collected data. In addition, organizations should seek out new and meaningful ways to visualize their data. Data visualization is as critical a part of the data analytic process as any other. End users simply cannot derive any meaningful interpretation or action from raw data. Visual aids that emphasize the power of the data, the influence and impact of the raw data in drawing specific conclusions, and that demonstrate trends and patterns in the data are all critical pieces for data adoption. Visualization tools such as Qlik, Tableau, and even Excel allow users to convert raw data of any kind and make them more interpretable for stakeholders at all levels;

Encourage a Data-Driven Culture: Finally, organizations should seek to promote a culture that emphasizes the importance of data-driven decision-making at all levels of the organization. Organizational leaders should try to avoid situations that encourage intuitive decision-making and rely more on decision-making processes that allow them to trace those decisions back to authoritative data. In this case, leading by example will also create an environment within a program office that encourages analytical thinking. The inculcation of this framework begins by encouraging those behaviors that are consistent with data-driven values. This includes providing ongoing training, creating incentives, and recognizing achievements in data-driven program management.

4. Methodology

The adoption of a data-driven culture can be a key enabler for program managers willing to transform their organizations. By gathering and properly labeling data for future programs, the U.S. Navy can experience numerous benefits, including the following:

1. Enhanced Decision Making: access to well-structured data will allow PMs to gain a deeper understanding of their programs, helping them to identify potential risks and opportunities for improvement;
2. Optimized Resource Allocation: data-driven insights can guide PMs in making more informed decisions about resource allocation, ensuring that scarce resources are deployed effectively;
3. Fostered Collaboration: the availability of relevant data can promote information sharing and collaboration between different departments and stakeholders, resulting in more efficient project management and better outcomes;
4. Improved Accountability: data transparency will improve accountability by enabling PMs to track progress more accurately, making it easier to identify and address inefficiencies.

4.1. Business Analytics Use Case

In March 2023, the Expeditionary Missions Program Office (PMS 408) and Naval Sea Systems Command (NAVSEA) initiated a use case through Advana Jupiter of the Department of the Navy's (DoN) enterprise data environment [49,50]. Through a partnership with Advana that includes access to data mining and machine learning engineers, product managers, full-stack developers, and data visualization experts, PMS 408 sought to create a shared understanding of organizational metrics through historical, current, and forward-looking algorithms. The goal of this effort was two-fold: (1) to foster a data-driven decision culture that allows program managers and analysts at all levels to inform decisions through authoritative data, and (2) to simplify and automate existing reporting metrics.

To accomplish these goals, a need for reducing qualitative or intuitive decision-making processes was recognized. This was carried out to increase confidence in programmatic planning by developing a data-driven framework for planning and execution. This begins first by identifying authoritative data sources that drive programmatic execution. Once identified, it was important to understand how these data facilitate or inhibit organizational performance. At this stage, it was critical to engage with organizational leadership to understand their goals and how these authoritative data can serve as a proxy for assessment toward those goals. As with any data-driven environment, it was also important to focus on those features that aligned most with the strategic vision of organizational leadership. This should be carried out a priori rather than using a data exploration approach. Such an approach was encouraged to prevent the Navy from responding to artifacts that might exist within the data. Consequently, those features that were the true drivers of organizational performance were identified. It should be noted, however, that given the breadth and scope of data pipelines, this could potentially lead to "false positives" and other data artifacts.

4.2. Advana Jupiter

With the above-discussed goals in mind, the Navy initiated the creation of a data analytic dashboard sitting on top of the Advana Jupiter infrastructure [49,50]. Advana Jupiter serves as the DoN enterprise data hub. Through a tiered "Wisdom of Crowds" approach, DON Information Data Stewards create disparate data hubs across a variety of data domains. The integration of these data hubs allows for the aggregation of the most authoritative and comprehensive view of enterprise data.

It should be noted that the Advana Jupiter provides several inherent advantages over local or distributed cloud architectures. For example, Jupiter allows for more flexible cloud computing. Specifically, Jupiter provides both dedicated and "on-demand" computing and storage capacity. In addition, Jupiter and its licensed applications allow for a more robust data pipeline for more efficient data ingestion, processing, and visualization. A more attractive feature of Advana is the ability to develop specific queries on new or existing data. Metadata are stored on Advana and can be accessed via data discovery tools, technical documentation, and a data catalog. Lastly, Jupiter provides perhaps the most modern toolset for data analytics in the acquisition enterprise. Tools such as Apache Spark allow for large-scale data processing that is agnostic to programming languages. For data analytics, developers have access to tools such as PyTorch and TensorFlow, which allow for the development and deployment of machine learning algorithms such as deep learning.

PMS 408 has initiated several efforts that leverage the tools within Advana Jupiter to assist in programmatic development. These efforts are designed to leverage the tools and algorithms within this environment to provide more quantitative metrics to describe overall programmatic health in areas including contract performance, requirement traceability, and portfolio visualizations. For example, the PMS 408 team and its developers have developed visualizations surrounding portfolio investments using the Qlik business intelligence (BI) and visualization platform. This tool can be used in areas such as data integration to assist in importing and integrating portfolio investment data from data sources such as Navy Enterprise Resource Planning (ERP) data. Navy ERP captures and manages financial data related to the Navy's budgeting, accounting, and financial transactions. This includes data related to budget allocation, expenditure tracking, payroll, and financial reporting.

Some of the key data sources being integrated into this specific use case include procurement data. Here, the system maintains data related to the procurement of goods and services, including purchase orders, vendor information, contract details, and procurement history. In addition, models based on asset management data were developed. In this case, Navy ERP can track and manage assets such as equipment, vehicles, and facilities. This includes data on asset maintenance, depreciation, and utilization.

Similarly, a focused approach to analyzing data surrounding reporting and analytics has been adopted. The ERP generates various reports and analytics based on the data it collects. These reports help Navy leadership make informed decisions about resource allocation, budget planning, and operational efficiency. Taken together, the historical data were used to build predictive models of future performance. For example, Navy ERP accumulates historical data that can be used for trend analysis, forecasting, and performance evaluation. Finally, historical data can provide valuable insights into the Navy's financial and operational performance.

4.3. The Qlik Platform

For this business use case, data from ERP and other government data on the Qlik platform were used. This integration allowed the development of data models within Qlik to organize our portfolio data. These models help to define relationships between different data tables, such as investments, asset classes, and performance metrics. This step is crucial for building meaningful visualizations. A second advantage of the Qlik tool is that it allows for ease-of-dashboard creation and visualization. Qlik's drag-and-drop interface created interactive dashboards that can be updated in near real time. In addition, users could customize these dashboards to filter and drill down into the data. Analysts and programmatic leadership can select specific investments, time frames, or asset classes to focus on specific aspects of the portfolio.

Visualizations only represent a small fraction of the capability developed through the Advana Jupiter business use case. Using additional tools allowed through their secure government cloud brokerage enabled the Navy to build models that track key performance indicators (KPIs) to provide additional insights into portfolio performance. Examples include calculating contract performance deviations, long product delivery delays, and other hindrances to programmatic performance. Making further use of the Advana pipeline allowed implementing alerts and notifications within Advana to automatically alert users when investments failed to meet predefined criteria or required attention.

Overall, the tools within the Advana pipeline are a catalyst for developing quantifiable models to better understand portfolio performance. This study discussed how it was possible to use these tools and the Advana platform in the Navy for analysis and visualization purposes. Such tools provide flexibility and interactivity, making them well-suited for portfolio managers, financial analysts, and resource sponsors who want to gain deeper insights into their investment portfolios and make informed decisions.

5. Agile Program Development in the U.S. Navy

Several studies examined various aspects of agile project management [51–54]. For example, Koch and Schermuly [53] suggest that agile project management practices can significantly impact organizational culture. Coram and Bohner [55,56] discussed the impact of agile methods on software project management, arguing that agile methodologies improve project delivery and faster adaptation to changing market requirements. Conforto et al. [57] explored the feasibility of adopting agile project management methodologies outside the software industry.

To ensure the development of the present framework is both impactful and delivered at a pace that is consistent with the demands of the Navy's GRGB program, this project focused on developing an agile approach to project management [57]. Historically, much of the program and project management efforts have been focused on iterative and/or incremental approaches toward delivery. More recently, an emerging debate has arisen comparing more traditional "heavyweight" methods with more agile and fluid "lightweight" methods [58]. Heavyweight methods for project management are those that view the development process as more linear, leading to over-reliance on processes and milestones.

Beck et al. [59] proposed the *Manifesto for Agile Software Development*, which emphasizes the ability to respond to changing market conditions, customer collaboration, and meeting functional software requirements. The document addressed 12 universal principles designed to deliver products to customers much more efficiently and to directly address the needs and wants of the customer. The above principles are illustrated below in the context of program management responsibilities and their use by the Navy to drive the business analytics use case within the framework of *Advana* (see Table 1).

Table 1. Principles of agile software (v. 2001) development (modified after Beck et al., 2001).

Software delivery	Deliver working software frequently, from a couple of weeks to a couple of months, with a preference for a shorter timescale. Too often, projects are conducted in a manner where there may be an initial envisioning session. Beyond that, developers may fail to interact with either thought leaders or end users. This was carried out to avoid this through continuous and transparent communication with all stakeholders.
Collaboration	Businesspeople and developers must work together daily throughout the project. The development team must work directly with end users to better understand their problems and how algorithms should be designed to address those root problems.

Table 1. *Cont.*

Motivation	Build projects around motivated individuals. Give them the environment and support they need, and trust them to complete the job. This is carried out to empower the development teams by giving them the opportunity to build innovation. The teams' creativity was perceived as a key ingredient to ultimate success.
Communication	Face-to-face conversation continues to be the most efficient and effective method of conveying information to and within a development team. While the demands of a distributed world were recognized, as much face-to-face collaboration as possible was encouraged to facilitate the sharing of ideas and more open innovation.
Demonstrations	Working software is the primary measure of progress. The goal is to share the success via live demonstrations with the stakeholders.
Development	Agile processes promote sustainable development. The sponsors, developers, and users should be able to maintain a constant pace indefinitely. An emboldened collaborator will continue to seek ways to improve processes.
Promotion	Continuous attention to technical excellence and good design enhances agility. Strong technical achievements, as often as possible, are promoted.
Simplification	Simplicity, the art of maximizing the amount of work not completed, is essential to the developed development approach. The teams should not be burdened with administrative work that inhibits their ability to deliver new and innovative product lines.
Teams	The best architectures, requirements, and designs emerge from self-organizing teams. However, while collaboration across the effort is optional, it occurs organically.
Adaptation	The team regularly reflects on how to become more effective, then tunes and adjusts its behavior accordingly. In-progress reviews, ad hoc scrum teams, and other means for self-reflection have been used as the key facilitators.

5.1. Applications of Data Analytics and Machine Learning

The previous section described how the Advana Jupiter platform was harnessed to develop a pipeline that ingests, processes, and applies quantifiable models to inform analysts and program managers. This was carried out using the adoption of data mining and machine learning approaches. More explicitly and in the context of the presented BI use case, it was postulated that data mining and machine learning could address specific challenges in program management within the context of the U.S. Navy by leveraging data-driven insights to improve decision-making, optimize resource allocation, enhance operational efficiency, and reduce risks.

For example, machine learning models can analyze historical program data to improve the accuracy of cost estimates for new projects. They can help with budget planning and allocation. Similarly, these models can conduct real-time data analysis to identify cost overruns or anomalies, allowing program managers to promptly take corrective action. Similarly, data mining and machine learning can assist in resource allocation decision-making. Machine learning algorithms can allocate resources more efficiently by considering project complexity, resource availability, and historical performance data. In addition, data mining can identify potential bottlenecks or resource constraints that may impact program timelines. Furthermore, machine learning can be used to analyze historical scheduling data to optimize project timelines and reduce delays. These tools can also be applied to help predict maintenance needs for Navy equipment, reducing downtime and ensuring operational readiness.

Finally, the above tools have been utilized to assist in decision support. Specifically, the applied data mining and machine learning models have helped support predictive insights and allow program managers to make informed decisions about resource allocation and risk mitigation. Similarly, data mining can be applied to simulate different program scenarios to evaluate their potential impacts on outcomes. By leveraging data mining and machine learning in program management, the U.S. Navy can enhance its ability to plan, execute, and monitor programs effectively, improving mission success, cost control, and overall operational efficiency. However, the extent to which these tools can influence the discussed aspects of planning and execution depends on the quality of the iterative feedback on model development and deployment provided by the users. Therefore, it is critical in instances such as the use case presented here and others like it that program managers are motivated and able to adopt a more flexible framework for model acceptance and deployment.

5.2. How the Agile Approach Impacts Program Management in the U.S. Navy

In this paper, it has been postulated that a comprehensive data pipeline inspired by agile software development principles represents a realization of the "*Get Real Get Better*" initiative. The specific instances of how agile principles can be used to emphasize iterative development, collaboration, adaptability, and customer centricity, which can be highly beneficial in the context of Navy program management, are discussed below.

It is all too common for Navy programs to face issues such as changing requirements and operational environments. An agile-inspired data pipeline can be designed to accommodate changes gracefully. They allow for quick adjustments and additions to data sources, transformations, and analytics as program requirements evolve. Similarly, Navy program managers are consistently challenged with high-risk decisions without the time necessary to comprehensively weigh all options. Agile practices enable the rapid development of data analytics and visualizations. Program managers can access up-to-date information and quickly make informed decisions.

Program offices are also required to have continuous stakeholder collaboration. Simply put, without effective collaboration, programs are not able to deliver on their promised capabilities. However, agile frameworks emphasize continuous collaboration between data teams and program managers. Frequent check-ins and feedback loops ensure that data solutions align with program objectives. Identifying and mitigating risks is a key program management aspect. Agile's iterative approach allows for the continuous monitoring of program data. This helps in the early detection of risk factors and adapting strategies accordingly.

By embracing agile-inspired principles in the development and management of data pipelines for program management, the U.S. Navy has enhanced its ability to address dynamic challenges, make data-driven decisions, and achieve successful outcomes in a rapidly evolving operational environment. This framework promotes a culture of adaptability and continuous improvement that is well suited to the Navy's mission requirements and consistent with the vision that has been outlined by the "*Get Better Get Real Framework*".

6. AI and Data Science in Agile Project Management

Many recently published studies have demonstrated the effective implementation of data analytics and AI in project management [4,5]. Other studies [18,19] have discussed the challenges of incorporating AI and data analytics into agile project management to improve software development outcomes. Gil et al. [2] reviewed the recent approaches to incorporating AI in project management to optimize project processes. Crawford et al. [20] present a survey of AI applications in software engineering, specifically focusing on project management. Most recently, Hoda et al. [60–62] introduced the concept of human-centered AI-assisted agile project management that augments software management processes and human decision-making. The above studies presented the benefits of integrating the principles of agile project management, AI, and data science into various project management applications. The current paper introduces the requirements for leveraging data analytics and AI to enhance program management in the U.S. Navy environment.

6.1. Artificial Intelligence and Machine Learning Applications

Over the past 10 years, there has been exponential growth in the use and adoption of artificial intelligence tools, including machine learning [63]. Generally speaking, machine learning is typically categorized into one of three different categories: supervised, unsupervised, or reinforcement. Each of these approaches varies in the way it is trained, the outputs it provides, and the application of its algorithms to various data types. In a very general sense, artificial intelligence and machine learning represent sophisticated forms of data analysis. Using algorithms that continuously learn from data, these approaches allow machines to recognize hidden patterns in data sets that are often too subtle for humans to identify and/or explain. In addition, through repeated exposure to disparate data sets (training), machines can then extrapolate those patterns to new data to predict future states.

6.2. A Case for Deep Learning

Recent advances in computing power and architecture have allowed deep learning algorithms to reach performance levels unmatched by other machine learning approaches. Deep learning has been a key enabler in several key technology areas, including driverless cars, image recognition, and human–machine interaction [12,64]. In its most basic form, deep learning allows a computer model to perform classification tasks directly from images, text, or sound. Deep learning models can achieve state-of-the-art accuracy, sometimes exceeding human-level performance [65].

6.3. Generative AI

Within the past five years, there has been a resurgence of interest in the area of generative artificial intelligence. Generative AI describes algorithms (such as ChatGPT) [66] that can be used to create new content. In this case, content describes new material created by the algorithm. This might include content such as audio files, programming code, images, contract language, or videos. Recent advances in the field of large language models (LLMs) have dynamically changed the way artificial intelligence and its applications are being viewed today. Generative AI opens a plethora of potential use cases within the program management space. The primary reasoning for this is that users need not be experts in AI and machine learning (ML) to apply these machine learning approaches. Rather, they need to be experts in their respective domains. Indeed, a new and growing field in machine learning is known as "prompt engineering" [67]. Prompt engineering is a new concept within AI and machine learning where the description of the task that should be accomplished by the AI is embedded within the input. Rather than the algorithm attempting to extract those features based on the training data, prompt engineering allows the user to embed features based on the questions asked of the algorithm.

6.4. ChatGPT: Example

To demonstrate the power and ease of generative AI, a simple query using ChatGPT has been implemented. ChatGPT is an AI chatbot developed by OpenAI. ChatGPT is built on top of large language models (LLMs) and has been optimized using both supervised and reinforcement learning techniques. The primary use of traditional chatbots is to model human behavior. However, ChatGPT and this newer generation of generative AI are much more versatile. These models have been applied in various use cases, including reading and writing code, generating art, and other complex tasks (see Table 2).

While generative AI appears to be the most promising application of AI for program management, caution must be exercised as well. On the one hand, using and applying LLMs has seen exponential growth in the past half decade [68,69]. However, surrounding their use, there has been extensive hype, misunderstanding, and misrepresentation regarding their capabilities. For example, Bender et al. [4] pointed out that LLMs have been built on foundational work from Natural Language Processing (NLP) [70]. However, these models do not code for Natural Language Understanding (NLU).

Another issue with generative AI revolves around the poorly understood problem of latent concept learning. Specifically, these models are learning relationships within the training data that are so abstract that they are unlikely to be perceived by a human audience. It is believed that the issues revolving around concepts such as trust and fairness [71] will become more pronounced as these models are deployed more frequently going forward.

Table 2. Example of a ChatGPT query.

>>Provide Some Examples in Which Generative AI Can Be Used to Assist Program Managers.<<
ChatGPT Reply:
Generative AI, such as GPT-3, can be used to assist in program management in a variety of ways.
Here are some examples:
1. Requirement Gathering:
Program managers can use generative AI to help with requirement gathering. They can provide the AI with the project's scope and goals, and the AI can generate a list of requirements that need to be fulfilled to achieve those goals;
2. Risk Management:
AI can help in identifying potential risks in the program by analyzing data from past projects and identifying patterns that indicate potential problems. This can help the program manager take proactive measures to mitigate those risks;
3. Resource Allocation:
Program managers can use AI to assist in the allocation of resources such as personnel, equipment, and funding. AI can help in predicting future resource needs based on past performance data and other relevant information;
4. Schedule Optimization:
Generative AI can assist program managers in optimizing schedules by analyzing historical data to identify the best way to sequence tasks and allocate resources;
5. Decision-Making:
AI can assist program managers in making better decisions by providing them with data-driven insights and recommendations. This can help the program manager make informed decisions that are more likely to lead to successful outcomes;
Overall, generative AI can help program managers streamline their processes, improve decision-making, and increase the chances of program success. However, it is important to note that AI should be used as a tool to assist program managers rather than a replacement for human decision-making.
Department of Defense (DoD) program management involves complex and high-stakes projects, and machine learning can be used to support decision-making, risk management, resource allocation, and other aspects of program management. Here are some examples of machine learning techniques that can be used in DoD program management:
1. Predictive analytics:
Predictive analytics can be used to forecast future outcomes and identify trends based on historical data. This can be useful for predicting project completion dates, identifying potential cost overruns, and estimating resource needs;
2. Natural language processing (NLP):
NLP can be used to analyze unstructured data, such as emails, chat messages, and reports. This can help program managers identify potential risks and issues that may not be captured in structured data;

Table 2. *Cont.*

3. Computer vision:
Computer vision can be used for surveillance, image analysis, and other tasks that require processing large amounts of visual data. This can be particularly useful in the defense industry, where there is a need for situational awareness and real-time decision-making;
4. Reinforcement learning:
Reinforcement learning can be used to optimize resource allocation and scheduling. This approach involves using algorithms to learn from experience and improve over time based on feedback;
5. Deep learning:
Deep learning can be used for a variety of tasks, including image and speech recognition, natural language processing, and predictive analytics. This approach involves using neural networks to learn from data and make predictions or decisions based on that learning.
In addition to these techniques, there are also specialized machine learning algorithms and frameworks that have been developed specifically for defense applications, such as the Defense Advanced Research Projects Agency's (DARPA) Explainable Artificial Intelligence (XAI) program.
Ultimately, the choice of machine learning techniques will depend on the specific needs of the DoD program and the available data.

6.5. Implications of Generative AIs for Agile Program Management Development

Generative AI holds considerable promise for agile program management by potentially enhancing creativity, automating certain tasks, and introducing rapid prototyping capabilities. However, it also brings challenges related to quality assurance, complexity, the need for developing new skills among program managers, and many ethical considerations. As with any disruptive technology, the successful integration of generative AI into agile program management practices in the U.S. Navy will require thoughtful planning, continuous learning, and adaptability.

Generally, generative AI systems can create new content such as text, design concepts, and software code [70,71]. The applications of generative AI for developing agile program management have many theoretical and practical implications. The key theoretical considerations include complexity and uncertainty, continuous learning and adaptation, and redefining value. Generative AI can also introduce a new level of complexity to agile management programs due to the unpredictable and innovative nature of the generated content. This could affect program risk assessment and the required approaches when applying agile methodologies.

Furthermore, generative AI can constantly change its outputs based on knowledge feedback loops when applying the agile principle of iterative development. However, this also raises questions about achieving the successful completion of specific program objectives and related tasks. Finally, as agile management's traditional notion of "value" evolves, determining the desired value of AI-generated versus human-designed system solutions or components becomes critical to fulfilling the program management objectives.

The practical implications of agile program management in the U.S. Navy are significant and include (1) enhanced creativity, (2) automated task completion, (3) feedback integration, (4) rapid prototyping, (5) skill requirements, (6) resource allocation, (7) quality assurance and testing, and (8) ethical and governance concerns. These implications are described in Table 3 below.

Table 3. Practical implications of generative AI for agile program management.

Enhanced creativity	Program managers can leverage generative models to brainstorm and visualize multiple scenarios, designs, or solutions, which can then be refined based on specific stakeholder feedback.
Automated task completion	Generative AI can automate the generation of code, reports, or other outputs for specific repetitive or well-defined tasks, freeing program managers to focus on more complex or creative aspects.
Feedback integration	Generative models can be retrained or fine-tuned for program management purposes based on feedback, aligning with the agile practice of regular reflection and adaptation.
Rapid prototyping	The use of generative AI can quickly produce multiple prototypes or solutions to a variety of program management tasks, adhering to the agile principle of early and continuous delivery.
Skill requirements	The introduction of generative AI in agile program management will require new skill sets for program managers, including data analytics and AI training, which should be considered during the planning and execution phases of the program.
Resource allocation	The use of generative AI will require additional resources, such as high-performance computing and specialized AI-powered software tools, which should be accounted for during program development, planning, and execution.
Quality assurance and testing	The use of generative AI will require new testing and quality assurance procedures to ensure the accuracy and reliability of program management outputs.
Ethical and governance concerns	The use of generative AI in agile program management should be guided by ethical and governance considerations to ensure the responsible and ethical use of these technologies.

7. Conclusions

Focusing on the tenets within the "*Get Real Get Better*" framework, this paper has postulated that program managers at the U.S. Navy should leverage data-driven decision-making to build quantitative program assessment criteria [72,73]. An approach to achieving this has been demonstrated using a use case study implemented through the partnership with Advana to create a machine learning pipeline for data analytics that program offices can harness. Addressing advanced and intelligent data analytics capabilities in the U.S. Navy's program management is crucial to ensuring the sustained success of national security safeguarding [74,75]. By prioritizing data collection, labeling, and analysis, unlocking advanced data analytics and artificial intelligence's full potential becomes feasible, leading to better decision-making and improved program outcomes. The time has come for all stakeholders, ranging from program managers to top leadership, to collaborate in cultivating a culture of organizational excellence that is data-driven and empowered by artificial intelligence, thus fueling innovation, efficiency, and collaboration as the U.S. Navy progresses toward being a more adaptable and resilient organization.

Author Contributions: Conceptualization, J.H., P.B.W. and O.B.; validation, J.H., P.B.W., O.B. and W.K.; writing—original draft preparation, J.H., P.B.W., O.B. and W.K.; writing—review and editing, W.K. and P.B.W.; supervision, P.B.W.; project administration, J.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: Author Olivia Berardi is employed by the company Cydecor, Inc. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

1. Niederman, F. Project management: Openings for disruption from AI and advanced analytics. *Inf. Technol. People* **2021**, *34*, 1570–1599. [CrossRef]
2. Gil, J.; Martinez Torres, J.; González-Crespo, R. The Application of Artificial Intelligence in Project Management Research: A review. *Int. J. Interact. Multimed. Artif. Intell.* **2021**, *6*, 54–66. [CrossRef]
3. Song, L.; Minku, L.L. Artificial Intelligence in Software Project Management. In *Optimising the Software Development Process with Artificial Intelligence*; Springer Nature: Singapore, 2023; pp. 19–65.
4. Bender, E.M.; Gebru, T.; McMillan-Major, A.; Shmitchell, S. On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? In Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, Virtual, 3–10 March 2021; pp. 610–623.
5. Ong, S.; Uddin, S. Data Science and Artificial Intelligence in Project Management: The Past, Present and Future. *J. Mod. Proj. Manag.* **2020**, *7*, 26–33.
6. Santos, P.D.O.; de Carvalho, M.M. Exploring the challenges and benefits for scaling agile project management to large projects: A review. *Requir. Eng.* **2022**, *27*, 117–134. [CrossRef]
7. Schrettenbrunnner, M.B. Artificial-intelligence-driven management. *IEEE Eng. Manag. Rev.* **2020**, *48*, 15–19. [CrossRef]
8. Canals, J.; Heukamp, F. *The Future of Management in an AI World*; Palgrave Macmillan: London, UK, 2020.
9. Cabrero-Daniel, B. AI for Agile development: A Meta-Analysis. *arXiv* **2023**, arXiv:2305.08093.
10. Auth, G.; Jöhnk, J.; Wiecha, D.A. A Conceptual Framework for Applying Artificial Intelligence in Project Management. In Proceedings of the 2021 IEEE 23rd Conference on Business Informatics (CBI), Bolzano, Italy, 1–3 September 2021; Volume 1, pp. 161–170.
11. Hofmann, P.; Jöhnk, J.; Protschky, D.; Urbach, N. Developing Purposeful AI Use Cases-A Structured Method and Its Application in Project Management. In *Wirtschaftsinformatik (Zentrale Tracks)*; FIM Research Center: Fraunhofer, Stuttgart, 2020; pp. 33–49. Available online: https://www.fim-rc.de/Paperbibliothek/Veroeffentlicht/1025/wi-1025.pdf (accessed on 17 July 2023).
12. Crawford, T.; Duong, S.; Fueston, R.; Lawani, A.; Owoade, S.; Uzoka, A.; Parizi, R.M.; Yazdinejad, A. AI in Software Engineering: A Survey on Project Management Applications. *arXiv* **2023**, arXiv:2307.15224. Available online: https://arxiv.org/pdf/2307.15224.pdf (accessed on 17 July 2023).
13. Wahl, B.; Cossy-Gantner, A.; Germann, S.; Schwalbe, N.R. Artificial intelligence (AI) and global health: How can AI contribute to health in resource-poor settings? *BMJ Glob. Health* **2018**, *3*, e00798. [CrossRef]
14. Lei, H.; Lai, W.; Feaster, W.; Chang, A.C. Artificial gence and agile project management. In *Intelligence-Based Cardiology and Cardiac Surgery*; Academic Press: Cambridge, MA, USA, 2024; pp. 401–405.
15. Odeh, M. The Role of Artificial Intelligence in Project Management. *IEEE Eng. Manag. Rev.* **2023**. [CrossRef]
16. Bento, S.; Pereira, L.; Gonçalves, R.; Dias, Á.; Costa, R.L.D. Artificial intelligence in project management: Systematic literature review. *Int. J. Technol. Intell. Plan.* **2022**, *13*, 143–163. [CrossRef]
17. Dam, H.K.; Tran, T.; Grundy, J.; Ghose, A.; Kamei, Y. Towards effective AI-powered agile project management. In Proceedings of the 2019 IEEE/ACM 41st International Conference On Software Engineering: New Ideas And Emerging Results (ICSE-NIER), Montreal, QC, Canada, 25–31 May 2019; pp. 41–44.
18. Taboada, I.; Daneshpajouh, A.; Toledo, N.; de Vass, T. Artificial Intelligence Enabled Project Management: A Systematic Literature Review. *Appl. Sci.* **2023**, *13*, 5014. [CrossRef]
19. Teslia, I.; Yehorchenkova, N.; Khlevna, I.; Yehorchenkov, O.; Kataieva, Y.; Klevanna, G. Development of reflex technology of action identification in project planning systems. In Proceedings of the 2022 International Conference on Smart Information Systems and Technologies (SIST), Nur-Sultan, Kazakhstan, 28–30 April 2022; pp. 1–6.
20. Bahroun, Z.; Tanash, M.; As'ad, R.; Alnajar, M. Artificial Intelligence Applications in Project Scheduling: A Systematic Review, Bibliometric Analysis, and Prospects for Future Research. *Manag. Syst. Prod. Eng.* **2023**, *31*, 144–161. [CrossRef]
21. Son, P.V.H.; Khoi, L.N.Q. Utilizing Artificial Intelligence to Solving Time–Cost–Quality Trade-Off Problem. *Sci. Rep.* **2022**, *12*, 20112. [CrossRef] [PubMed]
22. Morozov, V.; Kalnichenko, O.; Proskurin, M.; Mezentseva, O. Investigation of Forecasting Methods of the State of Complex IT-Projects with the Use of Deep Learning Neural Networks. *Adv. Intell. Syst. Comput.* **2020**, *1020*, 261–280.
23. Choetkiertikul, M.; Dam, H.K.; Tran, T.; Ghose, A. Predicting Delays in Software Projects Using Networked Classification. In Proceedings of the 2015 30th IEEE/ACM International Conference on Automated Software Engineering, Lincoln, NE, USA, 9–13 November 2015; pp. 353–364.
24. El Khatib, M.; Al Falasi, A. Effects of Artificial Intelligence on Decision Making in Project Management. *Am. J. Ind. Bus. Manag.* **2021**, *11*, 251–260. [CrossRef]

25. Münch, T. AI, Agile, and Organizations. In *System Architecture Design and Platform Development Strategies*; Springer: Cham, Switzerland, 2022; pp. 155–183.
26. Hassani, R.; El Bouzekri El Idriss, Y. Proposal of a Framework and Integration of Artificial Intelligence to Succeed IT Project Planning. *Int. J. Adv. Trends Comput. Sci. Eng.* **2019**, *8*, 3396–3404. [CrossRef]
27. Abedin, B.; Meske, C.; Junglas, I.; Rabhi, F.; Motahari-Nezhad, H.R. Designing and managing human-AI interactions. *Inf. Syst. Front.* **2022**, *24*, 691–697. [CrossRef]
28. Shang, G.; Low, S.P.; Lim, X.Y.V. Prospects, drivers of and barriers to artificial intelligence adoption in project management. *Built Environ. Proj. Asset Manag.* **2023**, *13*, 629–645. [CrossRef]
29. Fridgeirsson, T.V.; Ingason, H.T.; Jonasson, H.I.; Jonsdottir, H. An authoritative study on the near future effect of artificial intelligence on project management knowledge areas. *Sustainability* **2021**, *13*, 2345. [CrossRef]
30. Puranam, P. Human–AI collaborative decision-making as an organization design problem. *J. Organ. Des.* **2021**, *10*, 75–80.
31. National Academies of Sciences, Engineering, and Medicine. *Human-AI Teaming: State-of-the-Art and Research Needs*; The National Academies Press: Washington, DC, USA, 2022. [CrossRef]
32. Dellermann, D.; Ebel, P.; Söllner, M.; Leimeister, J.M. Hybrid intelligence. *Bus. Inf. Syst. Eng.* **2019**, *61*, 637–643. [CrossRef]
33. Akata, Z.; Balliet, D.; De Rijke, M.; Dignum, F.; Dignum, V.; Eiben, G.; Fokkens, A.; Grossi, D.; Hindriks, K.; Hoos, H.; et al. A research agenda for hybrid intelligence: Augmenting human intellect with collaborative, adaptive, responsible, and explainable artificial intelligence. *Computer* **2020**, *53*, 18–28. [CrossRef]
34. Sowa, K.; Przegalinska, A.; Ciechanowski, L. Cobots in knowledge work: Human–AI collaboration in managerial professions. *J. Bus. Res.* **2021**, *125*, 135–142. [CrossRef]
35. Zhang, H.; He, Y.; Wu, X.; Huang, P.; Qin, W.; Wang, F.; Ye, J.; Huang, X.; Luo, Y.; Chan, H.; et al. PathNarratives: Data annotation for pathological human-AI collaborative diagnosis. *Front. Med.* **2023**, *9*, 1070072. [CrossRef]
36. Reverberi, C.; Rigon, T.; Solari, A.; Hassan, C.; Cherubini, P.; Cherubini, A. Experimental evidence of effective human–AI collaboration in medical decision-making. *Sci. Rep.* **2022**, *12*, 14952. [CrossRef] [PubMed]
37. Creed, T.A.; Salama, L.; Slevin, R.; Tanana, M.; Imel, Z.; Narayanan, S.; Atkins, D.C. Enhancing the quality of cognitive behavioral therapy in community mental health through artificial intelligence generated fidelity feedback (Project AFFECT): A study protocol. *BMC Health Serv. Res.* **2022**, *22*, 1177. [CrossRef]
38. Kase, S.E.; Hung, C.P.; Krayzman, T.; Hare, J.Z.; Rinderspacher, B.C.; Su, S.M. The future of collaborative human-artificial intelligence decision-making for mission planning. *Front. Psychol.* **2022**, *13*, 850628. [CrossRef]
39. Shrestha, Y.R.; Ben-Menahem, S.M.; Von Krogh, G. Organizational decision-making structures in the age of artificial intelligence. *Calif. Manag. Rev.* **2019**, *61*, 66–83. [CrossRef]
40. Smolensky, P.; McCoy, R.; Fernandez, R.; Goldrick, M.; Gao, J. Neurocompositional computing: From the Central Paradox of Cognition to a new generation of AI systems. *AI Mag.* **2022**, *43*, 308–322. [CrossRef]
41. Zentner, M.; Stirm, C.; Gesing, S.; Quick, R.; Stubbs, J. The Impact of AI Computing Paradigms on Science Gateways and National Compute Resources. *PEARC23* **2023**. Available online: https://par.nsf.gov/biblio/10450536 (accessed on 21 August 2023).
42. Lycett, M.; Rassau, A.; Danson, J. Programme management: A critical review. *Int. J. Proj. Manag.* **2004**, *22*, 289–299. [CrossRef]
43. Gaddie, S. Enterprise programme management: Connecting strategic planning to project delivery. *J. Facil. Manag.* **2003**, *2*, 177–191. [CrossRef]
44. Jiang, J.J.; Klein, G.; Fernandez, W.D. From project management to program management: An invitation to investigate programs where IT plays a significant role. *J. Assoc. Inf. Syst.* **2018**, *19*, 1. [CrossRef]
45. Pellegrinelli, S. What's in a name: Project or programme? *Int. J. Proj. Manag.* **2011**, *29*, 232–240. [CrossRef]
46. Walenta, T. Projects & programs are two different animals, don't underestimate the gap. *Procedia Soc. Behav. Sci.* **2016**, *226*, 365–371.
47. de Groot, B.; Leendertse, W.; Arts, J. Learning across teams in project-oriented organisations: The role of programme management. *Learn. Organ.* **2022**, *29*, 6–20. [CrossRef]
48. Thiry, M. Combining value and project management into an effective programme management model. *Int. J. Proj. Manag.* **2002**, *20*, 221–227. [CrossRef]
49. Rorie, J.; Duclos, J.; Lee, D.; Michlin, B.; Sabater, A.; Williams, G.R. The DARTEBoard: Visualization of an Improved and Expanded DARTE. 2023. Available online: https://apps.dtic.mil/sti/trecms/pdf/AD1202414.pdf (accessed on 3 August 2023).
50. Whitlock, C.; Strickland, F. Leading the Technology. In *Winning the National Security AI Competition: A Practical Guide for Government and Industry Leaders*; Apress: Berkeley, CA, USA, 2022; pp. 195–225.
51. Pellegrinelli, S.; Murray-Webster, R.; Turner, N. Facilitating organizational ambidexterity through the complementary use of projects and programs. *Int. J. Proj. Manag.* **2015**, *33*, 153–164. [CrossRef]
52. Singh, H. *Project Management Analytics: A Data-Driven Approach to Making Rational and Effective Project Decisions*; FT Press: Upper Saddle River, NJ, USA, 2015.
53. Vanhoucke, M. The Data-Driven Project Manager. In *The Illusion of Control: Project Data, Computer Algorithms and Human Intuition for Project Management and Control*; Springer Nature: Berlin/Heidelberg, Germany, 2023; pp. 29–48.
54. Mahmood, A.; Al Marzooqi, A.; El Khatib, M.; AlAmeemi, H. How Artificial Intelligence can Leverage Project Management Information System (PMIS) and Data Driven Decision Making in Project Management. *Int. J. Bus. Anal. Secur. (IJBAS)* **2023**, *3*, 184–195. [CrossRef]

55. Koch, J.; Schermuly, C.C. Who is attracted and why? How agile project management influences employee's attraction and commitment. *Int. J. Manag. Proj. Bus.* **2020**, *14*, 699–720. [CrossRef]
56. Aponte, M. Modernization of Acquisition Planning and Communication. Doctoral Dissertation, Naval Postgraduate School, Monterey, CA, USA, 2021.
57. Joseph, B.B.; Pham, T.; Hastings, C. Topological Data Analysis in Conjunction with Traditional Machine Learning Techniques to Predict Future MDAP PM Ratings. Acquisition Research Program. 2021. Available online: https://dair.nps.edu/bitstream/123456789/4367/1/SYM-AM-21-060.pdf (accessed on 27 July 2023).
58. Coram, M.; Bohner, S. The impact of agile methods on software project management. In Proceedings of the 12th IEEE International Conference and Workshops on the Engineering of Computer-Based Systems (ECBS'05), Greenbelt, MD, USA, 4–7 April 2005; pp. 363–370.
59. Conforto, E.C.; Salum, F.; Amaral, D.C.; Da Silva, S.L.; De Almeida, L.F.M. Can agile project management be adopted by industries other than software development? *Proj. Manag. J.* **2014**, *45*, 21–34. [CrossRef]
60. Khan, A.I.; Qureshi, M.; Khan, U.A. A Comprehensive Study of Commonly Practiced Heavy & Light Weight Software Methodologies. *arXiv* **2012**, arXiv:1202.2514.
61. Beck, K.; Beedle, M.; Van Bennekum, A.; Cockburn, A.; Cunningham, W.; Fowler, M.; Grenning, J.; Highsmith, J.; Hunt, A.; Jeffries, R.; et al. Manifesto for agile software development. 2001. Available online: https://ai-learn.it/wp-content/uploads/2019/03/03_ManifestoofAgileSoftwareDevelopment-1.pdf (accessed on 30 July 2023).
62. Uysal, M.P. Machine learning and data science project management from an agile perspective: Methods and challenges. In *Contemporary Challenges for Agile Project Management*; IGI Global: Hershey, PA, USA, 2022; pp. 73–88.
63. Hoda, R.; Dam, H.; Tantithamthavorn, C.; Thongtanunam, P.; Storey, M.A. Augmented Agile: Human-Centered AI-Assisted Software Management. *IEEE Softw.* **2023**, *40*, 106–109. [CrossRef]
64. Jordan, M.I.; Mitchell, T.M. Machine learning: Trends, perspectives, and prospects. *Science* **2015**, *349*, 255–260. [CrossRef] [PubMed]
65. Xu, M.; Yoon, S.; Fuentes, A.; Park, D.S. A comprehensive survey of image augmentation techniques for deep learning. *Pattern Recognit.* **2023**, *137*, 109347. [CrossRef]
66. LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. *Nature* **2015**, *521*, 436–444. [CrossRef]
67. Deng, L.; Yu, D. Deep learning: Methods and applications. *Found. Trends®Signal Process.* **2014**, *7*, 197–387. [CrossRef]
68. George, A.S.; George, A.H. A review of ChatGPT AI's impact on several business sectors. *Partn. Univers. Int. Innov. J.* **2023**, *1*, 9–23.
69. Liu, V.; Chilton, L.B. Design guidelines for prompt engineering text-to-image generative models. In Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems, New Orleans, LA, USA, 29 April–5 May 2022; pp. 1–23.
70. Bianchi, F.; Hovy, D. On the gap between adoption and understanding in NLP. In Proceedings of the Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, Online, 1–6 August 2021; pp. 3895–3901.
71. Glikson, E.; Woolley, A.W. Human trust in artificial intelligence: Review of empirical research. *Acad. Manag. Ann.* **2020**, *14*, 627–660. [CrossRef]
72. Lewis, L.; Vavrichek, D. Center for Naval Analyses. In *An AI Framework for the Department of the Navy*; Center for Naval Analysis: Arlington, VA, USA, 2019; p. 29.
73. Chief of Naval Operations, A Design for Maintaining Maritime Superiority—Version 2.0, December 2018. Available online: https://www.navy.mil/navydata/people/cno/Richardson/Resource/Design_2.0.pdf (accessed on 29 July 2023).
74. Department of Defense. *Summary of the Department of Defense Artificial Intelligence Strategy*; Department of Defense: Arlington, VA, USA, 2019.
75. Hull, A.D.; Liew, J.K.S.; Palaoro, K.T.; Grzegorzewski, M.; Klipstein, M.; Breuer, P.; Spencer, M. Why the United States Must Win the Artificial Intelligence (AI) Race. *Cyber Def. Rev.* **2022**, *7*, 143–158.