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Using Large Language Models (LLMs) to Complement Expert-Based Hazard Identification under Limited Operational Data for Remotely Piloted Ships

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Remotely piloted ships are still under development, and therefore, real operational experience and data are limited. This limited real-world evidence makes it challenging to comprehensively explore potential hazards during the early stages of design. However, a substantial amount of collected data already exists through previous expert intuition, questionnaires and workshops with maritime pilots that provides a significant qualitative benchmark. Recently, synthetic data generation using Generative Artificial Intelligence (GenAI) has emerged to deal with problem of real-world data scarcity in various studies. This study investigates the potential of Large Language Models (LLMs) as a source of synthetic data to complement existing expert-based hazard identification processes. In this feasibility study, structured prompts are designed to extract possible hazards related to communication, remote control, and human–machine interaction. The LLM-generated hazard lists are then qualitatively compared with the hazards identified through expert workshops to highlight differences and potential synergies. Initial results indicate that LLM-generated outputs can complement existing human-derived insights by expanding the diversity of identified hazard scenarios. Nevertheless, careful consideration is needed when interpreting and integrating AI-generated content to ensure consistency, occurrence probability, feasibility, and reliability. The study aims to motivate discussion on how GenAI can responsibly contribute to structured hazard identification in the development of remote pilotage services.

Keywords: Remote Pilotage, Large Language Models, Generative AI, Hazard Identification, Expert Validation, Maritime Design.

1. Introduction

The development of smart maritime services has increased interest in remote pilotage as a means to enhance navigational safety and operational efficiency. Remote pilotage is a digital shore-based service that improves situational awareness and decision-making for the ship's master without transferring navigational or control authority. As remote pilotage services are still under development, real operational data remain limited. This lack of data presents challenges for early-stage hazard identification, although expert knowledge, operational feedback, and historical incident and accident information are available through reports, workshops, questionnaires, and expert discussions.

However, developments in remotely piloted and autonomous ship operations introduce new safety challenges due to system complexity, distributed control, and limited operational experience (Kim et al. 2019). Traditional maritime safety assessment relies heavily on expert judgement and historical data, which may be insufficient for emerging concepts such as remote pilotage (Wang et al. 2023; Campbell et al. 2022). Systems-theoretic approaches such as System-Theoretic Process Analysis (STPA) have therefore been widely adopted to analyse complex socio-technical systems, including remotely piloted ships (Basnet et al. 2023; Liu et al. 2025). STPA enables hazard identification by modelling control structures and unsafe control actions across human, technical, and organizational components. Hybrid approaches extend these analyses by integrating probabilistic reasoning through Bayesian networks (Wang et al. 2025; Zhang et al. 2025), although such analyses still depend strongly on expert input.

Artificial intelligence has recently been explored as a complementary approach for supporting safety analysis under limited data conditions. Large Language Models (LLMs) can generate structured, context-aware outputs, although their use must remain guided by expert oversight. AI-based techniques have increasingly been applied in maritime risk assessment (Campbell et al. 2022; Zhong et al. 2025; Anuja et al. 2025), and LLMs have shown potential in safety-related tasks such as hazard identification and scenario generation when combined with structured safety frameworks (Yuzui et al. 2025; Jin et al. 2026). However, limitations including hallucination risks, limited explainability, and constrained causal reasoning require careful expert validation before applying LLM outputs in maritime safety contexts (Dokas 2026; Lee et al. 2026).

This literature review demonstrates an opportunity to combine the strengths of safety analysis with LLM-based tools. They can assist experts by improving knowledge integration, structured scenario exploration, and coverage in hazard identification under limited data conditions (Reddicharla et al. 2024; Wei et al. 2026). In this context, this study explores whether LLMs can practically support early hazard identification in remotely piloted ship services under limited operational data conditions, rather than replace existing expert-based approaches. They are considered as a source of synthetic hazard suggestions that may expand the diversity of identified scenarios. The focus is on hazards related to communication systems, remote assisting functions, human–machine interaction, and cybersecurity, which are of main importance for remote pilotage operations.

Accordingly, this paper makes the following contributions:

- A structured feasibility approach for using LLMs to assist hazard identification for remotely piloted ships operating under limited operational data.
- A qualitative comparison between LLM-generated hazards and hazards identified through expert workshops.
- Expert verification to assess the operational relevance of AI-generated hazards.

The following section introduces an LLM-based structured hazard identification approach for remote pilotage, aligned with the specific characteristics of remote pilotage operations through a comprehensive prompt design.

2. Methodology

2.1. Benchmark Expert-Based Hazard Identification

An expert-based benchmark, including the remote pilotage process and its hazard list, is considered from previously conducted remote pilotage risk analysis research as the reference for benchmarking and evaluating the potential contribution of LLMs in early-stage hazard identification (Basnet et al. 2022, Basnet et al. 2023). In these studies, the remote pilotage process is divided into three phases of Preparation, Planning and Operation, including the tasks and their interactions controlled by Remote Pilot, Vessel Master, VTS Operator and other Deck Crew (see Fig. 1).

In addition, hazard list is derived through structured hazard analysis workshops, questionnaires, and discussions with experienced maritime pilots with professional experience in pilotage operations and safety analysis and experts in these studies. LLM-generated hazard suggestions are compared with this benchmark hazard list to identify overlaps, divergences, and potential enhancements. (see Table 1).

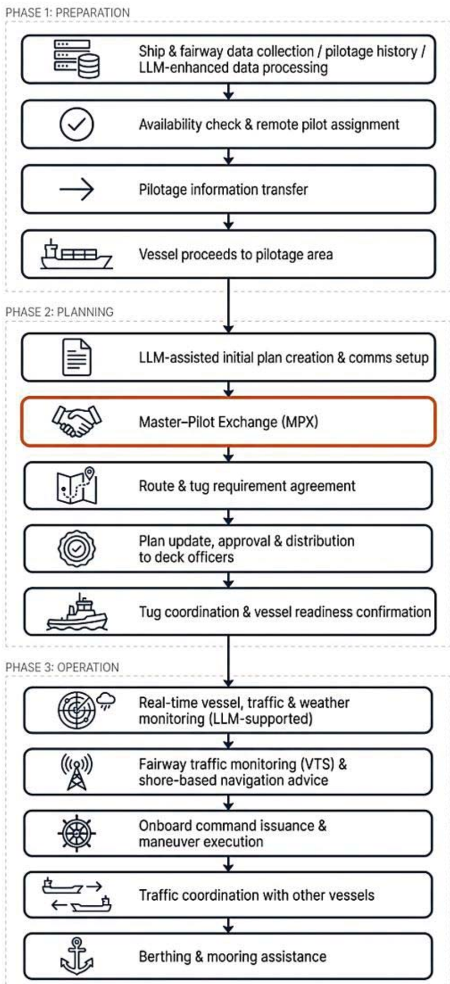

Fig. 1. Remote pilotage process phases (Basnet et al. 2022).

Table 1. Lists of System-level hazards in Remote Pilotage operation (RPO) (Basnet et al. 2023)

ID	System-level hazards
H1	Ship Violates minimum separation standards or under keel clearance in route
H2	Disruption or loss of ship manoeuvrability during RPO
H3	Lack of requisites for conducting RPO

Moreover, this hazard list is not used as the sole validation source. It supports a qualitative assessment of whether LLM-generated outputs align with, extend, or deviate from existing expert perspectives. According to the hazard list, this study aims to the remote pilotage hazards in Finnish fairways.

2.2. LLM-Based Hazard Generation

2.2.1. LLM Selection

The selection of the LLM in this study is guided by findings from recent comparative research on LLM applications in maritime operational knowledge. Pei et al. (2024) compared several LLMs in the context of ship handling knowledge and skills for Maritime Autonomous Surface Ships. Their study evaluated different models and based on their findings and comparisons, this study employs the GPT-4.1 as a practical tool for generating synthetic hazard suggestions in this study. The focus of this research is not to benchmark LLM performance, but it is employed as a supportive tool to assist in proposing acceptable hazard scenarios and not as a decision-making or validation mechanism. All LLM-generated outputs are evaluated and verified by experts.

2.2.2. Prompt Design

- Prompt Objectives

The prompt design is conducted to support early-stage hazard identification. It is intended to be consistent with expert-based practices and guide the LLM towards generating operationally and reasonably meaningful hazards in remote pilotage services. Specifically, it should reflect the operational concept and generate realistic hazards. However, prompts cannot strictly constrain the behavior of LLMs; they act as soft guidance that influences the likelihood of certain responses rather than enforcing deterministic outputs. For this reason, the hazards generated by the LLM are treated as candidate suggestions and are subsequently reviewed and validated by domain experts.

- Operational Context Specification

The remote pilotage process, considered as an expert-based benchmark, is explicitly embedded in the prompt to reduce ambiguity and ensure relevance. Moreover, remote pilotage is defined as a shore-based pilotage (SBP) service as "an act of pilotage carried out in a designated area by a maritime pilot licensed for that area to conduct the safe navigation of the vessel from a position other than on board the vessel concerned" (ISPO, 2021). In addition, the operational environment is specified as Finnish fairways to sufficiently clarify the context.

- Operational Hazard Categories as Prompt Anchors

Based on the benchmark remote pilotage process, a set of predefined hazard categories is employed to structure the hazard generation and enable following structured comparison. These categories served as anchors for the prompt and ensured structured coverage of the remote pilotage system: navigation and maneuvering, situational awareness and data transfer, communication, cybersecurity issues and maintenance and system availability. This categorization is intended to limit uncontrolled expansion of the hazards and reduce overlap.

- Structured Prompt and Constraints

A structured prompt template is used for all hazard generation tasks, defining the task, operational context, constraints, and expected output format. The template served as an interface between expert knowledge and the LLM to support structured exploration of hazard scenarios while maintaining expert interpretation and validation authority. By embedding operational context and functional constraints in the prompt, the LLM generated hazards comparable with expert-based hazard lists. However, LLM outputs may include factually incorrect information (Miller et al. 2025) and cannot be strictly controlled by prompts. To reduce unrealistic outputs, the prompts excluded quantitative risk estimation and regulatory interpretation and emphasized the generation of operationally meaningful hazards relevant to safety analysis. The structured prompt design provides traceability between the defined operational context, applied constraints, and the resulting hazard outputs, enabling a transparent link between expert knowledge and generated hazards.

2.2.3 Hazard Generation Procedure

The structured prompt applied to generate synthetic hazard suggestions in a structured and controlled approach to ensure coverage of the benchmark remote pilotage process, and consistency with the expert-based hazard list.

- Hazard Generation Objectives

Hazard generation prompt is executed separately in all defined hazard categories to ensure coverage of remote pilotage process phases and to reduce overlap between generated hazards. In each round, the LLM identified hazards relevant to each task, considering operationally meaningful hazards happening at task relations and interactions. No attempt is made to estimate risk and likelihood.

- Raw Generated Hazards

Each prompt execution produced a set of qualitative hazards, including hazard description and its potential cause and consequence. Applying the structured prompt for all hazard categories resulted in 50 initial LLM-generated hazards (raw outputs). The raw outputs are unfiltered material that derived from individual tasks to higher level process interactions. No ranking and validation is performed during generation. Table 2 presents some samples of LLM-generated raw hazard list.

Table 2. Sample LLM-Generated initial LLM-generated hazards (raw outputs)

ID	Initial LLM-generated hazards (raw outputs)	Category
RH1	Delayed manoeuvring advice due to communication latency	Navigation/ Maneuvering
RH2	Late helm command caused by delayed remote pilot input	Navigation/ Maneuvering
RH3	Incorrect engine command due to misunderstanding between remote pilot and bridge team	Navigation/ Maneuvering
RH4	Loss of situational awareness at remote pilot station	Situational Awareness
RH5	Missing sensor inputs leading to incomplete traffic picture	Situational Awareness

Table 2. Sample LLM-Generated initial LLM-generated hazards (raw outputs)

ID	Initial LLM-generated hazards (raw outputs)	Category
RH6	Corrupted AIS data causing incorrect traffic assessment	Situational Awareness
RH7	Temporary loss of primary communication link	Information/ Communication
RH8	Unstable communication causes intermittent data dropouts	Information/ Communication
RH9	Cyber manipulation of navigation data	Authority/ Integrity
RH10	Failure of autonomous collision avoidance system	Navigation/ Maneuvering

- Refinement of Raw Generated Hazards

As seen in Table 2, the raw LLM-generated hazards include overlapping and near-duplicate hazards (e.g. RH1 vs. RH2 and RH4 vs. RH5), hazards at different levels of perspective (e.g. RH4 vs. RH6), and hazards partially outside the defined scope of remote pilotage services (e.g. RH10). This proves the need for filtering before expert validation. Therefore, the raw LLM outputs are subjected to a qualitative refinement process in the next step. This process included: removing duplicate items, merging the items with the same underlying condition, removing out of scope items and clarifying ambiguous items further. Then the refined list is documented in a brief, transparent and standardized form for expert validation by maritime pilots.

2.2.4. Expert-Validated Hazard List

Following the hazard generation and refinement steps, the resulting hazard list is reviewed and verified by experienced maritime pilots with professional experience in maritime operations and remote pilotage-related safety analysis. The experts evaluated the relevance and plausibility of the LLM-generated hazards based on their operational knowledge and experience with maritime navigation and pilotage practices. Their feedback is used to confirm whether the generated hazards are operationally meaningful and consistent with realistic remote pilotage scenarios. The following section presents the results obtained from applying the proposed LLM-assisted hazard identification approach.

3. Results

Table 3 presents the final expert-validated hazard list. The hazards are grouped according to the predefined operational categories used throughout this study, showing potential safety concerns associated with remote pilotage services at an early design stage.

Table 3. Validated LLM-Generated Hazards

ID	Generated hazards	Category
H1	CPA violation	Navigation/ Maneuvering
H2	UKC violation	Navigation/ Maneuvering
H3	Deviated trajectory beyond fairway limits	Navigation/ Maneuvering
H4	Insufficient Manoeuvring Margin Capability	Navigation/ Maneuvering
H5	Vessel Motion Inconsistent with Intended Navigation Plan	Motion/ Timing
H6	Control or Communication Timing Exceeds Safe Limits	Motion/ Timing
H7	Insufficient Situational Awareness of Remote Pilot	Situational Awareness
H8	Degradation of shared situational awareness	Situational Awareness
H9	Navigation or control decisions made using incorrect, incomplete, delayed or unavailable data	Information/ Communication
H10	Communication Capability Insufficient for Safe Remote Operation	Information/ Communication
H11	Control Authority Mode Is Ambiguous or Inconsistent	Authority/ Integrity
H12	Degraded Integrity, Availability, Confidentiality, or Reliability of Navigation and Control Functions	Navigation/ Maneuvering

These results show how LLM-generated hazard suggestions can contribute to structured hazard identification under conditions of limited operational data, when constrained by process-based prompts and subjected to expert validation. The expert-derived hazards served as the benchmark reference. While several LLM-generated hazards (e.g., CPA and UKC violations) overlapped with expert-identified hazards, others did not, reflecting both consistency with known safety concerns and the generation of additional candidate hazards. The validated hazards are compared with expert-identified hazards, which served as the benchmark. Figure 2 demonstrates LLM-supported hazard identification workflow including the role of structured prompts, refinement, and expert validation.

4. Discussion

This study investigated the use of LLMs for hazard identification in remote pilotage under conditions of limited operational data. The results suggest that LLMs may assist hazard exploration in a structured manner. Initial LLM-generated output showed redundancy, different abstraction levels, and some out-of-scope hazards. Without expert refinement, such outputs could mislead the analysis. Therefore, expert validation is necessary to filter unrealistic hazards before incorporating them into risk assessment. The structured prompt design played an important role in improving the relevance of generated hazards by describing the remote pilotage workflow, defining controllers, and specifying task interactions. This indicates that the effectiveness of LLM-assisted hazard identification depends more on how expert and system knowledge are embedded into the prompt structure than on the generative capability of the model itself. After expert validation, the resulting hazard list is operationally meaningful. The results suggest that LLMs may help experts identify hazards that could be overlooked, particularly at system interfaces, such as shared situational awareness degradation and control authority inconsistencies. However, LLMs cannot replace established safety processes or expert judgement.

Overall, the findings suggest that LLMs may support structured exploration of hazards in safety-related domains; however, the present analysis is limited to qualitative hazard identification and a constrained operational context. In addition, LLM outputs may vary between executions due to the probabilistic nature of generative models; therefore, the generated hazards should be interpreted as candidate suggestions requiring expert validation. Future work should extend the approach by integrating a broader expert base, additional operational scenarios, and links to risk assessment and validation activities as remote pilotage services develop further. Within these limitations, LLMs may serve as a useful complement to traditional methods, particularly in early design stages where operational data is scarce.

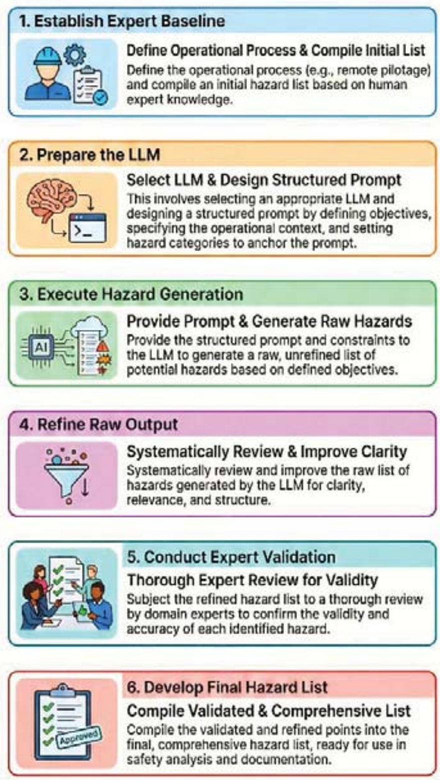

Fig. 2. LLM-supported hazard identification workflow illustrating the integration of prompt design, hazard generation, refinement, and expert validation steps.

5. Conclusion

This study presented a structured and structured approach for integrating Large Language Models (LLMs) into early-stage hazard identification for remote pilotage services under conditions of limited operational data. By embedding expert knowledge, operational context, and process structure directly into the prompt design, LLM-generated hazard suggestions are structuredally generated initially, then refined and validated by maritime pilots. The results demonstrate that, while raw LLM-generated hazards require careful refinement, LLMs can assist in expanding and structuring the hazard identification process. The study shows practically how LLMs can be applied within a structured workflow where traceability is supported by prompt design and expert validation, while expert authority is preserved. Overall, the results suggest that LLMs can be useful in early safety analysis of emerging maritime services, but only when their role is clearly limited and expert authority remains central.

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Appendix A. Template of Structured Prompt

An example version of the prompt template is indicated below, in a structured form while embedding limitations and considerations for maritime safety issues:

Role and Task Definition: *You are assisting an early-stage hazard identification (HAZID) activity for a remotely piloted ship service. Remote pilotage is a digitally enabled, shore-based pilotage service that enhances situational awareness and decision-making for the ship's master, without transferring navigational command or control authority. The ship's master remains fully responsible for navigation and manoeuvring decisions. Your task is to identify plausible operational hazards associated with remote pilotage.*

Operational Context: *The remote pilotage service operates in Finnish fairways, characterized by constrained waterways and defined fairway limits, interaction with other vessel traffic and VTS, reliance on digital navigation, communication, and situational awareness systems. Focus on realistic operational situations relevant to such fairway operations.*

Remote Pilotage Process Description: *Consider the following three phases of the remote pilotage process when identifying hazards. Hazards may originate in any phase or at the interfaces between phases. Phase 1 – Remote Pilotage Preparation: This phase includes activities prior to the start of pilotage operations, such as: retrieval of ship-specific information, fairway restrictions, and pilotage history, checking availability of remote pilotage services, assignment of a remote pilot, distribution of pilotage-related information to the ship and crew. Hazards in this phase may relate to incomplete, incorrect, or delayed information, coordination issues, or readiness of systems and personnel. Phase 2 – Remote Pilotage Planning: This phase focuses on collaborative planning between the remote pilot and the ship's master, including: creation of an initial pilotage plan, establishment of communication between remote pilot and master, exchange and discussion of the Master–Pilot Exchange (MPX), agreement on route, manoeuvring strategy, and tug requirements, dissemination of the finalized plan to relevant stakeholders. Hazards in this phase may involve misunderstandings, misalignment of plans, communication failures, or incorrect assumptions about vessel capabilities or environmental conditions. Phase 3 – Remote Pilotage Operation: This phase covers the execution of pilotage during navigation in the fairway, including: continuous monitoring of vessel dynamics, traffic, and weather, provision of manoeuvring advice and navigational suggestions by the remote pilot, execution of navigation commands by the ship's crew, interaction with VTS, tug operators, and other deck officers, support for berthing and mooring operations when applicable. Hazards in this phase may arise from degraded situational awareness, delayed or misunderstood advice, communication instability, or unexpected traffic or environmental developments.*

Hazard Category Focus: *Identify hazards related to the following category: Navigation and manoeuvring, Situational awareness and data transfer, Communication, Cybersecurity issues, Maintenance and system availability, Address one category at a time.*

Required Output Structure: *For each identified hazard, provide the following information: Hazard description – a concise statement of the hazardous condition. Primary cause – the main technical, human, or organizational contributing factor. Potential consequence – the possible impact on navigation or safety. Indicative control or mitigation – an existing or conceptual safeguard.*

Constraints and Safeguards: *Do not perform risk ranking, probability estimation, or severity assessment. Do not interpret or cite maritime regulations. Avoid speculative, non-maritime, or duplicate hazards. Focus on hazards that are operationally meaningful and relevant to early-stage safety analysis.*

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