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Review Article

A review of the application of artificial neural networks in the oil offloading process from FPSO to Tanker: Cargo loss perspective

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Abstract: Artificial Intelligence (AI) has shown remarkable progress and is increasingly applied to strengthening maritime security. One critical challenge lies in the offloading of oil from Floating Production Storage and Offloading (FPSO) units to shuttle tankers, which remain prone to sabotage and fraudulent actions, leading to potential cargo loss. Despite existing international laws and regulations, such risks cannot be fully controlled. This study presents a systematic review to explore how AI can be utilized to reduce sabotage-related cargo loss in FPSO–tanker operations. Using a structured review of studies published between 2015 and 2025, data were collected from leading databases such as Scopus, IEEE Xplore, and Web of Science, and analyzed through thematic coding to identify relevant AI methods and applications. Results show that current efforts largely emphasize automatic integrated monitoring systems, while the issue of sabotage is rarely addressed directly. The review highlights that cloud computing, Internet of Things (IoT), and big data analytics are essential in enabling real-time coordination and predictive security. Overall, integrating these technologies with AI offers a more sustainable framework to protect offshore oil transfers.

Keywords: Literature review, artificial Intelligence, payload sabotage, Offloading FPSO-Tanker

1. Introduction

Floating Production Storage and Offloading (FPSO) units are offshore floating facilities equipped with production equipment, enabling them to process crude oil as well as store and export it. In contrast, Floating Storage and Offloading (FSO) units only have storage and offloading capabilities without production functions [1]. FPSOs can distribute oil directly to tankers and onward to refineries [2], and in addition, they can produce oil by processing crude directly from reservoirs [3]. This dual functionality makes FPSOs highly versatile and advantageous for oil companies [4].

FPSOs are particularly effective in deep-water and marginal field operations where fixed platforms and subsea pipelines are not economically feasible [5]. Furthermore, they can be redeployed to other marginal fields once existing reservoirs are depleted, enhancing their economic value [6]. However, despite these advantages, FPSO–tanker offloading operations remain complex and risky. Collision risks during tandem and side-by-side offloading are well documented [7], and these operations depend critically on equipment such as hawsers and hoses that ensure stable oil transfer [8], [9]. Disruptions to these systems can cause operational failures, cargo loss, and environmental hazards [10].

Marine safety continues to be a critical concern. Although navigation technologies have improved, the risk of accidents remains high due to increased maritime traffic [11]. System-theoretic risk assessments show that FPSOs, while technologically sophisticated, still pose hazards to personnel, cargo, and the environment [12]. Supervisory risk control systems for autonomous vessels also highlight

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the need for more robust safety mechanisms [13]. Numerical analyses of cargo transfer operations in oil fields show that inefficiencies can lead to cargo loss and financial risks [14]. In addition, cargo loss is often tied to marine insurance mechanisms that attempt to mitigate financial damages [15].

Figure. 1 Offloading process

At the operational level, several studies have examined the potential for cargo loss during crude oil discharge. Losses may result from poor planning, incorrect target rates, pump inefficiencies, and improper tank stripping [24]. Moreover, factors such as long suction lines, valve leaks, and poor monitoring during startup further exacerbate cargo loss [22], [23], [32], [34]. These findings indicate that both intentional and unintentional losses remain a critical issue in FPSO–tanker logistics.

In recent years, Artificial Intelligence (AI) has shown potential in addressing maritime risks. Reviews highlight the application of artificial neural networks (ANNs) in ocean engineering [16], [17], the development of integrated ship information systems [18], and the implementation of quality management systems in Industry 4.0 [19]. FPSO design and operation in harsh environments has also benefited from digitalization [20]. AI is increasingly applied to traffic scenarios [21], human factor analysis in ship accidents [22], decision support systems [23], ontological models of transportation reliability [24], and multi-criteria decision making for offshore decommissioning [25]. Furthermore, digitalized Arctic logistics systems [26], organizational behavior frameworks [27], and path planning algorithms for autonomous vessels [28] demonstrate AI's growing role. Research on shipping 4.0 has shown potential to control accidents [29], while advanced data integration tools [30] and empirical project reviews [31] highlight broader industrial adoption.

Despite these advances, very few studies explicitly address the prevention of sabotage-related cargo loss in FPSO–tanker operations. Decommissioning reviews [32], AIS data analysis [33], and adaptive ship modeling [34] show the breadth of AI applications but seldom connect directly to intentional cargo loss. Therefore, this study aims to fill this gap by systematically reviewing AI applications and evaluating their potential to mitigate sabotage-induced losses in FPSO–tanker offloading.

2. Materials and Methods

2.1. Data Collection

This study employs a systematic literature review (SLR) method to identify, evaluate, and synthesize prior research on AI applications in FPSO–tanker offloading and cargo loss mitigation. Sources were collected from Scopus, Web of Science, and IEEE Xplore, with supplementary material from Google Scholar. The timeframe considered was 2015–2025 to ensure relevance to modern AI and offshore

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practices.

Keywords included FPSO offloading risk, cargo loss sabotage, AI maritime security, and oil logistics digitalization. The inclusion criteria were: (i) peer-reviewed studies; (ii) works related to FPSO operations, tanker offloading, or AI in maritime logistics; and (iii) studies addressing cargo loss or sabotage. Exclusion criteria included: (i) non-English texts; (ii) purely conceptual works without applied context; and (iii) papers unrelated to logistics or AI applications.

Out of 97 initial studies, 30 were deemed relevant, including major works on FPSO safety [5], [6], [7], [11], [theoretic frameworks [12], [13], [24], [32], and AI in maritime engineering [16], [21], [29].

2.2. Data Analysis

A thematic coding approach was applied to classify findings into four categories:

- Maritime Case Studies – FPSO–tanker risks, oil discharge, and operational safety [1], [5], [14].
- Cargo Loss Risks – sabotage, planning failures, pump inefficiencies, and organizational errors [22], [23], [24], [34].
- AI Subfields – neural networks, fuzzy logic, cognitive computing, and computer vision [16], [21], [23].
- AI–Maritime Integration – AI-enhanced supervisory control, logistics digitalization, and decision support systems [13], [19], [26].

To synthesize findings, Venn diagrams and tabulated evidence (Tables 1–3 from base study) were used to illustrate the overlap of maritime risks, cargo loss, and AI subfields.

3. Results

Based on the systematic literature review, 97 articles were initially screened from which 30 studies were selected for in-depth analysis. The findings are presented in five sections: (i) possibility of cargo loss during the offloading process, (ii) subfields of Artificial Intelligence (AI) relevant to maritime security, (iii) integration of AI in maritime risk management, (iv) publication trends, and (v) identification of research gaps.

3.1. Possibility of Cargo Loss During the Offloading Process

The systematic review identified several critical factors that may cause cargo loss during the FPSO–tanker offloading process. These factors can occur both unintentionally (due to technical inefficiencies) and intentionally (through fraudulent or sabotage-related actions). Table 1 summarizes the main causes reported in the literature.

Table 1. Possibility of cargo loss during the offloading process

Possibility of loss	Explanation	Indication	Ref
Planning the discharge	Poor planning reduces operational accuracy; without structured planning, crews may act inconsistently.	Intentional & unintentional	[24]
Setting target rate	Target rates must align with pumping and port capacity; unrealistic targets may damage equipment or delay operations.	Intentional & unintentional	[27]
Pump room disadvantage	Longer suction pipelines increase frictional losses, reducing efficiency compared to tanks closer to pumps.	Intentional & unintentional	[12]
Tank stripping	Residual oil remains at the bottom of cargo tanks; inaccurate estimation adds to cargo loss.	Intentional & unintentional	[34]
Starting the discharge	Valve leakage or abrupt pumping speed increase at start-up can trigger spills and significant losses.	Intentional & unintentional	[10], [22]

Table 1 illustrates that cargo loss emerges from both technical weaknesses such as excessive friction in suction lines [12] or unavoidable stripping residues [34] and potential manipulations that may indicate sabotage. For instance, poor discharge planning may be exploited to hide fraudulent practices [24], while unrealistic discharge targets could be set

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intentionally to disrupt operations [27]. This highlights the dual nature of risks in FPSO–tanker logistics: operational inefficiencies and intentional threats.

3.2. Subfields of Artificial Intelligence Relevant to Maritime Security

Several AI subfields have been widely studied in the maritime sector. These techniques provide capabilities that may be adapted to address cargo loss prevention in FPSO operations. Table 2 presents the most relevant subfields.

Table 2. Subfields of Artificial Intelligence relevant to maritime applications

Subfield	Explanation	Ref
Machine learning & Neural networks	Real-time anomaly detection in pumping and discharge data.	[16], [21]
Cognitive computing	Human–machine interactions for improved emergency decision-making.	[16]
Computer vision	Pattern recognition from imagery/video; potential to detect suspicious vessel activities during offloading.	[23]
Fuzzy logic & Decision support	Risk quantification under uncertainty; useful for modeling sabotage and collision risks.	[11], [29]

Machine learning and neural networks dominate maritime AI studies, especially for anomaly detection [16], [21]. Computer vision is increasingly applied for navigational safety and real-time surveillance [23], while fuzzy logic enhances decision support under uncertain conditions [11], [29]. Despite their broad adoption, these technologies have rarely been directed toward cargo loss prevention, particularly sabotage scenarios in FPSO–tanker offloading.

3.3. Integration of AI in Maritime Risk Management

AI applications in maritime safety extend beyond anomaly detection to broader systems integration. Table 3 outlines representative applications of AI in the maritime domain.

Table 3. Applications of AI in maritime safety and logistics

Application	Description	Ref
Risk assessment for autonomous ships	Framework for selecting Risk Control Options (RCOs).	[12]
Supervisory risk control	Integration of STPA and Bayesian Belief Networks for control systems.	[13]
Collision avoidance	Automated generation of collision scenarios for autonomous vessels.	[21]
Ship information systems	Development of integrated data management platforms.	[18]
Digitalized logistics	Arctic logistics management systems for oil transportation.	[26]
Path planning	Algorithms for safe navigation of autonomous vessels.	[28]
Shipping 4.0	Advanced digital technologies for accident prevention.	[29]

Table 3 confirms that AI has been extensively employed in navigation, automation, and digitalized logistics [12], [13], [21], [26], [28], [29]. However, specific applications for cargo loss and sabotage prevention remain underdeveloped. The Venn diagram (Figure 3 in the base study) illustrates this point:

- The overlap between Maritime Case and AI yields “Maritime AI.”
- The overlap between Loss of Charge and AI highlights “AI for Loss Prevention.”
- The intersection of all three Maritime Case, Cargo Loss, and AI represents AI for Maritime Risk Management, the novelty addressed by this study.

To further illustrate the integration of maritime risks, cargo loss factors, and AI subfields, a Venn diagram was developed based on the synthesized literature (Figure 3). The diagram highlights three major domains: Maritime Case, Possibility of Cargo Loss, and AI

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Subfields. The intersections among these categories reveal the following: (i) the overlap between Maritime Case and AI represents Maritime AI, which includes applications such as navigation safety, collision avoidance, and ship information systems [12], [18], [21]; (ii) the overlap between Cargo Loss and AI demonstrates AI for Loss Prevention, including neural networks and IoT-based anomaly detection [16], [26]; and (iii) the intersection of all three domains AI for Maritime Risk Management represents the novelty of this study, emphasizing the potential of integrated frameworks to address both technical inefficiencies and intentional sabotage in FPSO–tanker operations.

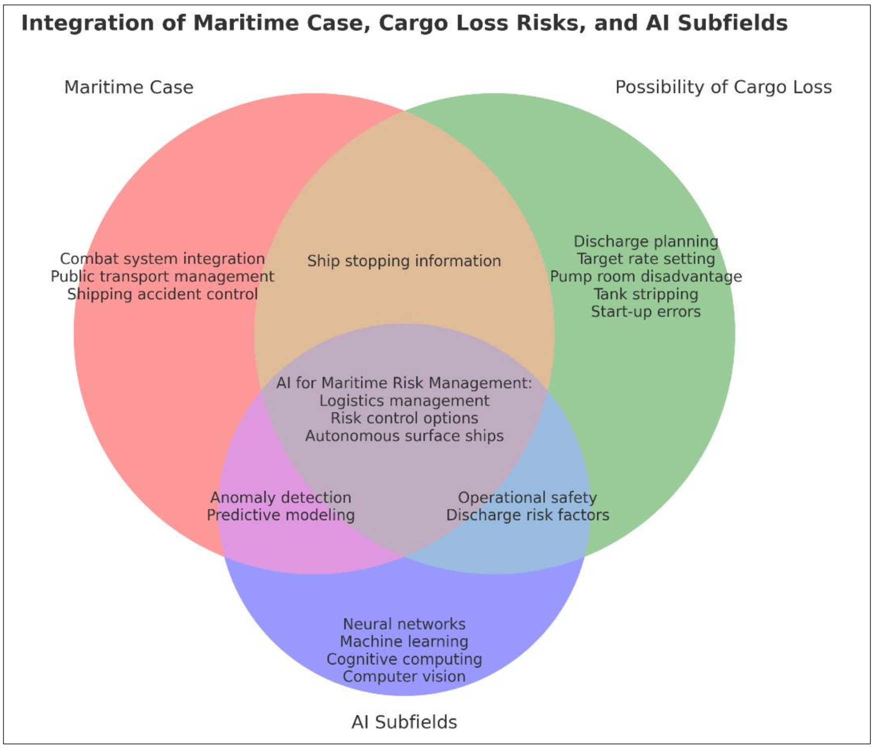

Figure 3. Venn diagram shows the critical overlap.

3.4. Publication Trends

The analysis revealed an upward trend in publications between 2019–2025, coinciding with global interest in Shipping 4.0 and autonomous maritime systems. Major outlets included Ocean Engineering and Transportation Research Procedia.

Findings, (1) Dominant focus: navigational safety, collision avoidance, and path planning [12], [13], [28]. (2) Minor focus: cargo loss and sabotage prevention [15], [24]. (3) This demonstrates a clear imbalance: while safety and automation have received attention, cargo loss particularly sabotage-related risks remain marginally addressed.

3.5. Research Gap Identification

From the synthesis of the reviewed literature, four primary research gaps were identified that significantly shape the future trajectory of research on FPSO–tanker cargo loss and maritime security. First, there is a notable lack of studies explicitly addressing sabotage-related cargo loss. Most research has concentrated on technical inefficiencies such as pump performance, valve reliability, or discharge planning, while the dimension of malicious intent remains largely overlooked [15], [24]. This indicates that intentional acts such as fraud, cargo theft, or deliberate system disruption have not yet been systematically integrated into existing risk models. Second, the reviewed studies reveal a limited integration of Artificial Intelligence with supporting digital technologies such as the Internet of Things (IoT), cloud computing, and big data. Current efforts frequently focus on isolated AI subfields, such as neural networks for anomaly detection or fuzzy logic for decision support, without building a holistic framework that combines these technologies into an integrated security system [16], [21], [26]. Such fragmentation reduces the potential of AI to

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deliver comprehensive solutions in real-time, high-risk environments. Third, there is a scarcity of empirical validation. While many contributions present promising conceptual models or simulations, very few have been tested in real-world FPSO–tanker operations, where environmental complexity, human factors, and operational uncertainty could challenge model robustness [10], [12]. This gap weakens the applicability of existing frameworks in practical offshore logistics. Finally, the lack of standardized datasets hinders the development of reliable AI models. Variability in data formats, incomplete records, and inconsistent quality across different operators or regions limit the capacity of AI systems to generalize findings and improve predictive accuracy [18], [33].

Taken together, these gaps highlight the urgency of advancing research towards hybrid AI frameworks that integrate neural networks, fuzzy logic, IoT, and big data analytics. Such integration would not only enhance real-time anomaly detection but also support predictive modeling of sabotage scenarios, providing a more resilient and proactive approach to maritime risk management. By addressing both unintentional inefficiencies and intentional threats, future frameworks can significantly improve the security and sustainability of FPSO–tanker offloading operations.

4. Discussion

4.1. Interpretation of Results

The results of this systematic review highlight that FPSO–tanker offloading operations remain highly vulnerable to both technical inefficiencies and intentional sabotage. Cargo loss occurs due to common issues such as poor discharge planning, stripping inefficiencies, pump limitations, and valve failures [12], [24], [27], [34]. However, intentional threats, including fraudulent practices and sabotage, introduce additional layers of complexity that cannot be addressed by conventional engineering measures alone [15]. This duality underscores the need for a multidimensional framework that considers both operational risks and malicious behavior. At the same time, the review shows that Artificial Intelligence has been extensively applied in maritime domains—particularly in collision avoidance [21], autonomous risk control [13], and digitalized logistics [26]—but its direct application to cargo loss prevention in FPSO–tanker operations remain scarce. These findings demonstrate that the potential of AI in enhancing maritime risk management is substantial yet underutilized in this specific domain.

4.2. Comparison with Previous Studies

Previous research has predominantly focused on safety and navigation in autonomous shipping, leveraging technologies such as Bayesian networks for risk control [13], fuzzy logic for accident prediction [11], and neural networks for pattern recognition [16]. While such contributions have been valuable in advancing maritime autonomy and safety, they have not sufficiently addressed the operational challenges of oil offloading from FPSOs. For instance, studies on shipping 4.0 technologies emphasize accident control and automation [29], but none have explored their utility for preventing sabotage or intentional cargo manipulation. Similarly, research on ship information systems [18] and digital Arctic logistics [26] demonstrates the advantages of digital integration but fails to bridge the gap between information management and cargo security. Compared to these previous studies, the present review contributes by explicitly identifying sabotage-related risks as a distinct research dimension and by highlighting the necessity of integrating AI subfields into a unified framework tailored to FPSO–tanker operations.

4.3. Theoretical and Practical Implications

Theoretically, this review advances maritime risk management by extending the scope of analysis beyond technical inefficiencies to include intentional threats. In doing so, it responds to the limitations of deterministic scheduling and reliability-based routing models, which often assume cooperative behavior among stakeholders [7]. By introducing the concept of AI for sabotage prevention, this study provides a novel theoretical lens that situates cargo loss within broader discussions of security, strategic behavior, and malicious intent. Practically, the findings suggest that combining neural networks, fuzzy logic, IoT, and big data analytics can deliver predictive insights into cargo loss events. Neural networks are particularly effective in forecasting abnormal discharge patterns [16], [21], while fuzzy decision models support risk assessment under uncertain operational conditions [11]. IoT

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devices provide real-time monitoring of cargo flows, and cloud computing enables distributed data integration for multi-stakeholder coordination [26]. Implementing these technologies in tandem would not only reduce the likelihood of technical failures but also strengthen resilience against sabotage, thereby enhancing the overall sustainability of offshore oil logistics.

4.5. Limitations and Future Research

Despite its contributions, this review is not without limitations. The reliance on secondary literature introduces potential biases, as the scope of included studies may not capture all ongoing industrial practices. Moreover, many reviewed studies remain simulation-based rather than empirically validated in real FPSO–tanker environments [10], [12]. This limits the generalizability of their findings to operational contexts characterized by high uncertainty and human factor variability. Additionally, the lack of standardized datasets across companies and regions constrains the development of AI models that can operate universally [18], [33].

From the synthesis, four key research gaps emerge. First, the scarcity of sabotage-related studies demonstrates that the intentional dimension of cargo loss is understudied and warrants urgent attention [15], [24]. Second, limited integration of AI with IoT, cloud computing, and big data analytics reduces the robustness of existing solutions [16], [21], [26]. Third, there is a need for empirical testing of AI-enabled sabotage prevention models in real-world FPSO operations to validate their reliability under offshore conditions [10], [12]. Finally, the absence of standardized, high-quality datasets restricts cross-industry learning and benchmarking [18], [33]. Addressing these gaps will require multidisciplinary collaborations that bring together marine engineers, data scientists, and policymakers to design hybrid frameworks capable of tackling both unintentional and intentional risks.

5. Conclusions

AI is the ideal technology for solving today's human problems. Therefore, the development of AI has enormous potential in marine engineering, especially when it comes to shipping operations. Although each case must be studied carefully, after reviewing 30 studies, some general patterns and rules were concluded. The system on the ship has yet to utilize AI fully. From all the studies that have been reviewed, it can be concluded that, in general, it is sufficient to model ship engineering problems. All research results are presented, discussing control systems that can be integrated.

After reviewing all these studies, combining different AI techniques, such as ship collision risk, autonomous ships, and ship speed control, is very profitable. Ships that operate using AI will reduce the risk of damage and casualties. In recent years, AI has produced excellent results in developing integrated information systems to predict Logistics delays.

However, there are still some unresolved issues regarding AI, such as whether AI can predict the loss of oil cargo in tankers for long-term predictions. The problem of shipload sabotage still needs to be solved, and there are still many questions about the quality and quantity of data required. Therefore, future lines of research should focus on this topic.

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