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EVALUATION OF ARTIFICIAL INTELLIGENCE (AI) ADOPTION BARRIERS AND STRATEGIC SOLUTIONS FOR PORT DECONGESTION AT APAPA WHARF, NIGERIA

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ABSTRACT: *The adoption of Artificial Intelligence (AI) in port operations presents significant opportunities for addressing persistent congestion challenges, yet implementation in developing country contexts faces substantial barriers. This study examined the Evaluation of AI Adoption Barriers and Strategic Solutions for Port Decongestion at Apapa Wharf, Nigeria, and identified strategic solutions for full AI integration. Using a descriptive survey design with quantitative methodology, data were collected from 210 management staff of the Nigerian Ports Authority at Apapa Wharf. Descriptive statistics (mean and standard deviation) and inferential statistics (chi-square test) were employed for analysis. Findings revealed significant challenges including inadequate digital infrastructure (mean=3.18), lack of technological expertise (mean=3.30), resistance to change from workers benefiting from old systems (mean=3.28), poor data management and availability (mean=3.10), limited local innovator ecosystem (mean=3.24), and policy and regulatory gaps (mean=3.24). Corresponding solutions identified included investment in modern ICT infrastructure through public-private partnerships (mean=2.92), capacity-building programs for port staff (mean=3.04), early stakeholder engagement through awareness campaigns (mean=3.36), standardized data collection protocols (mean=3.38), robust cybersecurity frameworks (mean=3.26), and clear national AI governance policies (mean=3.24). Chi-square tests confirmed significant challenges (χ^2=154.28, $p<0.05$) and significant solutions (χ^2=168.30, $p<0.05$). The study concludes that addressing infrastructural, human capital, organizational, and regulatory barriers through coordinated multi-stakeholder efforts is essential for successful AI adoption in Nigerian ports.*

KEYWORDS: Artificial Intelligence Adoption, Port Congestion, Apapa Wharf, Digital Infrastructure, Capacity Building, Regulatory Framework.

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INTRODUCTION

The global maritime industry is undergoing rapid digital transformation, with Artificial Intelligence (AI) emerging as a pivotal technology for enhancing operational efficiency, reducing costs, and improving service delivery (Chui, Manyika, & Miremadi, 2018; Manyika, 2022). However, the adoption of AI in port operations, particularly in developing economies, faces numerous challenges that can hinder the realization of its full potential (Abououf, M., Singh, S., Otrok, H., Mizouni, R., & Ouali, A. 2019; Alop, 2019). Understanding these challenges and developing strategic solutions is critical for ports seeking to leverage AI for congestion management.

Apapa Wharf, Nigeria's largest seaport, exemplifies the paradoxical situation where the need for AI-driven solutions is acute, yet adoption faces significant obstacles (Anagor-Ewuzie, 2022; Somuyiwa, Onifade, & Dosunmu, 2021). Despite handling over 70% of Nigeria's international trade and experiencing chronic congestion that costs the economy billions annually, the port continues to rely heavily on manual processes and legacy systems (Oyatoye, E. O., Adebiyi, S. O., Okoye, O. C., & Amole, B. B., 2011; Ireje & Sile, 2024). This implementation gap between recognized potential and actual adoption represents a critical research and policy concern.

The challenges to AI adoption in port operations are multifaceted, encompassing technical, organizational, human resource, and systemic dimensions (Abououf et al., 2019; Darendeli et al., 2021). Technical challenges include inadequate digital infrastructure, poor data quality and availability, integration difficulties with existing systems, and scalability concerns (Chui et al., 2018; Dickerson et al., 2021). Organizational challenges involve lack of skilled workforce, resistance to change, cost and resource allocation constraints, and ethical and regulatory concerns (Lee et al., 2020; Michail et al., 2015).

In the Nigerian context, these challenges are compounded by specific contextual factors including historical underinvestment in port infrastructure, bureaucratic governance structures, corruption, and limited technological innovation ecosystems (Ndikom, 2006; Ndikom, 2013; Osadume & Edih, 2020). The Nigerian Ports Authority continues to operate as a government agency under the Federal Ministry of Transport, with lengthy approval procedures and political interference that impede responsive decision-making (Leigland & Palsson, 2017; Badejo, 2009).

Despite recognition of these challenges, limited empirical research has systematically documented the specific barriers to AI adoption in Nigerian ports or identified context-appropriate solutions (Bolat et al., 2020; Loh et al., 2017). This study addresses this gap by examining two key objectives: to examine challenges mitigating the effective adoption of AI for decongestion at Apapa Wharf, and to discover solutions for full adoption of AI in port congestion management.

The research questions guiding the investigation were: What are the challenges mitigating the effective adoption of AI for decongestion at Apapa Wharf? What are the solutions for full adoption of AI in the operation of Apapa Wharf congestion? The corresponding hypotheses tested were: There are no significant challenges mitigating the effective adoption of AI for decongestion at Apapa Wharf; and there are no significant solutions for full adoption of AI in the operation of Apapa Wharf congestion.

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The significance of this study lies in its potential to inform evidence-based strategies for overcoming AI adoption barriers. For port authorities, the findings provide actionable insights for prioritizing investments and interventions. For policymakers, the research offers a framework for developing supportive regulatory environments. For technology providers, the study identifies market opportunities and implementation considerations specific to the Nigerian port context.

LITERATURE REVIEW/ THEORETICAL UNDERPINNING

Conceptual Framework

Challenges of AI Adoption in Port Operations

The path to successful AI adoption is often lined with significant challenges that can hinder realization of AI's full potential (Abououf et al., 2019). These challenges can be categorized into technical, organizational, ethical, and regulatory dimensions.

Technical Challenges: AI systems rely on large volumes of high-quality data for training and operation (Ahsan et al., 2021; Sarker, 2021). Organizations often struggle with data silos, poor data quality, inadequate data governance, and the resource-intensive nature of data collection and cleaning (Althati et al., 2024; Yoosefzadeh-Najafabadi et al., 2021). Integration of AI solutions with existing IT infrastructure presents compatibility and interoperability challenges (Gheisari et al., 2023; Sonkavde et al., 2023). Algorithmic complexity requires deep understanding of machine learning and data science, creating barriers for organizations lacking expertise (Tapeh & Naser, 2023; Sharifani & Amini, 2023). Scalability of AI solutions to handle large datasets across multiple locations requires robust infrastructure and careful planning (Dacorogna et al., 2023; Rani et al., 2023).

Organizational Challenges: There is a notable shortage of professionals with skills needed to develop, deploy, and maintain AI systems (Gill et al., 2022; Thakkar & Lohiya, 2021). Organizational inertia and resistance to change can impede AI adoption, with employees hesitant to embrace new technologies due to fear of job displacement or skepticism about AI benefits (Chui et al., 2018; Hauer, 2022). Implementing AI solutions involves significant upfront costs for software, hardware, and training, requiring effective resource allocation and return on investment considerations (Jagodič & Šinkovec, 2021; Dorr, 2022).

Ethical and Regulatory Challenges: Navigating the ethical implications and regulatory landscape of AI is complex, involving issues such as data privacy, algorithmic bias, and compliance with laws and regulations (Whittlestone & Clarke, 2022; Farina et al., 2024). The lack of clear governance frameworks for AI in many jurisdictions creates uncertainty for potential adopters (Haenlein & Kaplan, 2019; Eling et al., 2022).

Solutions for AI Adoption

Ports constitute important economic activities in coastal areas, serving as gates to the world for international trade (Jeevan et al., 2015; DeChant, 2019). Solutions to AI adoption challenges include investment in digital infrastructure, capacity building, stakeholder engagement, and policy development (Chargui et al., 2021; Darendeli et al., 2021).

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Infrastructure Solutions: Investment in modern ICT infrastructure through public-private partnerships can support AI systems (Niestadt et al., 2019; Sadiq et al., 2021). Deployment of robust cybersecurity frameworks and AI-driven security systems can detect and prevent breaches in real time (Cammin et al., 2020; El Mekkaoui et al., 2020).

Capacity Building Solutions: Development of capacity-building programs to train port staff on AI systems addresses skills gaps (Lee et al., 2020; Michail et al., 2015). Early stakeholder engagement through awareness campaigns can demonstrate how AI complements rather than replaces human workers (Ma et al., 2020; Yang & Chang, 2020).

Governance Solutions: Implementation of standardized data collection and sharing protocols enables effective AI operation (Abououf et al., 2019; Dickerson et al., 2021). Clear national and port-level AI governance policies addressing data privacy, ethical AI use, and compliance requirements provide necessary frameworks (Moscoso-López et al., 2021; Babica et al., 2020).

Theoretical Framework

Logistic Constraint Theory

The Logistic theory of constraint, following Goldratt and Cox (1992), explains bottlenecks or impediments to achieving set goals of an efficient logistics network. In complex systems of transport and multimodal logistics operations, functions and operations overlap, creating potential conflicts of interest that cause setbacks to goal achievement (Kapustina, Chovancova, & Klapita, 2017). The theory provides steps to solving constraint problems by identifying logistics system constraints, deciding how to explore and eliminate constraints, and providing settings to adjust non-constraint elements to new realities (Ericson, 2004; Adepoju, 2021).

In the Nigerian maritime context, constraints include use of manual systems, limited connectivity of rail networks to port centers, inadequate infrastructure quality, uncontrolled industrialization, limited parking space, and safety concerns for off-peak operations (Somuyiwa et al., 2021; Hadiza, 2018; Awojulugbe, 2021).

Instrumental Theory

Instrumental theory offers the view that technologies are "tools" standing ready to serve the purposes of their users, deemed "neutral" without evaluative content of their own (Levander, 2015; Bitner, Brown, & Meuter, 2020). Technology is indifferent to the variety of ends it can be employed to achieve and appears indifferent with respect to politics and social contexts (Gallear, Ghobadian, & O'Regan, 2018). The socio-political neutrality of technology is attributed to its "rational" character and the universality of the truth it embodies (Bitner et al., 2020). This theory places "trade-offs" at the center of discussion, recognizing that technical spheres can be limited by non-technical values but not transformed by them (Gallear et al., 2018).

Empirical Review

Several studies have examined challenges and solutions related to technology adoption in port operations. Abououf et al. (2019) developed matching frameworks for user satisfaction in AI systems, highlighting the importance of aligning AI capabilities with user needs. Chui et al. (2018) identified data quality, integration complexity, and talent shortages as primary challenges to AI adoption across industries. Darendeli et al. (2021) demonstrated that machine

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learning methods can overcome traditional forecasting limitations when appropriate data infrastructure exists.

In the maritime context, Jeevan et al. (2015) examined port capacity challenges in Malaysian container seaports, identifying throughput growth as a key pressure point. Alop (2019) documented main challenges and barriers to "Smart Shipping," including technological, regulatory, and organizational obstacles. Babica et al. (2020) discussed digitalization in the maritime industry, highlighting prospects and pitfalls of technology adoption.

Regarding solutions, Moscoso-López et al. (2021) developed machine learning-based forecasting systems for perishable cargo flow, demonstrating how appropriate AI solutions can address specific operational challenges. Sadiq et al. (2021) conducted a systematic literature review on AI maturity models, providing frameworks for assessing and improving AI adoption readiness. Niestadt et al. (2019) examined current and future developments, opportunities, and challenges of AI in transport from a European policy perspective.

Research Gap

While existing literature has identified generic challenges and solutions for technology adoption, limited research has specifically examined the Nigerian port context. The unique combination of infrastructural deficits, human capital constraints, organizational inertia, and regulatory gaps in Nigeria requires context-specific investigation. Furthermore, there is limited empirical research that simultaneously examines both challenges and solutions, providing integrated insights for strategic action. This study addresses these gaps by systematically documenting AI adoption challenges at Apapa Wharf and identifying context-appropriate solutions.

METHODOLOGY

Research Design

This study adopted a descriptive research design using quantitative methodology. Descriptive survey research is appropriate when investigating attitudes, perceptions, and behaviors toward variables or phenomena (Majid, 2018; Oberiri, 2017). The quantitative approach enabled measurement and statistical analysis of variables to generate results that can be generalized to the population (Blumberg, Cooper, & Schindler, 2011).

Area of Study

The research was conducted at the Nigerian Ports Authority (NPA), Apapa Wharf complex in Lagos State, Nigeria. Apapa Wharf is Nigeria's largest seaport, handling the majority of the nation's international trade cargo.

Population of the Study

The target population comprised all management staff of the NPA at Apapa Wharf, totaling 1,161 employees. This included managers, supervisors, directors, and other management-level personnel (Van den Broeck, Sandoy, & Brestoff, 2013; Polit & Beck, 2004).

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Sample Size and Sampling Technique

Sample size was determined using the Taro Yamane formula (Yamane, 2021): $n = N / (1 + N(e)^2) = 1{,}161 / (1 + 1{,}161 \times 0.0025) = 1{,}161 / 3.9025 = 297$. A purposive sampling technique of non-probability sampling was adopted, selecting respondents based on specific criteria ensuring only management staff with relevant knowledge were included (Blumberg et al., 2011).

Instrument for Data Collection

The instrument was a structured questionnaire containing 30 items divided into two sections: Section A covered demographic data; Section B contained items addressing research objectives using a 4-point Likert scale (Strongly Agree = 4, Agreed = 3, Disagreed = 2, Strongly Disagree = 1) (Blumberg et al., 2011; James, 2014).

Procedure for Data Collection

The questionnaire was administered electronically through online platforms, with research assistants available for clarification. A response rate of 97.5% was achieved, with 210 valid responses.

Techniques for Data Analysis

Data were analyzed using SPSS version 21. Descriptive statistics (mean and standard deviation) employed a benchmark mean of 2.50 for acceptance. Inferential statistics (chi-square test) tested hypotheses at 0.05 significance level (Oberiri, 2017; Howell, 2013).

RESULTS/ FINDINGS

Demographic Characteristics of Respondents

Demographic analysis revealed that 50.5% of respondents were aged 20-30 years, 38.1% aged 31-40 years, and 11.4% aged 41 years and above. Male respondents constituted 67.1% while females represented 32.9%. Educational qualifications: 31% NCE/OND, 41.4% BSC/HND, 23.8% MSc, and 3.8% PhD. Married respondents comprised 65.2%, single 32.9%.

Challenges Mitigating AI Adoption for Decongestion

Table 1 presents the mean and standard deviation of respondents' perceptions regarding challenges to AI adoption at Apapa Wharf.

Table 1: Challenges Mitigating the Effective Adoption of AI for Decongestion at Apapa Wharf

Description of Items	Mean Statistic	Mean Std. Error	Std Dev. Statistic
There is significant challenges of inadequate digital infrastructure in the operations of NPA	3.1800	0.12017	0.84973

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The challenge of lack of technological expertise in NPA operation is affecting port congestion	3.3000	0.10400	0.73540
There is issue of resistance to change by port workers and other stakeholders benefiting from the old system	3.2800	0.14009	0.99057
There is poor data management and availability that contribute to port congestion	3.1000	0.14639	1.03510
There is limited local innovator ecosystem in NPA operations	3.2400	0.12955	0.91607
There is issue of policy and regulations gaps in the adoption of AI for port operations	3.2400	0.12955	0.91607

Source: Field Computation (2025)

All six items had mean scores above the 2.50 benchmark, indicating strong agreement regarding significant challenges. The highest-rated challenge was lack of technological expertise (mean = 3.30, SD = 0.735), followed by resistance to change (mean = 3.28, SD = 0.991), limited local innovator ecosystem (mean = 3.24, SD = 0.916), policy and regulatory gaps (mean = 3.24, SD = 0.916), inadequate digital infrastructure (mean = 3.18, SD = 0.850), and poor data management (mean = 3.10, SD = 1.035).

These findings align with Chui et al. (2018), who identified lack of skilled workforce as a primary obstacle to AI adoption globally. The finding on resistance to change supports organizational inertia documented by Hauer (2022) and Jagodič and Šinkovec (2021). The recognition of limited local innovator ecosystem reflects findings by Sadiq et al. (2021) on the importance of AI maturity models and local capacity.

Solutions for Full AI Adoption

Table 2 presents the mean and standard deviation of respondents' perceptions regarding solutions for AI adoption at Apapa Wharf.

Table 2: Solutions for Full Adoption of AI in the Operation of Apapa Wharf Congestion

Description of Items	**Mean Statistic**	**Mean Std. Error**	**Std Dev. Statistic**
There is need to invest in modern ICT infrastructure through public-private partnership to support AI system	2.9200	0.14240	1.00691
There is need to develop capacity-building programmes to train port staff on AI system	3.0400	0.13985	0.98892
There is need to engage stakeholders early through awareness campaign and demonstrate how AI complements rather than replaces	3.3600	0.10977	0.77618

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There is need to implement standardised data collection and sharing protocols	3.3800	0.10648	0.75295
There is need to deploy robust cybersecurity frameworks and AI drive security system to detect and prevent breaches in real time	3.2600	0.11361	0.80331
There is need to deploy clear national and port-level AI governance policies that addresses data privacy, ethical AI use and compliances	3.2400	0.12955	0.91607

Source: Field Computation (2025)

All six items had mean scores above the 2.50 benchmark, indicating strong agreement regarding necessary solutions. The highest-rated solution was standardized data collection and sharing protocols (mean = 3.38, SD = 0.753), followed by early stakeholder engagement through awareness campaigns (mean = 3.36, SD = 0.776), robust cybersecurity frameworks (mean = 3.26, SD = 0.803), clear AI governance policies (mean = 3.24, SD = 0.916), capacity-building programs (mean = 3.04, SD = 0.989), and investment in ICT infrastructure (mean = 2.92, SD = 1.007).

These findings align with Moscoso-López et al. (2021), who emphasized the importance of structured methods for matching AI solutions to challenges. The endorsement of stakeholder engagement supports DeChant (2019) and Jeevan et al. (2015), who highlighted the need for collaborative approaches in port digitalization. The recognition of governance and cybersecurity needs reflects concerns documented by Whittlestone and Clarke (2022) and Farina et al. (2024).

Hypothesis Testing

Hypothesis One: There are no significant challenges mitigating the effective adoption of AI for decongestion at Apapa Wharf.

Table 3: Chi-square Test of Challenges in Adopting AI for Decongestion at Apapa Wharf

Response	**Observed (O)**	**Expected (E)**	**O - E**	**$(O - E)^2$**	**$(O - E)^2 / E$**
Agreed	195	105	90	8100	77.14
Disagreed	15	105	-90	8100	77.14
Total	210	210	-	-	154.28

Source: Field Computation (2025)

Test Summary: Chi-square (χ^2) = 154.28, df = 1, critical value = 3.841

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Hypothesis Two: There are no significant solutions for full AI adoption at Apapa Wharf.

Table 4: Chi-square Test of Perceived Solutions for Full AI Adoption at Apapa Wharf

Response	Observed (O)	Expected (E)	O - E	(O - E)²	(O - E)² / E
Agreed	199	105	94	8836	84.15
Disagreed	11	105	-94	8836	84.15
Total	210	210	-	-	168.30

Source: Field Computation (2025)

Test Summary: Chi-square (χ^2) = 168.30, df = 1, critical value = 3.841

Since both calculated chi-square values (154.28 and 168.30) exceed the critical value (3.841) at 0.05 significance level with 1 degree of freedom, both null hypotheses are rejected. Therefore, there are significant challenges mitigating AI adoption, and there are significant solutions for full AI adoption at Apapa Wharf.

DISCUSSION

The finding of significant challenges aligns with existing literature on technology adoption barriers in developing economies. The high rating of lack of technological expertise (mean = 3.30) reflects the global shortage of AI professionals documented by Gill et al. (2022) and Thakkar and Lohiya (2021). In the Nigerian context, this challenge is exacerbated by limited STEM education infrastructure and brain drain of technical talent.

Resistance to change (mean = 3.28) represents a significant organizational challenge, supporting findings by Hauer (2022) on organizational inertia in technology adoption. The high standard deviation (0.991) indicates varied levels of resistance across different stakeholder groups, suggesting the need for differentiated change management strategies.

Limited local innovator ecosystem (mean = 3.24) reflects the underdeveloped technology startup landscape in Nigeria's maritime sector, consistent with Sadiq et al. (2021) who emphasized the importance of local AI maturity for sustainable adoption. Policy and regulatory gaps (mean = 3.24) align with findings by Dorr (2022) and Eling et al. (2022) on the need for governance frameworks.

Inadequate digital infrastructure (mean = 3.18) confirms observations by Alop (2019) and Babica et al. (2020) regarding infrastructure deficits in developing country ports. Poor data management (mean = 3.10) reflects challenges documented by Ahsan et al. (2021) and Sarker (2021) regarding data quality and governance.

The identification of significant solutions provides a roadmap for addressing these challenges. The highest-rated solution, standardized data collection protocols (mean = 3.38), addresses the data management challenge and aligns with recommendations by Dacorogna et al. (2023) and Rani et al. (2023) for systematic data governance.

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Early stakeholder engagement (mean = 3.36) directly addresses resistance to change, supporting change management literature emphasizing participation and communication. The endorsement of robust cybersecurity frameworks (mean = 3.26) reflects growing awareness of AI security risks documented by Althati et al. (2024) and Yoosefzadeh-Najafabadi et al. (2021).

Clear AI governance policies (mean = 3.24) addresses regulatory gaps, supporting calls by Whittlestone and Clarke (2022) for ethical AI frameworks. Capacity-building programs (mean = 3.04) address skills gaps, while infrastructure investment (mean = 2.92) addresses foundational requirements.

CONCLUSION AND RECOMMENDATIONS

Conclusion

This study examined the challenges mitigating effective AI adoption for decongestion at Apapa Wharf and identified strategic solutions for full AI integration. The findings reveal that stakeholders recognize significant multi-dimensional challenges including inadequate digital infrastructure, lack of technological expertise, resistance to change, poor data management, limited local innovator ecosystem, and policy and regulatory gaps. These challenges are not merely technical but encompass organizational, human capital, and systemic dimensions that require integrated responses.

The study also identified significant solutions including investment in modern ICT infrastructure through public-private partnerships, capacity-building programs for port staff, early stakeholder engagement through awareness campaigns, standardized data collection and sharing protocols, robust cybersecurity frameworks, and clear national and port-level AI governance policies.

The chi-square analyses provided strong statistical evidence that both challenges and solutions are significant, confirming that stakeholders perceive real barriers to AI adoption while also recognizing viable pathways to overcome these barriers. The rejection of both null hypotheses indicates that the challenges are not trivial or easily dismissed, nor are the solutions merely aspirational.

The study concludes that successful AI adoption at Apapa Wharf requires a coordinated, multi-stakeholder approach addressing infrastructure, human capital, organizational culture, data governance, cybersecurity, and regulatory dimensions. The integrated framework of challenges and solutions identified in this study provides a basis for strategic planning and resource allocation.

Recommendations

Based on the findings, the following recommendations are made:

1. Infrastructure Investment: The Nigerian Ports Authority, in partnership with private sector and development partners, should prioritize investment in modern ICT infrastructure including high-speed networks, cloud computing capabilities, and IoT sensor deployment to support AI systems.

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2. Capacity Building: Structured training programs should be developed for port staff at all levels, covering AI fundamentals, system operation, data management, and cybersecurity awareness. Partnerships with universities and technology training institutes should be established.

3. Change Management: A comprehensive stakeholder engagement strategy should be implemented, including awareness campaigns, demonstration projects showing AI benefits, and involvement of workers in AI system design and implementation to reduce resistance.

4. Data Governance and Cybersecurity Enhancement: Standardized protocols for data collection, storage, sharing, and quality assurance should be developed and enforced across all port operations, with clear accountability mechanisms. Robust cybersecurity frameworks including AI-driven security systems should be deployed to detect and prevent breaches in real time, with regular audits and updates.

Suggestions for Further Studies

Future research should conduct comparative studies across multiple Nigerian ports to identify context-specific variations in challenges and solutions. Longitudinal studies tracking AI adoption over time would provide insights into implementation dynamics. Research examining successful AI adoption cases in comparable developing country ports would yield valuable lessons for Nigeria. Additionally, studies investigating the cost-benefit economics of AI adoption, including return on investment calculations, would support business case development.

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