Transforming Maritime SAR Operations: Towards a Theoretical Framework for Human-AI Collaboration

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Abstract. This paper examines how Generative AI and Large Language Models (LLMs) can support decision-making in Maritime Search and Rescue (MSAR) operations through a human-centered collaborative framework. The authors propose a theoretical Human-AI Deliberative Framework (HADF) based on the ExtendAI approach, into Maritime Rescue Coordination Centers. In this framework, the human operator first develops and explains an operational plan, after which the AI extends the reasoning by providing structured feedback, identifying cognitive gaps, and supporting reflection while keeping the final decision under human control. The model combines LLM interaction, optimization methods, and supporting datasets to enhance planning quality. Reported benefits include increased decision confidence and satisfaction, as well as improved reasoning depth, though at the cost of greater cognitive effort (the results are drawn from the main study Reicherts et al., not from primary data). Overall, the study argues that AI should function as a complementary reasoning partner, improving outcomes without replacing human judgment in critical MSAR operations.

Key Words: MSAR, Gen AI, LLM, Artificial Intelligence.

1. Introduction

In 1914, maritime nations convened to establish the first international framework for maritime safety (International Convention for the Safety of Life at Sea, SOLAS) following the Titanic disaster (1912). By 1959, the International Maritime Organization (IMO) assumed leadership, expanding the global mandate from basic accident prevention to the development of sophisticated emergency response frameworks.

Central to this modern infrastructure are the SAR Convention and the Global Maritime Distress and Safety System (GMDSS), the latter becoming fully operational in 1999. These systems leverage satellite and terrestrial telecommunications to ensure that both shore-based authorities and nearby vessels receive instantaneous distress alerts. This integrated approach facilitates rapid, coordinated search and rescue operations, significantly increasing survival rates during maritime emergencies.

The paper proposes utilizing the ExtendAI model, a Gen AI-LLM tool, within a Maritime Rescue Center (MRC) to integrate AI feedback into a user's decision-making process, aiming to enhance reasoning and improve SAR outcomes, despite requiring more cognitive effort from the user. Specifically, it proposes the use of Gen AI to complement and enhance the reasoning of the user performing MSAR operations, extending their initial plan through comprehensive feedback, with the aim of supporting reflection, identifying knowledge gaps, and improving decision-making outcomes, while keeping the user in ultimate control. Essentially, the present study is a conceptual framework paper, integrating existing models and literature to propose a novel application domain, rather than presenting original empirical findings.

2. Literature Review

2.1 Maritime Search and Rescue (MSAR)

Maritime Search and Rescue (MSAR) operations are critical humanitarian activities aimed at locating and assisting individuals in distress at sea. These operations are inherently complex, characterized by high uncertainty, dynamic environmental conditions, and significant resource constraints. The primary objective of any SAR action is the swift return of survivors to a place of safety (Laperrière-Robillard et al., 2025; Kilic et al., 2025).

The International Aeronautical and Maritime Search and Rescue (IAMSAR) manual outlines the standard operating procedures and hierarchical structure for MSAR. This framework typically involves five distinct stages (Figure 1) (ICAO-IMO, 2022):

- Awareness: This initial phase involves receiving a distress call and identifying the last known position (LKP) of the victim.
- Initial Action: This stage focuses on evaluating the distress call and making preliminary decisions, including identifying the On-Scene Coordinator (OSC) and gathering local meteorological and aeronautical data to calculate the probability of containment (PoC).
- Planning: This crucial stage is dedicated to formulating a response strategy, which includes conducting thorough risk assessments, determining necessary resources, identifying optimal entry points, and selecting the most effective search patterns.
- Operations (Execution): During this phase, the OSC directs the mission, utilizing sensors, updating sweep patterns, and coordinating with various agencies in real-time.
- Conclusion: Operations conclude when the distressed subjects are rescued, or it is determined that further efforts are unlikely to yield additional survivors.

Figure 1. IAMSAR MSAR Operational Stages – Block Diagram.

SAR mission coordinators (SMCs) are highly trained individuals responsible for the planning, coordination, control, and management of these operations (Laperrière-Robillard et al., 2025; Xu et al. 2011). Traditional MSAR (Maritime Search and Rescue) frameworks encounter several key challenges: the difficulty in pinpointing the initial incident location due to uncertain and imprecise data; the dynamic impact of changing weather, currents, and tides on survivor positions; limitations in available personnel, assets, and time; the need for continuous adaptation of plans based on new information; and structural rigidity within hierarchical, human-centered communication systems, which can cause slow adaptation to real-time changes, resulting in operational delays and the amplification of errors throughout the mission (Kilic et al., 2025).

2.2 Gen AI and LLMs

Artificial Intelligence (AI) is an overarching term encompassing computational algorithms capable of performing tasks that typically require human intelligence, such as understanding natural language, recognizing patterns, making decisions, and learning from experience. Machine Learning (ML) is a subfield of AI focused on algorithms that autonomously solve tasks through exposure to data without explicit programming. Deep Learning (DL), a more advanced subset of ML, utilizes artificial neural networks with multiple hidden layers to model complex data representations and automatically detect correlations and patterns in large datasets (Janiesch et al., 2021; Banh and Strobel, 2023).

The swift advancement of Generative AI has revolutionized the discipline, largely driven by architectures like the Generative Pre-trained Transformer (GPT) family. By utilizing immense neural networks, cutting-edge machine learning techniques, and colossal datasets for training, these systems have attained an exceptional ability to understand and generate text that closely mimics human language. The proliferation of open-source platforms and easy access to these tools have made powerful generative LLMs widely available, accelerating their deployment and application across a broad spectrum of industries such as conversational AI, medical services, and financial services.

In the early 2010s, Recurrent Neural Networks (RNNs) were effective for processing sequential data and generating coherent text, but they faced limitations such as difficulty capturing long-range dependencies, gradient instability, and slow computation. The introduction of transformer architectures marked a major shift by using attention mechanisms to analyze entire sequences simultaneously, enabling better context understanding, parallel processing, and improved handling of long-term dependencies. Models such as GPT surpassed RNNs through multi-headed self-attention and more advanced linguistic modeling. As transformer technology evolved, combined with larger datasets, increased computational power, and growing parameter sizes, Large Language Models (LLMs) rapidly advanced and became highly capable in complex natural language processing tasks. Today, LLMs are widely used across sectors including healthcare, finance, education, and technology. They support applications such as text generation, translation, summarization, and sentiment analysis; power chatbots and virtual assistants; assist in medical diagnosis and patient interaction; enhance financial operations through automated trading and fraud detection; enable personalized learning; and contribute to creative and technical fields through code generation, content creation, music composition, and visual art production (Gillioz et al., 2020).

2.3 Human-AI Collaboration

In the age of intelligent systems, core human interaction with technology is increasingly defined by partnerships with autonomous AI agents. This form of Human-AI collaboration (HAC) represents an emerging type of relationship, enabled by machines with independent decision-making capabilities. Within this framework, AI agents evolve beyond mere tools to become active teammates, working jointly with humans to achieve shared objectives. The human-centered AI (HCAI) approach reinforces the indispensable leadership role of humans within these teams. This human-led partnership adds new complexity to the traditional human-machine dynamic, demanding fresh research perspectives, methodologies, and priorities to tackle the distinct challenges inherent in HAC (Akata et al., 2024; Andrews et al., 2022). Furthermore, Human-AI collaboration (HAIC) refers to the synergistic interaction between human and AI agents working toward shared goals, where each party contributes unique capabilities to achieve outcomes superior to either working alone. This theoretical framework is grounded in several foundational concepts from cognitive science, human factors engineering, and information systems research (Seeber et al., 2020).

The integration of AI into decision-making processes represents a fundamental shift from traditional automation paradigms to collaborative human-machine systems. Unlike earlier automation that simply replaced human tasks, contemporary AI systems are designed to work alongside humans in complementary partnerships (Jarrahi, 2018). This collaborative approach is particularly critical in high-stakes domains such as maritime search and rescue (MSAR) operations, where the complexity of decision-making requires both human expertise and computational capabilities (Endsley, 2017).

3. Decision-Making Support for Maritime Search and Rescue Operations

The aim of this article is to explore decision-making support for planning maritime search and rescue (SAR) operations at a Maritime Rescue Center (MRC) with the help of Gen AI Tools. To plan the search operation, a likely starting point (datum) must be established. This calculation considers: the reported location and time of the incident, the delay until rescue vessels arrive, the surface drift of both the distressed and rescue vessels during that period, and the likelihood of a rescue aircraft reaching the site before the vessels (Figure 2).

When designing the search, it is also important for the surface search coordinator to determine the distances between approaching assisting vessels, their courses, and their speeds. These factors depend on the chosen search method, the maximum speed of the slowest vessel present, and the possibility of limited visibility in the search area. Furthermore, in addition to search and rescue planning, the evaluation and selection of assets available to the Maritime Rescue Center (MRC) for the specific search and rescue operation should also be included. Additionally, the international legal framework should be taken into account.

Figure 2. Search Area with datum

The ultimate goal of AI decision support tools is to work with hu mans to potentially reach the best performance that overcomes the limitations of either human or AI on their own **Error! Reference source not found.**. Decision-making is a highly complex process and AI support tools may vary profoundly in when, how, and what they provide. Research in AI-assisted decision-making largely focuses on providing AI-generated recommendations from model predictions **Error! Reference source not found.**. Users must then evaluate and consequently accept or reject the recommendation. Recommendations are either presented on their own or combined with additional AI support elements such as various types of model explanations or uncertainty. While sometimes successful in increasing accuracy and efficiency in generic or artificial tasks, AI-assisted decision-making has its challenges, including low user acceptance in more complex decision-making processes, and overreliance on (incorrect) AI recommendations (Wang and Yin, 2021; Reinchert et al., 2025).

On other hand, research on the use of LLMs for AI-assisted decision-making is still in its early stages, with the few existing studies mainly following three broad directions. The first is applying LLMs within the established paradigm of explainable AI. A second direction is the usage of LLMs to enrich AI recommendations with additional evidence that is related to the task rather than the AI model. Lastly, researchers have explored the use of LLMs for designing AI agents that can engage with users in various forms of discussions (Reinchert et al., 2025). Ma et al. (2024) on the other hand proposed the concept of Deliberative AI, where both the human and the AI first present their viewpoints. Afterwards, they deliberate on conflicting opinions and discuss individual features until a final decision is reached. Finally, the approach of Reicherts et al. **Error! Reference source not found.**, in which the user starts by presenting their own rationale and then receives the AI's perspective, but has more sophisticated procedures. That is, they propose that AI is extended and integrated into human reasoning, with the aim of engaging the user in a forward reasoning mode. Therefore, the user does not need to understand an independent perspective of AI (Figure 3).

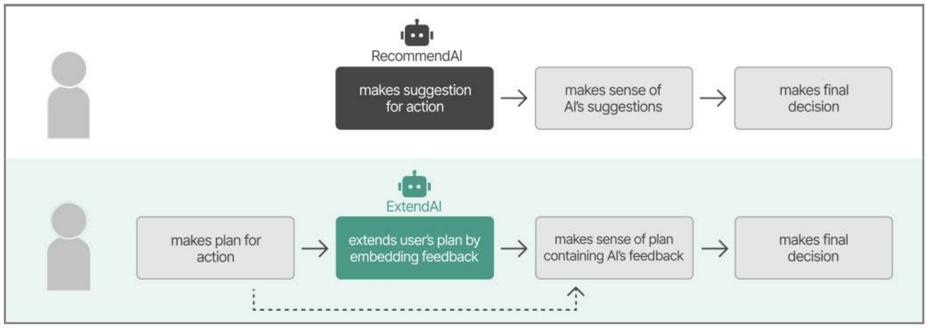

Figure 3. Illustrative comparison of the thought process when interacting with two ‘types’ of AI – RecommendAI and ExtendAI (Reinchert et al., 2025)

4. The Proposed Conceptual Framework

In MSAR case, we employ the ExtendAI model by Reicherts et al. (2025). In this model, the user "creates a plan for action" and then "articulates their reasoning" to the AI (a Gen AI-LLM tool). The AI (ExtendAI) then "extends the user’s plan by integrating feedback." This augmented reasoning is returned to the user, with the AI's feedback highlighted (in bold), so that the user can see the AI's suggestions directly within the context of their original thoughts. The user then "understands the plan containing the AI’s feedback" and "makes the final decision". The aim is to complement and enhance the user’s reasoning processes by more closely integrating the AI into their decision-making workflow. It seeks to help users reflect and identify potential gaps in their reasoning. According to the research by Reicherts et al. (2025), the model was more effectively integrated into people’s decision-making and personal thinking processes, leading to slightly better outcomes. It supported users in reflecting on their reasoning, resulting in more informed and improved decisions. Participants reported that it gave them more freedom to think independently and helped them to “think more deeply about their decisions,” while also expressing greater satisfaction with their decisions (67%) and reporting higher confidence (76%) (these results are derived from the original study by Reicherts et al. (2025), not from primary data). However, it does require more cognitive effort from the user, as they must articulate their reasoning, and the process of writing out this reasoning may be perceived as “annoying” or “somewhat tiring”. Similarly, the Figure 4 illustrates our adaptation of this model by incorporating the optimization algorithm presented in the study by Abi-Zeid et al. (2019), as well as a supporting material dataset that must be provided to the LLM to enable optimal decision support.

Thus, the core of proposed framework:

"The AI complements and enhances the user’s reasoning by extending their initial plan through integrated feedback, aiming to support reflection, identify cognitive gaps, and improve decision-making outcomes while keeping the user in final control."

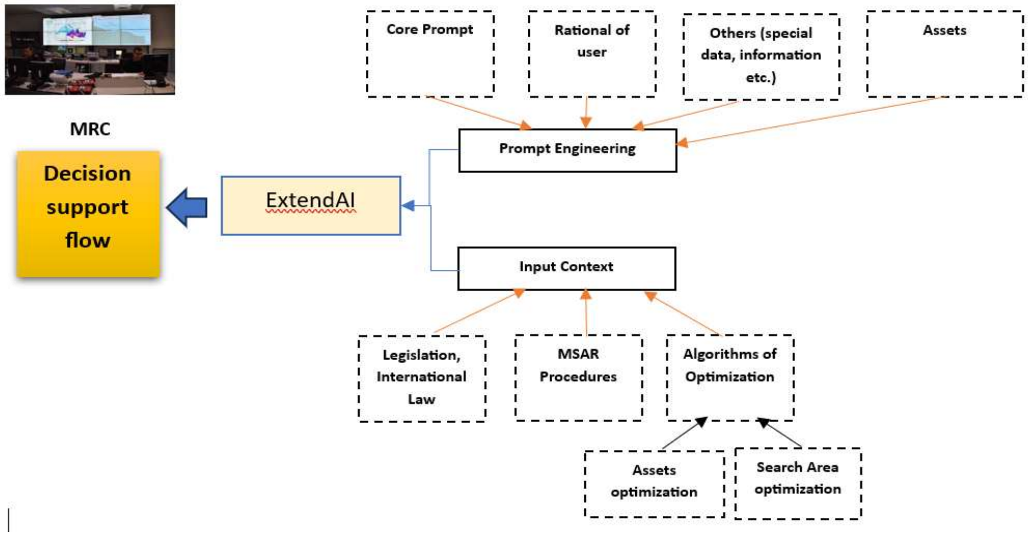

Figure 4. Decision Support process by using LLM for MSAR (by authors)

Specifically, the proposal follows a structured collaborative workflow between the user and the Gen AI (Table 1):

- *Articulation:* The user creates an action plan and articulates their reasoning to the AI.
- *Extension:* The Gen AI (ExtendAI model) analyzes the logic and provides highlighted feedback to fill gaps.
- *Integration:* The system incorporates an optimization algorithm and a specific supporting dataset to ensure high-fidelity decision support.
- *Final Decision:* The user reviews the augmented plan and retains ultimate authority over the final decision.

Table 1. Benefits vs. Challenges

Benefits	Challenges
76% increase in decision confidence.	Requires higher cognitive effort from the user
Identification of reasoning gaps.	The articulation process can be perceived as tiring.
67% higher satisfaction with outcomes.	Requires a robust dataset for optimal support

4.1 Case Study: Human-AI Deliberative Collaboration During a Maritime SAR Incident

Based on the Human-AI Deliberative Framework (HADF), a scenario of using the conceptual framework is presented. The scenario is hypothetical and designed to demonstrate the operation of the ExtendAI model in real time, without constituting primary research. The scenario highlights how the use of AI cannot and should not replace humans, but rather should function as an "external memory" and, at the same time, an "analytical controller," though it requires increased cognitive effort from the user to synthesize the necessary information. Specifically:

A. *Scenario Setup*

- *Incident:* A distress call is received from the 12-meter vessel "Blue Wave" reporting engine failure and water ingress.
- *Location:* 15 nautical miles Northwest of Ikaria.
- *Weather Conditions:* Northern winds at 6 Beaufort, heavy seas, and a water temperature of 18°C.
- *Available Assets*: 1 Coastal Patrol Boat (CPB), 1 Super Puma Helicopter, and 2 nearby commercial vessels.

B. *Step-by-Step HADF Implementation*

The process follows the standard IAMSAR stages, integrating the human-AI collaborative loop.

- Stage 1: *Awareness*. The SAR Mission Coordinator (SMC) receives the alert and logs the data into the system. AI Support: The system processes the coordinates and activates trajectory modeling to calculate the Initial Probability of Containment (PoC).
- Stage 2: *Initial Action*. The SMC classifies the incident as a "Distress Phase," requiring immediate intervention. Human Input: The SMC prioritizes the immediate launch of the helicopter to maximize the "golden hour" for survival.
- Stage 3: *Planning / ExtendAI Interaction*. This stage utilizes the core HADF innovation where the AI acts as a "complementary reasoning partner".

C. *ExtendAI Interaction Sample: SMC-AI Dialogue*

- *SMC (Proposed Action Plan):* "I intend to dispatch the CPB directly to the LKP while the helicopter initiates an 'Expanding Square' search pattern centered on the last known coordinates. The commercial vessels will stand by 5 miles to the West.".
- *ExtendAI (Feedback & Reasoning Extension):* "The plan is appropriate for rapid deployment. However, *based on drift analysis (6B North wind), the PoC has shifted 3.2 miles South-Southeast from the LKP. Reasoning Gap Identified:* Utilizing an 'Expanding Square' with the helicopter may delay detection due to the high drift rate.
    - *Proposed Extension*: It is recommended to use a 'Creeping Line' search along the drift axis. Furthermore, repositioning the commercial vessels to form a 'Visual Barrier' to the South will increase the Probability of Detection (PoD) by 15%.".
- *Final Decision*: The SMC evaluates the feedback, accepts the PoC shift, and modifies the search pattern, maintaining ultimate authority over the execution.

Also, the next table shows the step-by-step interaction:

Table 2. Step-by-Step Interaction Table

Operational Stage	Human Action (SMC)	ExtendAI Contribution (GenAI/LLM)	Collaborative Outcome
Awareness	Receives LKP and weather data.	Automated data organization and cross-referencing.	Rapid situational awareness.
Initial Action	Designates OSC and initial assets.	Drift prediction and survival time estimation (Lagrange model).	Accurate determination of search area.

Planning	Formulates initial operational rationale.	Identifies cognitive gaps and provides highlighted feedback.	Optimized plan based on computational algorithms.
Integration	Evaluates AI recommendations.	Incorporates real-time sensor and asset data.	Increased decision confidence (76%).
Final Decision	Final approval and execution.	Continuous monitoring and suggestion of dynamic adjustments.	Reduced human error and faster recovery time.

Finally, the next figure shows the relatives operations of this scenario:

Figure 4. Scenario operation (by authors)

4.2 *Deployment consideration*

The successful implementation of the proposed framework requires a careful system architecture strategy, adapted to the specific telecommunication conditions of a maritime environment. In land-based infrastructures, with Search and Rescue Coordination Centers (MRCC), the use of Cloud-based LLMs is satisfactory, as the reliable broadband connection offers a utilization of models with enormous computing power. On the other hand, for operations performed on board (shipboard deployment) or in remote maritime zones, limited connectivity forces the choice of Edge AI solutions.

In low bandwidth (denied/degraded environments), the use of locally installed open-source models (e.g. Llama, Mistral or Phi-3) offers an advantage as there can be an implementation of LLM use, without the need for constant access to the internet. At the same time, the integration of modern satellite technologies such as VSAT and Iridium, or the use of hybrid connectivity models, are key factors for the future expansion of the system. In general, the choice of the appropriate architecture (Cloud vs Edge) depends on the operational context and the respective real-time response requirements.

5. Conclusions

AI offers substantial benefits in maritime safety and efficiency, acting as a complementary tool to human expertise. Continuous research and collaboration among stakeholders are essential to address these limitations and unlock the full potential of AI in maritime operations. The goal of using Gen AI is to complement and enhance the reasoning processes of the MSAR (Maritime Search and Rescue) user within an MRC (Maritime Rescue Coordination Centre), integrating AI more closely into the decision-making process. It aims to assist users in reflecting on and identifying potential gaps in their reasoning, leading to slightly better outcomes in the SAR (Search and Rescue) process.

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