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Integrating Artificial Intelligence into Naval Capability Development

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ABSTRACT: The rapid advancement of artificial intelligence (AI) is transforming naval capabilities, reshaping ship design, lifecycle management, operational decision-making, and autonomous maritime systems. Naval platforms are among the most complex engineered systems, characterised by long service lives, safety-critical functions, and demanding operational environments, making AI integration both strategically attractive and technically challenging. This paper presents an engineering-oriented review of AI applications in the naval domain, focusing on their role across the capability development lifecycle. To illustrate practical implementation, a Random Forest regression model is developed to support early-stage prediction of the block coefficient of naval ships. The review highlights significant opportunities associated with AI integration, including enhanced decision-making, improved design efficiency, and increased operational effectiveness. However, successful AI adoption requires technological advancement alongside organisational adaptation, strong governance, and sustained investment in human expertise. AI should therefore be understood not as a replacement for naval engineering expertise, but as a force multiplier that augments analytical capacity and accelerates innovation across the maritime domain.

1 INTRODUCTION

Naval forces operate among the most complex engineered systems developed by modern societies. Warships, submarines, and associated maritime systems are characterised by long service lives, harsh and uncertain operating environments, strict safety requirements, and continuously evolving mission profiles. In parallel, Artificial Intelligence (AI) has gained prominence as a general-purpose technology with both civilian and military significance. Contemporary naval forces are therefore witnessing rapid and transformative technological changes that affect nearly all aspects of naval warfare and maritime security. Advances in unmanned systems, automation, and digitalisation, together with other disruptive technologies such as AI, are fundamentally reshaping how naval capabilities are designed, developed, and employed. This transformation is not a distant prospect but an ongoing process that is already influencing operational doctrines and force structures. As global competition in military technology intensifies, remaining passive or delaying adoption of these technologies is no longer a viable option for modern navies. AI has emerged as one of the primary drivers of this technological evolution. Its ability to process vast amounts of data, identify patterns, support decision making, and enable autonomous or semi-autonomous systems provides significant advantages across the full spectrum of naval activities. Recent military conflicts, most notably the Russia-Ukraine war, have demonstrated the practical utility of AI-enabled systems in operational environments. AI has been employed extensively in unmanned platforms for tasks such as object detection, tracking, target recognition, mission planning, and real-time decision support. These developments underscore the growing importance of AI not only in combat operations but also in upstream processes such as capability development, system design, acquisition, and lifecycle management.

In this context, the main objective of this work is to review and analyse the influence of artificial intelligence on naval capability development across a broad range of domains. These domains include naval ship design, naval project management, maintenance and sustainment, education and training, simulations, operational employment of naval forces, including intelligence, surveillance, reconnaissance, and the implementation of maritime unmanned systems. The literature review was conducted using a structured narrative approach aimed at capturing recent and relevant developments in artificial intelligence applications within naval capability development. Scientific and professional publications were identified through searches of major academic databases, including Scopus, Web of Science, IEEE Xplore, and ScienceDirect, supplemented by targeted searches of defence and maritime research repositories. The review focused primarily on publications from 2015 to 2025 to reflect contemporary technological maturity, with emphasis on peer-reviewed journal articles, conference proceedings, and authoritative technical reports. Sources addressing purely generic or non-maritime AI applications were excluded unless they provided transferable methodologies or concepts applicable to naval engineering contexts. The selected literature was analysed qualitatively and synthesised thematically to identify dominant application areas, enabling technologies, maturity levels, and technical, organisational, and regulatory challenges. This approach enables a comprehensive yet focused assessment of AI integration trends and challenges specific to naval engineering and maritime defence systems. In addition to the literature review, a practical use case is presented to illustrate the real-world application of AI methods in naval engineering. Specifically, the use case demonstrates the prediction of a ship's block coefficient using a Random Forest Model, representing one of the many AI-based tools applicable to data regression problems in naval ship design. The available literature is systematically analysed and synthesised to provide a comprehensive overview of current research trends, technological capabilities, and implementation challenges. By consolidating findings from diverse sources, this paper aims to identify both the opportunities and limitations associated with AI integration into naval capability development, with particular attention to application maturity and potential impacts on operational effectiveness, cost efficiency, and decision-making processes.

The remainder of the paper is structured as follows. Section 2 presents definitions and classifications of artificial intelligence relevant to the naval domain. Section 3 provides a comprehensive review of existing literature related to AI applications in naval project management, naval ship design, maintenance and logistics, training and education, simulations, AI-enabled naval operations, and maritime unmanned systems. Section 4 addresses key challenges associated with integrating AI into naval capabilities, including organisational adaptation, platform integration, lifecycle sustainment, training requirements, and considerations for future development. Section 5 presents a detailed use case of AI-based Random Forest modelling for block coefficient prediction in naval ship design. Finally, Section 6 summarises the key findings, discusses implications for naval planners and strategists, provides recommendations, and outlines directions for future research.

2 DEFINING AND CLASSIFYING AI TECHNOLOGIES

2.1 *General importance of AI*

Artificial Intelligence has emerged as a pivotal technology in the military sphere, with leading nations recognising its potential for rapid integration across defence and national security domains. AI is transforming the global security environment by enhancing military effectiveness while simultaneously accelerating the pace and complexity of emerging threats, thereby influencing collective defence, crisis management, and cooperative security. As advances in AI diffuse quickly from civilian to military applications, control over intelligent systems is likely to confer a decisive advantage in future warfare. Consequently, the military application of AI has the potential to disrupt existing balances of power and challenge strategic stability and deterrence among major powers. The following text presents several statements from the literature highlighting the importance of AI. In [51] United States views its pursuit of AI primacy as a critical element in safeguarding the nation against military, scientific, economic, and political threats. Under Xi Jinping, the People's Liberation Army (PLA) is directed to become a world-class military by mid-century, with AI seen as central to this goal [25]. Ukraine aspires to be among the top three countries in the world by 2030 in both AI development and practical adoption [41]. The UK must adopt and exploit AI at pace and scale for Defence advantage, establishing AI as one of our top priorities and a key source of strategic advantage [48]. The Russian view on AI importance considered through citation "The creation and development of systems is currently becoming one of the most important areas of scientific and technological progress, the very fundamental technology that can radically change the nature of not only armed struggle, but also the whole essence of power confrontation between states, including economic, information and cyber war" [6].

2.2 *Definitions and classification of AI*

In accordance with [39], AI is a set of interrelated technologies used to solve problems and perform tasks that, when performed by humans, require thinking. In addition, Artificial Narrow Intelligence (ANI), also referred to as weak AI or narrow AI, is the only type of artificial intelligence we have successfully realised to date. Narrow AI is goal-oriented, designed to perform singular tasks, i.e., facial recognition, speech recognition/voice assistants, driving a car, or searching the internet, and is highly intelligent at completing the specific task it is programmed to do. Machine Learning

(ML) uses statistical techniques to enable computer systems to recognise patterns in data without explicit programming. This pattern recognition can be used as a basis for AI implementation. Machine learning can be achieved through a range of methods that may not be specific to a task.

Artificial Intelligence is the computational science field of research that focuses on machine learning and smart decision-making. It is a major component of robotics R&D. This includes contributions from fields such as machine learning, natural language processing, pattern recognition, cluster algorithm improvement, and agent technology [38]. AI is the capability provided by algorithms of selecting optimal or suboptimal choices from a wide possibility space, to achieve goals by applying strategies that can include learning or adapting to the environment [51]. In accordance with [41] NIAG (NATO Industrial Advisory Group) Study Group SG-238 AI definition is: Artificial Intelligence refers to systems designed by humans that, given a complex goal, act in the physical or digital world by perceiving their environment, interpreting the collected structured or unstructured data, reasoning on the knowledge derived from this data, and deciding the best action(s) to take (according to pre-defined parameters) to achieve the given goal. AI systems can also be designed to teach people how to adapt their behaviour by analysing how the environment is affected by their previous actions. NATO Bilateral Strategic Command (BI-SC) final report on Joint Air Power Capabilities (JAPC) turned to the definition of the NIAG SG-231: Artificial Intelligence is the ability of a nonbiological system to achieve any complex goal through processes comparable to human cognitive processes, such as perception, deduction, recognition, memorisation, and learning. Machine learning is one of the most important technical approaches to AI and the basis of many recent commercial applications of AI. Modern machine learning is a statistical process that starts with data and tries to derive a rule or procedure that explains the data or can predict the future. Deep Learning is a subspecialty of Machine Learning that has yielded some notable successes in the development and prototyping of autonomous systems/vehicles. Deep learning uses structures loosely inspired by the human brain, consisting of a set of units (or "neurons"). Each unit combines a set of input values to produce an output value, which in turn is passed on to other neurons. Deep learning networks use many layers, and often use many units at each layer, to enable the recognition of extremely complex, precise patterns in data [7].

In conclusion, artificial intelligence encompasses a range of interconnected technologies that enable nonbiological systems to perceive, reason, learn, and act to achieve complex goals in ways comparable to human cognition. While current AI is primarily realised as Artificial Narrow Intelligence (ANI), focused on specific tasks, its capabilities are largely driven by machine learning and deep learning techniques that extract patterns from data to support intelligent decision-making. Together, these approaches form the foundation of modern AI applications across domains such as robotics, autonomous systems, and data-driven problem-solving.

3 CONTEMPORARY USES OF AI IN THE DEVELOPMENT OF NAVAL CAPABILITIES

3.1 *AI in ship design and project management*

Artificial Intelligence may enhance defence contracting processes, including naval projects, by addressing inefficiencies in the US DoD's (Department of Defense) slow and complex procurement system [43]. The study proposes using AI, particularly natural language processing (NLP) and machine learning (ML), to automate routine contract management tasks, analyse and generate documentation, and reduce administrative burden while improving consistency and compliance. AI-driven tools could streamline approvals, flag issues, and provide predictive insights based on historical data to support better contract strategies. Overall, adapting commercial AI contract management systems for DoD use could modernise procurement by increasing efficiency, reducing errors, and accelerating acquisition timelines. Fig. 1 presents the R.A.F.T. AI assistant, which is used throughout all phases of the acquisition process.

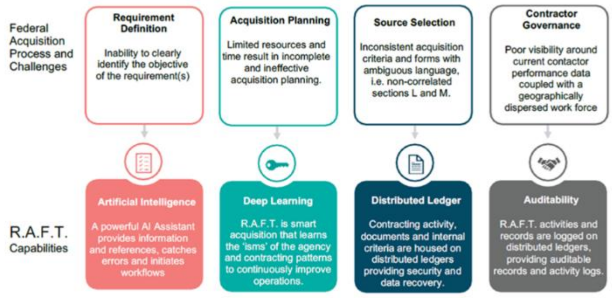

Figure 1. Acquisition Challenges and R.A.F.T. Solutions (Source: [43])

The paper [10] proposes a naval project management system that integrates generative AI and machine learning across the entire project lifecycle, from design to launch. Generative AI is used to automate key functions such as document analysis, activity planning, cost and timeline forecasting, and risk management, reducing manual effort and improving accuracy. AI-driven modules can extract regulatory and technical information, optimise schedules and resource allocation using historical data and optimisation algorithms, and enhance forecasting by identifying patterns from previous projects. The system also supports proactive risk management by analysing performance data and regulatory changes. The authors apply Adaptive Structuration Theory (AST) to explain how managers can adopt these technologies. A modular microservices and event-driven architecture is proposed to ensure flexibility, scalability, and maintainability in complex naval projects.

The modernisation of the Indian Navy increasingly involves cutting-edge technologies where AI plays a significant role in future naval capabilities, a domain in which micro, small, and medium enterprises (MSMEs) and technology partners are expected to contribute through research, design, and innovation. AI-enabled combat systems and autonomous platforms are central to next generation naval technologies, improving situational awareness and decision-making at sea. AI integration enhances the Navy's operational effectiveness by processing vast sensor data for faster threat detection, predictive maintenance, and optimised mission readiness. AI is considered a cornerstone of naval modernisation efforts, powering autonomous unmanned systems, automating complex tasks, and empowering more agile and resilient maritime operations [37].

The DAS (Daewoo Shipbuilding Scheduling) project implemented a neural network (NN) based person-hour estimator to provide reliable estimates of man-hour requirements for different assembly tasks, which traditional methods could not capture accurately due to complex, nonlinear relationships between work factors. This neural estimator was integrated into the broader intelligent scheduling architecture to improve planning accuracy and support dynamic scheduling decisions in the shipyard. By embedding neural networks within the scheduling system, the DAS approach enhanced the overall scheduling performance and productivity in shipbuilding operations, contributing to more effective long term and shop-floor scheduling outcomes [27].

Article [17] explains that artificial intelligence is a core enabler of digital twins (DT) for warship systems, allowing virtual models to evolve dynamically by learning from real-time and historical sensor data. Machine learning and AI algorithms are used to analyse large volumes of shipboard data to support predictive maintenance, anomaly detection (AD), and performance deviation analysis, and moving digital twins beyond static simulations. AI enhances digital twins by continuously recalibrating behaviour models, improving diagnostic accuracy, and enabling prescriptive decision-making for maintenance and operations. The integration of AI also enables higher-level system understanding through data-driven prediction and optimisation across the warship lifecycle. AI transforms digital twins into intelligent, adaptive systems that improve operational readiness, lifecycle management, and decision support for complex naval platforms.

The review [23] outlines diverse AI and machine learning techniques applied to ship design, with deep neural networks (DNN) widely used as surrogate models to predict ship resistance at near CFD accuracy but far lower computational cost. Generative models such as generative adversarial networks (GAN) and variational auto encoders (VAE), combined with optimisation algorithms, support automated hull-form exploration and resistance reduction. Physics-informed and hybrid ML approaches, along with methods such as support vector machine (SVM) and ensemble trees (ET), enhance robustness when data are limited, while genetic and evolutionary algorithms remain key for multi-objective structural optimisation. Emerging methods such as reinforcement learning (RL) and graph neural networks (GNN) further expand capabilities in sequential design decision making and fast structural response prediction.

The authors develop a deep learning neural network (DLNN) model to assist with the preliminary design of ship hull structures by enabling real-time prediction of total resistance based on geometric modification parameters, dramatically reducing reliance on computationally intensive CFD calculations. The trained model demonstrated high accuracy in predicting resistance within the design space, with an average testing error below 4%, and can be used interactively during early design phases. This AI-based approach represents a foundational step toward integrating artificial intelligence into naval architecture workflows to streamline hull design and performance evaluation [2].

An AI-based approach that employs neural networks and case-based reasoning (CBR) to automate metallographic analysis for assessing metal quality in shipbuilding, improving traditional manual diagnostics, is presented in [15]. Their multilayer neural network accurately identifies and quantifies metal microstructures, enabling the reliable determination of metal grades. The developed AI-driven software demonstrates high accuracy and offers a practical tool to streamline quality assessment in shipbuilding processes.

The paper [31] develops a multi-attribute concept design procedure for generic naval vessels that integrates a self-balanced concept design model with a genetic algorithm (GA) (artificial intelligence evolutionary computing) and Pareto optimal search to generate and evaluate balanced design solutions. The methodology uses a set of geometric, tactical, and technical design variables to produce designs that are evaluated on attributes such as life cycle cost and overall measure of effectiveness, identifying a set of non-dominated (Pareto optimal) solutions.

Using an artificial neural network (ANN) model, the authors try to improve the ship preliminary design process with the aim to speed it up using minimal resources. Fig. 2 presents the training data set and predicted design parameters such as length, breadth, and displacement of a ship. The method used provides very good accuracy of predicted data using only two input parameters and shows the efficiency of the applied AI method [33].

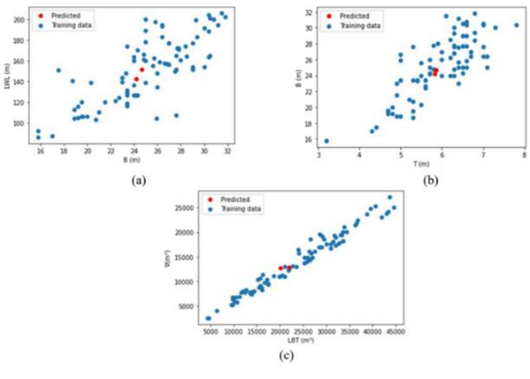

Figure 2. Predicted ship design parameters using the ANN model (Source: [33])

Grech La Rosa in [20] investigates how generative artificial intelligence (GAI) can be integrated into the early stages of concept ship design to support designers in handling complex tasks and decision-making that traditionally rely on approximation and expert judgment. It explores the potential of GAI tools to enhance various aspects of design workflows, including weight grouping, payload catalogues, technical analysis, and layout configuration to improve performance, sustainability, and inclusivity. The authors use a case study to examine how outputs from GAI models (e.g., text and image generation) can contribute constructively to design development and evaluation. This exploratory work highlights the opportunities and challenges of incorporating GAI into naval architecture and suggests that such tools could become valuable aids in conceptual design processes.

The work [9] reviews the use of artificial intelligence across the ship lifecycle, including design, manufacturing, operation, and maintenance. Machine learning and optimisation methods improve decision making, reduce trial-and-error processes, and accelerate design cycles. In early design stages, AI supports performance prediction and rapid exploration of design alternatives. During manufacturing, AI enhances CAD/CAM automation, anomaly detection, and quality control, improving efficiency and accuracy. In operation and maintenance, predictive analytics help forecast failures and optimise maintenance schedules. The article also highlights the role of deep learning (DL) and reinforcement learning (RL) in improving complex structural and hydrodynamic optimisation tasks.

The study [35] reviews AI applications across all phases of ship design, from concept development and detailed analysis to production and performance optimisation. It finds that machine learning, data analytics, and automation are increasingly used to reduce time and cost while improving the quality and reliability of design outcomes beyond conventional methods. AI is also applied in shipyards to enhance production planning and resource allocation, as well as to optimise operational performance, including fuel efficiency and lifecycle costs. However, the authors emphasise that further efforts are needed to bridge the gap between research advances and practical implementation.

The literature identifies three main categories of AI applications in naval ship design and project management: administrative and decision support automation, data-driven design optimisation, and lifecycle performance prediction. Initial adoption has concentrated on administrative tasks such as procurement, scheduling, and cost estimation, where AI offers efficiency gains with relatively low risk. More advanced uses involve machine learning and generative methods to optimise design spaces, particularly in early design stages where uncertainty is high and traditional tools are computationally demanding. To conclude, the most effective implementations combine AI with established naval architecture methods, emphasising hybrid and physics-informed approaches while recognising that lifecycle applications depend on strong data integration and organisational readiness.

3.2 *AI in naval operations*

The systematic review in [47] examines the integration of AI into naval operations, particularly in surveillance and reconnaissance for early threat detection. It highlights techniques such as deep learning, convolutional neural networks (CNN), and other machine learning models that improve object recognition, anomaly detection, and real-time maritime data analysis. The study shows that combining AI with radars, satellites, UAVs, and predictive models enhances early warning capabilities and enables more proactive defence responses, with applications including unmanned vessels and nano drones. While AI significantly strengthens operational effectiveness, the authors emphasise the need for continued investment in infrastructure, training, and interoperability standards [47].

The paper [13] provides a survey of current AI advancements in the Navy. It presents practical examples of AI use in the Navy, including productivity, navigation, logistics, threat detection, and training. As autonomy increased, research attention shifted toward human-machine interaction, explainable AI (XAI), and trust in AI-enabled systems.

Talpur et al. in [46] review recent deep learning–based AI techniques for maritime security, focusing on improved surveillance, threat detection, and situational awareness. They note that traditional methods such as radars, satellite imagery, and patrol vessels face coverage gaps and data overload, which deep learning models, including convolutional neural networks, recurrent neural networks (RNN), and transformers, help address by analysing satellite, AIS, SAR, radar, and unmanned sensor data. These systems enhance vessel classification, anomaly detection, and multimodal data fusion (DF), supporting identification of illegal activities and advanced functions such as real-time tracking and behaviour recognition. The authors conclude that deep learning is transforming maritime domain awareness, while emphasising the need to overcome data, computational, and interpretability challenges.

Vasankari & Saastamoinen in [49] investigate the use of multi-agent reinforcement learning (MARL) to support tactical decision making in complex littoral naval combat environments, where real-world data are limited, and conditions are dynamic and partially observable. They model engagements as partially observable stochastic games and implement double deep Q networks (DDQN) and proximal policy optimisation (PPO) algorithms to learn effective tactical policies under uncertainty. Through simulation-based training, agents can explore and evaluate alternative strategies without relying on extensive empirical datasets. The results indicate that MARL can reinforce existing doctrines while also generating novel strategic options, highlighting its potential to reshape naval decision-making processes.

Johnson in [24] examines how AI can enhance the naval tactical kill chain by supporting complex, time-critical decisions under uncertainty. Using models such as the OODA (Observe-Orient-Decide-Act) loop and F2T2EA (Find-Fix-Track-Target-Engage-Assess), the study maps 28 tactical functions to relevant AI approaches, including machine learning, data fusion, and cognitive AI (CAI) for tasks to support capabilities such as target detection, classification, and engagement assessment. It also considers broader approaches like explainable AI and human-machine teaming to improve decision support and operational performance. While AI shows promise for strengthening kill chain effectiveness, further research is needed to refine methods, ensure integration, and guarantee safe deployment.

A systematic review examining how AI is used to enhance cybersecurity in maritime environments, particularly for protecting vessels, ports, and maritime communication networks from sophisticated cyber threats, is presented in [34]. The review identifies and analyses key AI techniques such as machine-learning-based intrusion detection systems (IDS), anomaly detection, predictive threat modelling (PTM), and AI-enhanced zero-trust architectures that improve real-time threat detection and automated responses. While AI-driven approaches have shown notable effectiveness in identifying cyberattacks and improving defensive capabilities, the article highlights significant challenges, including data scarcity, lack of maritime-specific datasets, and vulnerability of AI models to adversarial attacks. To overcome these limitations, future research is recommended to focus on large scale maritime datasets, adversarial robustness, explainable AI (XAI), and integration with advanced technologies like federated learning, blockchain, and quantum cryptography.

Schubert et al. in [40] emphasise that AI can enhance military command and control (C2) decision support, particularly in time critical and complex scenarios. Based on user-centred workshops with military personnel, the study identifies key areas for AI support, including building a common operational picture, threat analysis, and evaluating alternative courses of action. Techniques such as information fusion (IF), natural language processing (NLP), and learning based analysis can improve data categorisation, anomaly detection, and planning through simulation-assisted evaluation. While AI is not intended to replace human commanders, it can significantly increase analytical speed and depth and offer operational advantages if effectively integrated into C2 systems.

Francavilla & Armstrong in [18] analyse how AI is transforming naval warfare by enhancing decision making, surveillance, and combat systems through real-time sensor processing and integration of manned and unmanned platforms. They outline varying levels of autonomy, from human-in-the-loop to human-out-of-the-loop systems, stressing the need for human oversight to ensure ethical and legal compliance. AI applications, including autonomous vehicles and geospatial systems such as SatShipAI, improve maritime intelligence, anomaly detection, navigation, logistics, and predictive maintenance. The authors conclude that successful integration of AI in naval operations depends on robust training, ethical frameworks, international cooperation, and sustained technological investment.

Absalon in [1] argues that integrating AI into submarine platforms can enhance operational effectiveness by improving prediction, detection, and decision-making capabilities. AI-driven predictive maintenance increases reliability and availability, while machine learning improves sonar data analysis and contact classification. AI-based tactical decision aids and sensor fusion support faster, data-informed manoeuvring and combat system responses, reducing crew cognitive load. However, successful implementation requires careful design of human-machine interfaces, trust in autonomous systems, and rigorous operational testing.

The deep learning approaches for classifying warship images using a unique dataset from the UK National Museum of the Royal Navy are investigated in [3]. Several pre-trained convolutional neural networks were evaluated, achieving high accuracy in both coarse and fine classification tasks. The use of a Grad-CAM enhanced model interpretability, enabling archivists and curators to better understand classification decisions. It could aid cultural heritage preservation through automated cataloguing of historical photographs and assist naval training by providing visual recognition tools. The methodology can be extended to broader maritime and defence applications, such as identifying ship types in intelligence, surveillance, and reconnaissance (ISR) imagery, monitoring naval fleets, and supporting maritime domain awareness.

AI is becoming a central component of modern naval operations, enhancing capabilities across surveillance, decision-making, combat, cybersecurity, and training. It improves maritime domain awareness through real-time anomaly detection, vessel classification, and predictive analytics, while also supporting tactical decision making and the operational kill chain by enabling simulations, reinforcement learning, and human-machine teaming. AI integration into platforms such as submarines and autonomous vessels enhances predictive maintenance, sensor fusion, and operational efficiency, though effective deployment requires trust, rigorous testing, and well-designed human-machine interfaces. Beyond operational uses, AI contributes to cybersecurity and cultural heritage management, showing its versatility across defence and analytical domains. Overall, AI can significantly strengthen naval effectiveness, but its success depends on investments in infrastructure, training, ethical oversight, and seamless integration across systems.

3.3 *Use of AI in unmanned naval vehicles*

The state-of-the-art path planning techniques for unmanned surface vehicles (USVs) are reviewed in [54]. It highlights how artificial intelligence methods such as neural networks and reinforcement learning are increasingly integrated to enhance navigation autonomy and decision-making in complex marine environments. AI-based approaches, including deep Q-networks and hybrid machine learning models, help USVs dynamically adjust paths in response to obstacles and environmental conditions by learning optimal strategies from sensor data. These intelligent algorithms improve the ability to handle unknown or changing scenarios compared with traditional search and optimisation methods, enabling real-time obstacle avoidance and more efficient trajectory generation. The review identifies limitations in current AI-driven methods, such as insufficient modelling of sea factors, and suggests future research directions that incorporate environmental dynamics into AI path planners to further boost performance.

The development of autonomy in unmanned surface vehicles with particular emphasis on intelligent collision avoidance manoeuvres that aim to reduce reliance on human intervention is examined in [8]. It highlights that integrating AI techniques, such as neural networks, fuzzy logic (FL), and other intelligent control and optimisation methods, can enhance USV perception, decision making, and compliance with the International Regulations for Preventing Collisions at

Sea (COLREGs) by enabling automatic recognition and response to dynamic obstacles. These AI-driven approaches address challenges inherent in open marine environments, including the classification of static versus moving obstacles and the adaptation of avoidance strategies in real time. It underscores the need for further research to improve the robustness and fail-safety of intelligent collision avoidance systems as part of broader autonomy goals for USVs.

The overview [53] provides a comprehensive presentation of developments and challenges in autonomous berths of unmanned surface vehicles (USVs), emphasising that intelligence and automation are critical for reducing human intervention and improving safety in complex marine environments. It discusses how advanced sensing, multi-sensor fusion, and intelligent decision-making systems, often supported by artificial intelligence techniques, enable USVs to perceive berthing scenarios, assess risk, and plan collision-free approaches without human control. The paper also highlights the importance of adaptive autonomy levels and real-time environmental modelling in handling uncertainties and dynamic conditions during autonomous berthing operations. Fig. 3 shows the neural network berthing control process.

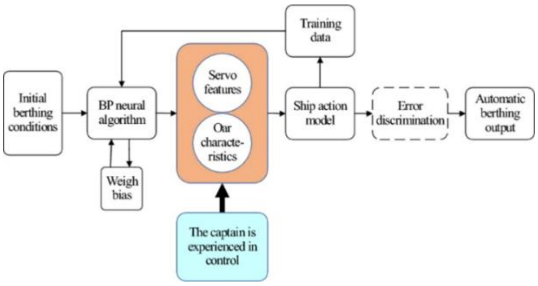

Figure 3. Neural network berthing control process (Source: [53])

A novel application of deterministic artificial intelligence (DAI) for autonomous control of remotely operated ocean vehicles, showing how integrating model-based AI with optimal learning enhances vehicle guidance and control performance, is shown in [36]. Unlike traditional stochastic or feedback-only controllers, the proposed DAI approach embeds the physical governing equations of the system into the control law and combines this with learning to adapt to dynamic changes, enabling highly precise heading control. Simulation results for a Seabotix vLBV 300 remotely operated vehicle demonstrate that the DAI controller achieves millidegree accuracy on initial heading commands and significantly reduces error over subsequent manoeuvres. The work suggests that physics-aware AI control can substantially improve the autonomous and remote operation of underwater vehicles in challenging environments.

The concept of human-centred explainable artificial intelligence (XAI) for marine autonomous surface vehicles (ASVs), emphasising the importance of interpretability, understandability, and trust in AI systems for broader real-world deployment beyond expert users, is introduced in [50]. It argues that as ASVs become more common, AI models must not only perform effectively but also be explainable and aligned with user values to support safety and user confidence. Drawing on examples from recent research, the authors structure human-centred XAI through cognitive processes such as analogy, visualisation, and mental simulation to illustrate how AI decisions can be made more transparent to diverse stakeholders. The work highlights that improving explainability not only aids developers but is essential for trust and interaction among passengers, other vessels, and remote operators in autonomous maritime contexts.

An extensive review of route planning and collision avoidance algorithms developed for unmanned surface vehicles, covering both simulated and real-world applications from the early 2000s to the present, is shown in [21]. It categorises these methods into global and local planning approaches and highlights trends in algorithm evolution, including the increasing use of hybrid strategies that combine different techniques to improve performance. The authors emphasise the importance of validating algorithms in real maritime environments as well as simulations to fully assess reliability, adaptability, and operational effectiveness. Key algorithmic paradigms such as artificial potential fields (APF), reinforcement learning, and fuzzy logic are identified as particularly promising based on their evaluation in diverse scenarios.

A ship target detection method tailored for unmanned surface vehicles (USVs) using the deep learning object detector EfficientDet, aiming to improve perception performance in complex maritime environments where reflections, haze, and lighting variations make detection challenging, is proposed within [28]. The authors highlight that the method is effective for identifying both static and dynamic ships on the water surface, improving USV situational awareness. They also discuss potential applications in autonomous navigation and maritime threat assessment, suggesting the approach provides a useful benchmark for USV perception systems. Fig. 4 shows the image of the ship targets from the USV.

Figure 4. The image of the ship targets from the USV. (Source: [28])

A Universal Autonomous Control and Management System (UACAMS) for a multipurpose unmanned surface vessel that enables operation from manual remote control to fully autonomous missions are presented in [45]. AI is applied through layered autonomy (LA) modules that perform sensor data fusion, environment perception, adaptive path planning, and collision avoidance. The system continuously interprets inputs from radar, LiDAR, sonar, and navigation sensors to support real time autonomous decision making without human intervention. AI-based control logic allows the vessel to dynamically modify its behaviour in response to environmental changes and mission objectives, which was validated during real-world sea trials.

Artificial Intelligence is becoming central to autonomy in unmanned naval vehicles, especially through neural networks, reinforcement learning, and hybrid control methods that improve navigation, collision avoidance, and perception. These systems enable adaptive decision-making, real-time obstacle avoidance, and more efficient trajectory planning in complex and dynamic marine environments. However, many AI models remain limited by weak integration of sea state dynamics, physical constraints, and real-world uncertainties, reducing their reliability outside simulations. Physics-informed and deterministic AI offer improvements by combining learning with physical system models, enhancing precision, stability, and control performance. At the same time, explainable and human-centred AI is increasingly important to ensure trust, safety, and regulatory acceptance. Despite clear progress, wider deployment requires more robust environmental modelling, explainability, and validation in real operational conditions.

3.4 *Discussion*

Table 1 provides an overview of how artificial intelligence is being integrated across different areas of naval capability development, spanning design activities, operational use, and unmanned systems. Synthesising the reviewed literature according to the thematic framework defined in the above sections reveals distinct patterns in the maturity and role of artificial intelligence across naval capability development domains. In ship design and project management, AI applications are predominantly decision support tools that augment early-stage design exploration, scheduling, and cost forecasting, reflecting relatively high technical readiness and low certification risk. In contrast, operational and command and control applications prioritise real-time data fusion, pattern recognition, and decision support under time pressure, where performance gains are significant, but trust, explainability, and human oversight remain critical constraints. For unmanned naval vehicles, the literature demonstrates the highest levels of AI maturity, with autonomy, perception, and path planning functions increasingly validated through simulation and sea trials. Across all domains, the review highlights a consistent transition from isolated, task-specific AI solutions toward more integrated, lifecycle-spanning systems, while simultaneously underscoring that full operational acceptance depends on human-AI teaming, verification and certification frameworks, and organisational adaptation rather than algorithmic performance alone.

Table 1. AI applications in the naval capability area (Source: The authors)

Section	Application type	Application description	Supporting AI techniques
Ship Design & Project Management	Contracting & Procurement	Automation of procurement documentation, compliance checks, and analysis of historical contracts	NLP, ML
	Naval Project Management & Scheduling	Optimised activity planning and resource allocation across complex projects	GAI, ML, AST
	Cost & Timeline Forecasting	Prediction of project costs and delivery timelines	GAI, ML
	Risk & Requirement Management	Early identification of risks and requirement conflicts	ML, GAI
	Shipyard Scheduling	Estimation of person-hours and dynamic production scheduling	NN
	Ship Design Optimisation	Hydrodynamic and structural optimisation of hull forms	DNN, GAN, GA, RL, GA, DLNN, VAE, SVM, GAI, ET, GNN, ANN
	Quality Control	Automated metallographic analysis for material quality assessment	NN, CBR
	Digital twins	Support of predictive maintenance and anomaly detection	DT
Naval Operations	ISR – Intelligence Surveillance and Reconnaissance	Detection and classification of maritime objects and threats	CNN, DL, ML
	Maritime Domain Awareness	Fusion of multisensory data for real time situational awareness	ML, DF
	Maritime Security	Detection of illegal activities such as smuggling or illegal fishing	DL, AD, RNN
	Tactical Decision Support	Learning and evaluation of tactical options in combat scenarios	MARL, DDQN, PPO
	Naval Kill Chain Support	Target detection, tracking, and engagement assessment	ML, CAI, XAI, DF, RNN
	Cybersecurity	Detection and mitigation of cyber threats in maritime systems	IDS, AD, XAI, PTM
	Command and Control (C2)	Course of action analysis and operational planning support	NLP, IF
Unmanned Naval Vehicles	Path Planning	Autonomous route planning in dynamic marine environments	NN, RL, DDQN
	Route planning & Obstacle Avoidance	Real time, COLREGs compliant collision avoidance	FL, NN, PSO, APF, RL, DL
	Autonomous Berthing	Collision free docking and manoeuvring in confined spaces	NN, DF
	Vehicle Guidance & Control	Precision heading and motion control of unmanned vehicles	DAI
	Perception & Target Detection	Detection and classification of vessels in complex sea conditions	CNN, DL
	Explainable Autonomy	Transparent AI decision making to support trust and safety	XAI
	Autonomous Mission Management	Adaptive mission execution using multisensory data	LA, ML

4 CHALLENGES IN AI INTEGRATION

Despite the increasing maturity of artificial intelligence technologies and their growing adoption across naval capability development, their integration into naval platforms and organisations remains constrained by a range of persistent challenges. These challenges cover technical, organisational, legal, and ethical domains and are particularly pronounced in naval environments characterised by safety-critical operations, long platform lifecycles, and complex human-machine interactions. Unlike conventional deterministic software, AI systems exhibit nondeterministic, data-dependent, and adaptive behaviour, which fundamentally challenges established naval engineering, acquisition, and certification paradigms [17], [22]. This section, therefore, focuses on the key barriers that continue to limit large scale and operationally unrestricted deployment of AI in naval systems.

4.1 *Verification, validation, and certification*

Verification, validation, and certification remain the most significant technical barriers to the operational use of AI-enabled naval systems. Existing naval certification frameworks are largely designed for deterministic systems with predictable behaviour and traceable requirements. In contrast, machine learning based systems derive their functionality from training data and statistical inference, making their behaviour difficult to formally verify across all operational conditions [22], [25]. This challenge is particularly acute in safety-critical naval applications such as navigation, collision avoidance, and platform control. While AI-driven autonomy has demonstrated promising performance in controlled and experimental settings, certification for unrestricted maritime operations remains limited due to the difficulty of guaranteeing safe behaviour under uncertain environmental conditions, sensor degradation, and adversarial interference [30], [29]. Emerging mitigation approaches, including physics-informed and hybrid models, aim to constrain learning based behaviour within known physical laws and engineering limits, thereby improving consistency and certifiability [25]. Explainable artificial intelligence further contributes by improving transparency and traceability, which are essential for both certification and operational trust [3]. Nevertheless, comprehensive certification methodologies for AI-enabled naval systems remain an open research and regulatory challenge.

4.2 *Integration with legacy platforms and digital infrastructure*

A second major challenge concerns the integration of AI technologies with legacy naval platforms. Many warships and submarines currently in service were designed before the advent of data-centric and AI enabled architectures and therefore lack the sensor integration, computing capacity, data accessibility, and open interfaces required for effective AI deployment [11], [26]. Although newer platforms increasingly adopt modular and open system architectures, retrofitting legacy platforms often requires extensive and costly upgrades to sensors, data buses, onboard processing, and cybersecurity infrastructure. In addition, AI systems increase cyber risk due to their reliance on large data flows, continuous connectivity, and frequent software updates. As a result, AI integration must be accompanied by robust cybersecurity measures and secure data pipelines to mitigate risks such as data manipulation, poisoning, and unauthorised access [5], [7].

Digital twin concepts illustrate both the opportunities and the challenges of integration. While digital twins can support predictive maintenance and lifecycle optimisation, their effectiveness depends on reliable, high-quality, and continuous data streams from the physical platform, conditions that are often difficult to achieve in legacy naval systems [17], [42].

4.3 *Human-AI interaction and organisational adaptation*

Human-AI interaction represents a critical nontechnical challenge that directly affects operational effectiveness. Naval operations remain fundamentally human-centric, with responsibility for command decisions and the use of force resting with human operators. Poorly designed interfaces, insufficient transparency, or over-reliance on automation can degrade situational awareness and undermine trust in AI systems [50]. Research on autonomous maritime systems emphasises the importance of maintaining appropriate levels of human oversight, particularly for systems operating in human-in-the-loop or human-on-the-loop modes [30], [8]. Human-centred design and explainable AI are therefore essential to ensure that operators understand system limitations, uncertainty, and failure modes [3]. Beyond the technical interface, organisational adaptation poses an equally significant challenge. AI adoption often requires changes in doctrine, training, and decision-making processes. Defence acquisition studies indicate that without institutional alignment and workforce upskilling, even technically mature AI solutions may fail to deliver operational benefits. Resistance to algorithmically supported decision-making remains a notable barrier in hierarchical naval organisations.

4.4 *AI integration in naval acquisition and sustainment*

AI integration challenges existing naval acquisition and sustainment models, which are traditionally optimised for hardware-centric systems with long development and upgrade cycles. In contrast, AI systems evolve continuously through data updates, retraining, and algorithm refinement [43]. This mismatch complicates requirements definition, testing, and contractual arrangements. Although AI-based tools offer potential benefits in procurement efficiency and contract management, their adoption requires regulatory adaptation, improved data governance, and revised intellectual property frameworks [43]. Furthermore, lifecycle sustainment of AI systems introduces new challenges, as model performance may degrade over time due to changing operational conditions and adversary behaviour. Continuous monitoring, validation, and retraining are therefore required capabilities that are not yet well integrated into traditional naval maintenance practices [16], [42].

4.5 *Ethical, legal, and strategic constraints*

Ethical, legal, and strategic considerations impose important constraints on AI integration in naval systems. Increased autonomy raises questions of accountability, escalation control, and compliance with international humanitarian law, particularly in contexts involving the potential use of force [4], [12]. While most navies retain human authority over lethal decisions, even nonlethal AI applications may have indirect lethal consequences, necessitating clear governance and oversight mechanisms. National and international AI strategies increasingly emphasise responsible, transparent, and human-centred AI development [41], [19], [25]. For naval forces, aligning rapid technological innovation with ethical principles and legal obligations remains a central challenge in maintaining legitimacy and strategic stability.

5 USE CASE OF AI-BASED RANDOM FOREST MODELING FOR BLOCK COEFFICIENT (CB) PREDICTION IN NAVAL SHIP DESIGN

This section showcases an example of using a Random Forest-based artificial intelligence model to predict the block coefficient (Cb) of naval ships. Accurately determining the block coefficient is essential during the initial design phase, as it significantly impacts lightship weight, total displacement characteristics, hydrodynamic resistance, and propulsion power needs. Thus, early and reliable predictions of Cb lead to better-informed design choices and enhance overall vessel performance. The model proposed is crafted using a database of main ship dimensions that encompasses a broad spectrum of naval vessel types, including coastal patrol vessels (CPV), fast attack crafts (FAC), offshore patrol vessels (OPV), corvettes (COR), frigates (FRI), destroyers (DST), and aircraft carriers (AC). This variety adds complexity but also increases the model's applicability to practical scenarios.

Random Forest is an ensemble machine learning method that builds numerous decision trees and combines their results to create a more precise prediction [14]. Random Forest regression is more reliable than traditional linear models for complex, high-dimensional problems, as it handles missing data, captures nonlinear relationships effectively, and delivers greater accuracy and prediction stability. Additionally, it can process large datasets with relatively few parameters while automatically identifying the most important features to further improve accuracy. As a form of ensemble learning, it integrates the collective knowledge of various decision trees, thereby enhancing both predictive accuracy and stability [52]. High predicted accuracy is provided by Random Forest Models, which are well known for their resilience and adaptability in a variety of regression and classification tasks. They offer comprehensible metrics of feature relevance, are resistant to overfitting, and need little data preprocessing. Specifically, Random Forests measure each input variable's relative contribution, making it possible to identify the features that have the biggest impact on the model's predictions. There are various crucial steps in the Random Forest Model's training and prediction process. Initially, bootstrap sampling is used to create several subsets of the original dataset by sampling with replacement, which encourages variation among the trees and permits some observations to appear more than once. Second, each decision tree is built by evaluating a random subset of input features at each node to find the best split. Third, the bootstrapped datasets and randomised feature selection are used to separately train many decision trees. Lastly, each tree generates a unique forecast for unseen data, and these predictions are aggregated to form the overall model output, usually by averaging for regression tasks. In this study, a Python-based Random Forest regression model was developed to estimate the block coefficient (Cb) of naval ships using ship length (L), breadth (B), draft (T), and speed (v) as input features. The database consists of 80 naval ships, and it is divided into training and testing subsets using a standard 70/30 split for model development and validation, respectively, although alternative ratios may also be applied. A 20-row excerpt from the database is presented in Table 2. Model training was performed using the training subset, followed by performance evaluation on the test dataset, and the feature importance values were subsequently computed. Reference Cb's from the dataset for all 80 ships, and predicted Cb for six ships in Table3 from the Random Forest Model are shown in Fig. 5.

A similar Random Forest Model applied to merchant ship performance prediction [44] was evaluated using the coefficient of determination (R^2), which measures the agreement between predicted and reference block coefficient values. That study reported a stable R^2 value of approximately 0.912, indicating strong predictive capability compared to traditional block coefficient estimation methods. In the present naval ship model, the R^2 value is lower (0.8502), primarily due to the relatively small dataset size and the wide variety of ship classes, which increases regression complexity. Model performance could be improved by expanding the database with additional naval ship examples. However, as this model is intended primarily for illustrative purposes, it is retained in its current form.

Table 2. Excerpt of 20 rows from the naval ship database (Source: The authors)

Type	Class	State	Lpp [m]	B [m]	T [m]	V [kn]	Δ [t]	Fn	Reference Cb
CPV	Omiš	HRV	39.11	7.50	2.02	28.00	260.95	0.74	0.43
CPV	Mirna	HRV	29.67	6.62	1.76	28.00	138.60	0.84	0.39
FAC	Kralj	HRV	49.66	7.87	2.12	36.00	365.10	0.84	0.43
FAC	Kralj	HRV	50.22	7.87	2.12	37.00	390.00	0.86	0.45
FAC	Končar	HRV	41.66	7.75	1.89	40.00	263.50	1.02	0.42
FAC	Saar 4	IZR	52.78	7.01	2.40	34.00	450.00	0.77	0.49
FAC	Saar 4.5	IZR	56.15	7.01	2.80	33.00	498.00	0.72	0.44
OPV	Gawron	POL	86.63	12.42	3.60	29.50	2150.00	0.52	0.54
OPV	River	GB	82.36	11.96	3.80	25.00	2000.00	0.45	0.52
OPV	Holland	RNN	98.64	14.72	4.55	21.50	3750.00	0.36	0.55
OPV	Cassiopea	ITA	72.62	10.86	3.60	21.00	1500.00	0.40	0.52
OPV	Saar 62	IZR	56.42	6.99	2.70	32.00	500.00	0.70	0.46
COR	Braunschwei	K130	81.10	11.82	3.50	26.00	1840.00	0.47	0.54
COR	Bosphorus	ADA	90.50	12.82	3.95	30.00	2400.00	0.52	0.51
COR	Khamronsin	THA	56.40	7.30	2.50	25.00	630.00	0.55	0.60
COR	Fatahillah	IND	76.44	9.88	3.30	30.00	1450.00	0.56	0.57
FRI	FREMM	FRA/ITA	129.22	17.80	6.00	27.00	6000.00	0.39	0.42
FRI	Sachsen	GER	130.13	15.13	5.30	29.00	5800.00	0.42	0.54
FRI	Alvaro de Bazan	SPA	133.50	16.55	4.75	28.00	6250.00	0.40	0.58
FRI	Iver Huitfeldt	NOR	126.22	17.58	6.00	28.00	5290.00	0.41	0.39

Ship length (L, 0.3046) is the most significant variable, followed by draft (T, 0.2917), width (B, 0.2672), and speed (v, 0.1365), according to feature importance analysis. Regarding the factors that determine hull fullness, these findings are consistent with accepted naval architecture concepts. Table 3 reports the referenced and predicted block coefficient values for six typical test ships. Lyashenko in [32] offers a concise tutorial on how to use Random Forest Models in Python and a comparison with similar machine learning techniques.

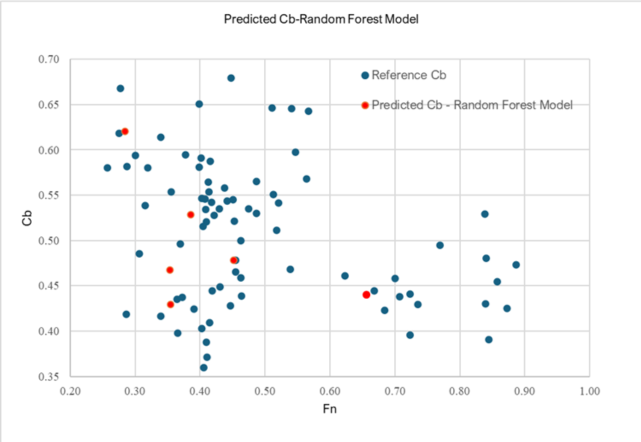

Figure 5. Cb predicted values by Random Forest Model and referenced Cb (Source: The authors)

Table 3. Cb predictions for 6 test ships (Source: The authors)

Type	Class	State	Lpp [m]	B [m]	T [m]	V [kn]	Δ [t]	Fn	Cb	RFM Cb
PV	Diana	DAN	39.13	7.22	2.20	25.00	280.00	0.66	0.44	0.45
FRI	Thetis	DAN	102.19	12.96	6.00	21.80	3500.00	0.35	0.43	0.47
FRI	Absalon	DAN	124.67	17.55	6.30	24.00	6600.00	0.35	0.47	0.47
FRI	La Fayette	FRA	113.75	13.86	4.10	25.00	3500.00	0.39	0.53	0.54
AC	J. F. Kennedy	USA	300.00	40.00	11.00	30.00	83981.00	0.28	0.62	0.58
DST	Visakhapatnam	IND	148.33	15.66	6.50	33.50	7400.00	0.45	0.48	0.51

6 CONCLUSIONS

This review has demonstrated that artificial intelligence is becoming a foundational enabler across the full spectrum of naval capability development. The literature clearly indicates that AI technologies are no longer confined to isolated decision support applications but are increasingly embedded throughout naval ship design, project management, maintenance and sustainment, education and training, simulations, operational employment, and maritime unmanned systems. Data-driven and hybrid AI approaches are complementing traditional physics-based and rule-based naval engineering methods, enabling improved performance prediction, design space exploration, and lifecycle optimisation. The analysis shows that AI has reached relatively high maturity levels in domains such as unmanned vehicle navigation, collision avoidance, perception, and path planning, while applications in ship design optimisation, digital twins, and lifecycle management are progressing rapidly. Conversely, AI integration into safety-critical combat systems, autonomous decision making, and fleet-wide command and control remain constrained by verification, validation, certification, and ethical considerations. The reviewed literature consistently emphasises that AI adoption in naval contexts is shaped as much by organisational, legal, and cultural factors as by technological readiness. For naval planners and strategists, the findings underline that AI integration is not merely a technological upgrade but a systemic transformation of how naval capabilities are conceived, developed, and employed. AI-enabled tools can significantly enhance decision-making speed, operational awareness, and resource efficiency. However, these benefits can only be realised if AI is incorporated early in the capability development lifecycle and aligned with doctrinal, organisational, and training frameworks. The review highlights the importance of viewing AI as a force multiplier that augments human expertise rather than replacing it. Effective human-AI teaming, explainability, and trust are critical for operational acceptance, particularly in complex and contested maritime environments. Strategically, navies that fail to adapt acquisition processes, digital infrastructures, and workforce competencies risk falling behind peers who successfully leverage AI to accelerate innovation and operational effectiveness. At the same time, premature or poorly governed deployment of AI-enabled systems may introduce new vulnerabilities, escalation risks, and legal challenges.

Based on the synthesised literature, several recommendations can be made. First, naval organisations should pursue a phased and domain-specific approach to AI integration, prioritising applications with clear operational value and manageable certification risks. Second, investment in digital infrastructure, including data governance, cybersecurity, and modular system architecture, is essential to enable scalable AI deployment across legacy and future platforms. Third, explainable and physics-informed AI methods should be promoted to support verification, validation, certification, and operator trust, particularly in safety-critical applications. From an organisational perspective, navies should adapt acquisition and lifecycle management frameworks to accommodate continuously evolving AI systems, including mechanisms for iterative testing, retraining, and sustainment. Strengthening collaboration with industry, research institutions, and small and medium-sized enterprises is also critical to maintaining access to innovation. Ethical, legal, and governance considerations must be embedded into AI development from the outset to ensure compliance with international law and to preserve legitimacy in naval operations. Despite significant progress, substantial research gaps remain. Future work should focus on developing standardised methodologies for the verification and certification of AI-enabled naval systems operating in open and adversarial maritime environments. Additional research is needed on human-AI interaction, particularly regarding workload management, trust, and decision accountability in multi-domain naval operations. Moreover, empirical validation of AI applications through large-scale trials and real-world operational data remains limited and should be expanded. In the end, interdisciplinary research addressing the strategic, ethical, and legal implications of increasing autonomy in naval warfare will be essential as AI capabilities continue to mature. Effectively addressing these challenges will determine whether AI becomes a reliable and trusted component of future naval capability development.

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