



Research Article

A Smart Port Readiness Index in Southeast Asia to support autonomous ship operations

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Article information	Abstract
Received: February 9, 2026 Revision: June 1, 2026 Accepted: June 10, 2026	The development of Maritime Autonomous Surface Ships (MASS) requires adequate smart port capabilities to support safe and efficient autonomous operations. This study developed a Smart Port Readiness Index (SPRI) to assess port readiness for MASS across five Southeast Asian countries: Indonesia, Malaysia, Thailand, Singapore, and the Philippines. The SPRI encompassed six capability dimensions: technological infrastructure, interoperability, communication, cybersecurity resilience, onshore operational support, and regulatory and operational procedures. Policy text mining was applied to a multilingual dataset of port-related documents from 2018 to 2024, and SPRI indicators were extracted and subsequently analyzed through a Contextual Multi-Armed Bandit (CMAB) simulation framework to evaluate adaptive policy prioritization under different readiness conditions. Results showed significant readiness disparities across the region, including that Singapore demonstrated the most advanced and balanced readiness profile and was capable of supporting routine and higher-level MASS operations. Malaysia exhibited conditional readiness, with relatively strong regulatory foundations but limited digital infrastructure and system integration. Indonesia, Thailand, and the Philippines consistently exhibited low readiness across most SPRI components, indicating very limited capacity to accommodate MASS. Based on these profiles, this study aligned SPRI outcomes with MASS capability levels and identified targeted strategies to address country-specific readiness gaps. The simulation results further indicate that investments in advanced autonomous technologies and cybersecurity generate the highest expected improvements in SPRI performance. The proposed framework offered a data-driven approach for evaluating smart port readiness and informing strategic decision-making for autonomous maritime development in Southeast Asia.
Keywords Contextual multi-armed bandit; Maritime autonomous surface ships; Reinforcement learning; Smart port; Sustainability governance	

1. Introduction

The development of Maritime Autonomous Surface Ships (MASS) represents a major innovation in the maritime sector, transforming traditional transportation and shipping systems into digitized operations with extensive automation. MASS offers potential improvements in safety, efficiency, and environmental performance (Chae et al., 2020; Yanchin & Petrov, 2020; Li & Yuen, 2022; Abudu & Bridgelall, 2024). Supported by automation technology, MASS represents a critical step towards the next generation of sustainable maritime logistics and supply chain resilience.

However, autonomous ship technologies alone are insufficient to ensure effective MASS operations. MASS connects numerous stakeholders, ports, and systems; therefore, the wider maritime ecosystem must also become smart and interoperable. Digital infrastructure is essential to integrate autonomous vessels with the port stakeholders (Malmquist & Munim, 2025). A prior study by Kurt and Aymelek (2024) provided a strong foundation for understanding the operational implications of MASS on port systems, emphasizing the need for ports to adapt their operational processes and digital systems. Nevertheless, the role of the surrounding environment is equally important.

Technological readiness is a major factor in MASS adoption, representing a critical prerequisite within complex port environments. The Technology-Organization-Environment (TOE) framework provided a comprehensive lens to conceptualize readiness as a multidimensional construct, comprising technological capabilities, organizational readiness, and environmental conditions (Tornatzky & Fleischer, 1990). Port readiness for MASS is primarily reflected in the availability and maturity of digital infrastructure. Drawing on digital transformation identity theory (Zimmer & Gierlich-Joas, 2026), such a transformation reshapes work practices and organizational structures through augmentation processes, requiring continuous adaptation of roles and capabilities. Readiness extends beyond mere technology availability to encompass how technologies are prepared, integrated, and embedded within specific organizational contexts. The concept of technology readiness (Webster & Gardner, 2019) highlighted that successful innovation adoption depends on aligning technological capabilities with institutional conditions. Therefore, assessing smart port readiness requires a holistic evaluation of technological preparedness.

Smart ports are crucial because they transform traditional port operations through digitalization, integrating automation, real-time data analytics, Internet of Things (IoT) applications, and intelligent systems (Yang et al., 2018; Karas, 2020; Molavi et al., 2020; Li et al., 2023; Pham, 2023). These technologies improve operational performance and enable the interoperability needed for MASS to operate safely within complex maritime networks (Chen et al., 2019). Evaluating smart port development offers insights into how well ports can support MASS operations, including assessing digital infrastructure, data management systems, and innovation ecosystems. Recently, global collaboration has led to the creation of MASSPorts, highlighting that autonomous vessels need interoperable and digitally capable port systems (O'Dwyer, 2025). Thus, smart port infrastructure and governance are vital for successful MASS integration.

Despite these advances, the implementation and commercialization of MASS have focused on developed maritime economies, such as Europe, China, South Korea, and the United States. China has become a leader in autonomous shipping, making rapid progress in developing and deploying unmanned vessels (Chen et al., 2025). This concentration is also evident in the MASSPorts initiative, launched in early 2025 by China, Denmark, Finland, Japan, the Netherlands, Norway, the Republic of Korea, and Singapore (O'Dwyer, 2025). These countries aim to create guidelines, interoperability frameworks, and environments for MASS operations, highlighting a geographic imbalance in research and implementation.

In contrast, Southeast Asian countries operate some of the world's busiest ports and major maritime traffic corridors yet remain underrepresented in systematic studies on smart port readiness and MASS integration. For instance, the port of Singapore ranks among the world's leading container ports, handling over 37 million TEUs annually and demonstrating advanced smart port capabilities (Maritime and Port Authority of Singapore, 2022; UNCTAD, 2023). Similarly, Malaysia operates along critical global trade routes such as the Strait of Malacca and the South China Sea (Othman et al., 2025). Consequently, Southeast Asia serves as an analytically robust setting to assess disparities in smart port readiness and their implications for MASS integration. This gap emphasizes the need to assess developing maritime economies, which face significant challenges in keeping pace with global maritime automation due to the varying levels of port digitalization, environmental governance, and regulatory capacity.

Several critical gaps remain in the existing literature. Prior studies focused primarily on barriers to autonomous shipping adoption and the need for supporting digital infrastructure (Chae et al., 2020; Malmquist & Munim, 2025) and the operational implications of MASS on port systems (Kurt & Aymelek, 2022; 2024; Corsi et al., 2025). However, these studies remain largely conceptual, sector-specific, or technologically oriented, with limited empirical assessment of port readiness as an integrated, multidimensional construct. Additionally, they do not explicitly link these capabilities to MASS operational requirements in a comparative regional context. To the best of the authors' knowledge, existing studies have not provided comparative insights into regional capability gaps or the readiness of regulatory frameworks for supporting MASS adoption, particularly in developing Southeast Asia (Chen et al., 2019; Karas, 2020; Kurt & Aymelek, 2024; Li et al., 2023; Rachmannullah et al., 2025). Addressing this gap, the present study created a multilingual index to evaluate smart port readiness across Southeast Asian countries by introducing a multi-stage computational framework in a comparative regional context, thereby offering a more comprehensive and operationalizable assessment of readiness for autonomous maritime systems. This integrated framework combines technological, operational, cybersecurity, interoperability, and regulatory dimensions to evaluate MASS readiness across Southeast Asian ports.

A structured multilingual corpus was developed, and complementary indices reflecting technological readiness were derived from policy documents, technical reports, and institutional records published between 2018 and 2024. The Smart Port Readiness Index (SPRI) evaluated technological and operational preparedness for autonomous and digital port operations (Chen & Negenborn, 2018; Kurt & Aymelek, 2022; 2024; Devaraju et al., 2023; Adnan et al., 2024).

The present study then employed a contextual multi-armed bandit (CMAB) framework (Mordjana et al., 2024), specifically using the LinUCB algorithm, to simulate the sequential and adaptive evolution of SPRI components under different contextual conditions. LinUCB assumes a linear relationship between contextual features and expected rewards (Mandai & Kaneko, 2016). It uses ridge regression to estimate the reward model and creates upper confidence bounds on the estimated parameters to guide sequential decisions, integrating exploration-exploitation trade-offs in a structured manner. Studies on LinUCB demonstrated that including context can greatly enhance sequential decision-making compared to context-free methods in dynamic situations (Mandai & Kaneko, 2016; Mordjana et al., 2024).

The simulation illustrates how policy interventions and technological investments (arms) affect the evolution of governance and readiness outcomes (rewards) as contextual conditions change over simulated time. Each "arm pull" represents a decision in the policy-technology space, and LinUCB updates its internal estimates of how contextual features relate to future improvements in the indices. This sequential learning method provides a data-driven approach to evaluating potential pathways for improving port sustainability and smart readiness, revealing which combinations of governance reforms and technological investments are likely to provide the most overall benefits amid real-world uncertainties (Gan & Kwon, 2022).

This study makes three key contributions. First, it develops a multilingual and regionally representative empirical dataset of smart port readiness across five major Southeast Asian economies—Indonesia, Malaysia, Thailand, Singapore, and the Philippines. While prior studies often relied on single-country or English-only datasets, this study captures institutional, linguistic, and policy diversity, enabling a more comprehensive and unbiased assessment of port readiness in a heterogeneous developing region. These five economies collectively account for a substantial share of regional maritime activity and exhibit varying levels of digitalization and governance maturity (Lam & Notteboom, 2014; Munim & Haralambides, 2022; UNCTAD, 2023), making them analytically suitable for comparative evaluation. Second, this study proposes a theory-grounded SPRI to assess readiness for MASS operations, providing a structured and holistic measurement framework to identify port preparedness for autonomous shipping integration. Third, this study contributes methodologically and practically by combining empirical mapping with an adaptive modeling

approach to support cross-country comparison. This integrated approach offers decision-support insights for policymakers and port authorities, thereby enhancing the applicability of the study in guiding smart port development and MASS readiness strategies.

The remainder of this paper is structured as follows. Section 2 reviews the literature on smart ports and the construction of the SPRI. Section 3 describes the research methodology. Section 4 presents the results and comparative analysis across Southeast Asian countries. Section 5 discusses the findings and their implications. Section 6 concludes the paper by summarizing key insights and outlining directions for future research.

2. Literature review

2.1 Smart port and MASS integration

Smart ports are ports that use digital technologies in port operations (Hsu et al., 2023). Prior studies reported the use of interconnected systems in port operations to monitor vessel movements, cargo flows, and logistics operations in real time (de la Peña Zarzuelo et al., 2020; Wang et al., 2021). Related work also noted the role of such systems in supporting information exchange among terminal operators, logistics providers, and regulatory agencies (Kurt & Aymelek, 2022). However, most studies discussed these technologies separately, and did not clearly explain how they prepare ports for new systems like MASS. As a result, the relationship between smart port capability and MASS readiness remains fragmented in the literature. Existing studies often emphasize individual technologies, such as automation or digital communication, without examining whether ports possess the integrated operational environment required for autonomous shipping.

The introduction of MASS significantly changes the role of ports. Ports are no longer just physical infrastructure but have become part of a connected system where ships and ports must continuously exchange data and coordinate operations. As discussed in Kurt and Aymelek (2024), autonomous ships could not operate effectively unless ports supported smooth and reliable communication and interoperability. Technologies such as IoT, AI, and automation are only useful if they can work together and support real-time interaction between ships and port systems. Existing research showed that the main challenge was not a lack of technology but a lack of integration across operations (Chae et al., 2020; Malmquist & Munim, 2025). For example, while some port activities such as cargo handling are already automated, other important functions- like pilotage, navigation in busy port areas, and coordination between ship and shore- still rely heavily on human involvement and disconnected systems (Kurt & Aymelek, 2024). This creates a gap between what autonomous ships can do and what ports are ready to support. Interoperability also involves coordination between organizations and alignment with regulations. Problems such as poor communication, lack of common standards, and weak collaboration between stakeholders can slow down MASS adoption (Ringbom, 2019). This suggests that developing smart ports is not just about adding new technologies but about improving how the related environment works together.

Therefore, the integration of MASS and smart ports should be seen as a readiness issue. Ports need to be prepared, in terms of infrastructure, coordination, and system integration, to support autonomous operations. This highlights the need for a more comprehensive approach to assess how well ports are prepared for MASS.

2.2 Smart Port Readiness Index (SPRI)

To strengthen the conceptual foundation of this study, the SPRI was grounded in the TOE framework (Tornatzky & Fleischer, 1990), which explained that technology adoption depends on technological capability, organizational readiness, and environmental conditions to support MASS operations. In addition, this study incorporated the concept of technology readiness (Webster & Gardner, 2019), which emphasizes that successful innovation adoption depends on how well smart port technologies are prepared within specific MASS operational contexts.

Based on these perspectives, the SPRI was developed not just as a descriptive tool but to measure how ready ports are to support MASS operations. The technological aspect was represented by port infrastructure and digital systems (Devaraju et al., 2018; Molavi et al., 2020; Merz et al., 2023); the organizational aspect was reflected in onshore operation centers (OOCs) (Adnan et al., 2024); and the environmental aspect was captured through interoperability and communication systems (Kurt & Aymelek, 2022, 2024). The technological infrastructure domain focuses on the use of automation and digital systems, such as automated cargo handling and smart equipment, which indicate whether a port can support autonomous operations (Devaraju et al., 2018; Molavi et al., 2020; Merz et al., 2023). The interoperability and communication domain examines how well port systems can connect and exchange data with ships and other stakeholders (Molavi et al., 2020). While related, interoperability refers to system compatibility, whereas communication refers to real-time data exchange. The OOCs domain focuses on the ability of ports to monitor and control operations through centralized systems, enabling remote supervision and decision-making (Adnan et al., 2024). This approach is also supported by digital transformation maturity concepts, where readiness depends on how well systems, processes, and institutions can support advanced operations (Zimmer & Gierlich-Joas, 2026). Unlike existing smart port indices that mainly focus on digitalization, automation, or sustainability separately, the SPRI framework integrates technological, operational, interoperability, cybersecurity, and governance dimensions within a single readiness structure specifically designed for MASS operations. This allows the framework to better capture the interdependent capabilities required for autonomous maritime systems, where operational readiness depends not only on infrastructure availability but also on system integration, coordination, and regulatory support.

To make the assessment clear, each SPRI domain is evaluated using observable indicators from policy documents, port reports, and institutional data. The index examines whether these elements are present and how they support MASS operations. Each domain is assessed based on the presence, implementation emphasis, and operational relevance of policy signals identified through multilingual policy text mining. The evaluation follows a structured process: identifying relevant indicators, converting information into comparable measures, and combining them to reflect overall readiness. This allows SPRI to provide a consistent and comparable assessment across ports. Applied in the Southeast Asian context, which includes ports at different stages of development, SPRI provides a practical and meaningful way to assess readiness for autonomous maritime operations.

To further clarify how each domain is defined and assessed, **Table 1** presents the SPRI pillars, along with their scope, operational definitions, and supporting references. This table provides a structured overview of how the conceptual framework is translated into measurable components used in the analysis.

2.3 Policy text mining and index construction

The use of quantitative indicators derived from policy texts has been applied in empirical studies of governance frameworks. Policy text mining processes collections of unstructured policy documents to extract information relevant for comparison across jurisdictions or time periods. Methods applied in this context included topic modeling techniques such as Latent Dirichlet Allocation (LDA), dimensionality reduction methods such as Principal Component Analysis (PCA), and clustering approaches to group policy documents or regulatory settings. In some studies, these methods were combined with index constructions to summarize policy characteristics numerically.

Recent work applied text-mining and index-based methods in studies of policy priorities and governance patterns. Hu and Wang (2025) used a combined LDA and Policy Modeling Consistency (PMC) framework to examine policy elements in green development initiatives. Zou et al. (2025) analyzed 441 green port policy documents in China using LDA, PCA, clustering, and PMC-index construction to describe patterns across policy documents over time. Outside the maritime context, Puri et al. (2023) applied commonsense-informed text mining in urban studies, while Gyódi et al.

(2023) used term-frequency measures, co-occurrence networks, and sentiment extraction to organize and compare policy-related text corpora.

Table 1 Smart Port Readiness Index pillars.

Domain	Pillars	Scope / Definition	Reference (Official Sources)
Advanced Port and Autonomous Technologies	Technological Infrastructure (1)	Deployment of automated port infrastructure supporting digital and autonomous operations, including automated cargo handling, smart yards, and digitally enabled port equipment.	(Government of Indonesia, n.d.-b; Maritime and Port Authority of Singapore., 2022; Philippine Ports Authority, n.d.; Port Authority of Thailand, n.d.-a; Port Klang Authority, 2020)
	Advanced Autonomous Technologies (2)	Adoption of systems enabling autonomous or remotely assisted vessel operations, including autonomous navigation, berthing, remote piloting, and vessel traffic management.	(BAPPENAS, 2023; Maritime and Port Authority of Singapore, 2022; Ministry of Transport Thailand, 2023; UN ESCAP, n.d.)
Interoperability and System Resilience	Interoperability and Communication (3)	Integrated information systems, port community systems, open standards, and data-sharing protocols enable interoperability between ports, vessels, and stakeholders.	(ASEAN Secretariat, 2023; Maritime and Port Authority of Singapore, 2022; Ministry of Transport Malaysia, n.d.; Philippine Ports Authority, n.d.)
	Cybersecurity and Digital Resilience (4)	Measures ensuring secure, resilient, and reliable digital port operations, including cybersecurity frameworks, network redundancy, authentication, and data protection.	
Operational Governance and Control	Onshore Operation Centers (5)	Provision of onshore facilities for remote monitoring, situational awareness, and operational control of port and vessel activities.	(Government of Indonesia, n.d.-a; Maritime and Port Authority of Singapore, n.d.-a, n.d.-b; Port Authority of Thailand, n.d.-b; UN ESCAP, n.d.)
	Regulation and Operational Procedures (6)	Formal operational guidelines, protocols, and authority approvals governing autonomous, digital, and remotely controlled port and vessel operations.	(Government of Indonesia, n.d.-a, n.d.-b; Government of Malaysia, 1963, n.d.; Maritime and Port Authority of Singapore, n.d.-b; Philippine Ports Authority, n.d.)

Despite these advances, systematic applications of policy text mining in the maritime port sector remains limited, particularly in multilingual and cross-country contexts. Existing studies typically focus on single-country policy environments or rely on manually constructed indicators that limit comparability (Gyódi et al., 2023; Puri et al., 2023; Hu & Wang, 2025). This study addresses this gap by applying multilingual policy text mining as an evidence-detection approach to assess smart port readiness across multiple Southeast Asian countries. This allows policy commitments related to technological infrastructure, interoperability, and operational governance to be systematically identified and translated into comparable indicators. The novelty of this study lies in

integrating policy text mining with an index-based readiness framework and reinforcement learning-based modeling. By combining document analysis, index construction, and adaptive modeling, the framework provides a structured way to analyze policy readiness in complex and heterogeneous regulatory environments. Nevertheless, keyword-based text mining does not capture the full contextual meaning of policy statements, particularly when policy language varies across countries or translations. Therefore, although multilingual text processing expands coverage, translation and interpretation may introduce minor classification bias.

2.4 Adaptive policy learning for smart port readiness

Adaptive policy learning approaches, particularly contextual multi-armed bandits (CMABs), provide a reinforcement learning framework for sequential decision-making under uncertainty. CMABs are reinforcement learning approaches for sequential decision-making under uncertainty, in which actions are repeatedly selected while learning from partial feedback over time. In a CMAB setting, a decision-maker observes a contextual state before selecting an action, after which a reward is realized only for the chosen action. The observed context-action-reward relationship is then used to adaptively update future decisions. Unlike static optimization or supervised learning, CMAB models operate under partial observability, where information is obtained only from implemented actions, creating an exploration-exploitation trade-off in policy learning.

CMAB methods have been widely applied to dynamic allocation problems, including recommendation systems, online platforms, and adaptive resource management (Bouneffouf et al., 2020). More recently, studies have examined fairness, robustness, and transparency issues in policy-oriented decision systems (Kallus & Zhou, 2018; Huang et al., 2022; Solanki et al., 2024). However, applications in maritime governance and smart port planning remain limited. Existing smart port studies primarily evaluate technological readiness descriptively or through static assessment frameworks (Molavi et al., 2020; Kurt & Aymelek, 2024), while limited attention has been given to how policy priorities evolve adaptively under heterogeneous institutional conditions.

This study positions CMAB as a policy decision-support framework for smart port readiness rather than as a standalone predictive model. The approach complements the SPRI framework by modeling how different policy priorities can yield varying improvements in readiness across countries with different institutional and technological conditions. Within this study, the contextual state is represented by multilingual SPRI indicators extracted from official policy and regulatory documents, including technological infrastructure, interoperability, cybersecurity, operational governance, and regulatory readiness. These indicators capture country-specific readiness conditions and function as observable contextual signals within the sequential learning environment.

The action space corresponds to alternative policy prioritizations across SPRI dimensions, while the reward structure reflects the simulated marginal improvement in smart port readiness. Consequently, the CMAB framework operationalizes adaptive governance logic by evaluating which readiness dimensions provide the greatest incremental contribution under different contextual conditions. This formulation is consistent with the TOE perspective adopted in this study, where technological capability, organizational coordination, and environmental governance jointly influence readiness trajectories for MASS integration. To implement this adaptive decision structure, the study employs the LinUCB algorithm, which estimates expected rewards using contextual information while balancing exploration and exploitation through upper confidence bounds (Mandai & Kaneko, 2016). The use of LinUCB is appropriate because policy interventions in smart ports are context-dependent and sequential, meaning that the effectiveness of investments in cybersecurity, interoperability, or autonomous technologies depends on existing readiness conditions. By integrating multilingual policy text mining, SPRI-based feature construction, and contextual reinforcement learning, the proposed framework provides a structured mechanism for analyzing how smart port policy priorities may evolve under uncertainty across heterogeneous Southeast Asian maritime systems.

3. Methodology

The study followed a multi-stage procedure to examine smart port readiness in Southeast Asia, including policy document collection, text mining and classification, and reinforcement learning-based modeling. **Figure 1** presents the SPRI-CMAB conceptual framework.

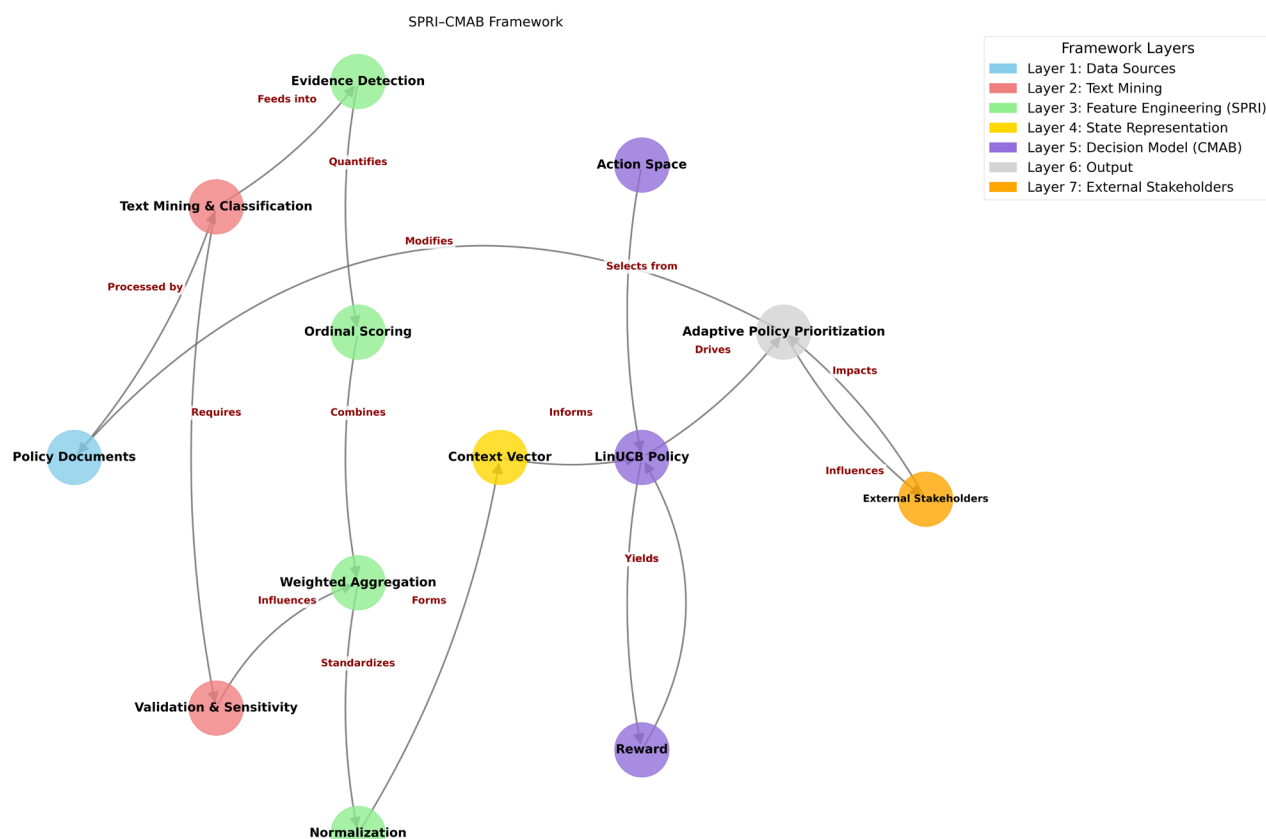


Figure 1 SPRI-CMAB conceptual framework.

Figure 1 depicts the proposed framework architecture, which facilitates a multi-layered transition from unstructured regulatory data to adaptive decision-making by integrating SPRI and CMAB. Information flow originates at the data source layer, where raw policy documents undergo text mining and classification to extract salient features, governed by a dedicated validation and sensitivity loop. These features are quantified and standardized within the SPRI feature engineering layer through evidence detection, ordinal scoring, and weighted aggregation, culminating in the synthesis of a multidimensional context vector. This vector serves as the state representation for the CMAB decision model, in which a LinUCB policy dynamically selects actions from an available action space to optimize policy prioritization based on iterative reward feedback. The framework closes the loop by outputting adaptive policy prioritization strategies that both respond to and influence external stakeholders while simultaneously providing a feedback mechanism that informs future document processing and model refinement.

3.1 Systematic policy data collection

The dataset consisted of policy documents, regulatory texts, and strategy reports issued between 2018 and 2024 by Indonesia, Malaysia, Thailand, Singapore, and the Philippines. All five countries were examined across the SPRI pillars using the same set of official sources. The listed references corresponded to documents in which relevant policy content was identified through automated collection. When a country was not recorded under a specific pillar, this reflected the absence of explicit publicly available documentation rather than omission from the dataset.

The corpus included both binding instruments, such as laws, decrees, and regulations, and non-binding materials, including guidelines, voluntary schemes, and award programs. Documents were drawn from national, regional, and international sources. The collected materials contained references to port capabilities related to digital infrastructure, interoperability, cybersecurity, and operational governance. To improve transparency and ensure consistent corpus construction across countries, the collected documents were categorized by governance function, institutional scope, and relevance to MASS-related smart port readiness, as summarized in **Table 2**.

Documents were included in the corpus if they satisfied three criteria: (1) the document was issued by an official governmental, port authority, ASEAN, IMO, or institutional source; (2) the document contained explicit references to smart port development, maritime digitalization, autonomous operations, cybersecurity, interoperability, or governance procedures relevant to MASS readiness; and (3) the document was publicly accessible and published between 2018 and 2024. Duplicate publications, non-official media reports, promotional materials, and documents lacking substantive policy or operational content were excluded. The final corpus consisted of 31 primary regulatory and policy sources distributed across the five Southeast Asian countries and regional/global governance institutions, as summarized in **Table 3**.

Table 2 Document category and details.

Category	Scope	Description	Document Details/Examples
Regulatory Frameworks (Binding Instruments)	National and regional maritime governance	Legally binding instruments that establish enforceable requirements for environmental standards, port operations, and safety compliance relevant to MASS readiness.	Laws, decrees, ministerial regulations, and maritime safety acts (e.g., Malaysia's Environmental Quality Act, Indonesia's Ministerial Regulation on Port Operations, ASEAN Framework Agreement on Multimodal Transport).
Policy Documents (Soft-law or Guideline-based Instruments)	National and organizational-level guidance	Non-binding instruments providing strategic direction or technical guidance to promote sustainable and smart port practices.	Government-issued policy papers, white papers, and national environmental or digital transformation guidelines (e.g., Philippines Green Port Initiative, Indonesia Smart Port Roadmap).
Strategy Reports (Long-term Development Frameworks)	National, regional, and global	Forward-looking frameworks setting targets for decarbonization, digital transformation, and maritime innovation, influencing policy and regulatory evolution.	ASEAN Transport Strategic Plan (2025), IMO GHG Strategy (2018, revised 2023), and national maritime masterplans.
Regional Frameworks and Declarations	ASEAN-level coordination	Multilateral commitments and cooperative programs that harmonize sustainability and technology adoption among member states.	ASEAN Strategic Transport Action Plan (STAP), ASEAN Green Transport Agenda, Maritime Connectivity Masterplan.
Global Conventions and Guidelines	International governance	Global standards and conventions that shape national and regional policy convergence toward sustainable and autonomous maritime systems.	IMO MARPOL Convention, IMO Initial GHG Strategy (2018), IMO Guidelines for MASS Trials (2021), UNCTAD Review of Maritime Transport Reports.

Documents were collected through automated retrieval from official online sources. Two document formats were processed: HTML pages parsed using requests and BeautifulSoup, and PDF files processed using pdfplumber. Each document was recorded with associated metadata, including issuing authority, country, year of publication, source category, download time, and text length. The extracted texts were stored in a structured file for reference.

The retrieval process included basic handling of inaccessible pages and dynamically generated links, and documents were assigned unique identifiers to prevent duplication across retrieval runs. Sources included ministerial websites and port authority portals, as well as materials from regional and international institutions such as ASEAN and the IMO. When primary sources were unavailable, additional documents were collected from institutional repositories. Documents in native languages (Bahasa Indonesia, Melayu, Thai, and Tagalog) were processed using multilingual sentence embeddings to ensure consistency across Southeast Asia and to maintain technical term integrity across translations. Selected technical terms were manually reviewed to confirm consistency between source and translated versions.

The study utilized a structured corpus of official documents to ensure transparency in the development of the SPRI. The complete source code, scraping parameters, and raw data processing scripts were maintained in a public repository to ensure reproducibility (available at GitHub). The dataset comprised 31 primary sources across Southeast Asian and global regulatory bodies. **Table 3** reports the distribution of documents collected.

Table 3 Distribution of collected documents and sources.

Country/Entity	Number of Primary URLs	Primary Document Types
Indonesia	6	Ministerial Regulations, Constitutional Court Decisions (e.g., Law No. 32/2009), Bappenas Roadmaps.
Malaysia	5	Port Authorities Act 1977, Ports (Privatization) Act 1990, MOT Strategic Plans, Green Port Policies.
Philippines	5	Environmental Policies, PPA Administrative Orders (AO), Green Shipping Circulars, MARINA Reports.
Singapore	5	Decarbonization Blueprint 2050, MPA Green Initiatives (MSGI), Sustainability Reports, Merchant Shipping Acts.
Thailand	5	National Maritime Strategies, PAT Green Port Initiatives (Eco-Efficiency 2023), MOT Policy Papers.
Regional/Global	5	IMO Strategy Papers, UNCTAD Maritime Reviews, ASEAN Outlooks (AMO), KL Transport Strategic Plan (KLTSP).
Total	31	—

Note: Variations in document counts reflect the decentralized versus centralized nature of policy publication across the Southeast Asian jurisdictions; all datasets were normalized to ensure comparative parity.

A formal validation protocol was observed to ensure the linguistic integrity of the multilingual keyword dictionaries. The translation of technical maritime terms into Bahasa Indonesia, Melayu, Thai, and Tagalog underwent manual expert verification by the research team to ensure contextual relevance within the maritime domain. Furthermore, a back-translation procedure was employed for primary indicators, where localized terms were translated back into English by independent reviewers to confirm that the original conceptual meaning of the SPRI pillars remained intact. The development of the keyword dictionary followed an iterative validation protocol to mitigate the inherent risks of bias and false positives associated with regular expression (Regex) detection. The initial pattern library was benchmarked against IMO regulatory frameworks and refined through three rounds of

pilot testing on a sample sub-corpus. A manual reliability audit was conducted by the research team, spot-checking 100 randomly selected keyword 'hits' to verify their contextual alignment with smart port readiness to ensure high precision. This audit yielded a precision rate of 94 %, indicating that automated detection highly correlated with expert manual assessment.

3.2 Text mining and classification

Each SPRI pillar was implemented using dictionaries of regular-expression patterns defined across five languages. The dictionaries were adjusted through manual inspection. For instance, the Indonesian term *subsidi* is restricted to co-occur with maritime-related terms such as *pelabuhan* (port) and *kapal* (ship). The Thai term corresponding to *standard* is similarly constrained using proximity rules to limit non-maritime occurrences. Pattern matching was applied at the document level, and evidence counts were aggregated by country and year. Token-length constraints were applied to reduce substring matches in unrelated compound words. To further assess classification reliability, the multilingual keyword dictionaries and Regex-based detection rules were validated through iterative pilot testing and manual verification. A random sample of detected policy fragments was independently reviewed by the research team to evaluate contextual consistency between automated classification and expert interpretation. The validation process focused on reducing false positive matches caused by linguistic ambiguity and cross-language translation differences. In addition, back-translation procedures and multilingual sentence embeddings were used to preserve semantic consistency across Bahasa Indonesia, Melayu, Thai, Tagalog, and English policy corpora.

The computation of the SPRI followed standard composite indicator procedures (Nardo et al., 2008). Let P^{SPRI} denote the set of six SPRI components. The raw SPRI score for the country c in year y is given by:

$$\text{SPRI}_{c,y}^{\text{raw}} = \frac{1}{6} \sum_{p \in \{\text{SPRI pillars}\}} S_{c,y,p}.$$

The SPRI was constructed using an evidence-detection approach, so the index did not rely on raw term frequency or TF-IDF weighting, as document length and structure vary substantially across countries. Instead, keyword occurrences were interpreted as policy-relevant signals subject to contextual validation. Evidence for the pillar p in country c and year y is defined as:

$$E_{c,y,p} = \sum_{d \in D_{c,y}} 1(\text{regex}_p \in d),$$

where $D_{c,y}$ denotes the set of documents associated with the country c and year y , and $1(\cdot)$ is an indicator function capturing validated multilingual pattern matches. To mitigate document-length bias and prevent outliers from skewing the results, raw evidence counts are transformed into an ordinal score:

$$S_{c,y,p} \in \{0,1,2\},$$

where 0 denotes no evidence ($E = 0$), 1 denotes emerging presence ($1 \leq E \leq 2$), and 2 denotes established presence ($E > 2$). This transformation ensures that the index captures the presence and maturity of policy signals rather than their raw frequency. To eliminate document-length bias and reduce sensitivity to document volume, raw counts are transformed into an ordinal scale:

$$S_{c,t,j} = \begin{cases} 0 & \text{no evidence} \\ 1 & \text{emerging presence} \\ 2 & \text{established presence} \end{cases}$$

Additionally, this study applied a differential weighting scheme (ω_p) rather than equal weighting to reflect the functional asymmetry of SPRI pillars in supporting MASS operations. Equal weighting was considered inappropriate because different readiness dimensions contribute unequally to operational autonomy and smart port integration. Therefore, pillar weights were assigned based on theoretical and operational criticality within the MASS ecosystem, as shown in the equation below:

$$SPRI_{c,y}^{raw} = \sum_{p=1}^6 (s_{c,y,p} \times \omega_p).$$

Unlike equal-weight indices, this study applied differential weights reflecting functional importance in MASS readiness, corresponding to Advanced Autonomous Technologies, Technological Infrastructure, Interoperability, Onshore Operations, Cybersecurity, and Regulation, respectively. **Table 4** presents the theory-driven weighting scheme, which reflects the relative contributions of each pillar to operational autonomy.

Table 4 SPRI pillar weights and selection criteria.

Pillar (p_i)	Weight (ω_p)	Justification
Advanced Autonomous Tech	1.3	Primary driver for vessel-port autonomy.
Technological Infrastructure	1.2	Physical foundation (cranes, AGVs).
Onshore Operations	1.2	Essential for remote situational awareness.
Interoperability	1.1	Data sharing and API standardization.
Cybersecurity	1.0	Baseline resilience requirement.
Regulation	0.7	Necessary, but often trails tech adoption.

To facilitate cross-country comparison, raw scores were normalized to a 0 - 100 scale using min-max normalization. A floor value of 0.1 was applied to ensure all active entities remained represented in logarithmic calculations. This produced a standardized index on a 0 - 100 scale:

$$SPRI_{c,y} = \frac{SPRI_{c,y}^{raw} - \min(SPRI^{raw})}{\max(SPRI^{raw}) - \min(SPRI^{raw})} \times 100.$$

3.3 Validation and sensitivity analysis

To assess the robustness of the SPRI with respect to the weighting scheme, a Monte Carlo sensitivity analysis was conducted by perturbing pillar weights within a bounded interval of $\pm 10\%$ while preserving their relative structure (Mandai & Kaneko, 2016). A total of 1,000 simulations were performed for the 2024 cross-sectional setting, and SPRI scores were recomputed in each iteration. The stability of country rankings was evaluated using the Spearman rank correlation coefficient between each perturbed realization and the baseline ranking. **Figure 2** presents the distribution of rank correlations.

The results indicated a high degree of robustness, with an average correlation of $\rho = 0.9816$, a minimum of $\rho = 0.9412$, and a maximum of $\rho = 1.0000$, with a standard deviation of 0.0273. The distribution was concentrated near unity, indicating that the overall ranking structure is largely preserved under moderate perturbations of the weighting scheme. These results indicate that the comparative SPRI structure is not materially driven by minor variations in weighting assumptions, supporting the robustness of the index construction procedure. To further examine ranking stability, **Table 5** reports rank-change frequencies across countries over all simulations.

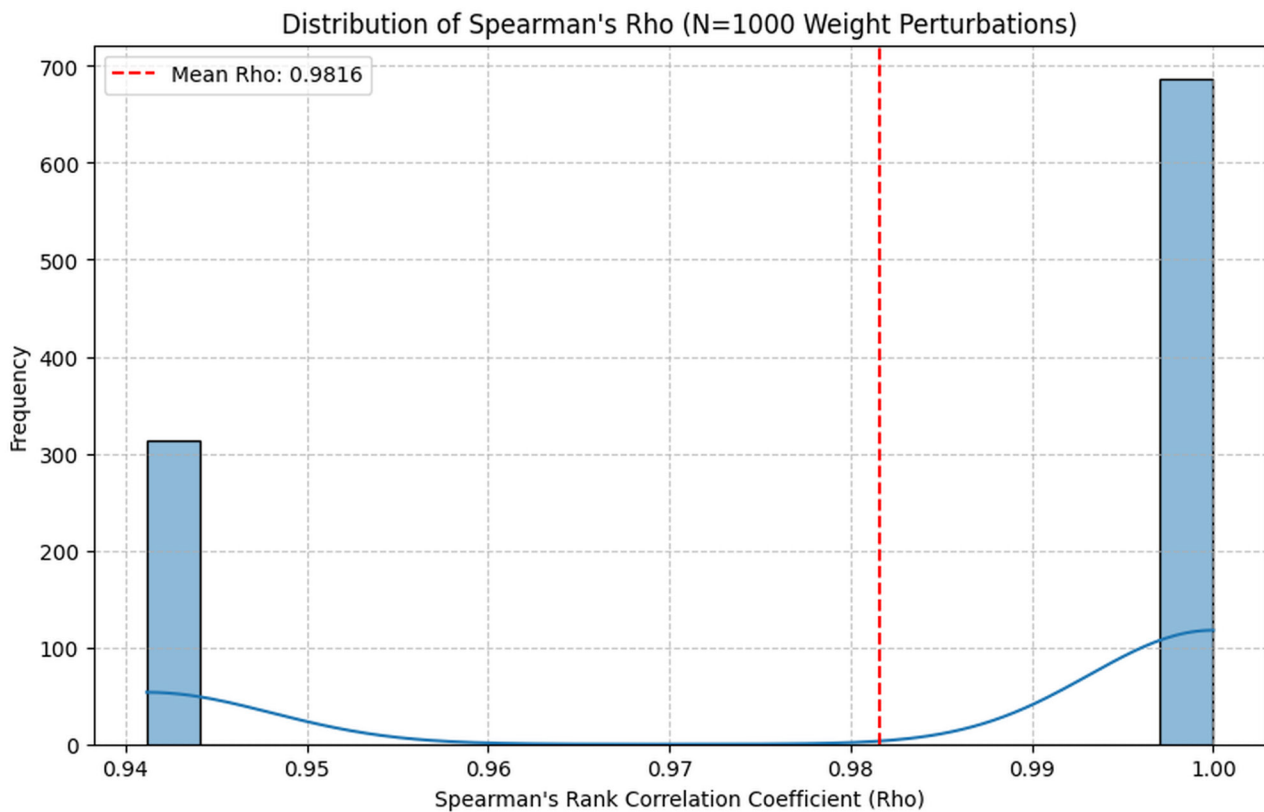


Figure 2 Distribution of Spearman's Rank Correlation Coefficient under Monte Carlo Weight Perturbations (N = 1,000).

Note: The dashed vertical line indicates the mean correlation ($\rho = 0.9816$).

Table 5 Rank stability under Monte Carlo weight perturbation (N = 1,000).

Country	Stable Rank (%)	Moved Up (%)	Moved Down (%)	Total Rank Changes
Singapore	68.70	31.30	0.00	313
Regional/Global Reference	68.70	0.00	31.30	313
Malaysia	100.00	0.00	0.00	0
Philippines	100.00	0.00	0.00	0
Thailand	100.00	0.00	0.00	0
Indonesia	100.00	0.00	0.00	0

The results showed that Malaysia, the Philippines, Thailand, and Indonesia exhibit complete rank stability across all simulations. In contrast, rank variability is confined to the top of the distribution, where Singapore and the regional/global reference exchange positions are in approximately 31.3 % of simulations. No multi-rank reversals or downward shifts beyond this pairwise exchange are observed.

3.4 Reinforcement learning framework

The reinforcement learning simulation was designed to evaluate the informational structure of the SPRI signal rather than to demonstrate algorithmic superiority. The environment was formalized through four primary components derived directly from the empirical dataset. First, the Action Space ($\mathcal{A}$) was defined as a set of discrete choices $a \in \{1, \dots, K\}$, where each arm represents

a strategic “investment” or prioritization of one of the six SPRI functional pillars (e.g., Cybersecurity Resilience or Advanced Autonomous Technologies). Second, the Context Variables ($x_t \in R^d$) characterized the environment at each decision round t , incorporating a multidimensional feature vector that includes one-hot encoded country identities, temporal indicators (normalized years), and baseline SPRI pillar scores. Third, the Reward Function (r_t) was operationalized as the simulated next-period marginal change in the total SPRI score (ΔSPRI), serving as a proxy for the effectiveness of a chosen policy lever in advancing maritime readiness.

The agent’s decision logic was governed by the LinUCB algorithm, which balances the exploration of under-prioritized pillars with the exploitation of known high-reward strategies. The agent maintained a linear model of the reward for each pillar, recursively updating a covariance matrix A_a and a weighted reward vector b_a at each step through the update rules $A_a \leftarrow A_a + x_t x_t^\top$ and $b_a \leftarrow b_a + r_t x_t$. By calculating the estimated coefficients $\widehat{\theta}_a = A_a^{-1} b_a$, the agent selected an action a_t by maximizing the upper confidence bound:

$$a_t = \arg \max_{a \in \mathcal{A}} \left(\widehat{\theta}_a^\top x_t + \alpha \sqrt{x_t^\top A_a^{-1} x_t} \right)$$

where α denotes the exploration parameter. To validate the agent's performance, a surrogate environment was constructed using a Random Forest Regressor trained on historical observed rewards, providing a stochastic and non-linear ground truth for the simulation. This RL-based modeling demonstrates whether the SPRI provides a sufficiently clear signal to guide complex, data-driven maritime strategy.

As detailed in **Table 6**, the reinforcement learning variables are directly mapped to the empirical SPRI dataset. By defining the reward (r_t) as the ΔSPRI (the marginal improvement in readiness), the model became a functional tool designed to identify which policy 'arms' (pillars) yield the highest strategic return for a specific country's context (x_t).

Table 6 Formal definition and operationalization of CMAB variables.

Variable	Description	Operationalization in the SPRI Context
a_t	Selected Action	Represents the specific SPRI pillar (out of the six) chosen by the agent for strategic prioritization at round t .
x_t	Context Vector	A multidimensional feature vector representing the environment state, including country identity, year, and current readiness scores.
r_t	Observed Reward	The numerical feedback received from the surrogate environment, defined as the marginal change in the total SPRI score (ΔSPRI).
$\widehat{\theta}_a$	Coefficient Vector	The estimated linear relationship between the context (x_t) and the expected reward for a specific pillar, calculated as $A_a^{-1} b_a$.
α	Exploration Factor	A hyperparameter (e.g., 0.1) that adjusts the Upper Confidence Bound to prioritize under-explored pillars with high uncertainty.
A_a^{-1}	Inverse Covariance	The inverse of the accumulated context covariance matrix; it represents the model's uncertainty regarding the potential reward of pillar a .
b_a	Weighted Reward	A cumulative vector that tracks the association between the observed contexts and the rewards received for action a .

The primary objective of the learning agent was to maximize the Cumulative Reward (R_T), which represents the total strategic progress made across all decision rounds. It is defined as:

$$R_T = \sum_{t=1}^T r_{a_t,t}$$

In this context, R_T signifies the total growth in the SPRI achieved through the agent's sequential prioritization of specific pillars. At each decision round (t), representing a discrete policy evaluation cycle, the agent selects an action (a_t) by choosing one of the six functional SPRI pillars for strategic prioritization. This decision is informed by the context vector (x_t), which captures the current environmental "state" including specific country identities and existing baseline readiness scores. The effectiveness of the chosen action is measured by the instantaneous reward ($r_{a_t,t}$), defined as the marginal change in the total readiness index (Δ SPRI). Over the course of the simulation, the agent seeks to maximize R_T , representing the total aggregated improvement in maritime readiness across all rounds. This learning process allows the agent to refine its weight vector ($\widehat{\theta}_a$), which serves as the learned estimation of how a specific country's context influences the successful implementation and reward of a given policy pillar.

Algorithm 1: Contextual bandit for SPRI strategy optimization

Require: Exploration parameter $\alpha > 0$; SPRI dataset D ; Number of simulation rounds T ; Number of arms (pillars) K .

Initialize: For each arm $a = 1, \dots, K$:

$A_a \leftarrow I_d$ (Identity matrix of dimension $d \times d$)

$b_a \leftarrow 0_d$ (Zero vector of dimension d)

1. **For** $t = 1$ to T **do**:
2. Observe context x_t (Country c , Year y , and current pillar scores).
3. **For** each arm $a \in \{1, \dots, K\}$ **do**:
4. Calculate the coefficient estimate: $\widehat{\theta}_a = A_a^{-1} b_a$
5. Calculate Upper Confidence Bound: $p_{t,a} = \widehat{\theta}_a^\top x_t + \alpha \sqrt{x_t^\top A_a^{-1} x_t}$
6. **End For**
7. Select arm $a_t = \arg \max_a p_{t,a}$
8. Execute policy action a_t in the surrogate environment.
9. Observe reward r_t (Observed change in SPRI _{c,y} score).
10. **Update Step (Learning):**
11. $A_{a_t} \leftarrow A_{a_t} + x_t x_t^\top$
12. $b_{a_t} \leftarrow b_{a_t} + r_t x_t$
13. **End For**

As illustrated in Algorithm 1, the simulation follows a recursive learning cycle. In each round, the agent observes a multidimensional context x_t and computes the expected reward for each policy pillar using its current estimation of $\widehat{\theta}$. The decision rule incorporates a term for uncertainty ($\alpha\sqrt{\cdot}$), ensuring that the model explores less-frequent policy combinations. After selecting the optimal arm a_t , the agent receives a reward r_t from the surrogate environment and immediately updates its internal parameters (A_a and b_a). This ensures that the policy logic evolves dynamically based on the specific readiness landscape of the Southeast Asian countries.

4. Results

4.1 Component-level normalization across countries

Normalization is defined as rescaling component scores to a 0 - 1 range to allow comparison across countries and policy dimensions. Higher normalized values indicate the presence of more

explicit documentary references for a given component, while lower values indicate fewer or no references in publicly available documents. **Figure 3** presents normalized component-level values of the SPRI for Southeast Asian countries and a regional or global benchmark in the latest year, and **Table 7** presents the cross-country distribution of normalized scores.

Table 7 Normalized SPRI component scores (latest year).

Country	Technological Infrastructure	Advanced Autonomous Technologies	Interoperability Communication	Onshore Operation Centers	Cybersecurity Resilience	Regulation Procedures
Singapore	1.00	0.00	1.00	0.00	1.00	1.00
Malaysia	0.00	1.00	0.00	0.00	0.50	1.00
Philippines	0.00	0.00	0.00	0.00	0.00	0.00
Thailand	0.00	0.00	0.00	0.00	0.00	0.00
Indonesia	0.00	0.00	0.00	0.00	0.00	1.00
Regional/ Global Reference	0.00	1.00	1.00	0.00	1.00	1.00

The normalized SPRI component scores reveal a highly non-uniform distribution of readiness across both countries and pillars. Singapore exhibits the broadest coverage across foundational dimensions, suggesting that readiness is anchored in enabling infrastructure and governance capacity, with limited observable evidence of full autonomy deployment. **Table 7** indicates that SPRI captures dimension-specific readiness, with countries specializing in distinct subsets of capabilities.

Additionally, **Figure 4** reports variation in normalized scores across countries and components. Singapore records high normalized values across several components, including technological infrastructure, interoperability and communication, cybersecurity, and regulatory procedures. Lower normalized values are observed for components related to advanced autonomous technologies and onshore operation centers. Malaysia shows high normalized values for advanced autonomous technologies and regulatory components, with lower values for cybersecurity. The Philippines, Thailand, and Indonesia display low normalized values across most SPRI components. These differences appear to reflect variations in governance coordination, digital investment capacity, and institutional maturity across Southeast Asian maritime systems. Singapore's broader readiness profile is consistent with long-term state-led investment in port digitalization, integrated maritime governance, and centralized coordination through the Maritime and Port Authority of Singapore. Malaysia demonstrates relatively stronger regulatory and strategic positioning but weaker infrastructure integration, suggesting that policy ambition has progressed faster than operational implementation capacity. In contrast, the lower readiness profiles observed in Indonesia, Thailand, and the Philippines may reflect fragmented institutional coordination, uneven development of digital infrastructure, and limited investment in interoperable port systems. The results, therefore, suggest that smart port readiness is shaped not only by technology adoption but also by governance systems' ability to coordinate infrastructure investment, regulatory alignment, and operational integration across port ecosystems. **Figure 4** presents a radar visualization of normalized SPRI component scores (0 - 1) for Southeast Asian countries across six pillars.

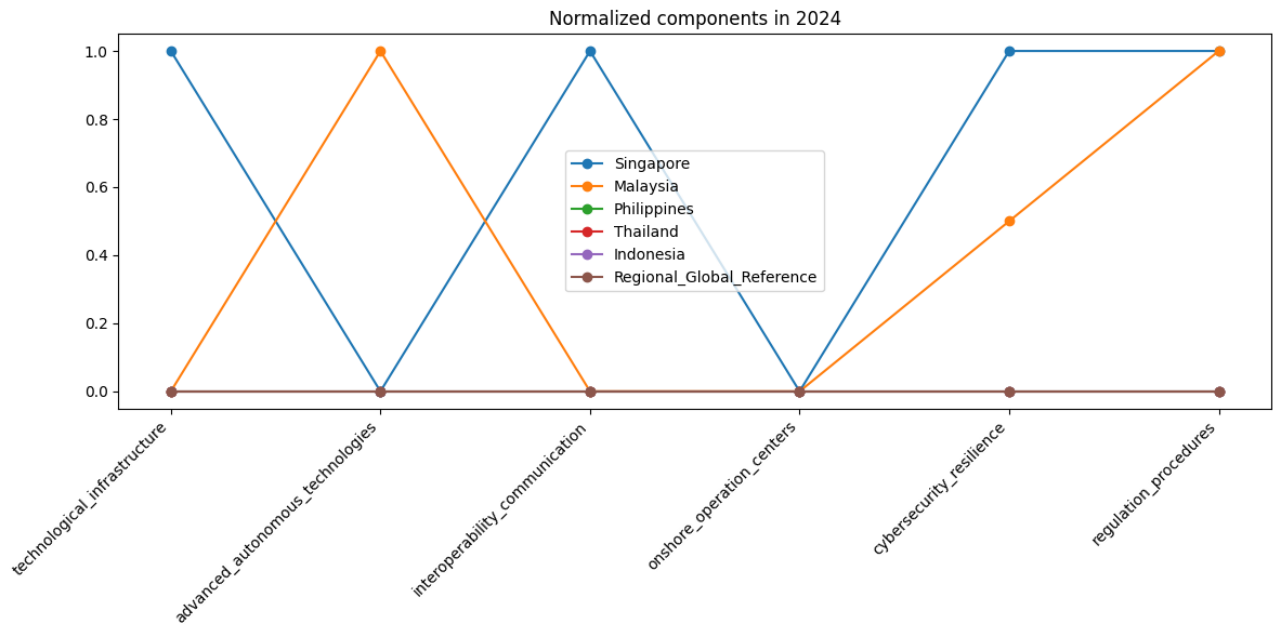


Figure 3 SPRI (0 - 100) trends by country (2018 - 2024).

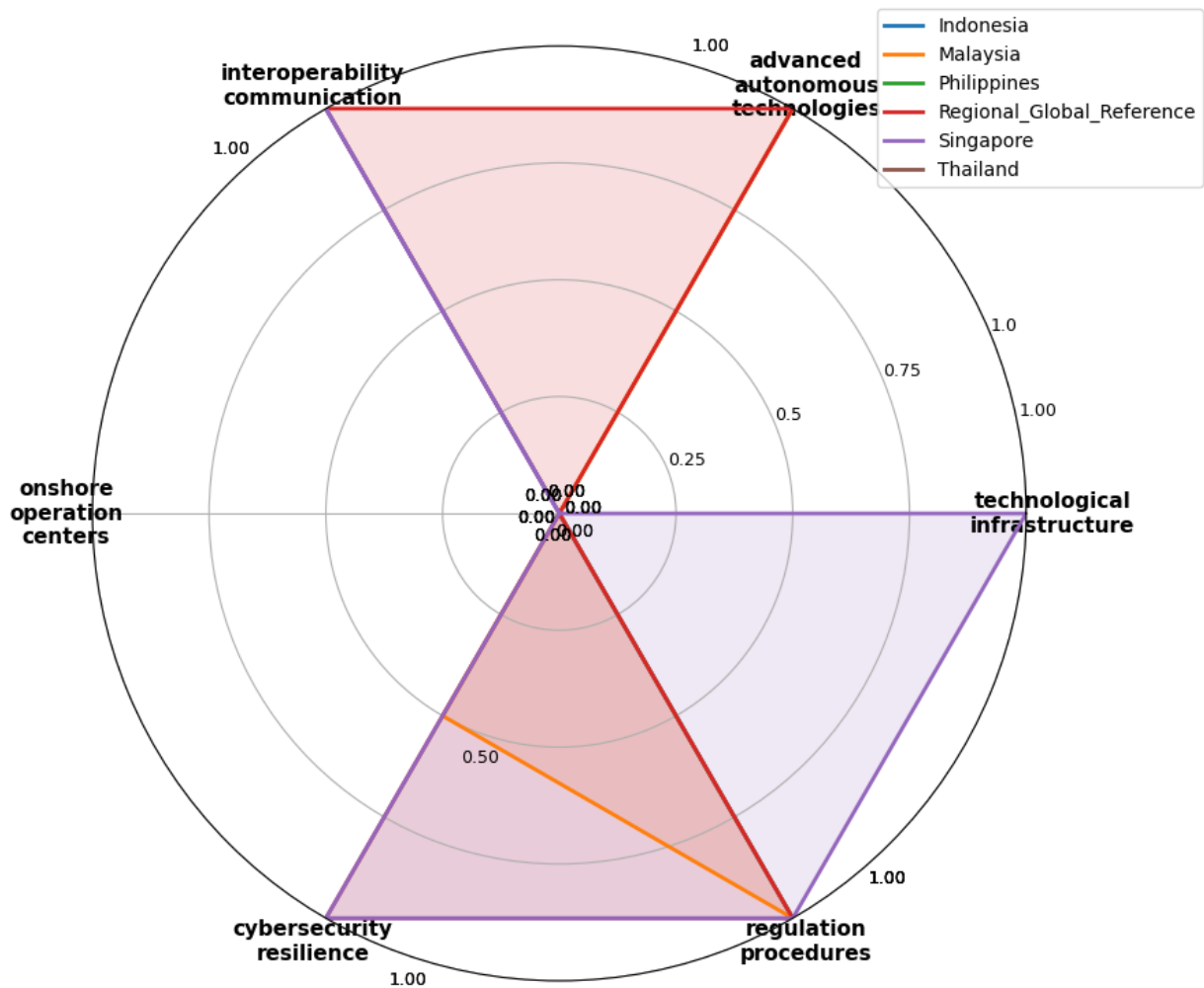


Figure 4 Radar chart of normalized SPRI components across Southeast Asia.

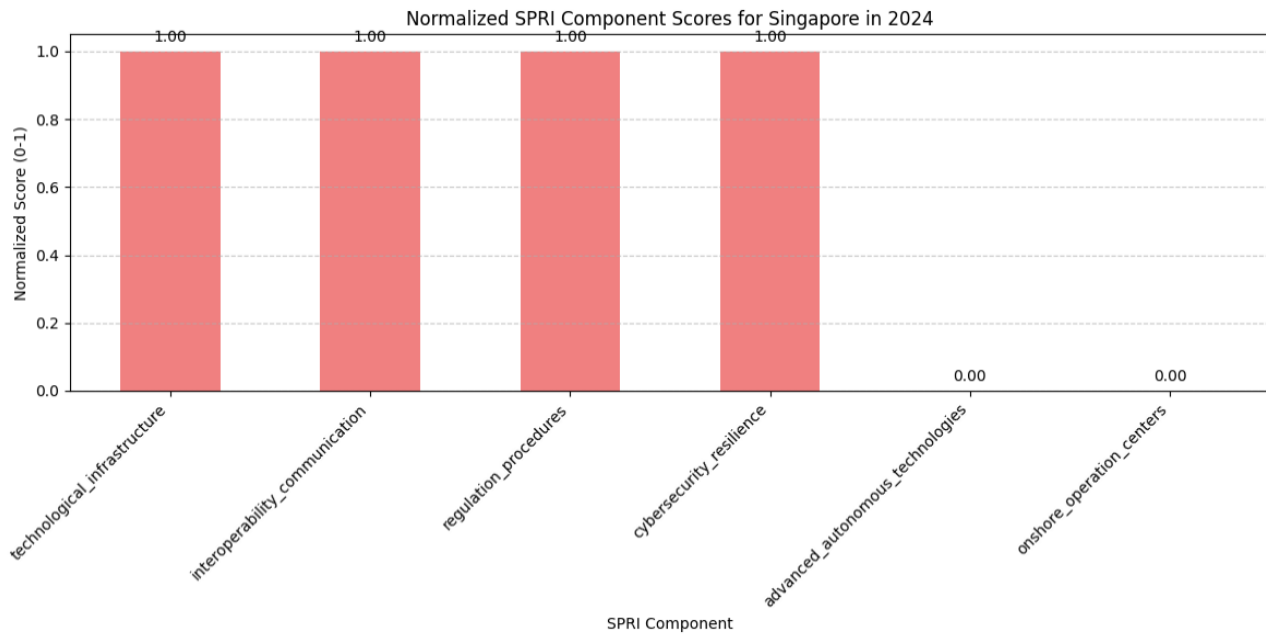


Figure 5 Normalized SPRI component scores for Singapore.

Note: Values were normalized to [0,1] based on min–max scaling across countries.

Figure 5 shows the component profile for Singapore in detail. Singapore shows high normalized values across most SPRI components, with lower values for advanced autonomous technologies. Component profile for Singapore shows full attainment (value = 1.00) in technological infrastructure, interoperability, cybersecurity resilience, and regulatory procedures, while advanced autonomous technologies and onshore operation centers remain at zero. This pattern suggests that Singapore’s readiness is driven by foundational digital infrastructure and governance capacity rather than the deployment of fully autonomous systems.

4.2 Reinforcement learning simulation of policy rewards

Cumulative rewards were computed from the contextual bandit simulation using SPRI increments ΔSPRI_t as the realized payoff and aggregated as $\sum_{t=1}^T \Delta \text{SPRI}_t$, depicted in **Figure 6**. The evaluated policies include LinUCB ($\alpha = 1.0$), a uniform random allocation policy, and an oracle policy derived from the surrogate reward model. The oracle policy generates the dominant trajectory over the full horizon, with cumulative reward increasing at a consistently higher rate relative to the learning-based and random benchmarks. The trajectory is characterized by limited drawdowns after the initial rounds, indicating stable exploitation under correct reward specification.

The LinUCB trajectory exhibits two distinct regimes. In early rounds ($t \lesssim 800$), cumulative rewards fluctuate with low net growth and occasional negative increments, reflecting exploration and high parameter uncertainty. In later rounds ($t \gtrsim 1,100$), the slope of the cumulative reward function increases, indicating improved estimation of the reward parameters and more frequent selection of high-reward actions. This transition is consistent with the convergence properties of upper confidence bound algorithms under sufficient sampling.

The random policy follows a lower-growth path with persistent variability across the entire simulation horizon. Differences between LinUCB and the random policy are limited in the initial phase but become more pronounced in later rounds, where LinUCB sustains a higher accumulation rate. Both policies exhibit intermittent drawdowns, attributable to stochastic reward realizations in the SPRI signal. A non-zero gap between LinUCB and the oracle persists throughout the simulation, reflecting exploration costs and estimation error inherent in the learning process.

Temporary segments in which LinUCB underperforms the random policy can be attributed to three interacting mechanisms. First, the upper confidence bound structure induces deliberate exploration through the term $\alpha\sqrt{x_t^\top A_a^{-1}x_t}$, which can prioritize arms with high uncertainty but lower realized reward, generating negative short-run regret relative to random allocation. Second, the reward-generating process is non-linear (Random Forest surrogate with interaction effects), whereas LinUCB imposes a linear parametric form; this misspecification can lead to biased estimates $\hat{\theta}_a$, particularly in regions of the context space with strong non-linearities, causing systematic mis-ranking of arms during intermediate rounds. Third, additive stochastic noise in rewards increases the variance of realized outcomes, so that even correctly ranked arms may yield lower realized rewards in finite samples. The combination of these factors implies that cumulative regret is locally non-monotonic, and short-horizon performance can temporarily fall below that of an uninformed random policy before converging towards higher-reward actions.

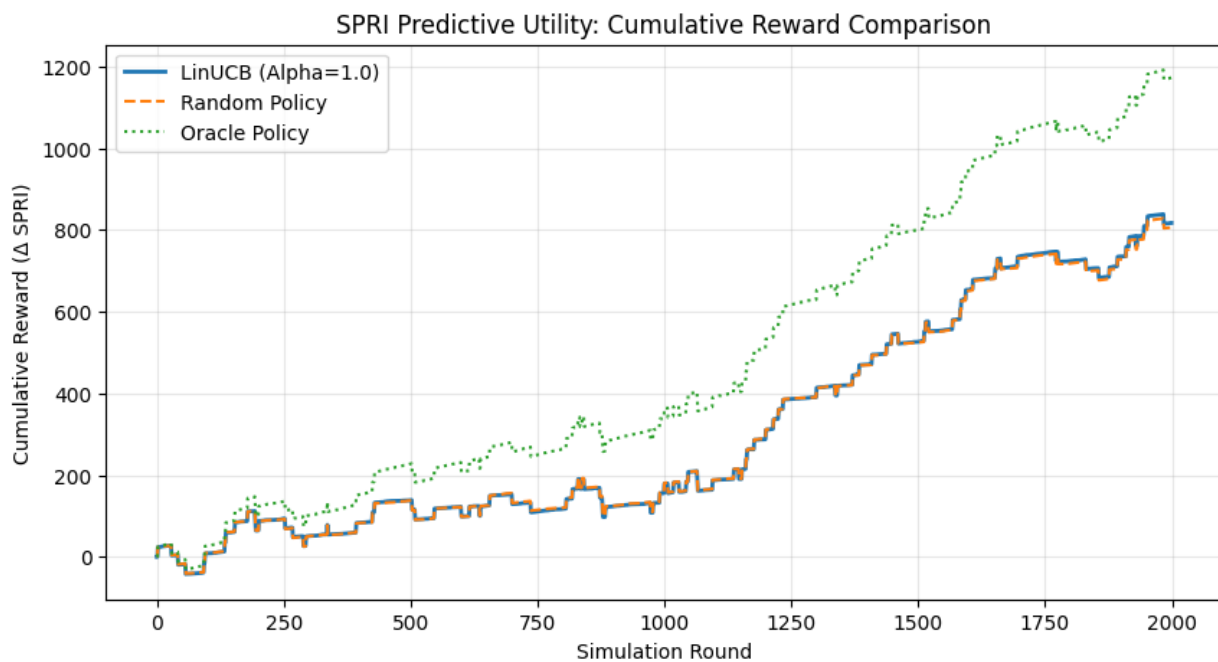


Figure 6 Contextual bandit baselines: cumulative reward of simulated Δ SPRI (0 - 100).

The observation that the random policy occasionally outperforms LinUCB in early and intermediate rounds reflects structural properties of the learning environment rather than model failure. First, the LinUCB algorithm deliberately allocates probability mass to under-explored SPRI pillars through the exploration term, which can induce short-run regret when high-uncertainty actions yield lower realized Δ SPRI. Second, the reward-generating process was constructed using a non-linear surrogate with interaction effects across SPRI components, whereas LinUCB imposes a linear approximation; this specification gap leads to biased arm valuation in regions where complementarities between infrastructure, interoperability, and governance are strong. Third, stochastic noise in Δ SPRI further increases variance in realized rewards, implying that short-horizon dominance by a random allocation does not contradict asymptotic learning properties.

From a policy perspective, these dynamics are informative rather than limiting. The simulation indicates that policy effectiveness is highly context-dependent and non-additive, such that isolated investments in single SPRI pillars may yield low or even negative marginal returns when complementary capabilities are absent. This is consistent with the observed heterogeneity across Southeast Asian ports, where countries with weak baseline infrastructure (e.g., Indonesia, Thailand, and the Philippines) exhibit limited gains from advanced autonomy investments due to missing

interoperability and control systems, while more mature systems (e.g., Singapore) derive higher marginal returns from cybersecurity and integration layers. The relatively modest performance gap between LinUCB and the random policy signals that the SPRI landscape contains weak gradients in early-stage environments, implying that optimal policy requires coordinated, multi-pillar development strategies. In practical terms, port authorities should avoid sequentially optimizing individual readiness components in isolation and instead adopt bundled policy interventions, for example, coupling investments in digital infrastructure with interoperability standards and regulatory alignment to unlock complementarities reflected in higher Δ SPRI trajectories.

4.3 Matrix evaluations

This subsection interprets the simulation results from a policy prioritization perspective, examining how different SPRI dimensions contribute to improvements in readiness across varying country conditions. The reported measures include cumulative rewards, comparisons with random and oracle benchmarks, and arm-selection frequencies across 2,000 simulated decision rounds. These metrics summarize outcomes from the simulated decision process rather than prediction accuracy. Cumulative reward records aggregate outcomes over sequential decisions, and arm selection frequencies record how often different policy components are selected across simulations.

The simulation links SPRI component gaps to potential improvement pathways by modeling policy prioritization as a contextual bandit problem, where the reward is defined as the one-period change in SPRI (Δ SPRI_t). Context variables include country characteristics, time information, and existing pillar scores to capture structural differences and current readiness levels. A Random Forest surrogate model estimates the expected reward for each policy action while accounting for complementarity between existing capabilities and incremental investments. The results show that the LinUCB algorithm achieves higher cumulative rewards than a random baseline, indicating that the model learns to prioritize actions with higher expected improvements over time. Action allocation frequencies reveal that advanced autonomous technologies and cybersecurity resilience generate the largest expected SPRI gains. In contrast, onshore operation centers and regulatory procedures contribute smaller marginal improvements. Technological infrastructure and interoperability show moderate but context-dependent importance. **Table 8** summarizes LinUCB action selection frequencies. **Table 9** reports the realized cumulative rewards $\sum_{t=1}^T r_t$ under the three policies evaluated in the same stochastic environment.

Table 8 LinUCB action selection frequencies.

SPRI Pillar	Times Chosen	Share (%)
Technological infrastructure	216	10.8 %
Advanced autonomous technologies	731	36.6 %
Interoperability communication	212	10.6 %
Onshore operation centers	119	6.0 %
Cybersecurity resilience	607	30.4 %
Regulation procedures	115	5.8 %
Total	2,000	100.0 %

Table 9 Cumulative reward comparison across policies.

Policy	Total Reward	Difference vs. Random	Difference vs. Oracle	Relative to Oracle (%)
LinUCB	817.191	+11.265	−355.651	69.7 %
Random	805.926	0.000	−366.916	68.7 %
Oracle	1,172.842	+366.916	0.000	100.0 %

The observation that LinUCB does not consistently outperform a random policy in all simulations does not contradict theoretical expectations for this setting. In contextual bandit models, performance guarantees hold under correct model specification and sufficiently large samples. In this study, the reward function was generated by a non-linear surrogate environment with interaction effects, whereas LinUCB imposes a linear structure on the expected reward. Thus, although the SPRI-based signal was informative, its effective exploitation depends on the alignment between the assumed reward model and the underlying data-generating process.

The matrix evaluation highlights that policy effectiveness depends strongly on existing readiness conditions and the sequencing of investments across SPRI dimensions. Advanced autonomous technologies and cybersecurity resilience generate the largest simulated readiness gains, primarily in countries where supporting infrastructure and interoperability systems are already established. This suggests that advanced autonomy investments are unlikely to yield substantial benefits in early-stage port systems unless foundational digital capabilities are first developed.

From a policy perspective, the results imply differentiated development priorities across Southeast Asia. Countries with limited baseline readiness, such as Indonesia, Thailand, and the Philippines, should prioritize foundational digital infrastructure, interoperability standards, institutional coordination, and cybersecurity governance before expanding autonomous operational capabilities. In contrast, more mature systems such as Singapore may derive greater benefits from scaling higher-level autonomous operations, remote control systems, and advanced cybersecurity integration. Malaysia occupies an intermediate position, where strengthening interoperability and operational integration may provide greater readiness improvements than isolated regulatory expansion. Overall, the findings suggest that smart port readiness requires coordinated, staged policy development rather than isolated investments in individual technologies.

Conversely, onshore operation centers and regulatory procedures are selected less often, suggesting diminishing short-run returns when implemented in isolation, particularly in early-stage systems lacking foundational capabilities. Thus, policy sequencing must reflect initial readiness: Indonesia, Thailand, and the Philippines should prioritize foundational digital infrastructure and integration before investing in advanced autonomy, while mature systems like Singapore can gain more from strengthening cybersecurity and interoperability.

4.4 Capability alignment for Smart Port-MASS integration readiness

The SPRI results provide an overview of how different countries perform across the six readiness components. To ensure that capability alignment and policy recommendations are systematically derived from the index results, the normalized SPRI component scores were interpreted using a simple readiness classification. Following common practices in digital maturity and infrastructure readiness studies (Molavi et al., 2020), normalized scores were grouped into three levels: high readiness (≥ 0.75), moderate readiness (0.40 - 0.74), and low readiness (< 0.40). Based on **Table 7**, Singapore demonstrates high readiness in technological infrastructure, interoperability, cybersecurity, and regulatory procedures (all = 1.00), but shows gaps in advanced autonomous technologies and onshore operation centers (0.00). This indicates that while the foundation is strong, further investment is needed in advanced autonomy and operational control systems. Malaysia shows a mixed readiness profile, with high scores in advanced autonomous technologies and regulatory procedures (1.00), moderate performance in cybersecurity (0.50), and low scores in infrastructure, interoperability, and OOC. This suggests that improvements should focus on system integration and digital infrastructure.

In contrast, Thailand, Indonesia, and the Philippines exhibit predominantly low scores (0.00) across most components, indicating early-stage readiness. Indonesia shows a relatively stronger regulatory component (1.00) but lacks supporting infrastructure and integration capabilities. These countries require foundational development before progressing towards MASS integration.

Table 10 synthesizes the SPRI results and facilitates interpretation by translating country-level readiness profiles into capability-aligned MASS readiness states. This table links each SPRI profile to the current state of smart ports, the MASS operations level that can realistically be supported, and the key gaps to be addressed for further improvements.

Table 10 Proposed strategy for smart port readiness.

Country	Key SPRI Gaps	MASS Capability Level	Priority Actions
Singapore	Advanced autonomous technologies, OOC	High readiness- capable of conditional MASS operations	• Develop advanced autonomous vessel systems (remote navigation, pilotage) • Expand OOC infrastructure for remote supervision • Scale higher-level autonomous operation trials
Malaysia	Technological infrastructure, interoperability, OOC, cybersecurity	Moderate readiness- pilot MASS operations possible	• Develop an integrated port digital infrastructure • Improve vessel-port interoperability standards • Strengthen cybersecurity systems • Establish OOC for coordination
Indonesia	Infrastructure, interoperability, OOC, cybersecurity	Low readiness- partial governance readiness	• Develop digital infrastructure and system integration • Strengthen interoperability frameworks • Establish OOC • Align governance with technical capabilities
Thailand, Philippines	All components are low (0.00)	Low readiness- foundational stage	• Implement port digitalization programs • Develop regulatory and governance frameworks • Strengthen cybersecurity and monitoring systems • Improve institutional coordination

5. Discussion

The SPRI results indicate considerable variability in smart port readiness among the five Southeast Asian countries. The Singapore experience suggests potential for using benchmarking to transfer knowledge and best practices (Acciaro et al., 2014; Lam & Notteboom, 2014). Malaysia's condition is more affected by infrastructure and integration issues than by regulation and procedures (Othman et al., 2025). This aligns with SPRI results, showing relatively stronger performance in regulatory and operational frameworks but weaker readiness in digital infrastructure and system integration, placing Malaysia in a conditionally prepared status for MASS deployment. In contrast, Indonesia, Thailand, and the Philippines have persistently low SPRI scores in most areas, indicating that critical smart port capabilities, especially in interoperability, cybersecurity governance, and operational integration, remain underdeveloped. As a result, MASS deployments are restricted to trial initiatives in these nations. These differences suggest that smart port readiness is determined by how effectively technological, organizational, and governance capabilities are coordinated within the port

ecosystem. The findings indicate that ports with fragmented institutional coordination may still face readiness limitations even when individual digital initiatives are already present. This explains why some countries demonstrate progress in regulations or isolated automation projects but still lack the operational integration required for MASS deployment.

The observed differences in SPRI across countries can be further explained through comparative governance perspectives, particularly policy capacity and institutional coordination. Countries with stronger policy capacity are better able to design, implement, and integrate complex technological systems (Wu et al., 2015). This helps explain why Singapore demonstrates more balanced readiness, while other countries exhibit fragmented development across components. Additionally, variations in regulatory governance and state capacity influence the ability to support large-scale infrastructure transformation (Issa et al., 2022; Osaloni & Ayeni, 2022). In ports and authorities new to MASS operations, governance-related issues are often prioritized over technology-related issues (Kim et al., 2020). As Eronen (2023) highlights, unresolved issues related to international regulations, liability distribution, and infrastructure responsibility are significant barriers to autonomous vessels. However, regional and national regulatory activities may be more important in the early stages of autonomous vessel adoption because they provide opportunities to test and implement autonomous vessels in controlled port environments. The SPRI results confirm this assumption, demonstrating that regulatory and procedural readiness continues to advance in Southeast Asian ports. However, the findings also indicate that regulatory advancement alone is insufficient to ensure operational readiness. Several countries demonstrate the existence of policy initiatives and strategic plans yet still experience weak interoperability and limited operational coordination. This reflects a common challenge in digital transformation, where institutional ambition develops faster than the supporting technical ecosystem. Consequently, readiness gaps in Southeast Asia are better understood as capability imbalance problems rather than simple technology shortages.

At the same time, the results align with digital transformation theory (Webster & Gardner, 2019; Tang, 2021; Gillani et al., 2024), which conceptualizes transformation as a staged and path-dependent process. The distribution of SPRI scores across components suggests that early investments in digital infrastructure and integration enable subsequent advances in automation. This finding reinforces prior work highlighting cumulative capability building and maturity progression in digital systems (Zimmer & Gierlich-Joas, 2026) and explains why advanced capabilities such as autonomous operations remain limited even in relatively mature ports. Previous research by Kurt and Aymelek (2024) highlights that port adaptation is one of the toughest challenges in integrating MASS, especially in complex operational areas like berthing maneuvers and cargo operations. This trend is consistent: basic smart port infrastructure, such as integration, secure data transfer, and procedures, is required for MASS readiness (Chen et al., 2019; Nguyen et al., 2025). While several Southeast Asian ports have shown good initial steps in applying digital technologies and establishing digital policies, the lack of integrative dimensions remains a critical factor in continuous ship-shore interaction. Hence, smart port readiness in the SPRI model is a staged concept in terms of the capability space that enables MASS operation.

5.1 Theoretical implications

This study contributes to the smart port and MASS literature by clarifying how smart port readiness should be conceptualized as an integrated governance capability rather than as a purely technological condition. Prior studies on smart ports and autonomous shipping primarily emphasized isolated dimensions such as automation technologies, digital infrastructure, or regulatory barriers (Acciaro et al., 2014; Heilig et al., 2017; Molavi et al., 2020; Kurt & Aymelek, 2024). In contrast, the SPRI framework developed in this study conceptualizes readiness as a multidimensional, interdependent system in which technological infrastructure, interoperability, operational coordination, cybersecurity, and regulatory procedures jointly shape a port's capacity to support MASS operations. The findings, therefore, extend existing smart port research by demonstrating that

readiness gaps emerge not only from missing technologies but also from weak integration across governance and operational dimensions.

Second, the study extends the TOE framework (Tornatzky & Fleischer, 1990) by applying it at the port ecosystem level. The findings demonstrate that MASS readiness is not driven by technological factors alone but by alignment among technological infrastructure (technology), operational and institutional coordination (organization), and regulatory frameworks (environment). This highlights the importance of interdependence across TOE dimensions. Additionally, the study contributes to digital transformation theory (Warner & Wäger, 2019) by showing that smart port readiness develops as a cumulative and path-dependent process, where higher-level capabilities such as autonomous operations depend on prior investments in integration, cybersecurity, and operational control systems.

Third, the study contributes to digital transformation theory by demonstrating that smart port readiness develops cumulatively and path-dependently rather than through isolated technological adoption. The SPRI patterns indicate that advanced autonomous capabilities rarely emerge independently; instead, they depend on prior development of foundational digital infrastructure, interoperability standards, cybersecurity systems, and operational control capabilities. This extends prior digital transformation studies (Warner & Wäger, 2019; Gillani et al., 2024) by showing how transformation maturity in port ecosystems evolves through sequential capability accumulation. In this context, higher-order autonomous operations represent a later-stage outcome of institutional and technological integration rather than a standalone innovation stage.

Finally, this study contributes to adaptive governance and computational policy analysis by operationalizing policy prioritization as a contextual learning problem. CMAB framework models policy prioritization as an adaptive process in which the effectiveness of interventions depends on country-specific readiness conditions. The study, therefore, demonstrates how reinforcement learning can be used not primarily for prediction accuracy, but for representing dynamic policy trade-offs under heterogeneous institutional environments. This contributes to the emerging intersection between maritime governance research and computational social science by introducing a structured mechanism for analyzing adaptive policy sequencing in smart port development.

Nevertheless, the CMAB framework remains a simplified representation of policy decision dynamics and does not fully capture the institutional complexity of real-world policy implementation. The reinforcement learning simulation relies on a surrogate environment and a reward function, Δ SPRI, which serves as a proxy for readiness improvement rather than a direct measure of operational performance. Consequently, the simulation should be interpreted as a diagnostic and exploratory framework for evaluating the informational structure of readiness indicators rather than as a prescriptive optimization model. Future studies may extend this approach by incorporating operational performance data, institutional feedback mechanisms, and alternative reward specifications to strengthen causal interpretation and policy applicability.

5.2 Practical implications

Beyond theoretical contributions, the study offers several practical contributions with policy implications for policymakers and port authorities in Southeast Asia. First, the multilingual regulatory corpus is a practically useful knowledge base to increase transparency and comparability of smart port policies in the region. The study consolidates fragmented national laws, regulations, and port authority regulations into a harmonized analytical framework.

Second, the SPRI results can be used as a diagnostic and prioritization tool. Port authorities can focus on component-specific improvements based on identified gaps. For example, countries with high regulatory readiness but weak infrastructure (e.g., Malaysia) should prioritize investment in integrated port digital systems, including port community systems and vessel–port data exchange platforms. In contrast, countries with consistently low scores (e.g., Indonesia, Thailand, and the Philippines) should focus on foundational digital infrastructure, interoperability frameworks, and

cybersecurity governance before advancing towards autonomous operations. For more advanced ports such as Singapore, the findings suggest a shift from general digitalization towards scaling advanced autonomous capabilities, including remote vessel operation systems and the expansion of OOCs. This indicates the need for targeted pilot programs and operational testing environments to support higher levels of autonomy. Thus, to strengthen the operational relevance of the recommendations, the proposed strategies may be translated into measurable implementation indicators. Rather than functioning only as general policy guidance, the SPRI results can support monitoring and evaluation of smart port readiness progress across countries. **Table 11** presents example operational indicators and implementation targets that may assist port authorities in translating readiness gaps into actionable programs and measurable outcomes.

Table 11 Example operational indicators for SPRI-based implementation.

SPRI area	Operational indicator	Example of implementation target
Technological infrastructure	Port automation capability	Expand smart terminal systems
Interoperability & communication	Vessel-port data integration	Increase real-time data exchange coverage across port stakeholders
Cybersecurity resilience	Cybersecurity governance	Establish continuous cybersecurity monitoring and incident response systems
Onshore operation centers (OOC)	Remote operational control	Develop centralized remote vessel monitoring facilities
Regulation & procedures	MASS operational governance	Develop MASS testing and operational guidelines
Advanced autonomous technologies	Autonomous operation capability	Conduct pilot autonomous navigation and berthing trials

Finally, for port authorities and regulators, the SPRI provides a decision-support tool. Policymakers can compare their preparedness against regional peers and set priorities for reforms based on MASS-readiness goals. This tool is useful for strategic planning and monitoring in transport and port infrastructure management. Taken together, these contributions provide a policy-relevant framework that supports evidence-based, adaptive, and context-sensitive decision-making to enable MASS operations in Southeast Asia.

6. Conclusions

This study developed and applied the SPRI to evaluate how well ports in Southeast Asia can support MASS. The findings show significant differences in smart port readiness across the region. More generally, the results highlight that successful MASS integration relies on coordination of regulatory preparedness, digital infrastructure, system interoperability, and port-level governance. The SPRI framework offers policymakers, port authorities, and researchers a clear tool for assessing readiness and supporting evidence-based planning for autonomous shipping. However, the study has limitations. The assessment relies only on publicly available policy, regulatory, and strategic documents. Therefore, the SPRI reflects documented readiness rather than actual operational performance. Future research should complement this document-based analysis with empirical assessments, such as field observations, port audits, interviews with port authorities and operators, or case studies of pilot MASS deployments. Including real-world operational data would allow for a more thorough evaluation and help validate and improve the SPRI framework. Additionally, the visualization framework prioritizes structural interpretability over statistical inference. As the SPRI is constructed from a complete corpus of policy documents, conventional measures such as

confidence intervals are not applicable. Similarly, the reinforcement learning analysis emphasizes cumulative reward trajectories rather than formal regret or convergence diagnostics, reflecting its role as a diagnostic rather than optimization tool. Future work may extend the analysis by incorporating statistical benchmarking and alternative visualization methods.

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Declaration of generative AI in scientific writing

During the preparation of this work, the author(s) used ChatGPT 5.2 solely to improve the flow, clarity, and grammatical quality of the text. With or without AI applications, the authors are fully accountable for every process of the work and manuscript writing. All final edits, interpretations, and conclusions are the sole responsibility of the authors. The authors academically and ethically confirmed that the stated AI statements are true, and the authors are ultimately responsible and accountable for the contents of the published work, including the correctness of the references in the reference list.

CRedit contribution statement

Afifah Nurrosyidah: Conceptualization, Formal analysis, Investigation, Writing – Original draft. **Pandu Dwi Luhur Pambudi:** Conceptualization, Methodology, Software, Validation, Formal analysis, Resources, Data curation, Writing – Original Draft, Visualization. **Ashari Fitra Rachmannullah:** Conceptualization, Validation, Formal analysis, Resources, Writing – Original Draft, Project administration, Funding acquisition.

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