Mapping Artificial Intelligence to the Naval Tactical Kill Chain

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Abstract

This work explores the use of artificial intelligence (AI) for enhancing the naval tactical kill chain. Naval operations place high demands on sailors to maintain situation awareness, conduct missions, and be prepared for conflict while operating a variety of warfare systems in concert with the fleet command structure. Naval operations become more complex as they involve the use of weapons. The series of tactical processes and decisions involving weapons use is referred to as a kill chain. An effective kill chain requires identifying and understanding threats, determining courses of action, executing selected actions, and assessing their effects. Kill chains are a particularly stressing category of tactical operations as they must be implemented with limited and uncertain knowledge, within critical and demanding timelines, relying on a variety of advanced technology systems, within highly dynamic and changing environments, and with grave consequences. The Navy is studying AI as an emerging technology for improving kill chain operations by reducing uncertainty, increasing the speed of decision-making, enhancing decision assessments. This paper presents an evaluation of AI methods for their efficacy in supporting the specific functions of the naval tactical kill chain.

Introduction

Naval operations are dynamic, and during conflict, they become highly complex. Operating a variety of advanced technology systems (including ships, aircraft, sensors, communication systems, and weapons) with teams of warfighters in the maritime environment establishes a baseline of challenging operations. In a conflict or crisis situation, the pace of operations increases and can become highly volatile; uncertainty abounds in situation awareness and knowledge of the battlespace; and effective decisions are critical to mission success and carry weighty consequences.

A naval tragedy involving a weapon engagement, was the tragic surface-to-air missile shot by the USS Vincennes cruiser that shot down the commercial aircraft, Airbus A300 in 1998, killing all 290 occupants on board (Pasley, 2020) (shown in Figure 1). This tragedy involved time-critical decision-making under stress (Johnston et al, 1998).

This incident represents the decision complexity involved in naval operations and specifically highlights challenges within the observe-orient-decide-act (OODA) loop, a model

FIGURE 1. USS Vincennes launching missile from its deck. Source: CBS News (n.d.).

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of operational activities developed by John Boyd in the 1950's (Jones, 2020). Human error, human cognitive limits, and the inherent decision complexity of naval operations lead to challenges in the OODA loop and more specifically in the kill chain process (Von Lubitz et al, 2008, Szeligowski, 2018). Kill chain functions are the tactical activities and decisions involving the use of weapon systems. An effective kill chain requires the proper setup and employment of shipboard sensors, the identification and classification of unknown contacts, the analysis of contact intentions based on kinematics and intelligence, awareness of the environment, and decision analysis and warfare resource selection (O'Donoughue et al, 2021, Smith, 2010, Zhao et al, 2016). This study stemmed from the desire to find methods to support sailors and warfighters and the often-complex decisions they must make during naval operations.

Recent advances in AI and advanced data analytics have led to naval studies to determine how these methods can be leveraged to support a wide range of naval applications. AI methods are being studied for their potential application to naval logistics, mission planning, physical security, autonomous systems, and cyber security (Heller, 2019, Mittu and Lawless 2015).

The kill chain is another primary application of interest as the Navy studies the use of AI methods. Conceptual studies are proposing the use of AI as a cognitive assistant and for human-machine teaming (Iversen and DiVita, 2019, Ding et al, 2022, Johnson 2019, Grooms, 2019, Albarado, et al, 2022). Research is maturing for the use of AI to extract knowledge and situation awareness of the operational environment from the fusion of data from multiple sources (Zhao et al, 2018).

This study looked across the naval

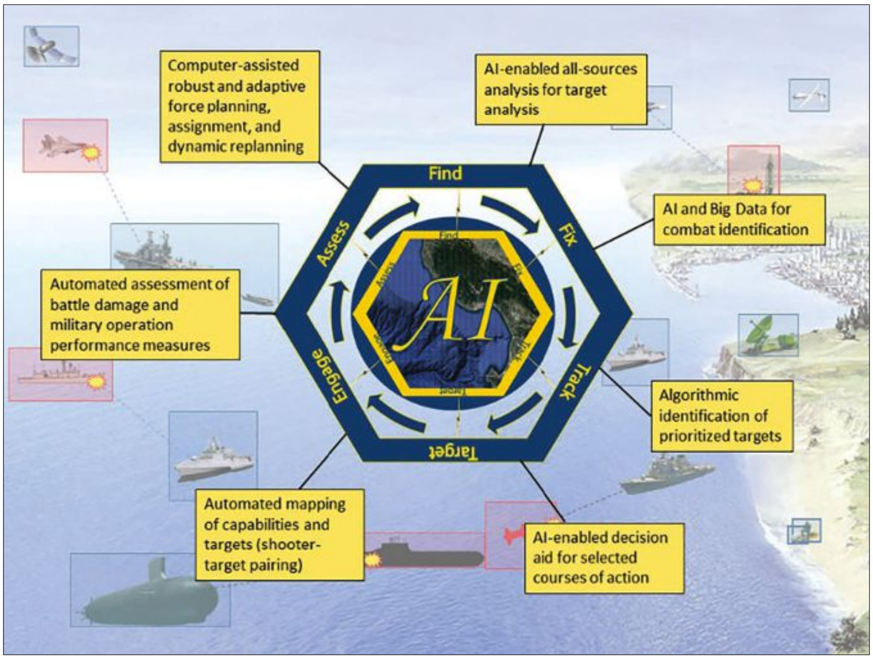

FIGURE 2. Conceptual illustration: leveraging artificial intelligence for naval tactical kill chain operations in the maritime domain.

tactical OODA loop to evaluate the use of AI for improving each specific kill chain function. Figure 2 shows a conceptual illustration of the naval maritime tactical domain as the focus for leveraging AI methods and technologies. This illustration depicts the cyclical nature of kill chain OODA loop functions using military vernacular: find-fix-track-target-engage-assess. The study explored the use of AI to enhance these functions as they are used for naval blue forces to defend against red force threats in the maritime domain.

The paper begins with a review of the naval tactical kill chain, describing tactical warfare process models and identifying a set of 28 kill chain functions as the subject of this study. The next section summarizes AI methods with applicability for the kill chain. Following this is a description of the evaluation framework developed for this study. The paper concludes with the results of this study—the mapping of AI methods to the kill chain.

Naval Tactical Kill Chain

The analysis began with a study of naval combat-related tactical operation models to capture a description of the kill chain in a form that could align with AI methods. The goal was to establish a description of the naval tactical kill chain to: (1) be representative of combat-related actions in the naval tactical domain, (2) be generic enough to model a wide spectrum of tactical decisions and actions, (3) and be decomposed to the right level to identify individual and distinct processes.

The term, kill chain, refers to the structure of an attack involving the use of a weapon. The process is described as a chain to illustrate that an integrated end-to-end set of decisions and actions are required to engage a target with a weapon and that an interruption at any stage can break the process. Clawson et al. (2015) describe the kill chain as the "mission tasks or functions required to successfully employ a specific weapon against a specific threat." Kill chain

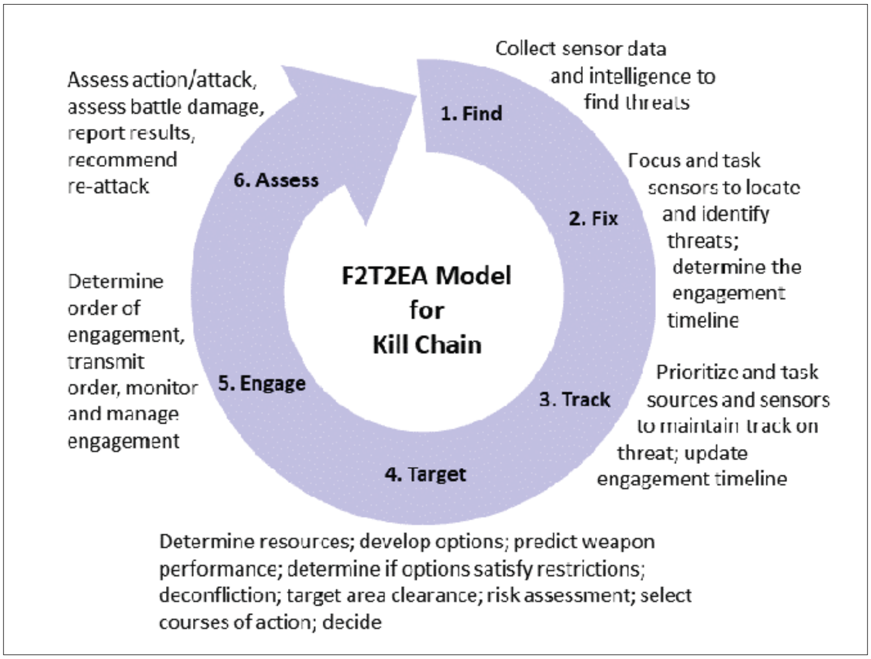

FIGURE 3. The kill chain OODA loop.

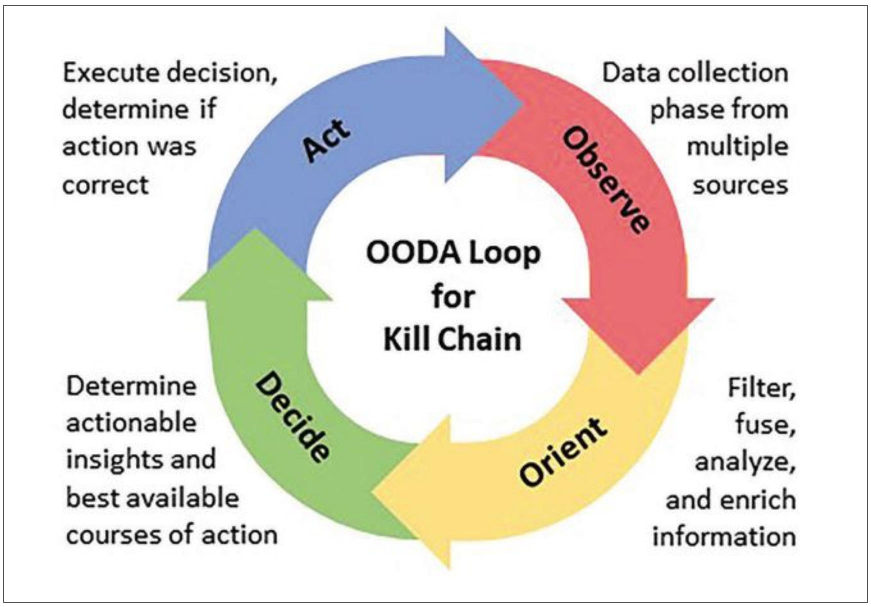

FIGURE 4. F2T2EA kill chain cycle. Adapted from: Joint Chiefs of Staff (2013).

processes include target detection, the decisions involved in choosing to engage a target and selecting a weapon, and the actual execution of the attack.

A foundation for understanding tactical operations is John Boyd's OODA loop model which stands for Observe, Orient, Decide, and Act. Figure 3 illustrates the OODA loop model—highlighting four phases of actions or processes that occur cyclically. During the observe phase, data and information is gathered. During orient, this information is processed, fused, and analyzed to provide situation awareness. In the decide phase, the blue forces decide whether actions are required and what those actions should be. In the act phase, actions are executed, and more information is gathered to determine if the desired effects resulted. The OODA loop has had over a half century of influence on military thought and has helped shape warfare system development and warfare doctrine (Angerman 2004). The OODA loop model has been used to predict and understand military operational reaction times (Hightower 2007), cognitive tactical decision-making (Plehn 2000), design goals of command-and-control systems and networks (Revay 2017), and even high-level military strategizing (Hasik 2013). In real-world tactical operations, many OODA loops of activities are occurring dynamically, cyclically, and concurrently.

The OODA loop model provided a foundation for understanding the kill chain process and led to the study of the Find-Fix-Track-Target-Engage-Assess (F2T2EA) kill chain process model (Joint Chiefs of Staff, 2013) shown in Figure 4. The F2T2EA is another process model that describes the kill chain in military terms. The F2T2EA model groups the tactical functions into six categories and highlights the cyclical nature of the tactical operations. The F2T2EA captures the nuances of tactical warfare functions, decisions, and actions, lending a more detailed framework for eliciting specific, comprehensive, and independent kill chain functions for the AI mapping.

This study developed a set of 28 kill chain functions that are listed in Table 1. The table shows how the functions are attributed to both the OODA and F2T2EA kill chain process models. The intent of establishing a set of distinct functions with some measure of independence was to support a mapping of specific AI methods to specific kill chain functions, while maintaining their ability to represent a variety of naval decisions and actions that occur during tactical operations.

The kill chain functions are intended to be universal—to apply to a wide variety of tactical operations involving a "kill" action. For this study, the kill chain could support offensive strike and defensive missions; and a kill could be hard or soft. This allowed for the use of non-lethal and countermeasure actions meant to neutralize an adversarial asset to accomplish a tactical mission.

During conflict or crisis, the implementation of tactical operations involves a complex, dynamic, and cyclical combination of kill chain functions. Functions will overlap, occur simultaneously, reoccur, and often require many instantiations depending on the threat situation. "Find" and "fix" will be on-going functions; "track" will arise for each object detected; "target" will be performed for objects deemed threats of interest; and "engage" and "assess" will be implemented for threats requiring a kill (or neutralization) action.

As the Navy explores the automation of kill chain functions and considers the use of AI methods, the characteristics of the kill chain functions comes into play. The kill chain is intimately connected to its threat situation. This operational context, in many ways, dictates the kill chain timeline, engagement

OODA	F2T2EA	#	Kill Chain Function
Observe	Find	1	Initial Detection
		2	Battle Damage Assessment (BDA) Detection
		3	Re-Task Detection
	Fix	4	Define Target/Threat
		5	Characterize
		6	Classify
		7	Identify
		8	Locate
		9	Validate Detection
		10	Disseminate Target /Threat Information
Orient	Track	11	Generate / Update Track
		12	Sort
		13	Determine Target / Threat Urgency
		14	Assess Blue Force Proximity
		15	Validate Target / Threat
Decide	Target	16	Nominate Engagement Option
		17	Prioritize Target / Threat
		18	Determine Time Available
		19	Maintain Track
		20	Select Attack Option
		21	Verify Rules of Engagement (ROE)
Act	Engage	22	Issue Order
		23	Attack Target / Threat
		24	Track Weapon
		25	Confirm Impact
		26	Task Re-Attack
	Assess	27	Conduct Dynamic Assessment
		28	Evaluate

TABLE 1. Derivation of 28 kill chain functions.

Characteristics of the Kill Chain Functions	
Mission-dependent: proactive or reactive	The mission will dictate whether the kill chain functions are proactive (for offensive/strike missions) or reactive (for defensive missions)
Cyclical	The functions may occur on a continuous, repeating loop; there may be multiple loops.
Dynamic	The functions are dynamic rather than static. They change in length (duration), risk (criticality), uncertainty, etc.
Architecture-dependent	The architecture of the systems involved will dictate whether functions are distributed, centralized, or a combination.
Blue force asset capabilities	The projected and actual performance of blue force assets—based on the number, different types, abilities, posture, and authority for their use will affect the ability to conduct kill chain missions (i.e., detection and tracking range of sensors, weapons performance, etc.)
Timeline	Many factors contribute to the time that can be allocated to specific functions (speed of threat, sensor detection range, weapon/asset range, engagement geometry, decision time, number of simultaneously occurring threats).
Engagement geometry	The posture, proximity, and kinematics of blue force assets in relation to red force threats will affect kill chain missions.
Level of automation	The level of automation will be selected during the engineering design process. Some functions are more conducive to being automated than others – often functions that carry more decision risk require human user involvement.
Decision-risk	Kill chain functions can be characterized by an associated level of risk that may be inherent to the function or dependent on the situation.
Threat/Situation-dependence	Kill chain functions are context dependent. The threat/situation context will dictate many aspects of how the functions are performed: how long, the risk associated, the level of uncertainty, the engagement geometry, the dynamics,
Uncertainty	Uncertainty is a critical factor affecting kill chains. There can be uncertainty in the inputs to kill chain function; and kill chain functions can introduce or increase uncertainty. Uncertainty inherent in the situation or context affects the overall kill chain process.

TABLE 2. Conditions of kill chain functions.

geometry, situational dynamics, level of uncertainty, and overall complexity. Table 2 identifies and describes conditions of the kill chain functions that affect how AI can be leveraged to increase automation and support tactical decisions.

The characteristics listed and described in Table 2 have interdependency that stems from the mission objectives, the complexity of the threat situation, and from the architecture and capabilities of the blue force assets. The nature of the mission—as offensive or defensive—establishes the initial timeline of events. The threat situation affects this timeline and affects the dynamics, level of decision risk, and overall uncertainty. The blue force assets' architecture and capabilities affects the decision options available. Kill chain decisions have many considerations ranging from sensor coverage, evaluation of adversarial intent, engagement strategies, rules of engagement, and weapons to be used. These complex and interdependent characteristics affect the acceptable level of decision-risk and uncertainty, and ultimately, the acceptable level of automation throughout the kill chain process.

This study examined and evaluated the potential of specific AI methods to enhance specific kill chain functions. The intent is to improve overall tactical missions by increasing automation—not necessarily replacing human decision-makers but supporting tactical decisions—especially as kill chain decision processes become highly complex.

Artificial Intelligence

The Department of Defense (DoD) describes AI as the "ability of machines to perform tasks that normally require human intelligence – for example, recognizing patterns, learning from experience, drawing conclusions, making predictions, or taking action – whether digitally or as the small software behind autonomous physical systems" (Allen 2020). AI is a field that includes many different approaches with the objective of creating machines with intelligence (Mitchell 2019). The field of AI is quickly advancing, and DoD is actively studying how AI can be effectively applied for military missions (GAO 2022).

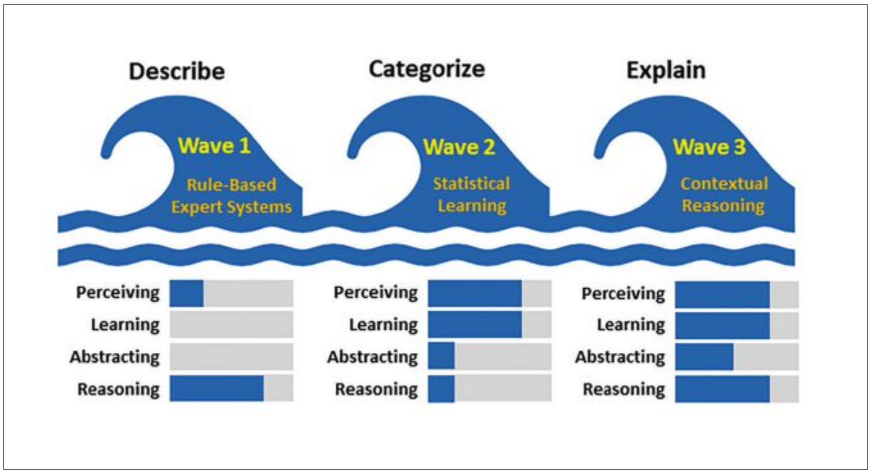

FIGURE 5. Three waves of AI advances. Adapted from Launchbury (2017).

Launchbury of DARPA (2017) describes the advancement of AI as three waves as illustrated in Figure 5. The first wave (circa 1970's–1990's) produced rule-based expert systems that could reason but did not have the ability to learn or generalize. The second wave (circa 2000's–present) has advanced statistical big data learning and deep neural nets that can perceive and learn but are limited in their ability to reason or generalize. The third wave, which is just beginning (2020's and beyond), will feature contextual adaptation and advances in reasoning and being able to generalize. Futurists predict a fourth wave (2030's and beyond) that will lead to artificial general intelligence that enables machines to perform any intellectual task that a human can (Jones 2018).

This study focused on AI methods from the three AI waves that have been demonstrated in different application domains or are currently being researched and developed. The team studied a broad range of AI-related topics (listed and described in Table 3) to provide a knowledge foundation for the evaluation.

The topics described in Table 3 are categories of approaches, disciplines, and supporting capabilities that may directly affect the ability to effectively deploy AI for the kill chain. The way in which each is implemented will dictate different aspects of the future AI-enabled kill chain. The explainability of the AI inner-workings and the ability for human-machine teaming will affect how the warfighter interacts with and trusts the AI system. Feature engineering, data management, and utility functions will affect the internal workings, and therefore outputs and decision recommendations, produced by the AI system. The ways in which the disciplines of game theory, decision theory, fuzzy logic, fusion, spatial-temporal reasoning, evolutionary and genetic algorithms, predictive and prescriptive analytics, and federated learning are incorporated will dictate the design and architecture of future AI systems. The AI-related topics in Table 3 were used for the qualitative evaluation explained in the next section of this paper.

The team selected eight specific AI methods (listed and described in Table

AI-Related Topics	Description
Explainable AI (XAI)	XAI seeks to overcome the black box issue inherent in AI systems – to provide human users insight into how AI systems arrive at outcomes (Gunning and Aha, 2019). This is critical to establish effective human-machine teaming and trust relationships.
Human-Machine Interactions (HMI) and Teaming (HMT)	HMI and HMT for decision-making related to AI systems is a large and varied field. Many AI systems will require human interaction (unless they are fully automated) (Desclaux and Prebot, 2018). Related topics include trust, explainability, level of automation, decision risk, cognitive strengths/weaknesses, etc. (Hui, 2021).
Feature Engineering	Feature engineering is a process of improving AI model performance by transforming features of the domain (or real world) into an effective representation (Nargesian, et alut, 2017).
Data Management	AI systems are intimately connected to the data they are trained on. Effective data management is needed to ensure data is secure, curated, valid, bias-free, etc. (French et al, 2021).
Utility Functions	Utility functions are used to prioritize alternatives or states based on preferences under uncertainty and/or risk. They can be used to select alternative courses of action based on strategies, preferences, perceived payoffs, acceptable level of risk, etc. (Cox 2015).
Game Theory	Game theory is the study of mathematical models of conflict and cooperation between intelligent rational decision-makers or agents (Myerson 1991). Game theoretic applications for AI have potential for wargaming and adversarial interactions. Game theory studies how rational agents maximize expected utility in situations with multiple agents.
Decision Theory	Decision theory studies how an individual agent can maximize expected utility (Cox 2015). Decision theory can take into account how decisions should be made, explanations for decisions, what decisions should be made to lead to certain objectives, and evaluations of decision alternatives based on utility functions.
Fuzzy Logic	Fuzzy logic is an AI method of reasoning that resembles human reasoning (Das 2020). It encompasses multi-valued reasoning, reasoning based on partial truths, reasoning based on inferences, fuzzy set theory (categorizing elements to a set based on degrees of membership), and non-binary (true/false) solutions.
Information and Data Fusion	Information and data fusion combine heterogeneous data from multiple and varying sensors and sources. Information and data fusion constitute a field that has been widely researched since the 1980's. The purpose it to combine data and information from different sources to produce a more meaningful understanding, awareness, and/or knowledge (Bostrom et al, 2007).
Spatial-Temporal Reasoning	Spatial-temporal reasoning conceptualizes three-dimensional relations of objects in time and space (Azuma et al, 2006). This facilitates observations of object/agent interactions and behaviors over time. It enhances contextual awareness.
Evolutionary and Genetic Algorithms	A genetic or evolutionary algorithm applies the principles of evolution found in nature to the problem of finding an optimal solution. Genetic algorithms produce many variations which can then be measured for fitness against predictive goals (survival of the fittest) (Mitchell, 1998).
Predictive and Prescriptive Analytics	Predictive analytics are methods used to predict what might happen in a given situation. Predictive analytics include historical data and modeling techniques. Prescriptive analytics are methods used to develop potential options (or courses of action) and evaluate their potential outcomes. Prescriptive analytics rely on statistical methods to generate recommendations and make decisions based on the computational findings of algorithmic models (Johnson, 2020b).
Federated Learning	Federated, or collaborative, learning is a machine learning technique that trains ML models in a distributed or decentralized architecture from different data sets (Bonawitz, et al, 2019).

TABLE 3. AI-related topics considered in this kill chain study.

4) for the kill chain mapping. These eight AI methods are different techniques that perceive, learn, abstract, and reason to gain better knowledge, predict performance, and develop and evaluate decision options (or tactical courses of action). They were identified as likely to provide value to different aspects of the kill chain process, while also representing a set of diverse AI approaches to foster a more encompassing evaluation of how AI can improve the kill chain.

Many advances in AI are currently underway. This study identified topics and specific methods of interest that show a strong potential for enhancing the tactical kill chain. This paper presents a summary of these topics and methods. More detailed descriptions of the AI topics and methods are contained in the capstone report for this study (Burns et al., 2021).

Evaluation Framework

This study developed a framework to evaluate AI methods for their applicability to specific functions of the kill chain. The evaluation includes two components: (1) a quantitative analysis from the kill chain function perspective, and (2) a qualitative analysis from the perspective of AI topics.

The first component was based on a set of four evaluation criteria in the form of decision point questions (listed in Table 5), a method for scoring (shown in Table 6), and an evaluation process associated with each of the four decision points. This component of the framework produced a quantitative evaluation in the form of points scored to indicate the level of applicability of a specific AI method for supporting or enabling a specific kill chain function. The team made subjective determinations when applying the scoring criteria.

The first decision point required an evaluation of each kill chain function to

AI Methods	Description
Linear Regression	A method to identify continuous linear relationships between input predictors (X) and output variables (Y) to develop a model that predicts a quantity.
Logistic Regression	A method to develop a model that predicts a classification or discrete class label. The model provides a maximum likelihood estimate, often as a yes/no or category 0/1 prediction.
Clustering	A method that separates datasets into groups based on similarities in properties and/or features to discover relationships and patterns within the data.
Association	A method to discover causal rules-based relationships (if-then statements) between variables by examining large datasets.
Random forest	A method consisting of many decision trees – it predicts by aggregating (often averaging) the predictions of many decision trees. It can be used for regression (predicting quantities) and classification problems (categorizing).
Neural Networks	A method that maps input (features) into output (responses) using complex (and nonlinear) transformations as data traverses through multiple layers. They can recognize hidden patterns and correlations in raw data, cluster and classify data and model highly volatile data and variances needed to predict rare events.
Generative Adversarial Networks (GAN)	A method based on deep learning and game theory that discovers regularities or patterns in input data and creates two sub-models: one that generates new examples and another that classifies examples as real or fake. The two models face off—the generator model produces novel dataset candidates with the goal of fooling the discriminator into thinking they are real (when they are synthesized).
Naïve Bayes	A probabilistic method based on applying Bayes' theorem to predict classifications (or discriminate different objects) based on certain features.

TABLE 4. AI methods of interest for this kill chain study.

#	Decision Point	Decision Point Options
1	What type of output is required?	Quantitative
		Qualitative
		Clusters
		Rules
2	What type of learning is required?	Supervised
		Unsupervised
		Reinforcement
3	What level of XAI is required?	XAI mandatory
		XAI desired
		XAI not needed
4	How many predictors (number of input features) exist?	1-9 predictors
		10-99 predictors
		100+ predictors

TABLE 5. Evaluation decision point questions.

Score	Description
+1	Method is well-suited for the task
0	Method is suited for the task but suboptimal
- 1	Method is ill-suited for the task

TABLE 6. Scoring criteria.

AI/ML Method	DP #1	DP #2	DP #3	DP #4	Total
Linear Regression	-1	-1	+1	+1	**0**
Logistic Regression	0	-1	+1	+1	**1**
Clustering	+1	+1	+1	+1	**4**
Association	0	-1	+1	+1	**1**
Random Forest	0	-1	0	+1	**0**
Neural Networks	0	-1	-1	+1	**-1**
GANs	0	-1	-1	+1	**-1**
Naïve Bayes	0	-1	0	+1	**0**

TABLE 7. Example scorecard for function #25—confirm impact

determine what kind of output is required and an evaluation of each AI method to characterize the type of output it produces. Table 5 shows the types of output for each of the decision points. Quantitative outputs contained real number values. Qualitative outputs consisted of categorical data. Output in the form of clusters refers to data grouped by strongly associated qualities that is often used for finding patterns in datasets. Rules-based outputs are series of if/then causal rules. Table 7 shows an example of a scoring evaluation of one the 28 kill chain functions, #25 "confirm impact." For this function, the team determined that clusters of data could be used to assist the characterization process and also noted that explainable output is mandatory, and the number of predictors is low to enable higher accuracy. The color scheme indicates that clustering is the best suited AI/ML method and logistic regression and association may also lend some support to the kill chain function.

The second decision point requires an evaluation of the kill chain process to determine what type of data is available and what type of learning style would be suitable for each function. If a fully labeled dataset containing predictors and response variables is available for AI training and development, supervised learning would be a suitable method. If a step in the kill chain process contains predictors in its dataset but no response variables, then unsupervised learning would be the appropriate method. Finally, if a kill chain process has partial or non-labeled datasets available and also is associated with a well-defined set of general rules that can provide feedback for training an AI learning system, then reinforcement learning would be a suitable method.

The third decision point evaluates each kill chain function according to how much explainability (or transparent insight) is needed into the inner workings of the AI method (XAI = explainable AI). For the purposes of this study, the three options were based on a qualitative assessment of requiring mandatory XAI, desired XAI, or not requiring XAI.

The fourth decision point evaluates the efficacy of specific AI methods based on the number of predictors (or features) required to adequately represent the different aspects of the kill chain process. The features that characterize the decision space associated with each kill chain function may change depending on the real-world situation. The ML model needs to represent these features and does so using input variables or predictors. The way in which the ML model represents the real world and is associated number of features will affect the choice of appropriate method. This study identified three categories of predictors based on the number of input features: 1-9, 10-99, and 100+.

The second component of the evaluation framework was based on a survey of AI-related topics and methods and a qualitative assessment of the benefits and limitations or challenges of each as they might apply to the kill chain domain. This part of the evaluation was conducted from the broader perspective of AI methods and their general applicability to the kill chain. Table 4 in the previous section lists the AI topics and methods that were evaluated.

Map of AI to the Kill Chain

The results of this study are summarized in two artifacts: the map in Table 8 that recommends the most suitable AI/ML methods for each kill chain function and the qualitative evaluation in Table 9 of the AI related approaches for the tactical domain.

The quantitative mapping shown in Table 8 is a result of the decision point evaluation of each of the 28 kill chain functions. The individual scorecards for each function can be found in the associated capstone report (Burns et al, 2021). While most scorecards resulted in a clear lead AI/ML method for suitability, there were four kill chain functions that were assessed to have more than one potential methods for selection. Of the eight scored AI/ML methods, only four scored high enough to make it into the final map: clustering, association, logistic regression, and linear regression.

Step	#	Function	AI/ML Method
Find	1	Initial Detection	Clustering
	2	Battle Damage Assessment (BDA) Detection	Clustering
	3	Re-Task Detection	Clustering
Fix	4	Define Target/Threat	Association
	5	Characterize	Clustering
	6	Classify	Logistic Regression, Association
	7	Identify	Logistic Regression, Association
	8	Locate	Clustering
	9	Validate Detection	Association
	10	Disseminate Target /Threat Information	Association
Track	11	Generate / Update Track	Clustering
	12	Sort	Linear Regression
	13	Determine Target / Threat Urgency	Linear Regression
	14	Assess Blue Force Proximity	Association
	15	Validate Target / Threat	Association
Target	16	Nominate Engagement Option	Logistic Regression, Association
	17	Prioritize Target / Threat	Linear Regression
	18	Determine Time Available	Linear Regression
	19	Maintain Track	Clustering
	20	Select Attack Option	Logistic Regression, Association
	21	Verify Rules of Engagement (ROE)	Association
Engage	22	Issue Order	Association
	23	Attack Target / Threat	Linear Regression
	24	Track Weapon	Clustering
	25	Confirm Impact	Clustering
	26	Task Re-Attack	Linear Regression
Assess	27	Conduct Dynamic Assessment	Clustering
	28	Evaluate	Clustering

TABLE 8. Map of AI/ML methods to the kill chain.

The qualitative analysis resulted in an evaluation of the AI-related approaches and topics and their relevancy to the kill chin application. Table 9 contains the results of the qualitative evaluation.

AI-Related Topic	Potential Application for Kill Chain
Explainable AI (XAI)	XAI is a critical aspect of the application of AI to the kill chain. Human warfighters relying on AI systems to support kill chain decision-making, will require an accurate and clear understanding of the automated processes and level of uncertainty associated with Ain recommendations so they can have a clear, accurate, and measured understanding of critical decisions.
Human-Machine Interaction and Teaming	Effective HMI and HMT are required for AI-enabled decision aids that have a human involved in the kill chain process. Automated kill chain systems based on AI/ML must be tailored and engineered to best suit the human warfighters for the specific weapon system and tactical operation. In some cases, the role of the human may vary depending on the kill chain function and the operational situation.
Feature Engineering	Feature engineering can be used in the "observe" functions of the kill chain to extract data features from sensor data to improve the AI system's internal representation of the real world. Feature engineering can convert raw observations into desired features that enhance model accuracy.
Data Management	Data management will play an important role during the development and training of AI/ML systems and during deployment or operations. Careful data management is required to ensure that training data is free of bias, secure, valid, and representative of future tactical real-world operations. During actual operations, data management needs to be secure and valid, and sources of error and uncertainty need to be tracked.
Utility Functions	Utility functions can be used to establish preferences and prioritization in kill chain functions that require the selection of an option among different alternatives. Kill chain functions 13 (determine target/threat urgency), 16 (nominate engagement option), 17 (prioritize target/threat), and 20 (select attack option) are examples.
Game Theory	A game theoretic approach considers decision-making during multi-agent interactions. Game theory for the kill chain would model the adversary's capabilities and possible intent, strategies, and courses of action. In theory, the AI system leveraging game theory could act as a real-time wargaming decision aid that plays out possible courses of action from both the blue (friendly) and red (adversary) sides to test out different tactics and strategies.
Decision Theory	The field of decision theory lends insights and approaches that are relevant to the kill chain domain. These include: (1) frameworks for applying utility functions, (2) incorporating risk analysis into decision-making, (3) addressing uncertainty, (4) considering human and machine decision-making, and (5) handling agent interaction and optimization.
Fuzzy Logic	A fuzzy logic approach to the kill chain brings different forms of reasoning into the decision-making. Fuzzy logic mimics human reasoning under uncertainty, can reason using partial truths, and can make inferences about unknowns.
Information and Data Fusion	The kill chain domain often has a variety of data sources from different types of sensors. The fusion of data and information is a key enabling capability that will be required to best support and AI/ML approach to the kill chain functions. It can also provide dimensionality reduction, reduce ambiguity and noise in the data, and support limited bandwidth conditions.
Spatial-Temporal Reasoning	Spatial-temporal reasoning is required for the dynamics of the kill chain. This type of reasoning can be applied to the kinematic nature of objects in the tactical domain that are moving with respect to one another. It is especially relevant for the kill chain functions for tracking target threat objects and determining engagement geometries. This type of reasoning can conceptualize three-dimensional relations of objects in time and space and facilitates object/agent interactions and contextual awareness.
Evolutionary and Genetic Algorithms	Genetic algorithms can generate a variety of COA kill chain options and evolutionary algorithms can determine which options are fittest or most effective for the kill chain. While these techniques are novel, this area of research may be useful for future kill chains.
Predictive and Prescriptive Analytics	The combination of predictive and prescriptive analytic methods can facilitate large-scale, high-fidelity simulations that present the warfighter with multiple scenarios, and potential actions and outcomes. These techniques may be particularly useful for more complex tactical scenarios involving multiple threats, a variety of blue force weapon and warfare assets to select from, and when different tactics (countermeasures, jamming, evasion, strikes, etc.) may be possible.
Federated Learning	A federated learning approach may be beneficial for distributed kill chain architectures involving multiple decentralized command and control systems and geographically distributed warfare systems. Future AI solutions for kill chains may involve multiple AI systems collaborating and requiring an integrated response. Federated learning may provide an architecture to support multiple AI systems functioning to support a system of systems kill chain.

TABLE 9. Qualitative evaluation of AI-related topics for the kill chain.

Conclusion

In conclusion, this mapping analysis was conducted in two directions: (1) starting with the kill chain and mapping AI methods to the individual kill chain functions, and (2) starting with AI approaches and related topics and evaluating their potential utility to the kill chain. The first approach, developed by this research team, followed a quantitative scoring method using four decision points. The second approach canvassed a variety of AI approaches and related topics and qualitatively evaluated each for its potential relevancy to future AI-enabled kill chain decision aids.

The quantitative analysis revealed that a small set of AI methods would be the best candidates to provide advanced automated support for kill chain functions. These methods were: clustering, association, logistic regression, and linear regression. Their assessed superior utility to the kill chain was based on the type of output they produce, the type of machine learning they use, their ability to be explainable to the user, and the number of representative predictors or features they need. This analytical mapping method is "bottom up" in the sense that the starting point is the traditional set of kill chain functions. It assumes that individual AI methods will be binned into individual independent kill chain functions. This presupposes a particular design solution and places a restriction on the future architecture of kill chain decision-aids.

The second mapping analysis, which was qualitative and high-level, imagined the future potential for a variety of AI approaches and related topics to enable and/or support a future AI-enabled decision aid for the kill chain. This analysis approach is "top down," as it starts with a type of AI methodology or field of interest and evaluates its general relevancy to the kill chain holistically without imposing a particular design or being assigned to a particular function. This analysis identified 13 AI-related topics that may provide utility to future kill chains.

AI is emerging as a technology for many military applications. The Navy stands to gain from the use of AI for many operations, including the kill chain. The effective and appropriate design and engineering of AI-enhanced and/or AI-enabled kill chains is critical to achieving tactical superiority over peer competitors and for ensuring safety and reliability for its use in support of weapon systems. This project provides an analytical foundation as a starting point for continued research into the application of AI for the kill chain. The analysis mapped specific AI methods to the 28 functions of the kill chain and identified AI approaches and related topics that show potential for enhancing and enabling the future naval kill chain. This study recommends continued research into the use of AI and ML for the tactical kill chain. NEJ

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