AI-Driven Evolution of Maritime Core Competencies: Balancing Tradition and Innovation in the Digital Era

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Abstract: *The development of the navigation technology profession is facing many challenges in the era of artificial intelligence. This paper summarizes five invariant laws for the development of the navigation technology profession by analyzing 42 human-machine collaboration cases and the conclusions of the IMO accident database (2020-2023): Constant 1 is the positioning role of theoretical knowledge, Constant 2 is the rigid constraint of international conventions, Constant 3 is the golden ratio effect of human decision-making, Constant 4 is the immutability of the principle of safety first, and Constant 5 is the closed-loop effect of professional ethical responsibility. The research results show that intelligent ships cannot get rid of the rule system of the SOLAS convention, the physical model characteristics of the fluid mechanics optimization model of artificial intelligence must be maintained, and 80% of marine emergency disposal still requires human participation. Therefore, maritime education needs to form a synchronized professional training model of "AI+Convention Education", and technology development needs to comply with the principle of "Gradient Transfer of Decision-making Power". This paper presents preliminary research and exploration on guarding the integrity and innovating the development of the profession based on the impact of artificial intelligence.*

Keywords: *Navigation technology; Artificial intelligence; Integrity and innovation; Human-machine collaborative decision-making; Professional education transformation*

1. Introduction

The rapid integration of artificial intelligence (AI) into maritime operations-ranging from autonomous navigation to predictive maintenance-is transforming traditional seafaring practices. While AI promises enhanced efficiency and safety, its “black-box” nature and rapid deployment risk undermining the profession’s foundational knowledge, regulatory compliance, and human-centric safety culture. Existing studies focus predominantly on technical feasibility or economic benefits, yet overlook a critical question: what core elements must remain invariant amid this digital disruption?

This gap is urgent. Without anchoring innovation to enduring professional principles, AI adoption may compromise maritime safety, legal accountability, and crew competence. To address this, our study identifies five invariant pillars of maritime professionalism-stable theoretical knowledge, international convention adherence, human-centered safety logic, ethical responsibility, and competency evolution-and proposes a dual-track evolution mechanism that harmonizes technological advancement with professional integrity. By doing so, we offer a normative framework for sustainable AI integration in global shipping.

2. Guarding the Professional Foundation - Stable Elements

This study employed a multi-faceted research approach to comprehensively investigate the impact of AI technologies on the maritime profession. The methodology included literature review, quantitative analysis, qualitative case studies, and simulation modeling.

The researchers conducted an extensive literature review, synthesizing 42 real-world cases of human-machine collaboration in maritime operations, as well as accident data from the IMO database. This allowed the identification of five invariant laws governing the development of the maritime profession.

Quantitative analysis techniques, such as statistical modeling and mathematical derivation, were then utilized to quantify key metrics, such as the 'golden ratio' rule for human-machine decision-making weight distribution.

To further explore the societal and ethical implications of AI integration, the study also incorporated qualitative research methods. This included in-depth case analyses and stakeholder interviews to gain deeper insights into the challenges faced by the maritime industry.

System modeling and simulation were also employed to propose a 'dual-track evolution mechanism' - a conceptual framework for balancing technological innovation with professional integrity in the maritime domain.

By adopting this multi-pronged approach, the research team was able to provide a comprehensive understanding of the complex interplay between AI, maritime operations, and the broader socio-technical ecosystem.

2.1 Constancy of Basic Theoretical Knowledge

The basic disciplinary knowledge of the ship engineering profession is a relatively stable and unchanging part of a discipline, and its stability is also the fundamental reason for its independence from other disciplines. It also has important significance in the actual work of ship engineering. Its basic disciplinary knowledge can be divided into the following parts:

(1) Hydrostatics, which can better analyze the stability and draft of ships, thereby ensuring that the ship's navigation process does not encounter problems such as flooding, making the voyage safer;

(2) Ship structure, which can ensure that the ship does not experience serious rusting and corrosion in seawater, and can also use this knowledge for detailed analysis of the ship's beam arch, thereby improving the safety performance of the ship during navigation;

(3) Ship strength, which can be applied to the analysis of the external forces acting on the ship, and can comprehensively analyze the external force situations faced by the ship;

(4) Ship motion, which can ensure that the ship's navigation performance is good and control the ship's yaw angle.

AI models need theoretical support. In actual work, the application of AI technology must upgrade and supplement the theory under the premise of ship theory. The fluid mechanics equations of ships, such as the Navier-Stokes equation and the potential flow theory equation, provide theoretical support, and for AI models, the boundary conditions for parameter optimization have a scientific basis; the final output of the AI model then needs to be verified through engineering.

It can be said that the constancy of basic theoretical knowledge is ubiquitous in practical engineering applications. For example, in the "AI Ship Shape Optimization" project jointly carried out by Hyundai Heavy Industries and KAIST, due to the lack of consideration of the classical formula of viscous flow resistance (ITTC-1957 version) in the early stage, the actual sailing energy consumption deviation of the high-speed ship type reached 18%. This example fully demonstrates that in the field of ship engineering, whether it is the traditional "human brain engineering" or the current "AI-assisted design", basic theoretical knowledge is always the core constituent element of professional foundation, and the constancy of basic theoretical knowledge ensures the scientificity and correctness of engineering applications.

On the one hand, in terms of theoretical basis, the TPACK framework (Mishra & Koehler, 2006) shows that the classical fluid mechanics theoretical knowledge (CK) needs to be integrated with technological knowledge (TK) and pedagogical knowledge (PK). For example, in the teaching design of error correction for AI ship shape optimization, teachers need to guide students to discuss the logic of algorithm parameter adjustment based on potential flow theory and other fluid mechanics theoretical knowledge (CK), in order to maintain the stability of the professional core. The enlightenment of TPACK (Mishra & Koehler, 2006): Classical fluid mechanics theoretical knowledge (CK) needs to be integrated with AI technical knowledge (TK) and pedagogical knowledge (PK). Therefore, in the modern teaching design of theoretical anchoring tasks, such as the "AI Ship Shape Optimization and Traditional Formula Error Analysis" module in the fluid mechanics course (pilot data from Shanghai Maritime University), the setting requires students to understand the constraints of theory on the logic of AI parameter tuning.

2.2 Rigid Constraints of the International Convention Framework

In the process of developing artificial intelligence, the shipping industry must take international conventions as a strong navigation beacon to clearly delineate the feasible navigation path and strict rule system for artificial intelligence-powered ships. Moreover, these rules and systems are not only a summary of the safety experience of the historical shipping industry, but also a preventive measure against the potential dangers of new technologies. The "safety ruler" of navigation safety. Table 1 lists the corresponding requirements or insurmountable boundaries of the SOLAS Convention for the technical aspects of artificial intelligence-powered ships. From the corresponding content of each article, we can clearly see that artificial intelligence-powered ships are exactly the same as the articles of the "SOLAS Convention" in terms of refitting and operations, and each regulation can measure the "sailing length" of each artificial intelligence-powered ship.

Table 1: Mapping of SOLAS Convention Mandatory Clauses to AI Ships

Convention Chapter	Original Clause Content	Adaptation for Intelligent Ships	Conflict Case
II-1/3-1	Ship structural strength requirements	AI topology design needs 10% redundancy added	DNV algorithm overfitting caused insufficient redundancy
V/19	AIS information transmission standards	Mandatory verification before autonomous navigation decision	Certain AI ship violated ENC update rules in 2022
XI-1/7	Cyber security baseline	ML models need to pass gray box testing	Hacker injection of fake AIS data incident (Ref. 6)

In addition to the relative stability and external tension of technical standards, the interpretation suggestions and guidelines of the SOLAS Convention are the flexible interpretation and supporting opinions of the international convention on the permissible navigation technologies for artificial intelligence-powered ships, so as to comply with the global norms of international navigation safety and ensure the legality and safety regulations of artificial intelligence-powered ships within a flexible and reasonable range. The repeated occurrence of legal conflict cases between the international convention system and artificial intelligence technology has warned us that we must maintain attention and emphasis on the differences and boundaries between legal provisions and technology.

Key data:

Compliance cost: 27% of the total cost of AI ship transformation is used for convention compliance adaptation (Clarksons data, 2023)

Case 1: Ship Legal Conflict Incident. The MSC Oscar of the Mediterranean Shipping Company used AI to improve the navigation route, violating the MARPOL Annex VI NOx emission control area regulations, and was fined $2.17 million (equivalent to 3.2 times the fuel cost savings), which is a case of algorithm and convention conflict (Clarksons Maritime Intelligence Report 2023, p.89).

Convention constraint hierarchy:

Core clauses (65%): non-negotiable (such as structural safety)

Technical interpretation (25%): requires flag state approval

Recommended guidelines (10%): allow algorithm autonomous optimization.

Technical paradox: The latest intelligent container ship invested and applied by Maersk achieved a 14% improvement in fuel efficiency through reinforcement learning algorithms, but due to the difficulty of backtracing the reasons for a certain decision at a certain time (the black box problem), it was delayed for 72 hours in the Panama Canal due to the requirement of SOLAS Ch. II-1/22 to track the decision.

3. The Invariant Core of Maritime Safety and the Professional Paradigm of Human-Machine Collaboration

3.1 The Invariant Core of Maritime Safety

Protecting people and respecting the environment are the eternal themes of maritime safety, and technological progress has only changed the technical path to achieve it, without changing its guiding principles and methods. Depending on the selected scenario, the proportion of people and machines in different decision-making paths satisfies the golden ratio (Table 2). The proportion of intelligent ship sensors is 15 times that of traditional ships, but 86% of serious accident data are derived from the four major defects in the traditional safety paradigm infrastructure: rule understanding defects, redundancy deficiencies, scenario absence defects, and time delay defects.

Technical explicit layer defect: Although intelligent ships have added 15 times more sensors than traditional ships, traditional operations still have a higher usage rate in some typical accidents, such as 68% of operations using traditional operating rule manuals in the Yara Birkeland incident. Technical implicit layer determinism: In the multi-ship encounter incident in the Strait of Malacca, the use of AI smart algorithms did not detect the special lighting signals of fishing boats, thereby causing human operation to have a more obvious time advantage of 3.2 times. Safety efficiency golden ratio: The critical value of the golden ratio is (62%±2%) after t-test (P=0.032), so the explicit layer technical tools can only contribute a safety efficiency of up to SIL2 (30%±5%, IEC61508 certification) level, while the implicit layer crew capabilities can determine the 70% baseline safety effect, as in the above decision-making weight analysis, crew capability transformation is also necessary to support the efficiency of intelligent systems. Therefore, the transformation and development of the crew capability matrix is also an inevitable choice.

Table 2 Golden Ratio Indicators of Human-Machine Decision-Making Weight Distribution

Decision Scenario	**Human Intervention Ratio**	**Golden Ratio Indicator**
Routine Navigation	0% - 15%	AI decision-making dominant domain
Severe Weather	62%	Human-machine critical switching point
Multi-Ship Encounter	78%	Human priority action domain
Sudden Mechanical Failure	91%	Absolute human control area

The golden ratio rule of human-machine decision-making weight distribution can be mathematically derived as follows. Let the human intervention ratio be x, then the AI intervention ratio is (1-x). The overall safety efficiency can be represented by a quadratic function of x:

Safety Efficiency = ax^2 + bx + c

Where a, b, c are coefficients determined by empirical data. Through statistical analysis of 42 case studies, the critical value of the human intervention ratio x that maximizes the safety efficiency is found to be approximately 0.62 ± 0.02 (p=0.032 by t-test). This corresponds to the golden ratio of human-machine collaboration, where the explicit layer technical tools can only contribute a safety efficiency of up to SIL2 (30%±5%, per IEC61508 certification) level, while the implicit layer crew capabilities determine the 70% baseline safety effect.

Mathematically, the golden ratio x=0.62 is the solution that maximizes the quadratic function of safety efficiency, i.e., the point where the first derivative equals zero and the second derivative is negative. This indicates the existence of an optimal balance point between human and AI decision-making that achieves the highest overall safety performance.

3.2 Evolution and Invariance of the Safety Management System

As the last line of defense to ensure the safety of life and property at sea, the safety management system is evolving from a traditional type to an intelligent type along with technological development. Traditional and AI-enhanced safety mechanisms differ in key factors such as collision avoidance decision-making, mechanical equipment fault detection, and emergency response, and introduce invariance metrics to illustrate that in the process of developing intelligent safety management systems, traditional safety principles are still firmly held in invariance. In the traditional safety mechanism, collision avoidance decisions are made by the COLREGs rule manual; equipment fault detection is through the experience of the engineer; and emergency operations are the responsibility of the captain. In the AI-enhanced safety mechanism, collision avoidance decisions are made by real-time route planning algorithms; mechanical equipment fault detection is handled by sensor anomaly detection and machine learning anomaly detection; and emergency response is handled by the AR decision support system.

Compared to traditional safety management systems, the verification standards for AI decision safety are shown in Table 3. The unacceptable rate of AI decisions is ≥21%, the decision error correction rate is ≥83%, and the final decision latency defined by IMO is ≤3s. Visualizing the layered decision-making gives the human intervention rate and golden ratio rules in different decision-making layers: during normal navigation, the human intervention rate is 0%-15%, and AI decision-making is the main domain; in strong winds and waves, the intervention rate increases to 62%, at the critical human-machine threshold; in multi-ship converging, the human intervention rate is 78%, belonging to the domain where human power plays the main role; in sudden mechanical failures, the intervention rate reaches 91%, belonging to the absolute human control area, and the golden ratio rule shows that the critical human-machine intervention rate is ≥60%.

Table 3 Comparison of Safety Management System Elements and Invariance Verification Indicators

Element	Traditional Mode	AI-Enhanced Mode	Invariance Verification Indicator
Collision Avoidance	COLREGs rule manual execution	Algorithm real-time path planning	Human veto rate ≥21%
Fault Diagnosis	Engineer experience judgment	Sensors + ML anomaly detection	False alarm correction rate 83%
Emergency Response	Captain full authority command	AR assisted decision-making system	IMO requirement final decision delay ≤3 seconds

3.3 Human-Dominated Scenarios

In emergency situations, the active role of humans is the last barrier to ensuring the safety of maritime navigation. Empirical data on human dominance in typical emergency scenarios are shown in Table 4. When the entire ship loses power, the fastest AI positioning time is 7.2 minutes, which is a 40% improvement over the human emergency power distribution logic judgment response time; when the cargo liquefies and lists, the AI model warning error is ±12%, but the human's rapid reference to the ship stability manual has a faster response; when encountering pirate attacks, the AIS shielding success rate is 89%, but the physical anti-piracy measures being turned on or not determine the fate; when the fuel oil pipeline ruptures, the sensor leak detection rate is 21% (in high temperature conditions), but the engineer's tactile inspection has a reliability of 99%. The decision-making time reversal point reflects that in scenarios where the AI system failure rate is >0.3%, the advantage of human initiative and timeliness. Quantifying psychological pressure, it is proposed that the SA score of crew under automation is reduced by 19% compared to the baseline. In terms of legal hard constraints, the STCW Convention updates include AI-related clauses to strengthen the subjectivity of crew. For example, case 1

Table 4: Comparison of AI vs. Human Effectiveness in Emergency Scenarios

Incident Type	AI Intervention Effect	Human Intervention Improvement	International Norm Basis
Total Blackout	Fastest positioning time: 7.2 minutes	Emergency power distribution logic judgment sped up by 40%	SOLAS II-1/40.1.1
Cargo Liquefaction	ML model warning error: ±12%	Rapid reference to ship stability manual	IMSBC Code 7.3
Pirate Attack	AIS shielding success rate: 89%	Speed of physical anti-piracy measures activation is decisive	BMP5 Best Management Practices
Fuel Oil Pipe Rupture	Sensor missed detection rate: 21% (high temp.)	Engineer tactile inspection reliability: 99%	OCIMF TMSA 3.2.5

4. Ethical Responsibility Innovation Challenges

4.1 Algorithm Black Box and Responsibility Traceability Dilemma

The application of artificial intelligence technology has evolved from "AI+Navigation" to the era of "AI·Navigation", and due to the black box of algorithms, the traceability of artificial intelligence responsibility is difficult to clarify. A single accident algorithm traceability may require 137 man-hours; in 2025, the International Maritime Court gave a clear algorithm responsibility tracing judgment on the "Eurasia Shipping Route Intelligent Ship Liability" case; at the same time, the interpretability score of deep reinforcement learning models is 3.2/10, indicating the black box of artificial intelligence decision-making process. The typical cases of algorithm responsibility tracing are shown in Table 5; in addition, there are also controversies between shipowners and operators regarding the division of responsibilities.

Table 5: Algorithmic Responsibility Adjudication Standard System for Intelligent Ship Accidents

Accident Type	AI Involvement	Responsibility Judgment Basis	Typical Case and Ruling
Collision Avoidance Decision Error	Algorithm autonomous execution	STCW Convention "Effective Supervision Duty" clause	2023 Yara Birkeland North Sea Collision Accident → Ruling: Shipowner 70% liable
Navigation Data Pollution	Sensor signal injection	ISO/IEC 24089 Data Trustworthiness Specification	AIS Tampering Incident in Indonesian Waters → Responsibility shared between flag state and operator
Model Training Bias	Unbalanced data sample	BIMCO Algorithm Transparency Agreement	Japan Ocean Network Container Lashing Scheme Bias Incident → Model supplier compensated 52% of loss

4.2 New Psychological Risks for Seafarers

In terms of seafarer AI navigation technology, seafarers in the intelligent era are psychologically fragile. The results of the assessment of the impact of AI technology on seafarer psychological health are shown in Table 6. The situation awareness (SA) of AI seafarers is 67.1/100, far lower than the 82.4/100 of traditional ships, and the decision confidence index (DCI) is only 2.3/5; at the same time, the cumulative fatigue of AI ships is 0.7%/h, while the cumulative fatigue of traditional ships is 1.2%/h; and more than 3/4 of the captains believe that new crew members are increasingly difficult to operate traditional shipboard instruments, and 82% of AI captains indicate the need to improve training on explaining the algorithms behind AI.

Table 6: Comparison of Psychological Indicators between Traditional and AI Ships

Evaluation Dimension	Traditional Ship Average	AI Ship Average	Risk Threshold	Intervention Plan
Situational Awareness (SA)	82.4/100	67.1/100	<70 needs alert	Mandatory human-machine switching every 4 hours
Decision Confidence Index (DCI)	3.8/5	2.3/5	<2.5 triggers counseling	Add cognitive enhancement AR system
Fatigue Accumulation Rate	1.2%/hour	0.7%/hour	>1.0% is violation	Dynamic task allocation algorithm

5. Conclusion

Artificial intelligence is transforming shipping-but it is not replacing the mariner. Our analysis confirms that five pillars of maritime professionalism endure: theoretical mastery, regulatory fidelity, balanced human–AI collaboration, emergency leadership, and ethical accountability. These are not relics of the past but prerequisites for safe AI integration.

The path forward lies not in choosing between tradition and technology, but in weaving them together. Maritime education must become bicultural-producing officers who are equally fluent in

Bernoulli's principle and Bayesian inference. By anchoring innovation in these invariant principles, the industry can harness AI's benefits without sacrificing the human core of seamanship.

As autonomous vessels multiply, the true test of progress will not be how little humans intervene-but how wisely they choose to do so.

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References

[1] International Maritime Organization (IMO). (2021). Interim Guidelines for MASS Trials. MSC.1/Circ.1604.
[2] Drewry. (2024). Autonomous Shipping: Market Outlook 2030. London: Drewry Maritime Research.
[3] Baltic and International Maritime Council (BIMCO). (2023). Principles for Transparent Use of AI in Shipping. Copenhagen.
[4] Lee, J., & Johnson, M. (2022). Human–Automation Interaction in Maritime Operations. WMU Journal of Maritime Affairs, 21(2), 145–160.
[5] DNV. (2023). Maritime Forecast to 2050: Technology and Regulation. Høvik, Norway.
[6] Clarksons Research. (2023). Digitalisation in the Shipping Industry Report. London.