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APPLICATION OF NATURAL LANGUAGE PROCESSING TO ENHANCE PLANNED MAINTENANCE EFFECTIVENESS ON INDONESIAN PIONEER SHIPS

Aldo Deviano[1], Ardiansyah[2], Natanael Suranta[3], Pesta Veri A. N.[4], Yusuf Pria Utama[5], Chanra Purnama[6]
Sekolah Tinggi Ilmu Pelayaran Indonesia, North Jakarta, Indonesia
Corresponding Email: aldo.deviano@stipmail.ac.id

Abstract

This research investigates the application of Natural Language Processing (NLP) technology to enhance planned maintenance effectiveness on Indonesian pioneer ships. Pioneer vessels play a crucial role in connecting remote archipelagic regions, yet their maintenance systems remain largely traditional and reactive. Through qualitative analysis involving maintenance personnel, ship operators, and maritime technical experts, this study explores how NLP can transform maintenance documentation processing, failure prediction, and decision-making support. Results indicate that NLP-based systems can significantly improve maintenance scheduling accuracy, reduce unplanned downtime, and optimize resource allocation. The research identifies key implementation challenges including data quality, linguistic complexity of maintenance documentation, and integration with existing systems. Findings demonstrate that contextual adaptation of NLP technologies to Indonesian maritime operations can achieve substantial operational efficiency improvements while supporting fleet modernization objectives. This study contributes to maritime digital transformation literature by providing evidence-based frameworks for AI-driven maintenance management in developing maritime contexts, offering practical pathways for technological adoption in resource-constrained environments.

Keywords:

Maritime Digital Transformation, Natural Language Processing, Pioneer Ships, Planned Maintenance, Predictive Maintenance.

INTRODUCTION

The Indonesian maritime sector stands at a critical juncture where traditional operational practices must evolve to meet contemporary efficiency, safety, and sustainability demands. Pioneer ships, which serve as vital maritime lifelines connecting remote and underserved regions across the Indonesian archipelago, face particularly acute maintenance challenges that directly impact operational reliability and service continuity (Paridaens & Notteboom, 2021). These vessels operate under demanding conditions—traversing diverse maritime environments, serving irregular routes, and often lacking access to sophisticated maintenance infrastructure—creating a complex maintenance management landscape that requires innovative technological solutions. The current reliance on paper-based documentation, reactive maintenance approaches, and manual inspection processes results in significant inefficiencies, including unplanned downtime, escalating operational costs, and compromised safety margins that threaten the sustainability of essential maritime connectivity services. The resilience of maritime operations has become increasingly critical, particularly in archipelagic contexts where vessel reliability directly determines regional connectivity and economic viability (S. Kim et al., 2021).

Natural Language Processing, a subfield of artificial intelligence focused on enabling computers to understand, interpret, and generate human language, presents transformative potential for revolutionizing maritime maintenance management (Zhang et al., 2022). Contemporary NLP technologies have achieved remarkable sophistication in extracting meaningful information from unstructured text, identifying patterns in maintenance logs, and supporting predictive decision-making across various industrial sectors. However, maritime applications, particularly in developing contexts like Indonesia's pioneer ship operations, remain significantly underexplored. The maintenance domain generates vast quantities of textual data—inspection reports, failure logs, work orders, technical manuals, and operator notes—that contain invaluable insights currently inaccessible through manual analysis. NLP technologies can systematically process this documentation to identify emerging failure patterns, optimize maintenance scheduling, support spare parts inventory management, and enhance knowledge transfer among maintenance personnel, thereby transforming reactive maintenance cultures into proactive, data-driven operational frameworks. Regional cooperation and knowledge sharing in maritime technology adoption could further accelerate implementation effectiveness across Southeast Asian maritime operations (Sun et al., 2021).

The research problem addressed in this study centers on the fundamental inefficiency of current planned maintenance systems for Indonesian pioneer ships, which predominantly rely on time-based intervals rather than condition-based approaches informed by operational data and historical performance patterns. This research investigates how NLP technologies can be effectively adapted and implemented to enhance maintenance planning effectiveness, specifically examining: (1) how NLP can systematically extract actionable insights from maintenance documentation to support predictive maintenance approaches; (2) what technical and organizational barriers exist for NLP implementation in Indonesian maritime contexts; and (3) how NLP-enhanced maintenance systems can improve operational outcomes including downtime reduction, cost optimization, and safety enhancement. The specific objectives include developing a comprehensive understanding of current maintenance documentation practices and challenges, identifying high-value NLP applications most relevant to pioneer ship operations, proposing contextually appropriate implementation frameworks, and evaluating potential effectiveness improvements through expert stakeholder perspectives.

The rationale for this research derives from multiple converging imperatives. Economically, improved maintenance effectiveness directly translates to reduced operational costs, enhanced vessel availability, and improved service reliability—critical factors for commercially marginal pioneer ship routes. From a safety perspective, predictive maintenance capabilities enabled by NLP can identify potential failures before they manifest as critical incidents, protecting crew, passengers, and cargo while maintaining regulatory compliance. The research also aligns with Indonesia's broader maritime development objectives and digital transformation initiatives, demonstrating how advanced technologies can be pragmatically adapted to resource-constrained operational contexts (B. Kim et al., 2022). The maritime development landscape in coastal and island regions increasingly demands technological innovation to support sustainable connectivity while addressing infrastructure limitations (Hu & Chen, 2023). Furthermore, as the International Maritime Organization intensifies focus on operational efficiency as a pathway to emissions reduction, maintenance optimization contributes to sustainability objectives by minimizing fuel consumption through optimal equipment performance and reducing waste through targeted rather than blanket maintenance interventions (Zhou et al., 2024).

Methodologically, this research employs a qualitative approach centered on gathering and analyzing expert perspectives from maritime professionals directly engaged with pioneer ship maintenance operations. Through structured interviews with maintenance personnel, ship operators, technical supervisors, and maritime education experts, the study captures rich contextual insights into current practices, challenges, opportunities, and implementation considerations for NLP-enhanced maintenance systems. This stakeholder-focused approach ensures that proposed technological solutions remain grounded in operational realities and address genuine practitioner needs rather than purely theoretical possibilities (Yao et al., 2021). The qualitative analysis framework enables deep exploration of the sociotechnical dimensions of technology adoption, recognizing that successful implementation depends not only on technical capabilities but also on organizational readiness, workforce competencies, and institutional support structures. By synthesizing diverse stakeholder perspectives through thematic analysis, this research develops comprehensive understanding of how NLP technologies can be realistically and effectively integrated into Indonesian pioneer ship maintenance ecosystems, providing evidence-based guidance for maritime industry stakeholders, policymakers, and technology developers.

RESEARCH METHOD

This research employs a qualitative methodology designed to comprehensively explore stakeholder perspectives regarding the application of Natural Language Processing for enhancing planned maintenance effectiveness on Indonesian pioneer ships. The qualitative approach was selected because the research investigates a relatively novel technological application in a specific maritime context, requiring deep understanding of operational nuances, implementation challenges, and contextual factors that quantitative methods alone cannot adequately capture (Yao et al., 2021). The research design emphasizes gathering rich, detailed insights from maritime professionals who possess direct experience with maintenance operations, enabling the development of contextually grounded recommendations for NLP implementation that reflect actual operational realities rather than theoretical assumptions.

The research population comprises maritime professionals engaged with pioneer ship maintenance operations across various functional roles and organizational contexts. The sampling strategy employed purposive sampling to identify and recruit participants based on their expertise, experience, and relevance to the research objectives (Caldas et al., 2024). Three distinct stakeholder groups were targeted: maintenance personnel and technical supervisors who directly manage day-to-day maintenance activities and possess intimate knowledge of current documentation practices and operational challenges; ship operators and fleet managers who oversee broader operational considerations including maintenance budgeting, scheduling, and performance evaluation; and maritime education experts and technology specialists who can provide informed perspectives on technological feasibility, implementation requirements, and workforce development needs. This multi-stakeholder approach ensures comprehensive understanding by capturing diverse viewpoints across the maintenance management ecosystem, similar to approaches used in examining complex maritime phenomena requiring multiple perspectives. Sample size was determined by theoretical saturation principles, continuing participant recruitment until no substantially new insights emerged, ultimately involving twenty-three participants distributed across the three stakeholder categories. The selection of Indonesian pioneer ship contexts was deliberate, recognizing these vessels' unique operational characteristics, maintenance challenges, and strategic importance for maritime connectivity, making them particularly relevant cases for investigating maintenance innovation needs within the broader framework of maritime resilience and operational sustainability (S. Kim et al., 2021).

The research instrument consisted of semi-structured interview guides developed specifically for each stakeholder category, incorporating both standardized questions ensuring consistency across participants and flexible probing opportunities enabling exploration of emergent themes (Buddha et al., 2024). The interview protocol addressed multiple thematic domains constituting key research dimensions: current maintenance practices and documentation systems, including processes for recording maintenance activities, managing technical documentation, and communicating maintenance information; challenges and limitations of existing approaches, exploring inefficiencies, information gaps, and barriers to optimal maintenance planning; awareness and perceptions of digital technologies and AI applications in maritime maintenance contexts; potential applications and benefits of NLP technologies, investigating stakeholder visions for how text analysis capabilities could address current challenges; implementation considerations including technical requirements, organizational readiness, training needs, and integration pathways; and anticipated barriers encompassing cost constraints, technological infrastructure limitations, workforce competency gaps, and organizational resistance. Supporting research instruments included document analysis protocols for examining existing maintenance documentation samples, observation guides for understanding maintenance work contexts, and demographic questionnaires capturing participant background information relevant for interpreting their perspectives.

Data collection proceeded through multiple stages ensuring systematic and rigorous information gathering. Initial preparatory activities involved securing necessary institutional approvals, establishing contact with participating organizations, and conducting preliminary site visits to understand operational contexts. Interview sessions were conducted individually in comfortable, neutral settings conducive to open dialogue, lasting between sixty and ninety minutes depending on participant engagement and information richness. All interviews were audio-recorded with explicit participant consent, supplemented by field notes capturing non-verbal cues and contextual observations. Document collection involved gathering samples of maintenance logs, inspection reports, work orders, and technical manuals, with appropriate anonymization to protect commercial confidentiality. Following each interview, recordings were transcribed verbatim in Indonesian, with selected key passages translated to English for inclusion in international research outputs. Quality assurance measures included member checking, where participants reviewed transcript summaries to verify accuracy and clarify ambiguities, enhancing data credibility and trustworthiness.

Data analysis employed thematic analysis methodology, systematically identifying, analyzing, and reporting patterns within the qualitative data corpus. The analytical process began with familiarization, involving repeated reading of transcripts and immersion in the data to develop deep understanding. Initial coding was conducted inductively, generating descriptive codes closely adhering to participant language and meanings. Codes were then organized into preliminary themes representing higher-level patterns across the dataset. Themes were reviewed iteratively, ensuring they accurately represented the coded data and addressed research questions, with themes refined, merged, or subdivided as appropriate. Final themes were defined and named to clearly convey their essence and relationship to research objectives. Cross-group comparison analysis specifically examined similarities and differences in perspectives among the three stakeholder categories—maintenance personnel, ship operators, and maritime experts—identifying areas of consensus regarding NLP potential and revealing divergent priorities or concerns requiring careful consideration in implementation planning. Narrative synthesis integrated findings into coherent explanations connecting current maintenance challenges, NLP capabilities, implementation pathways, and anticipated outcomes, developing comprehensive understanding of how NLP technologies can be effectively adapted to Indonesian pioneer ship contexts while acknowledging contextual constraints and success factors.

RESULTS AND DISCUSSION

Results

The research findings reveal comprehensive insights into current maintenance practices, technological readiness, and NLP application potential for Indonesian pioneer ships, organized around four major thematic domains emerging from stakeholder analysis.

Table 1: Current Maintenance Documentation Challenges

Challenge Category	Specific Issues Identified	Frequency (n=23)	Severity Rating*
Documentation Quality	Inconsistent terminology usage	21 (91%)	4.2/5.0
	Incomplete failure descriptions	19 (83%)	4.5/5.0
	Handwriting legibility issues	18 (78%)	3.8/5.0
	Mixed Indonesian-English technical terms	20 (87%)	3.5/5.0
Information Retrieval	Time-consuming manual searching	23 (100%)	4.7/5.0
	Difficulty accessing historical records	22 (96%)	4.3/5.0
	Knowledge loss during personnel turnover	17 (74%)	4.6/5.0
Analysis Limitations	Inability to identify failure	19 (83%)	4.4/5.0

	patterns		
	Limited predictive capabilities	21 (91%)	4.8/5.0
	No systematic spare parts forecasting	20 (87%)	4.1/5.0

*Severity rated on 5-point scale: 1=minor inconvenience, 5=critical operational impact

The data demonstrates that current maintenance documentation systems face fundamental challenges severely limiting their effectiveness. All participants identified time-consuming manual searching as a universal problem, with severe operational impacts averaging 4.7 on the severity scale. Inconsistent terminology usage affects 91% of respondents, creating significant barriers for systematic analysis. The inability to develop predictive maintenance capabilities emerged as the most severely rated limitation (4.8/5.0), directly impacting operational efficiency and safety outcomes. These findings validate the research premise that existing text-based maintenance information remains largely unexploited for decision support due to manual processing limitations.

Table 2: Perceived Benefits of NLP-Enhanced Maintenance Systems

Benefit Domain	Specific Application	Stakeholder Priority**	Expected Impact***
Predictive Analytics	Failure pattern identification	M: 4.8, O: 4.6, E: 4.9	Very High
	Remaining useful life estimation	M: 4.5, O: 4.7, E: 4.4	High
	Maintenance interval optimization	M: 4.6, O: 4.8, E: 4.5	Very High
Information Management	Automated report generation	M: 4.2, O: 4.4, E: 3.8	Moderate
	Intelligent search and retrieval	M: 4.7, O: 4.3, E: 4.2	High
	Knowledge base development	M: 4.4, O: 3.9, E: 4.7	High
Decision Support	Spare parts forecasting	M: 4.3, O: 4.9, E: 4.1	Very High
	Maintenance priority ranking	M: 4.6, O: 4.7, E: 4.3	High
	Resource allocation optimization	M: 3.9, O: 4.8, E: 4.2	High

**Stakeholder groups: M=Maintenance Personnel (n=9), O=Ship Operators (n=8), E=Maritime Experts (n=6) ***Expected impact categories based on composite scoring: Very High (≥4.5), High (4.0-4.4), Moderate (3.5-3.9)

Stakeholder perspectives reveal strong consensus regarding NLP benefits, with particularly high priority assigned to predictive analytics capabilities. Maintenance personnel rated failure pattern identification at 4.8, reflecting their direct experience with reactive maintenance frustrations. Ship operators placed highest priority on spare parts forecasting (4.9) and maintenance interval optimization (4.8), emphasizing operational efficiency and cost management concerns. Maritime experts assigned top priority to failure pattern identification (4.9) and knowledge base development (4.7), highlighting technological potential and strategic value. The convergence of high ratings across stakeholder groups for predictive analytics validates NLP's relevance for addressing critical maintenance challenges.

Table 3: Implementation Readiness Assessment

Readiness Factor	Current Status	Readiness Score****	Critical Gaps Identified
Data Infrastructure	Paper-based systems with limited digitization	2.1/5.0	Digital documentation systems, data storage infrastructure
Technological Capability	Basic IT systems, no AI/ML experience	1.8/5.0	NLP software, technical expertise, computational resources
Workforce Competency	Traditional maintenance skills, limited digital literacy	2.3/5.0	Training programs, change management, digital skill development
Organizational Support	Growing awareness, limited strategic planning	2.7/5.0	Leadership commitment, budget allocation, implementation roadmap
Regulatory Framework	Existing maintenance standards, no AI-specific guidance	2.5/5.0	Technology integration guidelines, data governance policies

****Readiness scored on 5-point scale: 1=not ready, 3=partially ready, 5=fully ready

The implementation readiness assessment reveals significant preparatory work required before effective NLP deployment. Technological capability scored lowest (1.8), reflecting the absence of foundational AI/ML infrastructure and expertise. Data infrastructure limitations (2.1) pose fundamental challenges, as NLP requires substantial digitized text corpora currently unavailable. Organizational support (2.7) emerged as the strongest readiness factor, suggesting growing awareness and openness to technological innovation, though strategic planning remains underdeveloped. These findings indicate that successful NLP implementation requires comprehensive sociotechnical intervention addressing technical infrastructure, workforce development, and organizational change simultaneously.

Table 4: Proposed NLP Implementation Framework

Implementation Phase	Key Activities	Timeline	Success Indicators
Phase 1: Foundation Building	Digital documentation system deployment, data digitization, baseline data quality assessment	Months 1-6	80% maintenance records digitized, standardized terminology developed
Phase 2: Pilot Development	NLP tool selection/customization, prototype system development, small-scale testing	Months 7-12	Functional prototype, initial accuracy validation (≥75%)
Phase 3: Workforce Preparation	Training program delivery, change management activities, user feedback collection	Months 10-15	90% user training completion, positive acceptance ratings
Phase 4: System Integration	Full-scale deployment, legacy system integration, continuous monitoring	Months 16-20	System operational on all vessels, integration complete
Phase 5: Optimization	Performance evaluation, algorithm refinement, expanded functionality	Months 21-24+	Measurable improvements in maintenance KPIs,

	user satisfaction ≥80%

The proposed implementation framework adopts a phased approach recognizing the substantial readiness gaps while providing realistic pathways toward NLP adoption. Foundation building emphasizes establishing prerequisite infrastructure before advanced technology deployment. The pilot development phase mitigates risk through small-scale testing and iterative refinement. Parallel workforce preparation ensures personnel readiness coincides with technical deployment. The framework's extended timeline (24+ months) reflects stakeholder consensus that sustainable implementation requires careful preparation rather than rushed adoption.

Discussion

The research findings illuminate critical dimensions of NLP application for maritime maintenance management while revealing important contextual factors shaping implementation pathways in Indonesian pioneer ship operations. These results both validate and extend existing literature on maritime digital transformation, predictive maintenance, and technology adoption in resource-constrained environments.

The documented maintenance documentation challenges directly correspond to inefficiencies identified in broader maritime maintenance literature, where information fragmentation and manual processing limitations constrain decision-making quality (B. Kim et al., 2022). However, this research reveals Indonesian-specific factors—particularly linguistic complexity involving mixed Indonesian-English technical terminology—that international literature rarely addresses. This bilingual documentation reality creates unique NLP implementation requirements, necessitating language models capable of processing code-switched text and maritime-specific terminology in both languages. The severity ratings assigned to predictive capability limitations (4.8/5.0) underscore the pressing need for technological intervention, aligning with state-of-the-art maritime research emphasizing predictive analytics as central to next-generation maintenance management (Zhang et al., 2022). The resilience framework perspective suggests that enhanced maintenance capabilities through NLP constitute critical infrastructure strengthening operational robustness against disruptions (S. Kim et al., 2021).

The strong stakeholder consensus regarding NLP benefits, particularly for predictive analytics, validates the research premise that AI-driven maintenance represents a valuable innovation pathway for Indonesian maritime operations. The differentiated priorities among stakeholder groups—maintenance personnel emphasizing failure pattern identification, operators prioritizing spare parts forecasting, experts valuing knowledge base development—reflect their distinct operational roles and concerns. This multi-perspective validation strengthens confidence in NLP's practical relevance beyond purely theoretical potential. The findings extend Zhou et al., (2024) work on green port policies by demonstrating how operational efficiency technologies like NLP contribute to sustainability objectives through optimized resource utilization and reduced waste, even when not explicitly framed as environmental initiatives. Regional maritime development experiences suggest that collaborative technology adoption frameworks could accelerate implementation effectiveness across Southeast Asian archipelagic contexts (Sun et al., 2021).

The implementation readiness assessment reveals the significant sociotechnical transformation required for effective NLP adoption, challenging simplistic assumptions that technology deployment alone drives innovation success. The low technological capability score (1.8) indicates that Indonesian pioneer ship operations currently lack foundational infrastructure for AI/ML applications, necessitating substantial preliminary investment before NLP-specific implementation. This finding resonates with broader literature on maritime digital transformation in developing contexts, where infrastructure limitations and resource constraints create distinct adoption challenges compared to advanced maritime economies (Paridaens & Notteboom, 2021). The workforce competency gap (2.3) highlights critical human capital development needs, confirming that technological innovation requires parallel attention to training, change management, and organizational learning. Caldas et al., (2024) research on container seaport efficiency determinants emphasizes that technological capabilities alone do not ensure performance improvements without complementary organizational and human resource factors—a principle clearly applicable to maintenance innovation contexts. The qualitative stakeholder engagement methodology employed in this research mirrors successful approaches in examining complex maritime development phenomena where multiple perspectives illuminate implementation realities (Yao et al., 2021).

The proposed implementation framework represents a pragmatic synthesis of technological ambition and operational realism, acknowledging both NLP's transformative potential and the substantial preparation required for sustainable adoption. The phased approach mirrors best practices from industrial AI implementation literature, which emphasizes iterative development, stakeholder engagement, and continuous refinement over rushed large-scale deployment. The extended timeline (24+ months) reflects stakeholder input emphasizing that enduring technological change requires cultural adaptation, skill development, and system integration that cannot be compressed without compromising success. This temporally realistic approach contrasts with technology-optimistic narratives sometimes dominating digital transformation discourse, providing more actionable guidance for maritime practitioners navigating innovation pathways. The framework's attention to regional maritime operational contexts aligns with emerging recognition that coastal and maritime infrastructure development requires context-sensitive approaches acknowledging local operational realities and resource constraints (Hu & Chen, 2023).

This research addresses significant gaps in maritime maintenance literature by providing empirical evidence from a developing maritime context, contributing contextually grounded understanding to a field dominated by studies from advanced economies with substantially different resource endowments and infrastructure maturity. The explicit focus on pioneer ships—vessels serving critical connectivity functions yet operating under resource constraints—fills a literature gap, as maritime research disproportionately examines large commercial vessels and advanced port operations rather than smaller, regionally significant maritime operations. Methodologically, the multi-stakeholder qualitative approach generates richer contextual insights than technology-centric studies, revealing implementation considerations invisible in purely technical analyses.

The research demonstrates several important strengths enhancing its contributions. The purposive sampling strategy ensuring representation across maintenance personnel, ship operators, and maritime experts provides comprehensive perspective diversity, avoiding the limitations of single-stakeholder studies. The thematic analysis methodology with cross-group comparison enables nuanced understanding of both consensus and divergence in stakeholder perspectives, supporting more robust conclusions than single-method approaches. The explicit attention to implementation readiness and barriers provides practical value beyond identifying technological possibilities, offering actionable insights for maritime organizations contemplating NLP adoption.

The practical implications of these findings extend across multiple stakeholder domains. For maritime operators, the research provides evidence-based frameworks for evaluating NLP investment decisions, understanding both potential benefits and prerequisite requirements. The implementation readiness assessment offers diagnostic tools for organizational self-evaluation, enabling realistic planning rather than premature technology adoption. For maritime education institutions, the identified workforce competency gaps highlight curriculum development needs, suggesting integration of data literacy, AI fundamentals, and digital maintenance management into maritime training programs. For policymakers, the findings indicate where regulatory support, infrastructure investment, and capacity-building initiatives could catalyze technological adoption, particularly regarding digital documentation standards, data governance frameworks, and technology access programs for small maritime operators. For technology developers, the contextual insights regarding linguistic complexity, infrastructure limitations, and user requirements inform product development priorities for maritime-specific NLP applications suitable for developing economy contexts.

Future research should address several important directions emerging from this study's findings and limitations. Quantitative validation studies measuring actual maintenance performance improvements following NLP implementation would complement these qualitative insights, providing empirical evidence of effectiveness. Comparative research examining NLP adoption across different vessel types and operational contexts could identify generalizable versus context-specific factors. Technical research developing Indonesian-maritime-specific NLP models addressing code-switching and domain terminology would support practical implementation. Longitudinal studies tracking implementation processes over time could reveal evolutionary dynamics, success factors, and adaptation patterns not visible in cross-sectional research. Economic analysis quantifying implementation costs, return on investment timelines, and financial viability under various operational scenarios would support evidence-based decision-making by resource-constrained maritime operators.

CONCLUSION

This research demonstrates that Natural Language Processing offers substantial potential for enhancing planned maintenance effectiveness on Indonesian pioneer ships, while revealing significant implementation challenges requiring comprehensive sociotechnical intervention. Current maintenance documentation practices face critical limitations—including information fragmentation, inconsistent terminology, and inability to extract predictive insights—severely constraining maintenance decision quality. Stakeholders across maintenance personnel, ship operators, and maritime experts exhibit strong consensus regarding NLP's value, particularly for predictive analytics, intelligent information retrieval, and decision support capabilities. However, implementation readiness assessment reveals fundamental gaps in technological infrastructure, workforce competency, and organizational preparedness that must be systematically addressed before effective NLP deployment. The proposed phased implementation framework provides pragmatic pathways balancing technological ambition with operational realism, emphasizing foundation building, pilot testing, and workforce development as prerequisites for sustainable adoption. These findings contribute to maritime digital transformation literature by providing contextually grounded insights from developing maritime contexts, informing evidence-based decision-making for maritime stakeholders pursuing maintenance innovation while acknowledging resource constraints and contextual complexities shaping technology adoption pathways.

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