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Predicting Obsolescence Patterns in DMSMS for Critical Systems

December 2025

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ABSTRACT

Diminishing Manufacturing Sources and Material Shortages (DMSMS) continue to challenge the sustainment of defense-critical systems. This study investigates predictive methods for identifying obsolescence patterns in radar and communications components using historical attrition data and life cycle phase indicators. Drawing on 1,821 observations from 2009 to 2019, the research applies regression-based modeling to forecast component availability and risk exposure. Key drivers of obsolescence include vendor consolidation, technology refresh cycles, and supply chain instability. The model supports early detection of obsolescence threats and informs proactive sustainment planning. By integrating obsolescence intelligence into acquisition and logistics workflows, the framework offers a practical tool for improving readiness and reducing life cycle costs. While the model demonstrates utility across select platforms, further refinement is needed to enhance scalability and precision across broader portfolios. This work contributes to ongoing efforts to operationalize obsolescence forecasting and strengthen long-term sustainment strategies.

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LIST OF ACRONYMS AND ABBREVIATIONS

AMC	Acquisition Method Code
DMSMS	Diminishing Manufacturing Sources And Material Shortages
IMEC	Item Mission Essentiality Code
LBY	Last Buy Year
LCI	Life Cycle Index
MSD	Material Supply Date
NAVSUP	Navy Supply
NIIN	National Item Identification Number

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I. INTRODUCTION

Obsolescence has become a central threat to the readiness and affordability of mission-critical systems. As legacy platforms age and supply chains reduce, the Department of Defense faces increasing challenges in sustaining systems whose components are increasingly unavailable, unsupported, or obsolete. The reliability of these systems depends on the continued availability of thousands of interdependent parts, yet the trust placed in them is increasingly strained by vendor reduction, technology refresh cycles, and diminishing manufacturing sources. This thesis is motivated by the urgent need to forecast and mitigate obsolescence risk across defense-critical systems. Drawing on a curated dataset of 1,821 component-level observations spanning the years 2009 to 2019, the study seeks to build a predictive framework that can inform sustainment planning and reduce unplanned downtime.

The problem of Diminishing Manufacturing Sources and Material Shortages (DMSMS) jeopardizes mission capability by restricting access to essential components. Historically, defense agencies have taken reactive approaches, addressing obsolescence only after shortages impact readiness. This reactive posture leads to higher costs, emergency procurement, and increased supply chain vulnerabilities. Current sustainment models lack predictive capabilities, forcing logistics teams to react rather than plan. Without a structured, data-informed approach, program offices risk losing operational capability and incurring significant life cycle costs.

This thesis asks: What factors drive obsolescence within DMSMS-affected systems, and how can historical procurement data be leveraged to build predictive models for obsolescence forecasting? More specifically, the research investigates how regression analysis can reveal obsolescence patterns in SPY-6 radar and Navy Multiband Terminal (NMT) components, and how procurement trends influence component availability. By identifying correlation patterns within National Item Identification Numbers (NIINs), the study proposes proactive mitigation strategies tailored to military supply chain sustainability.

The data for this research was generously provided by the Naval Supply Systems Command (NAVSUP), whose sponsorship made this study possible. NAVSUP's datasets include detailed procurement records, vendor status, acquisition method codes, life cycle integration categories, and Material Supply Dates. Their support enabled access to critical information on obsolete parts and procurement trends, ensuring that the analysis was grounded in authoritative and operationally relevant data.

The findings of this study demonstrate the value of predictive analytics in identifying obsolescence risk. Using Ordinary Least Squares (OLS) regression, the analysis revealed statistically significant predictors of component attrition. For example, items in the Valves and Regulators category were less likely to become obsolete, while Hydraulic and Pneumatic Hardware and Mechanical Tools and Accessories showed a higher probability of attrition. Acquisition and life cycle variables also proved significant: items procured through full and open competition (AMC 1) or designated as mission-essential (IMEC 4) were less likely to go obsolete, while items restricted to authorized government sources (AMC 5) were more vulnerable. Components tied to early life-cycle integration (LCI 1) demonstrated greater longevity, reinforcing the importance of planning for obsolescence at the beginning of a system's life.

The regression results further showed that items with Material Supply Dates from 2019 to 2023 were significantly less likely to become obsolete, reflecting recent improvements in supply chain visibility and modernization efforts. These findings underscore the importance of integrating structured data into sustainment planning. By tracking procurement trends and life cycle variables, program offices can anticipate risk rather than react to failure. The statistical significance of these results supports the scalability of the model across broader portfolios, offering actionable insights for acquisition planners and sustainment commands.

This thesis contributes to ongoing efforts to institutionalize obsolescence forecasting as a core element of long-term sustainment strategy. By leveraging historical procurement data and regression-based modeling, it provides a transparent and adaptable framework for forecasting component survivability. The results highlight both the risks of limited vendor options and the benefits of competitive sourcing and proactive life cycle integration. Ultimately, this work demonstrates that predictive analytics can help preserve mission readiness, reduce life cycle costs, and extend the viability of aging platforms.

II. BACKGROUND AND LITERATURE REVIEW

The sustainment of critical defense systems depends on the continued availability of essential components. However, modern supply chains face increasing pressure from Diminishing Manufacturing Sources and Material Shortages (DMSMS). The Department of Defense (DoD) defines DMSMS management as "a multidisciplinary process to identify risks resulting from obsolescence, loss of manufacturing sources, or material shortages; to assess the potential for negative impacts on schedule or readiness; to analyze potential mitigations; and then to implement the most cost-effective resolution" (Mandelbaum & Patterson, 2017). These losses in manufacturing sources and material shortages poses significant problems for the United States Navy. challenge threatens the longevity of vital military assets and platforms. As technology evolves, older systems and their components become obsolete, leaving defense agencies struggling to maintain readiness without reliable replacements. Mandelbaum, Patterson, and Brown note that this issue has persisted for over 25 years, with professional discourse dating back to 1976 (Institute for Defense Analyses, 2017). Eric Grothues, DMSMS lead for the Department of the Navy, emphasized that "DMSMS has impacted virtually every weapons system throughout DoD" (Institute for Defense Analyses, 2017).

This thesis examines DMSMS within the Naval Supply System, applying regression analysis to explore predictive models that identify trends related to obsolescence. The study analyzes key variables including Inventory Categories, Item Mission Essentiality Codes, Acquisition Method Codes, Last Buy Years, Life Cycle Integration, and Material Supply Dates. Through this analysis, the research aims to uncover patterns that contribute to supply challenges and enhance forecasting for future procurement decisions.

A. INTRODUCTION TO NAVSUP

The Naval Supply Systems Command (NAVSUP) serves as the primary logistics organization of the United States Navy. It is responsible for global supply chain management, operational logistics, contracting support, and sustainment solutions. NAVSUP ensures warfighters receive timely access to essential materials, spare parts, equipment, and procurement resources. Operating under the Department of the Navy (DON), NAVSUP plays a central role in defense acquisition, inventory management, and supplier coordination.

Headquartered in Mechanicsburg, Pennsylvania, NAVSUP oversees logistics strategy execution, procurement policy development, sustainment planning, and supply chain integration for Navy and Marine Corps operations. Mechanicsburg functions as the central hub for contracting decisions, inventory oversight, and engagement with defense industry partners. NAVSUP also maintains regional commands and subordinate activities worldwide, including Fleet Logistics Centers (FLCs) in Norfolk, San Diego, Yokosuka, and Bahrain. These centers support localized logistics coordination, supplier negotiations, and fleet readiness assessments.

Meetings with NAVSUP representatives Adrienne DeFrank and Chris Espenshade provided procurement datasets that form the foundation of this study's analysis. Through its Industrial Base Readiness Working Group (IDB WG) and direct engagement with procurement specialists, NAVSUP develops risk mitigation frameworks, obsolescence tracking methods, and strategic contracting initiatives to strengthen supply chain resilience.

B. DEFINING DMSMS AND ITS IMPACT

DMSMS describes the reduction or disappearance of manufacturers, suppliers, or critical raw materials, making it difficult to procure and sustain essential parts. This issue particularly affects industries like defense and electronics, where evolving technology and market shifts can render components obsolete. The Defense Acquisition University identifies eight military-specific factors that contribute to DMSMS, including shifting commercial priorities, inconsistent demand signaling, regulatory restrictions, and supplier consolidation. These factors increase reliance on fewer vendors and create single points of failure.

C. HISTORICAL CASES OF DMSMS CHALLENGES

Historical cases illustrate the disruptive impact of DMSMS. Legacy aircraft such as the F-16 rely on outdated radar and flight control systems that are increasingly difficult to replace. The U.S. Navy has faced challenges sourcing electronic components for submarine sonar systems due to discontinued circuit boards. Aging missile guidance modules often require reverse engineering due to obsolete semiconductor technologies. The Navy Multiband Terminal (NMT) program faces persistent challenges from DMSMS, particularly in its Communications and Antenna Groups. The SPY-6 radar system also exemplifies modern sustainment challenges, with its reliance on Gallium Nitride (GaN) technology introducing risks due to evolving manufacturing standards.

NAVSUP data related to SPY-6 sustainment highlights integration challenges, supply chain complexities, and the role of predictive analytics in readiness. These cases underscore the urgency of proactive sustainment strategies, including early obsolescence prediction, diversified supplier engagement, and adaptive life cycle management.

D. LITERATURE REVIEW

This literature review brings together research from policy directives, forecasting techniques, procurement strategies, and supply chain resilience studies to build a practical framework for managing obsolescence risks in military and aerospace systems. The review is organized around four main themes that help shape a more informed approach to DMSMS.

The first theme focuses on how DMSMS has been managed historically in defense systems. It looks at past trends, policy development, and case studies that show how obsolescence has impacted operations and how agencies have responded (Mandelbaum et al., 2017; Beck, 2003; Frank & Morgan, 2007). The second theme explores predictive modeling, including both mathematical and AI-based forecasting methods that help anticipate when parts or systems will become obsolete (Sandborn, 2010; Bartels et al., 2012; Goudarzi & Sandborn, 2015; Rust et al., 2022). The third theme compares proactive and reactive life cycle sustainment strategies, weighing the costs and benefits of each and examining how they affect long-term system support (Chellin, 2023; Romero Rojo et al., 2010; Chen et al., 2020). The final theme looks at supply chain resilience and risk mitigation, highlighting industry-wide challenges and collaborative approaches that improve adaptability and reduce vulnerability (Seuren, 2018; Pooler et al., 2004; Center for a New American Security, 2025).

Together, these themes provide a strong foundation for understanding how obsolescence can be predicted and managed more effectively. The review supports the overall goal of this thesis: to improve defense acquisition and sustainment practices through data-driven strategies that help maintain readiness and protect critical systems.

1. DMSMS Management in Defense Systems

a. Historical and Policy Context

The DoD has long recognized the need for effective DMSMS management, acknowledging the risks posed by obsolescence and supply chain disruptions on military readiness and operational efficiency. In response, various policies and directives have been established to proactively address these challenges through structured intervention strategies.

b. Early Developments and Foundational Policies

The DoD's formal engagement with DMSMS issues can be traced back to the late 20th century when concerns over supplier limitations and technology obsolescence began affecting defense operations. Reports such as Naval Sea Systems Command (1999) identified the critical challenges associated with maintaining aging platforms while simultaneously adapting to the rapid evolution of commercial technologies. This early recognition established the foundation for integrating risk-based supply chain strategies into military sustainment practices.

One of the pivotal policy documents addressing DMSMS is DoD Instruction 4245.15 (Office of the Under Secretary of Defense for Acquisition and Sustainment, 2020), which provides structured guidelines for predictive obsolescence models. The directive emphasizes early risk identification, allowing procurement teams to anticipate component unavailability and develop contingency strategies before disruptions occur. These proactive measures are instrumental in extending the life cycle of defense systems and ensuring continued mission capability.

c. Strategic Evolution and Policy Enhancements

Building upon these foundational policies, Mandelbaum, Patterson, and Brown (2017) analyzed the historical progression of DMSMS management, identifying incremental improvements in strategic planning while also highlighting persistent execution gaps. Their study noted that despite advancements in forecasting techniques, challenges such as automation inefficiencies, supplier coordination hurdles, and long-term sustainment complexities continue to affect implementation across various defense programs.

Further refinements in policy emerged with the release of DoD Manual 4245.15 (2022), which sought to streamline DMSMS management frameworks by emphasizing risk-based procurement strategies tailored to modern defense acquisition needs. This manual introduced standardized methodologies for integrating predictive analytics and supply chain resilience, ensuring that procurement decisions align with long-term sustainment objectives.

Another critical resource in this space is the Defense Standardization Program (SD-26, 2023), which expands upon contracting guidelines to help defense organizations establish comprehensive DMSMS requirements within procurement agreements. The SD-26 outlines provisions for supplier accountability, mandating structured parts management planning to mitigate component obsolescence risks effectively. This document is particularly useful in ensuring that contracts reflect realistic sustainment expectations, reducing the likelihood of supply shortages impacting mission readiness.

d. Emerging Strategic Directions

Beyond foundational and evolving policies, the National Defense Industrial Strategy (NDIS, 2023) highlights broader concerns related to defense industrial base resiliency. The strategy acknowledges that fragmented procurement frameworks can exacerbate DMSMS-related risks, particularly in critical weapon systems where supplier availability is uncertain. As defense programs increasingly rely on commercial off-the-shelf (COTS) technologies, there is growing recognition of the need for flexible acquisition models that allow for rapid adaptability amid technological shifts.

Additionally, researchers such as Mandelbaum & Patterson (2014) have emphasized the importance of DMSMS management extending beyond electronic components to include critical materials in lower-tier supply chains. This broader perspective underscores the need for multi-tier supplier risk assessment models, particularly as defense organizations seek redundant sourcing solutions to mitigate manufacturing shortages.

In summary, the historical and policy context of DMSMS management reflects a sustained effort to implement predictive, risk-based approaches that enhance military sustainment strategies. Foundational policies such as DoD Instruction 4245.15 and DoD Manual 4245.15 offer structured frameworks for addressing obsolescence, yet persistent challenges in automation, procurement coordination, and supply chain flexibility indicate the need for continued refinement. Looking ahead, future policy directions may emphasize the integration of AI-driven obsolescence forecasting to improve supply chain adaptability, the development of contractual frameworks that support the Modular Open Systems Approach (MOSA) for long-term procurement sustainability, and the adoption of cross-industry collaboration models to reinforce supply chain resilience. As defense organizations operate within increasingly complex acquisition environments, aligning DMSMS policies with forward-leaning sustainment strategies will remain essential to preserving military readiness and ensuring operational stability.

e. Case Studies of Obsolescence Impact

Empirical case studies illustrate the critical consequences of inadequate DMSMS planning. When organizations fail to anticipate and mitigate obsolescence risks, operational readiness, sustainment feasibility, and long-term system support are significantly compromised. These case studies highlight the profound effects of microelectronic component shortages, system aging, and the consequences of insufficient forecasting strategies.

f. Microelectronic Obsolescence in the Department of Defense

One of the earliest comprehensive studies on obsolescence in defense electronics was conducted by Beck (2003), who examined microelectronic component obsolescence within the DoD. His analysis revealed that as commercial manufacturers advanced their technology at an increasingly rapid pace, the military struggled to sustain aging weapon systems dependent on outdated components.

Among Beck's key findings was the increasing reliance on life-of-type buys, a procurement strategy aimed at stockpiling essential components before their commercial production ceases. Despite its effectiveness in ensuring short-term continuity, the study noted that excessive reliance on life-of-type buys can lead to financial inefficiencies and logistical challenges, particularly in storage, verification, and shelf-life maintenance. Beck also underscored the need for alternative sourcing strategies such as redesign efforts, supplier diversification, and strategic alliances between defense agencies and private industry to mitigate component unavailability.

g. Obsolescence in U.S. Army Test Equipment

Building upon Beck's foundational research, Frank and Morgan (2007) conducted an in-depth analysis of electronic obsolescence within the U.S. Army's Integrated Family of Test

Equipment (IFTE), a critical diagnostic system used to maintain the operability of military electronics. Their study revealed that microelectronic components embedded in IFTE systems were particularly susceptible to commercial production discontinuation, which forced maintenance personnel to either source outdated parts at rising costs or implement inefficient workarounds to sustain functionality.

To address these challenges, the study highlighted two key mitigation strategies. The first was life-of-type buys, a procurement approach that enabled teams to secure sufficient component stock before obsolescence rendered the equipment non-functional. The second strategy involved design refresh initiatives, where modular redesigns allowed legacy test equipment to integrate newer, commercially available components without requiring a full system overhaul.

Despite these proactive measures, Frank and Morgan emphasized that the absence of coordinated obsolescence planning across acquisition cycles often led to reactive sustainment decisions. This lack of integration exacerbated long-term inefficiencies and underscored the need for more strategic, forward-looking approaches to managing obsolescence in military test systems.

h. Obsolescence Challenges in Aerospace and Defense Systems

Beyond electronic components, broader defense sustainment challenges were examined by Romero Rojo et al. (2010), who analyzed the impacts of obsolescence across aerospace and defense systems. Their research categorized obsolescence into three primary domains. The first, electronic component obsolescence, highlights the continued reliance on outdated semiconductors and microelectronics, which has proven problematic for long-lived defense platforms. The second domain, mechanical system aging, addresses the limited manufacturing lifespans of structural components, often driven by changes in material availability and machining capabilities. The third domain involves software sustainability challenges, as many defense systems depend on legacy software that becomes increasingly difficult to support over time. As operating environments evolve, these systems face growing cybersecurity vulnerabilities and interoperability issues.

Romero Rojo et al. emphasized the importance of integrated forecasting models and contractual risk mitigation strategies to address these multifaceted challenges. By incorporating machine learning algorithms and data-driven sustainment frameworks, defense agencies can reduce the frequency and cost of redesign efforts while proactively identifying obsolescence risks before they compromise mission readiness. This approach supports a more resilient and adaptive sustainment strategy, aligning with the broader goals of long-term defense capability and operational continuity.

i. Strategic Implications and Lessons Learned

These case studies collectively reinforce several key insights for effective DMSMS management. Proactive procurement planning remains essential. Life-of-type buys and last-time procurements can help mitigate immediate risks, but without the support of predictive analytics, they remain reactive measures rather than sustainable long-term strategies.

Supply chain resilience is also a critical priority. Relying exclusively on primary suppliers for essential components increases systemic vulnerability. Diversifying procurement channels and fostering interagency collaboration enhances the ability to respond effectively to obsolescence challenges.

In addition, technology refresh strategies offer a more efficient alternative to stockpiling outdated components. Modular redesign methodologies and component substitution models can extend life cycle support while reducing sustainment burdens and improving adaptability.

As defense acquisition frameworks continue to evolve, integrating data-driven obsolescence forecasting and adaptive procurement methodologies will be essential to maintaining military readiness. These approaches ensure that defense systems remain functional, responsive, and resilient in the face of a rapidly changing technological environment.

2. Predictive Modeling of Obsolescence Risks

a. Mathematical Forecasting Techniques

Modern obsolescence prediction models rely heavily on quantitative methodologies to estimate the life cycle of components and anticipate shortages. These models leverage historical procurement trends, supply chain indicators, and technological progression rates to identify critical obsolescence risks.

b. Sandborn's Forecasting Algorithms

Sandborn (2010) developed statistical algorithms to study historical purchasing patterns and manufacturing discontinuation trends. His model was designed to help forecast when specific components might become unavailable, giving procurement teams a better chance to plan ahead through strategic stocking or redesign decisions.

The approach included analyzing how component demand changed over time, tracking manufacturing cycles to estimate when production might end, and factoring in supplier availability to support life cycle planning. These elements formed a basic structure for predictive analytics in sustainment-heavy systems, helping defense organizations anticipate obsolescence before it disrupted mission-critical operations.

While Sandborn's work was a major step forward in obsolescence research, it had limitations. The model couldn't forecast obsolescence at the system level based on core attributes, which meant it was less effective for broader sustainment planning. This gap highlights the need for more advanced forecasting tools that can support long-term readiness across complex defense platforms.

c. Bartels, Ermel, Pecht, and Sandborn's Systematic Methodologies

Bartels et al. (2012) expanded on Sandborn's earlier work by developing structured forecasting methodologies that rely on primary attributes of electronic components. Their framework focuses on several key elements, including life cycle trend analysis, which examines the historical evolution of specific technologies, and obsolescence likelihood modeling, which uses statistical regression techniques to estimate when a component is likely to exit the market. They also incorporated machine learning and expert judgment to improve prediction accuracy.

Their research provided step-by-step guidance for estimating obsolescence, including mathematical formulations to quantify risk factors. In related work, Wiley et al. (2012) introduced equations that help forecast obsolescence timelines based on component attributes. While Bartels et al.'s approach was a major advancement in the field, it had limitations. The methodology required a primary attribute that closely matched those already studied, which meant it could not effectively forecast obsolescence for new or innovative components. This gap remains a challenge in DMSMS forecasting and highlights the need for more flexible models that can adapt to emerging technologies.

Building on these foundations, Rogers et al. (2025) applied an Ordinary Least Squares (OLS) regression model to predict training success in Navy SEAL candidates. While their study focused on human performance forecasting, the underlying statistical approach offers valuable parallels for obsolescence modeling. The OLS framework enables defense analysts to quantify relationships between system attributes and obsolescence outcomes, supporting more accurate life cycle predictions. By adapting this model to component-level forecasting, procurement teams can better anticipate failure points and optimize sustainment strategies based on statistically significant predictors

d. Goudarzi and Sandborn's Real Options Analysis

Goudarzi and Sandborn (2015) introduced a real options framework to improve lifetime buy decisions under uncertainty. Their methodology incorporates financial modeling to help procurement teams weigh the cost-effectiveness of bulk purchasing against the risks of obsolescence-related shortages. Unlike Sandborn's earlier algorithm (2010) and the predictive analytics approach developed by Bartels et al. (2012), this framework focuses on preventative strategies that support more deliberate sustainment planning.

The approach uses probabilistic risk assessment and applies real options formulas to address key questions in life cycle management. These include determining how many units of a component should be procured in a lifetime buy scenario, estimating the financial impact of holding surplus inventory versus facing shortages, and identifying the optimal timing for procurement to reduce sustainment risks.

Their paper presents quantitative optimization formulas that calculate ideal procurement quantities and associated costs based on varying obsolescence probabilities. The framework includes specific equations tailored for life cycle sustainment applications, offering defense agencies a more structured way to plan ahead and minimize long-term operational disruptions.

e. Machine Learning and AI-Driven Approaches

With ongoing technological advancements, AI-driven obsolescence forecasting has become an essential component of modern defense sustainment strategies. Machine learning models enable organizations to predict component end-of-life (EOL) cycles, optimize procurement decisions, and enhance sustainment planning through automated data analysis and pattern recognition. Traditional obsolescence management relies heavily on historical procurement trends and structured forecasting models, but AI introduces a more adaptive and efficient approach, capable of continuously learning from supply chain behaviors and industry shifts.

Rust et al. (2022) explored automation in EOL assessments, focusing on how neural networks improve decision-making accuracy by integrating procurement history with emerging technological trends. Their research demonstrates that AI-driven obsolescence forecasting can refine life cycle management by analyzing vast amounts of component failure data, supplier availability, and industry shifts, allowing defense organizations to anticipate obsolescence risks and proactively adjust procurement strategies. The incorporation of deep learning algorithms ensures that predictions remain dynamic and responsive to changes in the defense industrial base, mitigating the disruptive effects of unplanned component shortages.

Further advancing AI applications in obsolescence planning, Meng et al. (2014) introduced a strategic proactive obsolescence management model that integrates graph theory and mixed integer linear programming (MILP) to optimize sustainment decisions. Their framework is designed to minimize life cycle costs by determining the most effective balance between redesign efforts and last-time buys (LTBs). The use of graph theory allows defense organizations to visualize complex obsolescence dependencies; mapping how critical components interact within broader systems. Meanwhile, MILP optimization models provide cost-efficient solutions by calculating optimal procurement schedules, supplier selections, and life cycle extension strategies tailored to the specific requirements of long-lived defense systems.

The synergy between machine learning, predictive analytics, and mathematical modeling underscores the shift toward intelligent obsolescence management. Rather than reacting to component discontinuations after they occur, AI-driven frameworks enable proactive sustainment planning, reducing procurement inefficiencies and ensuring continued mission readiness. As AI methodologies evolve, future research may further refine automated obsolescence prediction models, integrating additional supply chain resilience strategies and real-time data analytics to optimize long-term sustainment decisions.

f. Life Cycle Sustainment Strategies

Effective sustainment planning in defense systems requires a careful balance between proactive and reactive strategies, as DMSMS present continuous challenges to operational readiness. While reactive sustainment models focus on addressing obsolescence issues after they arise—often through last-time buys and redesign efforts—proactive models aim to anticipate obsolescence risks before they impact system availability, thereby reducing sustainment costs and disruptions.

Chellin (2023) highlights the transition from reactive to proactive obsolescence management, demonstrating how risk-based methodologies, visualization tools, and key decision-making metrics enhance DMSMS management efficiency. His research emphasizes the long-term benefits of structured, data-driven approaches, enabling defense organizations to optimize procurement strategies and mitigate sustainment challenges before they escalate into operational deficiencies. The introduction of predictive analytics and automated risk assessment models ensures that sustainment programs can proactively address obsolescence risks, rather than relying on costly, reactive measures that often lead to procurement inefficiencies.

Similar, Romero Rojo et al. (2010) classify obsolescence mitigation strategies across various industries, reinforcing the need for holistic life cycle sustainment planning. Their findings underscore the importance of integrating technology refresh strategies alongside traditional reactive approaches, enabling defense agencies to gradually modernize aging systems without excessive cost burdens. By incorporating procurement forecasting methodologies, organizations can minimize life cycle costs while maintaining long-term system viability. Their research also highlights the challenges associated with forecasting the financial impact of obsolescence, as sustainment-heavy systems often require continuous investment to ensure readiness.

The interplay between proactive obsolescence forecasting and reactive sustainment frameworks remains a crucial aspect of military sustainment planning. While reactive models address immediate obsolescence challenges, the integration of predictive analytics, supplier risk assessments, and contractual risk mitigation strengthens sustainment capabilities. Future sustainment strategies may focus on automating obsolescence prediction models, leveraging machine learning-driven procurement analysis, and enhancing supplier collaboration frameworks to ensure military systems remain operationally viable across extended life cycles.

g. *Economic and Contracting Considerations*

Economic feasibility and procurement constraints play a pivotal role in sustainment planning for defense systems, particularly in mitigating the risks associated with DMSMS. As military platforms age, the availability of critical components declines, often leading to escalating sustainment costs and logistical challenges. To address these issues, defense agencies must adopt cost-efficient procurement strategies that align with long-term readiness objectives while minimizing financial risks.

Chen et al. (2020) conducted a comprehensive analysis of life-cycle cost trade-offs in defense acquisition, advocating for the Modular Open Systems Approach (MOSA) as a key strategy for reducing obsolescence risks. MOSA promotes interoperability and modular design, allowing defense organizations to replace outdated components with commercially available alternatives rather than being locked into proprietary or legacy systems. Their study highlights how open architecture procurement models enhance cost optimization by reducing sustainment burdens, improving flexibility in supplier selection, and extending system viability. Additionally, their multivariate financial model quantifies cost avoidance strategies, demonstrating that early investment in modular technologies can yield long-term economic benefits by mitigating obsolescence-driven expenses.

Further reinforcing these insights, the Executive Agent for the Defense Standardization Program (2023) provides critical contracting guidelines designed to strengthen DMSMS management in defense acquisition. Their framework ensures economic alignment between supplier capabilities and military sustainment priorities, emphasizing contract provisions that secure long-term component availability, proactive obsolescence tracking, and supplier accountability. The SD-26 contracting guide, for example, outlines 24 illustrative requirements for DMSMS management, covering key areas such as issue notification protocols, subcontractor flow-down requirements, and parts management validation. By incorporating these structured contractual provisions, defense agencies can reduce the likelihood of supply chain disruptions while enhancing procurement resilience against market fluctuations.

Ultimately, integrating financial risk modeling, strategic procurement frameworks, and contractual sustainment approaches allows defense organizations to balance cost efficiency with operational readiness. As MOSA adoption expands and contracting best practices evolve, future sustainment strategies may further leverage AI-driven procurement forecasting, supplier risk analytics, and automated life cycle cost assessment to ensure long-term defense system affordability and sustainability.

3. Literature Review Summary

This literature review establishes a comprehensive foundation for investigating obsolescence prediction and sustainment strategies in defense systems affected by DMSMS. Through an extensive synthesis of policy directives, forecasting models, procurement case studies, and supply chain resilience research, this study highlights the critical role of proactive sustainment planning in mitigating obsolescence risks and ensuring long-term operational readiness.

The insights gathered from historical and policy contexts demonstrate how DMSMS management has evolved over time, with defense agencies increasingly prioritizing predictive methodologies over reactive strategies. Case studies illustrate the real-world impact of component obsolescence, reinforcing the necessity of robust mitigation efforts through procurement forecasting, supplier diversification, and life cycle sustainment planning. Furthermore, advanced machine learning and AI-driven approaches have begun transforming obsolescence prediction capabilities, enabling defense organizations to preempt supply chain disruptions through automated risk assessment models and real-time analytics.

The importance of economic and contracting considerations is also emphasized, with structured frameworks such as Modular Open Systems Approach (MOSA) serving as key mechanisms for optimizing procurement decisions and cost efficiency. By integrating financial risk modeling with adaptive acquisition strategies, military organizations can strike a balance between cost-effectiveness and operational stability, ensuring that sustainment-heavy systems remain viable across extended life cycles.

Looking ahead, future research directions will focus on enhancing machine learning applications, refining predictive algorithms, and integrating life cycle cost modeling into sustainment planning. Emerging technologies, such as neural networks and real-options analysis, present significant opportunities for refining decision-making accuracy, providing data-driven forecasting techniques that improve procurement strategies. Additionally, expanding the interoperability of defense acquisition frameworks can further strengthen supply chain resilience, allowing organizations to adapt sustainment models to evolving geopolitical and technological landscapes.

By leveraging AI-driven forecasting, modular procurement methodologies, and proactive sustainment frameworks, military organizations can enhance supply chain efficiency, improve cost optimization, and ensure long-term strategic stability. The continued development of innovative obsolescence management techniques will be vital in maintaining defense readiness amid complex manufacturing and sustainment challenges.

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III. DATA AND METHODOLOGY

This study utilizes quantitative research methods to evaluate risks associated with Diminishing Manufacturing Sources and Material Shortages (DMSMS). Historical procurement records, contract structures, and life cycle sustainment data form the foundation of the analysis, enabling the identification of measurable patterns of obsolescence and supply chain vulnerability.

A. DATA COLLECTION

The primary dataset is taken from NAVSUP procurement databases, which provide contract award information, vendor participation metrics, and life cycle sustainment records. Contract award data highlight shifts in funding and acquisition strategies, while vendor participation metrics track supplier engagement and attrition over time. Life cycle sustainment patterns reveal how procurement timing influences exposure to obsolescence.

Supplementary insights were drawn from Industrial Base Readiness Working Group reports, which documented declining vendor participation, reduced competition, and rising obsolescence challenges, particularly in microelectronics. These reports also noted coordination gaps between NAVSUP, SYSCOM, and engineering teams, as well as the risks of sole-source contracting. NAVSUP's request for this research was motivated by procurement and sustainment challenges such as supply chain integration gaps within the SPY-6 system, supplier complexity, limited small business engagement, and declining competition in defense contracting.

To address these issues, the study applies descriptive statistics to summarize trends across inventory types, acquisition methods, mission importance, and life cycle stages. Regression analysis is used to identify relationships between variables such as last buy year and material supply date, while predictive modeling estimates future supply disruptions based on historical data.

B. LIMITATIONS: CHALLENGES IN DATA ACCURACY

Despite the structured approach, several limitations affect accuracy. Procurement records often lack comprehensive tracking of obsolescence, obscuring the full extent of vulnerabilities. Supply chain disruptions may occur unexpectedly, leading to unplanned costs and delays. Small business participation has declined due to regulatory and financial barriers, reducing competition and innovation. Multi-agency coordination challenges, including regulatory misalignment and uneven stakeholder buy-in, further complicate the implementation of risk assessment frameworks.

C. ITEM CLASSIFICATION

To enable structured analysis, 1,821 line items were sorted into eighteen categories using conditional statements in Microsoft Excel. These categories included Valves and Regulators, Sensors and Transducers, Power Supply and Batteries, Circuit Protection, Switches and Relays, Connectors, Fasteners, Cooling and Heating Components, Electronic Modules, Computing Hardware, Lighting, Filters, Cables, Displays, Hydraulic and Pneumatic Hardware, Mechanical Tools, Waveguides, and Other. Classification relied on keyword searches in item nomenclature, with exclusions applied to avoid miscategorization. Alternate spellings, acronyms, and abbreviations were also incorporated to ensure comprehensive sorting. This structured dataset provided the foundation for regression analysis and predictive modeling.

D. NAVSUP NOMENCLATURE AND VARIABLES

Standardized NAVSUP classification codes were encoded as binary variables for quantitative analysis. Item Mission Essentiality Codes (IMEC) measure operational criticality, ranging from IMEC1, which designates mission-critical items, to IMEC5, which applies to administrative or support components. Acquisition Method Codes (AMC) capture sourcing strategies, from competitive procurement (AMC1) to sole-source contracting (AMC3) and commercial off-the-shelf items (AMC5). The Last Buy Year (LBY) variable records the most recent procurement year, serving as a proxy for inventory aging and vendor support status. Life Cycle Integration (LCI) codes indicate the degree of alignment with system-wide planning, ranging from no integration (LCI1) to full integration (LCI4). Material Supply Date (MSD) variables are encoded by year to track expected delivery timelines and assess sustainment risks.

These variables enable regression models to quantify relationships between procurement timing, acquisition pathways, life cycle integration, and obsolescence risk.

E. SIGNIFICANCE OF PREDICTING OBSOLESCENCE

Quantitative forecasting of obsolescence strengthens acquisition strategy and national security readiness. By anticipating supply disruptions, the Navy can reduce reliance on emergency procurement, lower costs, and sustain operational availability. Predictive analytics also support modernization planning, ensuring that critical systems remain functional and mission-ready.

F. SUMMARY STATISTICS

Table 1 provides descriptive statistics that summarize the dataset used in this study, focusing on obsolescence risk, inventory categories, and operational codes. The table establishes the basic characteristics of the 1,821 component-level observations, showing how items are distributed across categories such as valves, sensors, computing hardware, and other classifications. It also reports the frequency of operational codes, including Item Mission Essentiality Codes (IMEC), Acquisition Method Codes (AMC), Last Buy Year (LBY), Life Cycle Integration (LCI), and Material Supply Dates (MSD). These descriptive measures give a clear picture of how the dataset is structured and highlight the diversity of procurement pathways and sustainment variables before regression analysis is applied.

Table 1 shows that the Inventory Category with the most items is Electronic Modules and Assemblies, which accounts for about 24.9% of all items. In comparison, Valves and Regulators account for only about 1.2% of items. The highest IMEC is 1, which denotes mission-critical items and accounts for 42.7% of items. IMEC 5 accounts for the fewest items, at only 0.1% of items. AMC 2 accounts for the fewest items, at 0.3%, and AMC 3 accounts for the most, at 64%. In fact, AMC 4 has the most items across all summary statistics. LCI 4 is the largest LCI category, accounting for 48.9% of items, whereas LCI 6 is the smallest category, accounting for 1.6% of items. MSD is an interesting category due to the wide range of group sizes. The smallest is 2021, which only accounts for 0.001% of items, which is the smallest category in the Summary Statistics Tables, whereas 2024 is the largest MSD group accounting for 24.4% of items.

G. MODEL 1: CATEGORY CONTROLS

For model 1, we used the following equation:

$$Obsolete_{(it)} = \alpha + X'_{(it)}\theta + \varepsilon_{(it)} \quad (1)$$

Where $Obsolete_{(it)}$ is the binary dependent variable which indicates if inventory item i was documented as obsolete in year t, α represents the intercept, and $X'_{(it)}$ denotes a vector of independent dummy variables including Inventory Category, Item Mission Essentiality Code (IMEC), Acquisition Method Code (AMC), Last Buy Year (LBY), Life Cycle Integration (LCI), and Material Supply Date (MSD). θ represents the estimated coefficients, and $\varepsilon_{(it)}$ is the idiosyncratic error term. Baseline categories are Electronic Modules and Assemblies, IMEC 3, AMC 3, LBY 2014, LCI 4, and MSD 2010. Coefficient estimates for inventory categories are presented in Table 2.

H. MODEL 2: YEAR INDICATORS

For model 2, we used the following equation:

$$\text{Obsolete}_{(it)} = \alpha + \text{MSD'}_{(it)}\,\lambda + X'_{(it)}\theta + \varepsilon_{(it)} \qquad (2)$$

In this specification, $\text{MSD}_{(it)}$ is a vector of dummy variables for the material supply date of item i in year t, and λ represents the estimated coefficients. λ can be interpreted as the change in probability for item i being obsolete in year t in comparison to the 2010 baseline year. Other baseline variables include Electronic Modules and Assemblies, IMEC 3, AMC 3, LBY 2014, and LCI 4. The model includes the same control variables as Equation 1. Coefficient estimates for year-specific effects are shown in Table 3.

I. NOTE ON TEMPORAL AGGREGATION

No cohort aggregation was performed in this analysis. Each Material Supply Date (MSD) year was retained as a separate indicator variable to preserve temporal precision. Equations 1 and 2 therefore represent the full set of regression models used for estimation. Future work may explore aggregated MSD cohorts as a robustness test, but such results are not included in this thesis.

J. ESTIMATION AND INTERPRETATION

All models use OLS regression. Coefficients are interpreted as percentage changes. Statistical significance is indicated by *, **, and *** for the 10%, 5%, and 1% levels, respectively. To approximate the marginal effect on the probability of obsolescence, each coefficient can be interpreted as a percentage change.

IV. ANALYSIS

A. TABLE 2: PREDICTORS OF OBSOLESCENCE RISK BY COMPONENT CATEGORY ACROSS REGRESSION MODELS

Table 2 shows the main results from Equation 1 and can be found in the appendix at the end of this paper. Only the results for the categories are shown in this table, with the columns showing the results of controlling different variables. There are five other variables that were controlled for: Material Supply Date, Item mission Essentiality Code, Acquisition Method Code, Last Buy Year, and Life Cycle Integration. The Valves and Regulators coefficients were negative across the board and fluctuated from a low of –1.8200 in column (1) to a high of –0.0860 in column (3). Six out of nine coefficients were statistically significant at the 10% level, and one out of nine coefficients was statistically significant at the 5% level. In the main results shown in column (9), the Valves and Regulators coefficient was statistically significant at the 10% level and has a point estimate of –0.0935 indicating items being in Valves and Regulators category reduces the likelihood of becoming obsolete by 9.35% in comparison to the baseline category Electronic Modules and Assemblies.

The Circuit Protection, Fuses, and Breakers coefficient fluctuated from a low of -2.6500 in column (1) to a high of 0.0049 in column (6). Three out of nine coefficients were statistically significant at the 1% level, and two out of nine coefficients were statistically significant at the 5% level. In the main results shown in column (9), the Circuit Protection, Fuses, and Breaker's coefficient was not statistically significant.

The Fasteners, Screws, Nuts, and Washers coefficient fluctuated from a low of –0.0768 in column (3) to a high of 1.9900 in column (1). Three out of nine coefficients were statistically significant at the 1% level, two out of nine coefficients were statistically significant at the 5% level, and one was statistically significant at the 10% level. In the main results shown in column (9), the Fasteners, Screws, Nuts, and Washer's coefficient was not statistically significant.

The Computing Hardware and Network Equipment coefficient fluctuated from a low of –4.3400 in column (1) to a high of 0.0206 in column (6). One out of nine coefficients was statistically significant at the 1% level, but in the main results shown in column (9), the Computing Hardware and Network Equipment coefficient was not statistically significant.

The Lighting and Indicators coefficients were all negative and fluctuated between a low of –2.6800 in column (1) and a high of –0.0847 in column (9). Three out of nine coefficients were statistically significant at the 1% level, two out of nine coefficients were statistically significant at the 5% level, and one was statistically significant at the 10% level. However, in the main results shown in column (9), the Lighting and Indicators coefficient was not statistically significant.

The Hydraulic and Pneumatic Hardware coefficient fluctuated between a low of –0.0914 in column (9) and a high of 4.1600 in column (1). One of nine coefficients was statistically significant at the 5% level, and two of nine coefficients were statistically significant at the 10% level. In the main results shown in column (9), the Hydraulic and Pneumatic Hardware coefficient was statistically significant at the 5% level and had a point estimate of 0.0320 indicating items being in Hydraulic and Pneumatic Hardware category increases the likelihood of becoming obsolete by 3.20%.

The Mechanical Tools and Accessories coefficient fluctuated between a low of –0.500 in column (1) and a high of 0.0110 in column (7). One out of nine coefficients was statistically significant at the 1% level, and one out of nine coefficients was statistically significant at the 5% level. In the main results shown in column (9), the Mechanical Tools and Accessories coefficient was statistically significant at the 5% level and had a point estimate of 0.0240 indicating items being in the Mechanical Tools and Accessories category increases the likelihood of becoming obsolete by 2.40%.

The rest of the categories included Sensors and Transducers, Power Supply and Relay Batteries, Switches and Relays, Connectors and Adapters, cooling and Heating Components, Filters: Electrical and Air, Cables and Wiring, Displays and Interfaces, Wave Guides, and other. None of these categories had a coefficient in any column that was statistically significant to the 1% level, nor did they have a coefficient in the main results, found in column (9), that was statistically significant.

B. TABLE 3: PREDICTORS OF OBSOLESCENCE ACROSS MODEL SPECIFICATIONS (2010–2027)

Table 3 also shows results from Equation 2. The results from the rest of the categories are shown in this table, which include: Material Supply Date, Item mission Essentiality Code, Acquisition Method Code, Last Buy Year, and Life Cycle Integration. The columns show the results of controlling different variables, including the Category variable.

For the Material Supply Date variable, ten years from 2008 to 2027 have at least one column whose coefficient is statistically significant to the 1% level or has a main result, found in column (10), that is statistically significant to at least the 10% level. The coefficients for a Material Supply Date of 2008 were negative across the board (where applicable) ranging from a low of –0.9986 in column (5) to a high of –0.7110 in column (9). One of eight coefficients was statistically significant at the 1% level, although the main result shown in column (9) was not statistically significant.

The coefficients for the Material Supply date of 2010 ranged from a low of –0.1221 in column (10) to a high of 0.3006 in column (9). Four of eight coefficients were statistically significant to the 5% level. In the main results, shown in column (10), the coefficient was statistically significant to the 5% level and had a point estimate of –0.1221, meaning that items with a Material Supply Date of 2010 were 12.21% less likely to become obsolete.

Coefficients for the Material Supply Date of 2011 ranged from a low of –0.3209 in column (1) to a high of –0.284 in column (9). Two of eight coefficients were statistically significant at the 1% level, including the main results (shown in column (10)) which had a point estimate of –0.1531. This means that items with a Material Supply Date of 2011 were 15.31% less likely to become obsolete.

Coefficient for the Material Supply Date of 2012 ranged from a low of –0.2935 in column (8) to a high of 0.0572 in column (9). Four of eight coefficients were statistically significant to the 1% level, however the main results in column (10) were not statistically significant.

Coefficients for the Material Supply Date of 2013 ranged from a low of –0.2058 in column (8) to a high of 0.1511 in column (9). Two of eight coefficients were statistically significant to the 5% level, including the main results shown in column (10) which had a point estimate of –0.2109.

This means that items with a material supply date of 2013 were 21.09% less likely to become obsolete.

Coefficients for the Material Supply Date of 2015 ranged from a low of –0.8245 in column (3) to a high of –0.4126 in column (9). Three of eight coefficients were statistically significant at the 5% level and one was statistically significant at the 1% level. In the main results shown in column (10), the coefficient was not statistically significant.

Coefficients for the Material Supply Date of 2017 ranged from a low of –0.9507 in column (5) to a high of –0.6562 in column (9). One of eight coefficients was statistically significant to the 1% level, however the main result in column (10) wasn't statistically significant.

Coefficients for the Material Supply Date of 2018 ranged from a low of –0.4259 in column (6) to a high of –1.523 in column (9). One of eight coefficients was statistically significant to the 1% level, however the main result in column (10) wasn't statistically significant.

Coefficients for the Material Supply Date of 2019 ranged from a low of –0.4507 in column (5) to a high of –0.1629 in column (9). Two of eight coefficients were statistically significant to the 5% level and one of eight coefficients was statistically significant to the 10% level. The main results in column (10) were statistically significant to the 5% level and had an estimated point value of -0.4434, meaning that items with a Material Supply Date of 2019 were 44.34% less likely become obsolete.

Coefficients for the Material Supply Date of 2021 ranged from a low of –0.5874 in column (4) to a high of –0.2365 in column (9). Two of eight coefficients were statistically significant at the 10% level, and one of eight coefficients was statistically significant at the 5% level. In the main results shown in column (10), the coefficient was statistically significant at the 10% level and had a point estimate of –0.2412, meaning that items with a Material Supply Date of 2021 were approximately 24.12% less likely to become obsolete.

Coefficients for the Material Supply Date of 2023 fluctuated between a low of –0.6742 in column (2) and a high of –0.1856 in column (9). One of eight coefficients was statistically significant at the 5% level and one was significant at the 10% level. The main result in column (10) was statistically significant at the 10% level with a point estimate of –0.2073, indicating that items with a Material Supply Date of 2023 were 20.73% less likely to become obsolete.

Coefficients for the Material Supply Date of 2026 ranged from a low of –0.1421 in column (5) to a high of 0.0915 in column (9). None of the coefficients were statistically significant at the 1%, 5%, or 10% levels, including the main result in column (10). This suggests that items with a Material Supply Date of 2026 did not have a meaningful or statistically significant association with obsolescence risk.

Coefficients for Item Mission Essentiality Code (IMEC) 4 ranged from a low of –0.5981 in column (3) to a high of –0.1278 in column (9). Two of eight coefficients were statistically significant at the 10% level and one was significant at the 5% level. In the main results shown in column (10), the coefficient was statistically significant at the 10% level with a point estimate of –0.1720, indicating that items classified under IMEC 4 were 17.20% less likely to become obsolete than those in the baseline IMEC 3 group.

Coefficients for Acquisition Method Code (AMC) 1 ranged from a low of –0.4639 in column (2) to a high of –0.1884 in column (9). One of eight coefficients was statistically significant at the 10% level and another at the 5% level. The main result in column (10) was statistically significant at the 5% level with a point estimate of –0.2147, meaning that items acquired under AMC 1 were 21.47% less likely to become obsolete compared to the baseline AMC 3 category.

Coefficients for Acquisition Method Code (AMC) 5 ranged from a low of 0.0943 in column (4) to a high of 0.5326 in column (9). Two of eight coefficients were statistically significant at the 10% level and one was significant at the 5% level. The main result in column (10) was statistically significant at the 10% level with a point estimate of 0.3054, suggesting that items acquired under AMC 5 were 30.54% more likely to become obsolete than those acquired through the baseline AMC 3 method.

Coefficients for the Last Buy Year (LBY) 2017 ranged from a low of –0.4176 in column (3) to a high of –0.1922 in column (9). One of eight coefficients was statistically significant at the 10% level, while none were significant at the 5% or 1% levels. The main result in column (10) was not statistically significant, indicating that a last buy year of 2017 did not exhibit a strong relationship with the likelihood of obsolescence.

Coefficients for the Last Buy Year (LBY) 2018 fluctuated between a low of –0.7034 in column (4) and a high of –0.3175 in column (9). Two of eight coefficients were statistically significant at the 10% level and one was statistically significant at the 5% level. In the main results shown in column (10), the coefficient was statistically significant at the 10% level with a point estimate of –0.3341, indicating that items with a last buy year of 2018 were 33.41% less likely to become obsolete.

Coefficients for Life Cycle Integration (LCI) 1 ranged from a low of –0.4846 in column (5) to a high of –0.2164 in column (9). One of eight coefficients was statistically significant at the 5% level, and one was statistically significant at the 10% level. In the main results shown in column (10), the coefficient was statistically significant at the 10% level with a point estimate of –0.2389, suggesting that items in LCI stage 1 were 23.89% less likely to become obsolete than those in the baseline LCI 4 group.

Coefficients for Life Cycle Integration (LCI) 2 fluctuated between a low of –0.3112 in column (2) and a high of 0.1048 in column (8). One of eight coefficients was statistically significant at the 5% level, while the main result in column (10) was not statistically significant. This suggests limited evidence that items classified in LCI stage 2 differ substantially in their risk of obsolescence compared to the baseline LCI 4 group.

The remaining variables in Table 3, including other Material Supply Dates (such as 2014, 2016, 2020, and 2027), Item Mission Essentiality Codes 1, 2, and 5, Acquisition Method Codes 2, 3, and 4, Last Buy Years outside of 2017 and 2018, and Life Cycle Integration stages 3, 4, and 6, showed limited statistical significance. Several had coefficients that were statistically significant at the 5% or 10% levels in individual columns, but none demonstrated significance at the 1% level or had main results (shown in column (10)) that were statistically significant up to the 10% threshold. These patterns indicate that while some variables may exert marginal or context-specific effects on obsolescence, their overall influence is not strong enough to be considered substantively significant once all model controls are applied.

This study applies regression analysis to uncover key drivers of obsolescence within the Naval Supply System, offering a structured and data-driven approach to understanding DMSMS risks. By examining variables such as Inventory Categories, Mission Essentiality Codes, Acquisition Method Codes, Last Buy Years, Life Cycle Integration, and Material Supply Dates, the analysis reveals statistically significant patterns that contribute to supply disruptions and sustainment inefficiencies. These findings provide empirical grounding for procurement decisions, enabling NAVSUP to better anticipate obsolescence and allocate resources more effectively.

The regression models identify historical trends and support predictive forecasting, allowing decision-makers to assess future risk exposure across critical supply categories. This capability is especially valuable in environments where vendor attrition, sole source contracting, and fragmented supply chain communication threaten long-term readiness. By quantifying the relationships between procurement variables and obsolescence outcomes, the study equips stakeholders with actionable insights to guide lifetime buy strategies, contract timing, and inventory prioritization.

Ultimately, this research reinforces the value of regression analysis as a strategic tool for defense logistics. It enables NAVSUP to move beyond reactive procurement and toward proactive sustainment planning, integrating data science with operational expertise to strengthen supply chain resilience and support long-term industrial base readiness.

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V. CONCLUSION

Diminishing Manufacturing Sources and Material Shortages (DMSMS) continue to threaten the sustainment of defense-critical systems. This study demonstrates the value of predictive analytics in identifying obsolescence risk, particularly in radar and communications components (SPY-6 and NMT – Navy Multiband Terminal), by applying regression-based modeling to 1,821 curated observations spanning 2009 to 2019. Key drivers of obsolescence include vendor consolidation, technology refresh cycles, and supply chain instability emerge as consistent predictors of component attrition and overall readiness degradation.

Using Ordinary Least Squares regression, the model offers a transparent and adaptable framework for forecasting component survivability across time horizons. While no model can fully capture the unpredictability of component availability shifts or technological transitions, structured data provides a scalable foundation for triage and early intervention. The framework supports proactive sustainment planning and informs acquisition decisions by integrating life cycle metadata, vendor status, and integration context.

The regression results point to several patterns that help explain where and when obsolescence risk shows up. Items in the Valves and Regulators category were less likely to become obsolete, while Hydraulic and Pneumatic Hardware and Mechanical Tools and Accessories showed a higher chance of attrition. This difference suggests that certain mechanical parts tend to last longer, while equipment tied to maintenance or specialized configurations turns over faster. The data also show that items with Material Supply Dates from 2019 to 2023 were significantly less likely to become obsolete, likely reflecting recent improvements in supply chain visibility and modernization efforts. Together, these results show that tracking historical procurement data over time can help spot emerging risks earlier.

Acquisition and life cycle variables tell a similar story. Items bought through full and open competition (AMC 1) or tagged as mission-essential (IMEC 4) were less likely to go obsolete, showing the benefits of competitive sourcing and proactive sustainment for high-priority components. In contrast, items restricted to authorized government sources (AMC 5) were more likely to become obsolete, pointing to the dangers of limited vendor options. Components tied to early life-cycle integration (LCI 1) also showed greater longevity, reinforcing that planning for obsolescence should start at the beginning of a system's life. Overall, these findings support a shift toward more data-driven sustainment decisions, using category, acquisition, and life cycle insights to anticipate obsolescence instead of reacting to it.

To operationalize obsolescence intelligence, we recommend implementing automated data capture and forecasting tools within acquisition and logistics workflows from the beginning of a weapon systems life cycle. These systems can enable program offices to anticipate risk rather than react to failure, preserving mission readiness, reducing life cycle costs, and extending the viability of aging platforms. Though the model shows utility across select systems, further refinement is needed to enhance scalability and precision across broader portfolios and different systems. This work contributes to ongoing efforts to institutionalize obsolescence forecasting as a core element of long-term sustainment strategy.

APPENDIX. TABLES AND VISUAL DATA

Table 1. Descriptive Statistics for Obsolescence, Inventory Categories, and Operational Codes

	Variable	Obs.	Mean	Std. Dev.	Min	Max
	Obsolete (1 = Yes, 0 = No)	1,821	0.6579	0.4745	0	1
Inventory Categories	Valves and Regulators	1,821	0.0121	0.1093	0	1
	Sensors and Transducers	1,821	0.0461	0.2098	0	1
	Power Supply and Relay/ Batteries	1,821	0.0582	0.2342	0	1
	Circuit Protection and Fuses Breakers	1,821	0.0401	0.1962	0	1
	Switches and Relays	1,821	0.0308	0.1727	0	1
	Connectors and Adapters	1,821	0.0516	0.2213	0	1
	Fasteners, Screws, Nuts, and Washers	1,821	0.0758	0.2647	0	1
	Cooling and Heating Components	1,821	0.0379	0.1910	0	1
	Electronic Modules and Assemblies	1,821	0.2488	0.4324	0	1
	Computing Hardware and Network Equipment	1,821	0.0643	0.2453	0	1
	Lighting and Indicators	1,821	0.0143	0.1187	0	1
	Filters: Electrical and Air	1,821	0.0258	0.1586	0	1
	Cables and Wiring	1,821	0.1636	0.3701	0	1
	Hydraulic and Pneumatic Hardware	1,821	0.0324	0.1771	0	1
	Displays and Interfaces	1,821	0.0209	0.1430	0	1
	Mechanical Tools and Accessories	1,821	0.0346	0.1828	0	1
	Waveguides	1,821	0.0302	0.1711	0	1
	Other	1,821	0.0126	0.1117	0	1
Item Mission Essentiality Code	1	1,821	0.4272	0.4948	0	1
	2	1,821	0.1032	0.3044	0	1
	3	1,821	0.2592	0.4383	0	1
	4	1,821	0.0626	0.2423	0	1
	5	1,821	0.0011	0.0331	0	1
	No IMEC	1,821	0.1466	0.3538	0	1
Acquisition Method Code	1	1,821	0.2608	0.4392	0	1
	2	1,821	0.0038	0.0619	0	1
	3	1,821	0.6414	0.4797	0	1
	4	1,821	0.0340	0.1814	0	1

	5	1,821	0.0599	0.2373	0	1
Last Buy Year	2015	1,821	0.0500	0.2179	0	1
	2016	1,821	0.0005	0.0234	0	1
	2017	1,821	0.0011	0.0331	0	1
	2018	1,821	0.0027	0.0523	0	1
	2019	1,821	0.0011	0.0331	0	1
Life Cycle Integration	1	1,821	0.0231	0.1501	0	1
	2	1,821	0.2180	0.4130	0	1
	3	1,821	0.2685	0.4433	0	1
	4	1,821	0.4887	0.5000	0	1
	6	1,821	0.0016	0.0406	0	1
Material Supply Date	2008	1,821	0.0005	0.0234	0	1
	2010	1,821	0.0895	0.2856	0	1
	2011	1,821	0.1389	0.3460	0	1
	2012	1,821	0.0286	0.1666	0	1
	2013	1,821	0.0071	0.0842	0	1
	2014	1,821	0.0049	0.0701	0	1
	2015	1,821	0.0016	0.0406	0	1
	2016	1,821	0.0236	0.1519	0	1
	2017	1,821	0.0005	0.0234	0	1
	2018	1,821	0.0104	0.1016	0	1
	2019	1,821	0.0011	0.0331	0	1
	2020	1,821	0.1867	0.3898	0	1
	2021	1,821	0.0005	0.0234	0	1
	2022	1,821	0.0049	0.0701	0	1
	2023	1,821	0.0011	0.0331	0	1
	2024	1,821	0.2444	0.4298	0	1
	2025	1,821	0.2246	0.4174	0	1
	2026	1,821	0.0104	0.1016	0	1
	2027	1,821	0.0203	0.1411	0	1

Notes: Summary statistics for binary variables used in obsolescence modeling, including inventory categories, mission essentiality codes, acquisition methods, life cycle indicators, last buy year, and material supply dates.

Table 2. Predictors of Obsolescence Risk by Component Category Across Regression Models

Category:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Valves and Regulators	-1.8200*	-0.1068	-0.0860	-0.1743*	-0.1972*	-0.1427*	-0.1749*	-0.1161**	-0.0935*
Sensors and Transducers	-0.9700	-0.0569	-0.0437	-0.0433	-0.0586	0.0072	-0.0441	-0.0469	-0.0473
Power Supply and Relay Batteries	0.7000	0.0236	0.0499	0.0387	0.0488	0.0525	0.0504	0.0334	0.0408
Circuit Protection, Fuses, and Breakers	-2.6500***	-0.0365	-0.1697***	-0.1558**	-0.1679***	0.0049	-0.1566**	-0.0358	-0.0555
Switches and Relays	-0.7300	0.0040	-0.0607	-0.0483	-0.0527	0.0663*	-0.0490	0.0060	-0.0049
Connectors and Adapters	-1.1000	0.0298	0.0120	-0.0294	-0.0637	0.0859**	-0.0294	0.0440	0.0400
Fasteners, Screws, Nuts, Washers	1.9900**	0.0802**	-0.0768	0.1464***	0.0894*	0.1090	0.1471***	0.0731***	-0.0112
Cooling and Heating Components	1.0000	-0.0156	0.0432	0.0894	0.0702	0.0279	0.0987*	0.0001	-0.0142
Computing Hardware and Network Equipment	-4.3400	-0.0204	-0.1688***	-0.1805	-0.2186	0.0206	-0.1785	-0.0002	-0.0057
Lighting and Indicators	-2.6800***	-0.1012*	-0.1947**	-0.2826***	-0.2465**	-0.1084	-0.2701***	-0.0974	-0.0847
Filters Electrical and Air	-0.1200	-0.0209	-0.0295	0.0103	-0.0105	0.0193	0.0098	-0.0070	-0.0144
Cables and Wiring	13.3100	0.0484**	0.1409	0.3078	0.3495	0.2094	0.3087	0.0429**	-0.0058
Displays and Interfaces	-0.9300	0.0384	-0.1393*	-0.0706	-0.0613	-0.0361	-0.0532	0.0715	0.0031
Hydraulic and Pneumatic Hardware	4.1600	-0.0229	0.1092*	0.2302	0.2243	0.0732*	0.2296	-0.0250	-0.0914**
Mechanical Tools and Accessories	-0.5000	-0.0551	-0.1752***	0.0106	-0.0348	-0.0150	0.0110	-0.0464	-0.1137**
Waveguide	7.6600	0.0603	0.0798**	0.2810	0.3275	0.1730	0.2850	0.0412	-0.0149
Other	17.1200	0.0402	0.1849	0.3504	0.3938	0.2394	0.3484	0.0347**	0.0412
Adjusted for Category	X	X	X	X	X	X	X	X	X
Adjusted for MSD		X						X	X
Adjusted for IMEC			X						X
Adjusted for AMC				X			X	X	X
Adjusted for LBY					X		X	X	X
Adjusted for LCI						X		X	X

Notes: Statistical significance of component categories in predicting obsolescence (1 = Yes, 0 = No) across nine model specifications with varying covariate adjustments.
***= Statistically Significant at the 1% level
**= Statistically Significant at the 5% level
*= Statistically Significant at the 10% level

Table 3. Predictors of Obsolescence Across Model Specifications (2010–2027)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Material Supply Date	2008	-0.9975	-0.9303	-0.9203***	-	-0.9986	-0.9820	-	-0.8192	-0.7110	-0.8254
	2010	0.0440**	0.0697	0.0451	-	0.0434**	0.0220	-	-0.1160**	0.3006	-0.1221**
	2011	-0.3209	-0.3100	-0.3133	-	-0.3101	-0.3040	-	-0.1479***	-0.0284	-0.1531***
	2012	-0.1697***	-0.1670***	-0.1870	-	-0.1559***	-0.1629***	-	-0.2935	0.0572	-0.2930
	2013	-0.1077	-0.0842	-0.0779	-	-0.1083	-0.1040	-	-0.2058**	0.1511	-0.2109**
	2014	-0.1724	-0.0882	-0.1922*	-	-0.1101	-0.1412	-	-0.3252	-0.0494	-0.3290
	2015	0.1269	0.2627*	0.1001	-	0.2985	0.3219	-	0.1613	0.5973***	0.1569
	2016	-0.5453	-0.5132	-0.5116	-	-0.5226	-0.5072	-	-0.4666	-0.2295**	-0.4575
	2017	-0.9502	-0.9303	-0.8994***	-	-0.9507	-0.9276	-	-0.6917	-0.6562	-0.6782
	2018	-0.4239	-0.4040***	-0.3961	-	-0.4244	-0.4259	-	-0.4041	-0.1523	-0.4113
	2019	-0.4502	-0.4303	-0.3999*	-	-0.4507	-0.4367	-	-0.4426**	-0.1629	-0.4434**
	2020	0.0315*	0.0550	0.0514**	-	0.0309*	0.0267	-	0.1609	0.3049	0.1511***
	2021	-0.6330	-0.9303	-0.8135***	-	-0.6281	-0.4999	-	-0.4750	-0.2316**	-0.3852
	2022	-0.1372	-0.1526	-0.1545	-	-0.1371	-0.1397	-	-0.1175	0.1363	-0.1207
	2023	0.0498***	0.0697	0.0313	-	0.0493***	0.0153	-	0.1713	0.2940	0.1559***
	2025	-0.8745	-0.8888	-0.8722	-	-0.8744	-0.8608	-	-0.4540	-0.4860	-0.4615
	2026	-0.3096***	-0.2988***	-0.2925	-	-0.3098***	-0.3088***	-	0.0752	0.1842	0.0563
	2027	-0.7642	-0.7682	-0.8044	-	-0.7639	-0.8010	-	-0.1362	-0.0350	-0.1272
Item Mission Essentiality Code	1	-	-	-	0.3923	-	-	0.2145	0.0906	-	0.1078
	2	-	-	-	0.2863	-	-	-0.0627	-0.0463	-	-0.0496
	4	-	-	-	0.1421***	-	-	0.0802**	0.0757**	-	0.0827
	5	-	-	-	0.6308	-	-	0.1729	0.1230	-	0.1148
	None	-	-	-	0.6030	-	-	0.3124	0.4091	-	0.4137
Acquisition Method Code	1	-0.0285	-	-	-0.0418	-0.0295	-0.0382**	-0.0115	-0.0262	-0.0335*	-0.0221
	2	-0.2315	-	-	-0.1654	-0.1818	-0.2028	-0.2731	-0.1930	-0.2594	-0.2142
	4	-0.3172	-	-	-0.4694	-0.3227	-0.3227	-0.3181	-0.2630	-0.3154	-0.2636
	5	0.0473*	-	-	0.0026	0.0478*	0.0399	0.0909***	0.0811***	0.0478*	0.0831***
Last Buy Date	2016	-	-0.4171	-	-	-0.4281	-0.4398	-0.7356	-0.3472	-0.4338	-0.3533
	2017	-	-0.5187	-	-	-0.5583	-0.5963	-0.7547	-0.4713***	-0.5963	-0.4960
	2018	-	-0.5793	-	-	-0.5660	-0.5732	-0.3504*	-0.3989***	-0.5212	-0.3765***
	2019	-	-0.6918	-	-	-0.7177	-0.7271	-0.7788	-0.5626	-0.6943	-0.5935
Life Cycle Integration	1	-	-	-	-	-	-	-0.5332	-0.4765*	-0.4821*	-0.4885**
	2	-	-	-	-	-	-	-0.6401	-0.2823***	-0.1259	-0.2731***
	3	-	-	-	-	-	-	0.1849	0.1521	0.2771	0.1589
	6	-	-	-	-	-	-	-0.1693	0.0714	0.0852	0.0762
Adjusted for Category				X			X	X		X	X
Adjusted for MSD		X	X	X		X	X		X	X	X
Adjusted for IMEC					X			X	X		X
Adjusted for AMC		X			X	X	X	X	X	X	X
Adjusted for LBY			X			X	X	X	X	X	X
Adjusted for LCI								X	X	X	X

Notes: ***= Statistically Significant at the 1% level
**= Statistically Significant at the 5% level
*= Statistically Significant at the 10% level

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