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Text Mining of Port Loading and Unloading Safety Accidents

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Abstract

Port loading and unloading operations constitute one of the most safety-critical components of maritime logistics, involving complex interactions among workers, heavy equipment, vessels, and cyber-physical infrastructures. Despite the high frequency and severity of accidents, existing research has predominantly focused on statistical records or mechanical failure analyses, leaving the socio-technical dimensions reflected in public media discourse largely unexamined. This study applies an integrated text mining and keyword network analysis framework to systematically analyze Korean news media coverage of port loading and unloading accidents from 2015 to 2025. A total of 189 manually verified articles were processed through noun-based keyword extraction, TF-IDF weighting, Latent Dirichlet Allocation (LDA), and centrality-based network modeling. The results reveal three dominant thematic clusters: (1) Safety Inspection and Incident Response, (2) Maritime Infrastructure and Operations, and (3) Occupational Hazards in Cargo Handling. High-frequency terms such as worker, inspection, container, and accident site indicate that media narratives emphasize human vulnerability, regulatory oversight, and operational risk concentration. Centrality analysis further identifies pier, container, and accident site as critical structural hubs bridging distinct discourse domains, suggesting that public perception of port safety is shaped by interconnected concerns spanning human factors, equipment reliability, and infrastructural constraints. The findings highlight systemic risk patterns not captured in conventional statistical datasets and provide actionable insights for improving safety management, inspection protocols, and risk communication strategies. This study demonstrates the value of text-driven analytical approaches in understanding emerging risk themes and complements traditional accident analysis frameworks by revealing the narrative logic embedded in public discourse.

Keyword : Text Mining, Data Analysis, Safety Accident Analysis, Port Safety, Natural Language Process

1. Introduction

Ports have historically been pivotal to international trade, handling an estimated 80-90% of global maritime cargo [1][2], involving complex interactions among vessels, cargo-handling equipment, cyber-physical systems, human operators, and the natural environment. Growing trade volumes and the

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arrival of mega-vessels have intensified operational density, increasing both the likelihood and severity of accidents [3][4]. Safety accidents in these operations cause serious human and economic losses [5]. In Korea, there were 109 port accidents per year and 2.56 fatalities annually on average (2015-2023), with entrapment, collision, and collapse being the most fatal accident types (Author's calculation based on Korea Port Logistics Association, 2015-2023). Worker fatigue, particularly during night shifts, has been identified as a major contributor to human errors in port operations leading to the increased adoption of standardized procedures to mitigate these risks [6]. While learning from past incidents is essential for improving process safety, existing analyses largely rely on structured statistical data, which may overlook contextual information embedded in textual accident descriptions of how and why accidents occur. The public and organizational understanding of these risks is profoundly shaped by their portrayal in the media. Media coverage plays a critical role in shaping public and organizational perceptions of safety risks, influencing policy decisions, resource allocation, and organizational priorities [7][8], while also raising awareness and encouraging preventive behavior [9]. Therefore, analyzing media discourse provides insights into which risks are emphasized and how they may affect safety management practices. Despite its value, a significant research gap exists. First, existing port safety literature has predominantly focused on sea-based operations or the handling of hazardous cargo, with land-side container operations receiving less attention. Second, while accident statistics are collected, the unstructured nature of textual reports such as news articles, makes systematic analysis challenging and tedious for human agents [10]. Consequently, no prior study has employed text mining methodologies to systematically analyze Korean media's coverage of land-side port accidents. This gap prevents a deeper understanding of the dominant themes, root causes, and evolving discourse patterns that statistics alone cannot reveal. To address this gap, this study employs text mining techniques such including TF-IDF, topic modeling, and keyword network analysis to analyze Korean media discourse on port operation accidents. The study aims to identify dominant themes and central keywords shaping public perception and to derive insights into systemic risk factors relevant to port safety management.

The structure of this paper is as follows. Section 2 reviews the literature on port loading and unloading safety accidents, including the analytical methods employed in previous research. Section 3 describes the application of text mining and centrality analysis techniques used to identify key themes. The results and discussion are presented in Section 4, while Section 5 concludes the study, addresses its limitations, and offers recommendations for future research.

2. Literature review

2.1 Port loading and unloading accidents

Port loading and unloading operations are economically essential but inherently hazardous due to heavy machinery, complex logistics, and dense interactions among workers, vehicles, and cargo [11]. Accordingly, port safety research has shifted from reactive analyses toward proactive, systemic, and intelligent risk management frameworks.

The growth of Automated Container Terminals (ACTs) has transformed safety concerns from isolated equipment failures to system-wide cyber-physical vulnerabilities, including supervisory gaps and network disruptions [12]. Beyond container terminals, studies highlight the continued importance of human cognition and intelligent decision-support systems in reducing operational disruptions and machinery-related risks [13][14].

Safety risks also arise at the interface between maritime and landside systems, particularly in berths and storage yards where congestion amplifies hazards. Simulation-based berth planning with buffer strategies has been shown to reduce cascading delays and safety risks [15], and integrated decision-support platforms have improved coordination among production, storage, and vessel operations [16].

Despite increasing automation, many port areas remain labor-intensive, making human behavior a critical safety factor. Tsai found that perceived risk severity and vulnerability significantly influence workers' willingness to purchase accident insurance [17]. More broadly, recent studies adopt a resilience-oriented perspective, emphasizing proactive risk assessment [18], protection against combined physical and cyber threats [19], and efficient recovery strategies that account for interdependencies across port infrastructure [20].

Although existing research provides a strong techno-centric and quantitative understanding of loading and unloading accidents, it largely overlooks socio-technical dimensions, particularly public framing and perception of accidents. Given the influence of media reporting on risk perception and regulatory responses, systematic analysis of media discourse remains limited. To address this gap, this study applies text mining and keyword network analysis to media reports, offering a complementary perspective to traditional port safety models.

2.2 Text Mining and Keyword network analysis

The rapid growth of unstructured text data has increased the demand for methods capable of extracting meaningful patterns. Text mining addresses this need through preprocessing, feature extraction (e.g., TF-IDF), and modeling techniques such as topic modeling [21]. Its application has expanded across multiple academic and industrial domains [22], including risk and safety research, where it has been used to identify causal factors in pipeline accidents [23], extract risk indicators from supply chain documents [25], and analyze traffic violation patterns in crash records [25].

Preprocessing is a critical step that includes tokenization, stop-word removal, and stemming or lemmatization, directly influencing analytical reliability [26]. Topic modeling, particularly Latent Dirichlet Allocation (LDA), is widely applied to uncover latent themes based on word co-occurrence and probabilistic distributions [27]. TF-IDF complements this by highlighting terms that are both frequent and distinctive within a corpus [28].

Keywords are central to organizing and interpreting knowledge across diverse fields, including literature, culture, and information systems [29-32]. Advances in analytical tools have enabled systematic keyword analysis through co-occurrence-based approaches, commonly referred to as keyword network or co-word analysis [33]. This method maps relationships among keywords to identify core themes and underlying knowledge structures [34], offering a macro-level understanding of research trends and discourse patterns [35].

Recent studies demonstrate the effectiveness of combining text mining with keyword network analysis. For example, Cho and Lee analyzed research trends in urban regeneration and tourism [35], while Lim and Hwang examined hybrid intelligence research using similar methods [36]. Keyword networks can be structured as two-mode networks (topic-keyword) for topic extraction and visualization, or one-mode networks (keyword-keyword) for centrality analysis. Centrality measures-degree, betweenness, and closeness-quantify the influence and connectivity of keywords within the network, as defined in [37], and have been widely applied to identify dominant concepts and structural shifts in discourse [22][38].

3. Data and Methodology

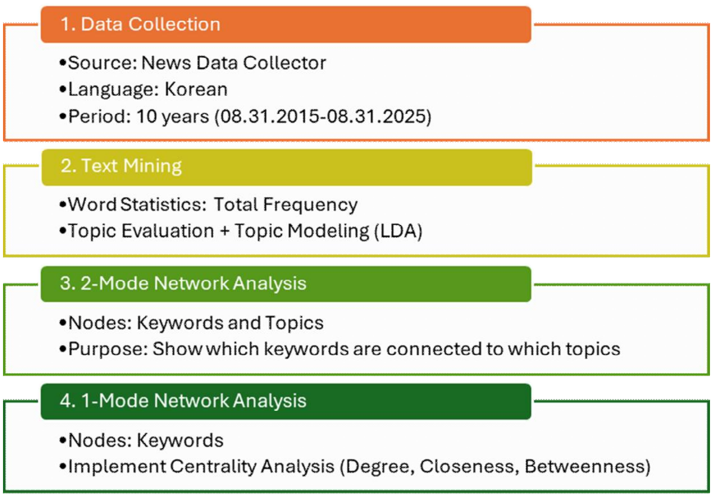
3.1 Data Collection

This research investigates loading and unloading accidents occurring at ports, as reported in Korean news media. Data were obtained through the News Data Collector using NetMiner 5, covering a ten-year period from August 31, 2015, to August 31, 2025. Following collection, the dataset was manually refined to remove unrelated cases such as offshore incidents, safety inspections, and accidents outside port areas. The keywords applied for data retrieval included ‘port accident’, ‘port safety’, ‘loading/unloading accident’, and ‘loading/unloading safety’.

A total of 1,100 news articles were initially gathered, of which 189 were identified as relevant after manual screening. The SNS text data were then preprocessed to extract only nouns, which were subsequently reviewed to build a thesaurus comprising defined and distinctive terms. Previous studies indicate that nouns play a crucial role in representing thematic meaning [39][40]. In total, 116 keywords were extracted for analysis.

3.2. Analysis Method

The overall research process is illustrated in [Fig. 1]. A total of 116 keywords, selected based on their frequency, were used to create a Word Cloud. Subsequently, Latent Dirichlet Allocation (LDA) topic modeling was applied to uncover underlying thematic structures.



[Fig. 1] Research analysis flow chart

After topic extraction, a two-mode network was developed to visualize the relationships between topics and keywords, and then transformed into a one-mode network to examine structural connections among the nodes. To assess the relative importance of individual keywords within the network, centrality analysis was performed. All analyses were conducted using NetMiner 5. To provide both intuitive and quantitative insights into the relationships between topics and keywords, a two-mode network graph was visualized. In this co-occurrence network, nodes represent extracted keywords, while edges indicate their co-occurrence relationships within the text corpus.

In this study, centrality analysis was performed to identify the most influential nodes within the constructed network. Based on the results of the one-mode network analysis, three commonly used centrality measures, degree, closeness, and betweenness centrality, were applied. Together, these indicators offered a comprehensive understanding of the structural significance of key nodes, allowing for the identification of central elements and patterns of influence within the dataset.

4. Result and Discussion

4.1 Keyword Frequency Analysis

A word frequency analysis was conducted on news titles and full-text content concerning port accidents during cargo handling operations. For analytical consistency, only noun-type words were included. After refinement, a total of 116 keywords were retained. The results are presented in both tabular format [Table 1] and a Word Cloud to offer complementary visual and quantitative perspectives.

Among the extracted terms, the most frequently occurring keywords were Worker (338), Inspection (304), and Container (272). Keywords with a frequency of 30 or more accounted for 37.07% of all extracted terms, whereas only 3.45% surpassed the 200-time mark. These results suggest that, despite a broad range of vocabulary, a relatively small subset of keywords appeared with high frequency, reflecting a concentrated thematic focus in the dataset.

[Table 1] Analysis of keyword frequency

Frequency	Keywords
200 times or more (n=4)	Worker (338), Inspection (304), Container (272), Accident site (229)
100-199 times (n=5)	Loading/Unloading (180), Ship (175), Fatality (165), Pier (144), Equipment (120)
30-99 times (n=34)	Investigation (91), Forklift (73), Terminal (59), Violation (55), Berthing (50), Fall (46), Police (31), Sentence (31), Coast Guard (31), Rescue (27),Collision (24), Supervisor (21), Transport (21), Hazardous Material (21), Docking (19), Preparedness (18), Berth (18), Entry (18), Yard (17), Mooring (16), Aging (16), Suspension (16), Repair (15), Protective gear (14), Disaster (13), Scrapped Ship (13), Wharf (12), Driver (12), Maintenance (11), Asphyxiation (11), Handling (11), Enforcement (10), Report (10), Guideline (10)

The high frequency of Worker and Accident site underscores that media reports personalize these incidents, focusing on the immediate human cost and the physical location of the tragedy. Inspection suggests a strong media focus on accountability, prevention, and the institutional response following an accident. The fact that these few keywords dominate the discourse indicates a concentrated narrative, potentially overshadowing other systemic issues like management practices or long-term infrastructure investment.

4.2 Word Cloud

The visualization provides an intuitive snapshot of the thematic emphasis within the collected news content, drawing attention to recurring issues such as worker-related accidents, inspection procedures, and causes of port incidents. [Fig. 2] and [Fig. 3] display the top-ranked keywords based on both total frequency and TF-IDF values. These keywords represent the themes emphasized by the media and the public, reflecting real-world concerns and ongoing discussions in society. Overall, keywords with high total frequency generally show relatively low average TF-IDF values. Conversely, terms with the highest average TF-IDF, such as Control, Blind Spot and Captain appear only one to three times in the dataset.

This inverse pattern arises because frequently occurring words such as Worker, Inspection, and Container appear across many documents, which lowers their inverse document frequency (IDF) values and, consequently, their TF-IDF scores.

Hence, while high-frequency but low-TF-IDF keywords capture the core and widely recognized concepts of the topic, less frequent yet high-TF-IDF terms highlight more specific or emerging themes, potentially signaling new issues or alternative research directions.

[Fig. 2] Word Clouds (Total Frequency)

[Fig. 3] Word Clouds (TF-IDF)

4.3 Topic Extraction

To identify underlying thematic topics, topic modeling was adopted. To minimize noise and exclude weakly represented terms, only keywords with a total frequency of four or higher were included, resulting in 79 keywords, while 37 low-frequency keywords were excluded. A topic evaluation procedure was then conducted to determine the optimal number of topics for analysis.

[Table 2] Keywords by Topic Allocation Probability

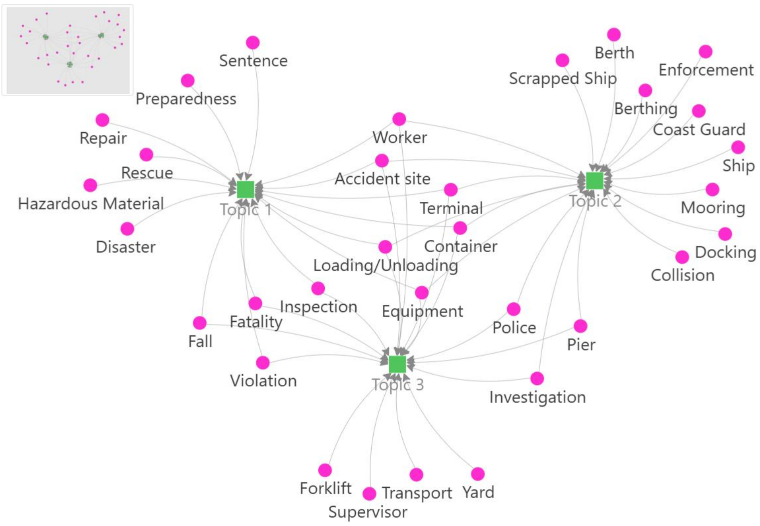
Topic	Keywords of each topic
Safety Inspection & Incident Response	Inspection (0.2811), Accident site (0.1540), Worker (0.0980), Loading/Unloading (0.0433), Equipment (0.0366), Violation (0.0357), Terminal (0.0327), Fatality (0.0296), Fall (0.0288), Sentence (0.0285), Hazardous Material (0.0221), Preparedness (0.0184), Disaster (0.0155), Repair (0.0128), Container (0.0104), Rescue (0.0101)
Maritime Infrastructure & Operations	Ship (0.1988), Pier (0.1520), Berthing (0.0736), Container (0.0539), Coast Guard (0.0384), Investigation (0.0357), Collision (0.0295), Docking (0.0280), Berth (0.0248), Mooring (0.0234), Worker (0.0213), Scrapped Ship (0.0190), Terminal (0.0186), Equipment (0.0179), Loading/Unloading (0.0173), Accident site (0.0123), Enforcement (0.0112), Police (0.0101)
Occupational Hazards in Cargo Operations	Worker (0.1557), Container (0.1430), Fatality (0.0865), Loading/Unloading (0.0843), Accident site (0.0637), Inspection (0.0510), Equipment (0.0495), Forklift (0.0447), Investigation (0.0368), Pier (0.0241), Violation (0.0158), Police (0.0147), Terminal (0.0127), Transport (0.0126), Fall (0.0118), Supervisor (0.0114), Yard (0.0104)

[Table 2] shows the allocation ratios of selected keywords within each topic and the assigned topic names summarizing the main keywords. The topic modeling results reveal three primary themes Safety Inspection and Incident Response, Maritime Infrastructure and Operations and Occupational Hazards in

Cargo Operations. Topic 1 reflects the media's focus on the legal, regulatory, and post-accident phases. The narrative here is about failure of oversight, assignment of blame, and the mechanisms of emergency response and recovery. Topic 2 centered on Ship, Pier, Berthing, Docking, and Coast Guard. This topic addresses the maritime environment and accidents arising from vessel movements, mooring, and ship–shore interactions. Topic 3 with core keywords like Worker, Forklift, Fatality, Transport, and Yard, this theme highlights daily hazards to personnel from equipment (e.g., forklifts) and operational processes in the terminal yard.

The three topics share critical keywords, revealing the interconnected nature of port operations and safety. Container and Loading/Unloading are critical, high-risk activities that bridge maritime and onshore operations, while Inspection and Worker safety are central concerns across the entire port environment. Although text mining does not generate quantitative measures in the same way traditional statistics do, it uncovers the underlying narrative logic of public discourse by mapping how keywords relate to one another through topic modeling.

4.4 Two-mode network between topics and keywords



[Fig. 4] Topic-Keyword 2-mode Network

[Fig. 4] illustrates the two-mode network linking topics and their top keywords. Certain keywords appear across multiple topics, such as inspection, accident site, and worker, indicating their cross-cutting relevance and the interconnected nature of issues within port safety and operations. Their prominence indicates that public and media discourse consistently emphasizes port workers, operational safety failures, and institutional investigation.

Other keywords are topic-specific such as Scrapped Ship, Mooring, Docking which connect primarily to Topic 2 (Maritime Infrastructure), or Forklift, Supervisor, Yard which connect primarily to Topic 3 (Occupational Hazards), or Sentence, Violation, Hazardous Material which connect primarily to Topic 1 (Safety Inspection & Response).

Many shared keywords Worker, Accident Site, Inspection, Container, Pier suggest that institutional response, operational safety, and accident outcomes are heavily interlinked in media discussions. The overlap of these keywords across the 3 topics suggests that media discussions do not treat port incidents as isolated events but as connected to broader issues of accountability of corporations and regulators, and the systemic vulnerability of workers.

4.5. Centrality Analysis

The results of the centrality analysis are presented in [Table 3]. This analysis measures the relative importance of each keyword within the network, revealing how closely terms are connected and indicating their overall influence in the dataset.

[Table 3] Centrality Analysis

Rank	Degree Centrality		Closeness Centrality		Betweenness Centrality		Keywords	Total Freq.
	Keywords	Value	Keywords	Value	Keywords	Value		
1	Terminal	0.6134	Pier	4.4797	Pier	0.3935	Worker	338
2	Equipment	0.6047	Inspection	4.2908	Container	0.3032	Inspection	304
3	Loading /Unloading	0.5539	Accident site	3.9326	Accident site	0.2903	Container	272
4	Worker	0.5466	Ship	3.5652	Inspection	0.243	Accident site	229
5	Investigation	0.525	Berthing	3.5652	Ship	0.0029	Loading/ Unloading	180
6	Accident site	0.5141	Coast Guard	3.5652	Berthing	0.0029	Ship	175
7	Police	0.512	Collision	3.5652	Coast Guard	0.0029	Fatality	165
8	Container	0.4928	Docking	3.5652	Collision	0.0029	Pier	144
9	Violation	0.4898	Berth	3.5652	Docking	0.0029	Equipment	120
10	Fall	0.4846	Mooring	3.5652	Berth	0.0029	Investigation	91

Degree Centrality is dominated by operational and investigative terms such as Terminal, Equipment, Loading/Unloading, Worker, Investigation. This suggests the core discussion revolves around the processes and locations of port work and the subsequent response to incidents. However, Closeness

Centrality is dominated by the immediate context of the accident such as Pier, Inspection, Accident site, Ship, Berthing. These keywords are conceptually central. Information or influence can spread from these points to the entire network most efficiently. For example, from the Accident site to operational, investigative, and legal concepts. Regarding Betweenness Centrality, there is a massive gap between the top four and the rest (lower than 0.003). This tells us that Pier (0.3935), Container (0.3032), Accident site (0.2903), and Inspection (0.2430) are critical structural bottlenecks. They connect different parts of the network that would otherwise be disconnected. For instance, Inspection is the bridge between regulatory bodies (Coast Guard, Enforcement) and operational failures (Violation, Accident site).

5. Conclusion

This study used text mining and keyword network analysis to examine themes and discourse patterns in Korean media coverage of port loading and unloading accidents. Analyzing 189 news articles revealed dominant themes, core concepts, and structural relationships shaping public portrayals of port safety.

The results indicate that media discourse centers on three interconnected themes: Safety Inspection and Incident Response, Maritime Infrastructure and Operations, and Occupational Hazards in Cargo Operations. Frequent keywords such as Worker, Inspection, Container, and Accident site suggest that port safety is framed as an interaction among human factors, procedures, and infrastructure rather than as isolated events. Centrality analysis further clarified the discourse structure. Keywords such as Terminal and Equipment showed high degree centrality, reflecting their role as core operational elements, while Pier and Accident site exhibited high closeness and betweenness centrality, functioning as conceptual hubs that link operational failures with regulatory and response-related discussions.

These findings offer important implications for practice and policy. The prominence of occupational hazards and specific equipment, including forklifts and containers, highlights the need for enhanced training, stricter enforcement of protective measures, and improved supervision during high-risk operations. The interconnected keyword structure indicates that accidents arise from systemic failures, underscoring the importance of integrated safety strategies addressing equipment maintenance, infrastructural integrity, and human factors simultaneously. The central role of inspection-related keywords further emphasizes the need for proactive safety inspections and effective post-accident feedback mechanisms within safety management systems. Given the media’s influence on public risk perception, these insights can inform data-driven policy making and more effective risk communication. Policymakers and port authorities may use the results to prioritize regulations at the interface of infrastructure and worker safety and to design public awareness initiatives that align with prevailing discourse.

Despite its contributions, this study has limitations. It relies solely on Korean news media, which may reflect editorial biases and incomplete coverage. The focus on noun-based keywords may have excluded relevant contextual information, and the analytical approach identifies associations rather than causal mechanisms. Future research should extend this work by incorporating broader data sources and causal analysis to better understand the underlying dynamics of port accidents.

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