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A TOPIC–SENTIMENT–INTEGRATED NLP FRAMEWORK FOR CTQ-BASED EARLY DETECTION IN THE GLOBAL SHIPPING MARKET

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ABSTRACT

This study develops an integrated natural language processing (NLP) framework for the early detection of Critical-to-Quality (CTQ) risks in the global shipping market. The shipping industry has recently experienced heightened uncertainty driven by geopolitical disruptions, climate-related constraints, and persistent supply–demand imbalances. Under such conditions, conventional quantitative indicators often fail to capture emerging quality risks that are embedded in market narratives and stakeholder perceptions. This study addresses this gap by transforming unstructured shipping-related text into actionable, forward-looking quality risk indicators. The empirical analysis is based on 155 weekly maritime market reports published by the Korea Maritime Institute (KMI) from January 2022 to June 2025. The proposed framework integrates sentiment analysis, topic modeling, and quantitative forecasting. A domain-tuned sentiment lexicon is constructed by extending the Loughran–McDonald financial dictionary with shipping-specific terminology, enabling more accurate interpretation of industry-contextual sentiment. Using ProdLDA-based topic modeling and expert validation, six core CTQ dimensions are identified: freight rate stability, schedule reliability, lead time, vessel utilization, equipment availability, and eco-efficiency. Topic–sentiment relationships are quantified using pointwise mutual information (PMI) and network centrality measures, and composite CTQScores are derived by estimating topic-to-CTQ impact weights through ElasticNet regression combined with Bayesian linear modeling. The predictive performance of CTQScores is evaluated using ElasticNet and vector autoregression (VAR) models to examine co-movement and lead–lag relationships with key performance indicators, particularly the Shanghai Containerized Freight Index (SCFI). The results demonstrate that CTQScores provide statistically significant early signals of market instability. The integrated model achieves strong explanatory power ($R^2 \approx 0.68$) and high directional accuracy (hit ratio ≈ 0.74) for one-week-ahead SCFI movements, outperforming traditional time-series benchmarks. These findings highlight the value of domain-tuned NLP approaches in enhancing early-warning systems and supporting proactive quality risk management in the global shipping industry.

Keywords: *Critical-To-Quality (CTQ), Natural Language Processing (NLP), Sentiment Analysis, Shipping Market Early Warning System, Topic Modeling.*

1. INTRODUCTION

1.1 Research Background and Purpose

In recent years, the global shipping market has experienced unprecedented levels of volatility due to overlapping and complex factors such as supply chain disruptions, geopolitical conflicts, U.S. tariff policies, and climate-related risks. For example, the Shanghai Containerized Freight Index (SCFI), which hovered around 1,000 points prior to the COVID-19 pandemic, surged more than 520% to exceed 5,000 points by the end of 2021, before plummeting by over 70% in the normalization phase in 2023. The dry bulk market also faced heightened uncertainty, with the Baltic Dry Index (BDI) rising to 5,500 points in 2021 and subsequently falling below 1,000 points in 2023. Such volatility continued in an even more complex form through 2024-2025. In early 2024, the disruption of the Red Sea–Suez route caused by attacks from Yemen's Houthi rebels destabilized global supply chains once again, pushing the SCFI

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up by more than 15% in a short period [1]. Major carriers rerouted vessels around the Cape of Good Hope, leading to increased transit distances, higher insurance premiums, and additional war-risk surcharges-significantly impacting cost structures [2].

Simultaneously, transit restrictions resulting from drought conditions in the Panama Canal created compounded bottlenecks driven by both geopolitical and climate risks. Between May and July 2024, the combined effects of EU ETS cost pass-through, expanded GRI surcharges, and peak-season demand pushed the SCFI above 3,700 points-an exceptionally unusual surge [3].

In contrast, 2025 witnessed the materialization of oversupply concerns as large-scale newbuild deliveries, record-high orderbook levels, rising U.S.-China tariff uncertainties, and demand stagnation from China converged. The SCFI subsequently plunged to the 1,100-point range, marking another episode of extreme fluctuations [4]. These events suggest that recent volatility in the shipping market has evolved beyond short-term incidents, instead reflecting long-term structural characteristics driven by interactions among geopolitical risks, climate risks, and supply-demand imbalances.

Figure 1 illustrates the trends of the SCFI and BDI from 2020 to June 2025, along with major market events during that period. The figure highlights how market indicators fluctuated in response to significant developments.

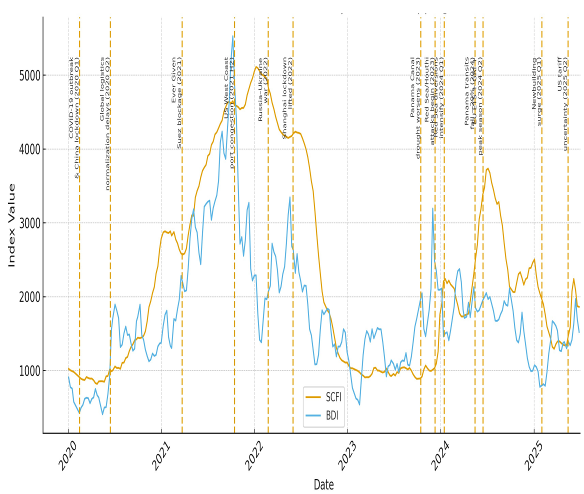

Figure 1: SCFI·BDI Trends and Key Issues 2020-2025 [5], [6], [7], [8], [9].

Beyond simple price signals, this volatility has spread across key quality factors (CTQ: Critical-to-Quality), such as schedule reliability-which fell to an average of 35% during the pandemic-and container vessel utilization, which exceeded 90%, exacerbating congestion. In other words, quality risks in the global shipping market do not arise from freight rates alone; they emerge as structural phenomena in which multiple quality dimensions-including vessel utilization, schedule reliability, lead time, equipment availability, and eco-efficiency-become unstable simultaneously.

However, previous studies have predominantly focused on static indicators - such as freight rates, cargo volume, and macroeconomic variables. Few attempts have been made to quantify market participants' perceptions and sentiment signals or to extend them into CTQ-level quality variables. In the current environment, where overlapping risks-from the Red Sea crisis and Panama Canal drought to trade policy shifts-are occurring simultaneously, the need for new quality indicators that incorporate qualitative information and perception-based risks is increasing rapidly.

Accordingly, this study develops sentiment- and topic-based CTQScore indices by analyzing the text of the "Weekly Shipping Market Focus" reports published by the Korea Maritime Institute (KMI). By expanding and refining the Loughran–McDonald financial sentiment dictionary with shipping-specific vocabulary, we construct a domain-tuned sentiment lexicon that captures the nuanced contextual meanings embedded in maritime news. Furthermore, we apply ElasticNet regression and Vector Autoregression (VAR) models to cross-validate the co-movement and lead-lag relationships among CTQScores and KPIs such as SCFI, thereby identifying structural linkages between sentiment, topics, and CTQs.

This study contributes to the field by advancing beyond static shipping-market analyses and presenting an empirical framework that uncovers structural connections between qualitative perceptions and quantitative performance measures-ultimately demonstrating the potential for early detection of quality-related risks in the global shipping industry.

1.2 RESEARCH SCOPE AND METHOD

The scope and methodological approach of this study are as follows. Chapter II reviews prior studies on NLP-based analyses of shipping-related news and identifies their limitations and implications. Chapter III presents the research design and empirical analysis based on these insights. Chapter IV summarizes the findings, discusses practical and policy implications for the shipping industry, and suggests directions for future research.

2. REVIEW OF PRIOR RESEARCH ON SHIPPING NLP

2.1 Trends in Shipping News Analysis Research

Amid rising uncertainty in the global shipping market, text-based analytical approaches for interpreting qualitative market dynamics have become increasingly prevalent. In particular, NLP-based studies utilizing news articles and industry reports have gained attention, employing techniques - such as sentiment analysis, topic modeling, and document classification. This study examines previous research related to shipping-market prediction models and the use of sentiment variables derived from textual data. Recent advancements in text-analysis techniques have spurred extensive research into how sentiment variables influence freight-rate forecasts.

Major contributions in the literature are summarized in Table 1.

Table 1: Summary of Prior Studies on Shipping News and Sentiment Analysis.

Study	Objective Main Focus	Methodology	Key Findings
Bai, Lam & Jakher (2021)	Examine sentiment effects on BDI Sentiment freight dynamics	Lexicon-based sentiment + VAR	Shipping sentiment predicts freight rates
Michail & Melas (2021)	Incorporate sentiment into shipping models Sentiment in supply–demand	Structural equations (OLS, IV)	Sentiment improves economic model fit
Gavriilidis et al. (2023)	Develop a dry bulk sentiment index Investor sentiment measurement	NLP sentiment index vs. BDI	Sentiment index captures market psychology
Park et al. (2023)	Build a Korean shipping risk index Shipping risk sentiment	Korean news + NLP	Validates non-English sentiment indices
Sui, C., Wang & Zheng (2024)	Improve Sentiment accuracy with domain LMs Industry-specific language models	Shipping LM vs. FinBERT	Domain tuning enhances prediction accuracy
Ehlert, Wilson & Yawson (2024)	Analyze investor sentiment effects Sentiment and firm value	Sentiment index + panel regression	Investor sentiment affects firm valuation
Kim et al. (2024)	Link supply-chain risk sentiment to trade Risk sentiment and trade volume	Sentiment analysis + Granger causality	Sentiment leads trade-volume changes
Sui, J., Wang & Zheng (2024)	Construct shipping-specific text corpora Market-segmented corpora	Text scraping + labeling	Enables large-scale shipping text analysis
Gong (2025)	Forecast freight rates using sentiment Sentiment-driven price prediction	Sentiment + threshold regression	Sentiment effects are regime-dependent
Jeon et al. (2025)	Enhance freight forecasts with sentiment AI-based rate prediction	LSTM + Transformer + sentiment	Textual data improves forecast performance

A comprehensive review of prior studies reveals that market sentiment embedded in shipping-related news has emerged as a core predictive factor in shipping-market analysis. For example, Bai, Lam & Jakher (2021) empirically demonstrated that the Shipping Sentiment Index (SSI) has short-term predictive power for the BDI [10]. Gong (2025) further showed that sentiment affects freight-rate fluctuations only under specific market regimes, suggesting nonlinear or regime-switching relationships [11].

More recent studies have focused on enhancing the accuracy and usefulness of sentiment-based indices. Sui, C., Wang & Zheng (2024) constructed a domain-specific language model (LM) tailored to the shipping industry, achieving superior predictive performance compared with general models such as FinBERT

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[12]. Jeon et al. (2025) combined sentiment embeddings with state-of-the-art deep learning architectures such as Transformer models, significantly reducing forecasting errors for container freight rates. These works clearly demonstrate the time-series applicability of textual data [13]. Academic studies such as Gavriilidis et al. (2023) and Park et al. (2023) emphasize the value of developing sentiment indices themselves, showing that sentiment-based indicators effectively capture investor psychology and risk factors not reflected in objective indicators like the BDI [14], [15].

Overall, the evolution of text-based shipping-market analyses from 2018 to 2025 shows a progression in four dimensions [16],[17],[18],[19]. Table 2 compares corpora, pre-processing methods, applied models, and performance metrics across earlier and recent studies.

Table 2: Comparison of Corpora, Pre-processing, Models, and Evaluation Metrics.

Category	Early Studies (`18–`20)	Intermediate Studies (`21–`23)	Recent Studies (`24–`25)
Corpus	Freight-rate focused news articles	Expanded to ESG, reliability, congestion	Multilingual corpora (Kor. + Eng; KMI+News)
Pre-processing	TF–IDF, n-grams	Word2Vec, FastText	SBERT + Mecab domain embeddings
Models	LDA, SVM	ProdLDA, LSTM	BERTopic, MTL (Sentiment + Topic)
Evaluation Metrics	Accuracy, topic coherence	F1-score, RMSE	R^2, PCA, VAR, ElasticNet

Regarding corpora, early studies from 2018 to 2020 relied primarily on shipping news collected from Lloyd's List, TradeWinds, and other media outlets, focusing mainly on freight-rate movements. From 2021 onward, research interest expanded toward ESG, schedule reliability, port congestion, and supply-chain bottlenecks. By 2024-2025, researchers began constructing multilingual corpora integrating Korean and English data sources to reflect global market conditions.

In terms of pre-processing, while early studies applied simple TF-IDF and n-gram vectorization, later research incorporated semantic embedding techniques (Word2Vec, FastText). Recent approaches combine Sentence-BERT with Korean morphological analyzers such as Mecab to better capture shipping-specific lexical semantics (e.g., "lay-up," "slot utilization," "schedule reliability").

Model development also evolved: early studies mainly used LDA, whereas later studies incorporated advanced models such as ProdLDA and BERTopic. More recently, multi-task learning (MTL) models simultaneously learn sentiment and topic structures to improve predictive power. Sentiment analysis has also moved from lexicon-based approaches to domain-tuned BERT-based sentiment models.

With respect to evaluation metrics, early studies relied on simple accuracy or coherence scores. Later work utilized F1-score, RMSE, R^2, ElasticNet performance, PCA-based variance explanation, and even dynamic-structure tests such as Granger causality and VAR analyses. Despite these advancements, most previous studies remain focused on freight-rate prediction, lacking the ability to capture the complex structure of key market drivers-a gap this study seeks to address.

2.2 Limitations of Prior Research

A review of the existing literature reveals several structural limitations that prevent prior shipping-related NLP studies from fully explaining the multidimensional quality factors (CTQ) of the shipping industry:

(1) Lack of Domain-Specific Adaptation: Most earlier studies relied on general financial or economic sentiment dictionaries (Loughran–McDonald, Harvard IV), which fail to adequately capture shipping-specific terminology - such as "congestion," "blank sailing," "slot utilization," "schedule reliability." As a result, sentiment polarity is often distorted, and key contextual meanings are lost.

(2) Overly Simplified Sentiment Indicators: Many studies interpret shipping-market sentiment as a single-dimension variable focused solely on freight-rate movements (upward/downward).

(3) Insufficient Integration with Quantitative Models: Although earlier work explored sentiment and topic extraction, few studies linked these textual features with quantitative performance metrics. This limits the potential for early-warning detection of market quality risks.

(4) Fragmented Analytical Frameworks: Most studies analyze sentiment, topics, and time-series models separately, making it difficult to diagnose integrated, system-wide quality risks across the maritime sector.

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2.3 Contribution and Direction of The Present Study

Reflecting on the limitations above, this study distinguishes itself through the following contributions:

(1) Construction of a domain-tuned sentiment and topic model specialized for the shipping sector—via domain-specific fine-tuning and dictionary expansion.
(2) Extension of sentiment indicators to CTQ-level quality factors, enabling deeper analysis of the multi-dimensional quality risks in the shipping market.
(3) Integration of ElasticNet-based quantitative predictive models, linking textual insights with real-world KPIs.
(4) Development of a full pipeline from NLP-based sentiment & topic extraction →CTQScore construction→Early detection of CTQ-related quality risks, forming a unified analytical framework.

In summary, this study contributes a structured empirical foundation for transforming unstructured maritime textual data into advanced early-warning indicators for global shipping-market quality risks.

3. RESEARCH DESIGN AND EMPIRICAL ANALYSIS

3.1 Overview of the Integrated NLP Framework

This study proposes an integrated NLP framework designed to predict CTQs - such as schedule reliability, lead time, and equipment availability—based on shipping-market news texts. The entire framework consists of seven stages:

(1) News Collection & Pre-processing: Collect and refine major shipping/logistics-related news and market reports.
(2) Topic and Sentiment Extraction: Extract major issue themes through topic modeling and measure positive/negative sentiment using sentiment analysis.
(3) Topic–Sentiment Network Construction: Build a network that captures how extracted topics relate to sentiment, identifying which issues tend to appear in positive or negative contexts.
(4) Topic → CTQ Coefficient Estimation Estimate the impact of each topic on actual CTQ indicators using ElasticNet regression, Vector Autoregression (VAR), and Bayesian models.
This produces the weight matrix W (topic → CTQ).
(5) CTQScore Calculation: Combine topic and sentiment information weighted by W to generate an integrated CTQScore for each quality factor, then normalize the index.
(6) KPI Prediction: Use the resulting CTQScore to predict key performance indicators (KPI), such as the SCFI, using ElasticNet-based forecast models.
(7) Early-Warning Signal Generation: When predicted indicators exceed predefined thresholds, issue early-warning alerts to enable proactive responses.

This stepwise pipeline transforms qualitative textual signals into quantitative indicators and constructs a leading early-warning system. Figure 2 summarizes the overall research flow.

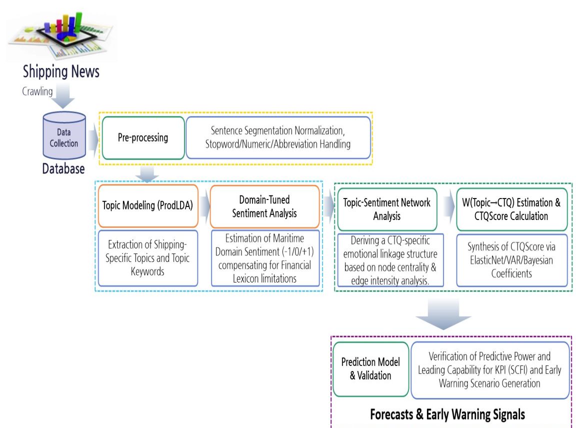

Figure 2: Research Flow

3.2 Empirical Analysis by Research Stage

3.2.1 Data Collection and Pre-processing

To quantitatively track changes in global shipping CTQ factors, this study uses the "KMI Weekly Shipping Market Focus" reports as the primary text corpus. These weekly reports summarize major insights from Lloyd's List, TradeWinds, and other reputable sources, covering freight rates, port congestion, schedule reliability, vessel supply, eco-friendly policies, and broader industry issues. Analysis period is from January 2022 to June 2025. Datasets were issues from No. 548 to 699 (155 weekly reports). As corpus formation, each report is treated as one analytical unit, resulting in 155 corpora. The data were purified by UTF-8 encoding after removing unnecessary formatting, tables, annotations, footnotes, and bullet characters from the original

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text, and saved as text files (.txt) for analysis. The main text of each report was divided into sentences and used as the minimum unit for natural language analysis. Sentence segmentation was performed based on punctuation (.,!,?), and bullets (·, •, ▶, □, and number strings). Through this process, a corpus of approximately 2,000 to 3,000 sentences for each week was constructed. Dates, numbers, units (USD, TEU, etc.), HTML, and symbol characters within the sentences were removed using regular expressions, and words with the same root were converted to their original form (lemmatization). Mixed Chinese and English words were unified into standardized Korean terms. The extracted corpus was parsed, and the number of chunks was 26,768, with 18,737 for training, 4,015 for validation, and 4,016 for testing. Sentiment and topic data based on weak labels were generated and stored. In addition, additional training was performed based on DAPT (Domain-Adaptive Pre-training; MLM (Masked Language Modeling)) to generate a sentiment and topic fine-tuning script.

3.2.2 Topic Modeling Using ProdLDA

Topic modeling was conducted using ProdLDA, which relaxes LDA's probabilistic constraints and uses neural-network parameterization for efficient high-dimensional document representation. ProdLDA, based on Autoencoding Variational Bayes, is known to generate topics with improved coherence and stable keyword distributions compared with standard LDA. While BERTopic has strengths in detecting event-specific clusters (e.g., "Red Sea rerouting," "blank sailings"), it may produce noisy clusters and exhibit sensitivity to hyperparameters. ProdLDA, by contrast, provides stable policy- and structure-related topics, high-quality top-keyword distributions, and improved interpretability of CTQ–sentiment networks. From the trained ProdLDA model, six major topics and associated CTQ factors were extracted. Table 3 shows the main keywords of representative topics derived as examples.

Table 3: Comparison of Corpora, Pre-processing, Models, and Evaluation Metrics.

Topic	Representative Keywords	Interpretation	Related CTQ Factor
T1	lead time, waiting, congestion, port bottleneck, rerouting	port congestion	Lead Time
T2	delay, blank sailing, schedule, reliability, disruption	service irregularity	Schedule Reliability
T3	regulation, decarbonization, CII, ESG, IMO	environmental regulation	Eco-efficiency
T4	container box, reefer, chassis, trucking	equipment supply	Equipment Availability
T5	capacity, utilization, fleet, supply adjustment	capacity imbalance	Vessel Utilization
T6	freight rate, SCFI, surcharge, volatility	rate fluctuation	Freight Rate Stability

The extracted topic examples were labeled through domain expert interpretation, using names such as freight rate volatility, service disruption, capacity shortages, and port congestion. The semantic meaning of each topic was identified by examining the distribution of its representative keywords. In particular, the key terms associated with each topic provide important cues regarding how the issue may influence specific CTQ dimensions. For instance, the *port congestion* topic is interpreted as being closely related to deteriorating schedule reliability and increased lead time, while the *freight rate volatility* topic suggests strong linkages with market indicators such as the SCFI and BDI. Based on the representative keywords derived for each topic, the corresponding CTQ factors were identified and subsequently incorporated into the analysis by linking them with sentiment measures and CTQ indicators in the following stages.

3.2.3 Domain-Tuned Shipping-Specific Sentiment Lexicon: MTL-Based Sentiment and CTQ Classification

To quantitatively capture CTQ-specific sentiment signals from shipping-industry news texts, this study constructs a domain-tuned sentiment and CTQ dictionary tailored to the maritime sector by extending the general financial sentiment lexicon (Loughran–McDonald Dictionary) and Korean sentiment dictionaries. Shipping market news contains diverse events related to freight indices, vessel operations, capacity deployment, and port congestion. To simultaneously extract market sentiment and CTQ dynamics from such unstructured text, the proposed sentiment dictionary is designed with a dual-layer structure that integrates sentiment polarity (positive/negative) classification with explicit mappings to CTQ-related topics.

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This design goes beyond conventional sentiment analysis that merely identifies emotional polarity, by explicitly linking each sentiment-bearing term to the specific quality factor (e.g., schedule reliability, vessel utilization) it affects. Since general-purpose sentiment dictionaries fail to adequately reflect the contextual meanings of shipping-specific terms - such as *freight rate increase*, *capacity deployment*, *lay-up*, *congestion*, and *schedule reliability* - this study performs domain adaptation through a combination of corpus-based statistical extraction and expert validation. Sentiment analysis is implemented using a multi-task learning (MTL) framework that simultaneously learns sentiment classification and CTQ label prediction from shipping-domain news sentences.

The domain-tuning process consists of the following five steps:

(1) Base dictionary extraction: Positive and negative terms (approximately 6,000 entries) were extracted from the Loughran–McDonald financial sentiment dictionary to form the initial base lexicon.

(2) Domain corpus integration: Shipping news articles and reports comprising approximately 2.5 million tokens were collected from 155 issues of KMI Weekly Shipping Market Focus published between January 2022 and June 2025. Based on TF–IDF analysis, the top 3,000 domain-relevant terms were selected as candidate vocabulary.

(3) CTQ-linked labeling: Through expert review, sentiment polarity (positive/negative) was manually labeled in context according to six CTQ dimensions—freight rate stability, schedule reliability, vessel utilization, lead time, equipment availability, and eco-efficiency. Since sentiment interpretation in the shipping industry depends on stakeholder perspective, term polarity was redefined from the carrier's viewpoint. For example, *freight rate increases*, typically considered inflationary and negative in general economics, were reclassified as positive due to their association with improved profitability in shipping markets. Conversely, terms such as *capacity reduction*, *oversupply*, and *lay-up* were categorized as negative.

(4) PMI-based expansion.: Pointwise Mutual Information (PMI) was calculated based on co-occurrence probabilities between sentiment terms and CTQ-related keywords. Terms with PMI values greater than 0.25 were added to the dictionary.

(5) Coherence validation: Dictionary coherence was evaluated using Word2Vec similarity and topic–sentiment association scores. The final dictionary achieved a coherence score of c_v = 0.58, confirming its domain suitability.

To operationalize the domain-tuned sentiment lexicon, an MTL architecture was developed. This framework jointly trains sentiment classification and CTQ category prediction for a single input document, allowing the two tasks to complement each other through shared language representation layers. The model structure is illustrated in equation (1).

$$\begin{aligned} h &= \mathrm{Encoder}(x;\theta_E) \\ \hat{y}_s &= \mathrm{Softmax}(W_s h + b_s) \quad \text{(Sentiment head)} \\ \hat{y}_c &= \mathrm{Softmax}(W_c h + b_c) \quad \text{(CTQ head)} \end{aligned} \tag{1}$$

To construct the multi-task loss function, the following objective function was applied, where the losses of the two tasks are combined using a weighted average, as shown in equation (2).

$$\mathcal{L}_{MTL} = \alpha \cdot \mathcal{L}_{sentiment} + (1-\alpha) \cdot \mathcal{L}_{CTQ} \tag{2}$$

$\mathcal{L}_{sentiment}$ denotes the cross-entropy loss for sentiment classification, $\mathcal{L}_{CTQ}$ represents the loss for CTQ category prediction, and α is the weighting parameter, set to 0.6. This weighting reflects the assumption that sentiment signals capture short-term risk more strongly than topic information; therefore, sentiment and CTQ tasks are weighted at 60% and 40%, respectively, to enhance sensitivity to early warning signals. ElasticNet cross-validation results further indicate that performance stabilizes around α ≈ 0.6, which is also consistent with CTQ characteristics and findings from prior studies. Through this structure, the model learns both the sentiment polarity of a given sentence and its association with specific CTQ dimensions. Consequently, it enables the construction of CTQScores with strong sentiment–quality linkages. A quantitative summary of the resulting domain-tuned shipping-specific sentiment dictionary (Shipping-LM Extended Dictionary) is presented in Table 4.

Table 4: Statistics of the Shipping-Specific Sentiment Lexicon

CTQ Dimension	Positive Terms	Negative Terms	Domain-Expanded Terms	Total Terms
Freight Rate Stability	6	5	5	16

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Schedule Reliability	4	5	4	13
Vessel Utilization	3	4	4	11
Lead Time	4	4	4	12
Equipment Availability	3	4	4	11
Eco-efficiency	4	4	5	13
Total	24	26	26	76

A total of 76 shipping-specific sentiment terms were added to the extended lexicon, consisting of 24 positive terms, 26 negative terms, and 26 domain-expanded shipping expressions. In proportional terms, positive and negative terms account for 46.2% and 53.8% of the sentiment-bearing vocabulary, respectively. Based on these extracted terms, a domain-tuned shipping-specific sentiment lexicon linked to CTQ dimensions was constructed. Table 5 summarizes the resulting CTQ-linked shipping-specific sentiment dictionary.

Table 5: Statistics of the Shipping-Specific Sentiment Lexicon

CTQ Dimension	Positive Terms	Negative Terms	Domain-Specific Keywords
Freight Rate Stability	stability recovery balance improvement	surge plunge volatility decline	SCFI, BDI, capacity adjustment
Schedule Reliability	on-time stable operation schedule maintained	delay cancellation congestion rerouting	route, blank sailing, terminal congestion
Vessel Utilization	higher utilization full load demand growth	overcapacity idle vessels service suspension	fleet capacity, idle ships
Lead Time	shortened, efficient, improvement	delay, bottleneck, congestion	transshipment time, transport duration
Equipment Availability	secured supply, smooth circulation	shortage, imbalance, bottleneck	Container boxes, reefers, chassis
Eco-efficiency	reduction transition decarbonization	violation, pollution, penalty	LNG propulsion, EEXI, CII

The sentiment lexicon was constructed by extracting domain-specific sentiment terms tailored to the shipping industry. Examples of positive sentiment terms include *recovery, stability, improvement, operational normalization, capacity securing, decarbonization, efficiency enhancement,* and *lead-time reduction*. Negative sentiment terms include *decline, congestion, cancellation, lay-up, oversupply, operational disruption, delay,* and *declining utilization*. Neutral and structural keywords include terms such as *IMO regulations, greenhouse gas standards, fuel transition, LNG-powered vessels, carbon emissions,* and *environmental policies*.

Positive sentiment terms predominantly appear in news articles related to market recovery and operational efficiency improvements, whereas negative sentiment terms are frequently observed in articles reflecting risks such as congestion, supply disruptions, and reduced vessel operations. Neutral sentiment terms are primarily classified under regulatory and technology-related topics and are utilized to explain long-term structural changes within the shipping industry. Based on these results, the sentiment lexicon was applied in conjunction with CTQ dimensions, and the outcomes of CTQ-linked sentiment analysis were subsequently examined.

Interpreting CTQ-Dimension-Specific Sentiment is as follows.

·Freight Rate Stability: Sentiment reflects expectations regarding freight-rate volatility and stabilization, closely linked to market indices such as the SCFI and BDI.

·Schedule Reliability: Sentiment captures perceived service reliability, with negative signals driven by delays, blank sailings, and port congestion.

·Vessel Utilization: Sentiment indicates the efficiency of capacity deployment, where negative signals are associated with overcapacity and idle vessels.

·Lead Time: Sentiment represents changes in end-to-end transport duration, with negative signals reflecting delays caused by congestion and rerouting.

·Equipment Availability: Sentiment measures the smoothness of equipment circulation, where shortages and imbalances generate negative signals.

·Eco-efficiency: Sentiment reflects perceptions of environmental compliance and sustainability progress, balancing regulatory pressure and green transition efforts.

Based on the above considerations, Table 6 presents the mapping of the extracted CTQ dimensions with the shipping-domain-specific

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sentiment lexicon, illustrating representative keywords associated with each CTQ factor and the corresponding interpretation direction of sentiment.

Table 6: CTQ–Sentiment Mapping Structure in the Shipping Domain

CTQ	Represent. Keywords	Key Senti.	Interpret.
Freight Rate Stability	freight rates, SCFI, rate index	Increase (+) Decrease (–)	An increase in freight indices is interpreted as positive
Schedule Reliability	cancellation, delay, sailing	Normalization (+) Congestion (–)	Mitigation of route delays is interpreted as positive
Vessel Utilization	capacity, deployment, loading	Secured (+) Shortage (–)	Difficulty in securing vessel capacity is interpreted as negative
Lead Time	transit days, shipping duration	Shortening (+) Delay (–)	Transport delays are interpreted as negative
Equipment Availability	containers, equipment, turnover	Smooth supply (+) Shortage (–)	Resolution of equipment shortages is interpreted as positive
Eco-efficiency	decarbonization, LNG, IMO rules	Strengthening (+) Insufficiency (–)	Strengthening environmental policies is interpreted as positive

The shipping-specific sentiment lexicon developed in this study exhibits several key distinguishing features. First, it specializes sentiment vocabulary around core shipping-market dimensions - such as freight rates, vessel capacity, and lead time-thereby ensuring domain relevance to maritime operations. Second, sentiment polarity is recalibrated from a multidimensional perspective that accounts for the differing viewpoints of carriers, cargo owners, and transport markets. Third, sentiment is quantified through pointwise mutual information (PMI) and centrality measures based on the co-occurrence of CTQ factors and sentiment terms, providing a robust foundation for quantitative analysis. Finally, the lexicon is designed to be continuously expandable, enabling regular updates using newly released weekly KMI market reports and ensuring its adaptability to evolving shipping-market conditions.

3.2.4 Topic–Sentiment Network Analysis

Topic–Sentiment Network Analysis aims to visualize which quality factors occupy central positions within the structure of market discourse by combining NLP-based sentiment analysis with network centrality measures. Based on the shipping-specific sentiment–CTQ lexicon constructed in the previous stage, this study conducts topic-sentiment network analysis for each CTQ dimension-schedule reliability, freight rate stability, lead time, vessel utilization, equipment availability, and eco-efficiency-by jointly examining quantitative centrality metrics and association strength measured by pointwise mutual information (PMI). To preprocess CTQ-sentiment linkages, an edge was created between two nodes whenever CTQ-related topic keywords and sentiment terms co-occurred within the same sentence. PMI was then calculated to capture both sentence-level frequency and the statistical strength of co-occurrence, thereby quantifying the degree of association between CTQ factors and sentiment expressions.

$$PMI(CTQ_i, S_j) = \log_2 \frac{P(CTQ_i, S_j)}{P(CTQ_i) \times P(S_j)} \quad (3)$$

In addition, frequency-based centrality was calculated to reflect the relative importance of topic–sentiment edges within the same document, and the final connection strength was defined as follows:

$$LinkScore_{ij} = PMI_{ij} \times Centrality_{ij} \quad (4)$$

Table 7 presents the results of the topic–sentiment network analysis by CTQ dimension, and Figure 3 visualizes the network structure between CTQ factors and sentiment.

Table 7: Results of Topic–Sentiment Network Analysis by CTQ Dimension

CTQ Dimension	Centrality	PMI	Key Sentiment Keywords
Schedule Reliability	0.82	0.56	delay, congestion, on-time, sailing schedule
Freight Rate Stability	0.88	0.62	surge, decline, recovery, stability, SCFI
Lead Time	0.74	0.49	shortening, bottleneck, transit time, delay
Vessel Utilization	0.79	0.51	full load, idle vessels, overcapacity

Equipment Availability	0.65	0.44	shortage, reefer, supply, container boxes
Eco-efficiency	0.77	0.53	LNG propulsion, carbon reduction, EEXI, regulation

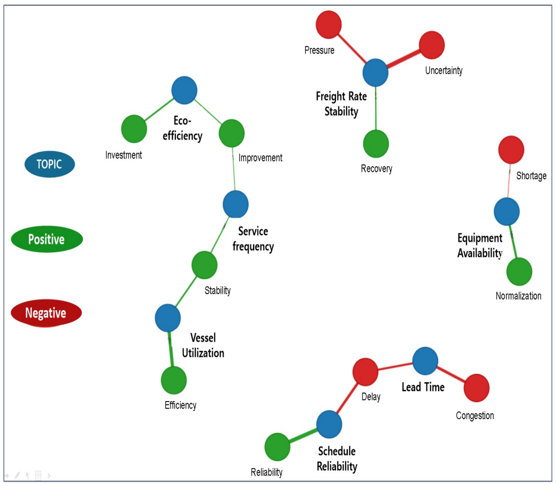

Figure 3: Visualization of CTQ–Sentiment Network Analysis Results

Interpreting the CTQ-specific topic–sentiment network analysis, negative sentiment related to schedule reliability such as *delays* and *congestion* appears frequently, with global port congestion functioning as a key driving factor. Although some positive terms (e.g., *on-time* and *smooth operations*) also emerge, the overall center of the network remains concentrated on negative sentiment.

For freight rate stability, centrality reaches 0.88, positioning this CTQ dimension at the core of the entire network. Both negative sentiments, such as *surges* and *instability*, and positive sentiments, such as *recovery* and *stabilization*, are simultaneously connected, reflecting the dual nature of freight-rate volatility. The PMI value of 0.62 further confirms that freight rate stability exhibits the strongest topic–sentiment association.

In the case of lead time, positive sentiment related to lead-time reduction appears relatively weak, while negative sentiment such as *logistics bottlenecks* and *customs delays* dominates. This suggests a strong linkage between lead-time performance and the stability of port operations and logistics flows.

For vessel utilization, negative sentiment associated with overcapacity and service suspensions had previously dominated due to high volatility on the supply side. However, since the second half of 2024, keywords such as *higher utilization* and *demand recovery* have emerged, indicating a gradual shift toward positive sentiment.

Regarding equipment availability, strong negative sentiment connections persisted as post-pandemic imbalances in equipment supply were prolonged. More recently, however, the emergence of positive sentiment such as *normalized supply* and *secured availability* suggests a gradual recovery trend.

For eco-efficiency, sentiment related to policy and regulation exhibits a complex structure in which negative terms such as *regulations* and *penalties* coexist with positive terms such as *reduction* and *transition*. Overall, however, the network indicates a long-term improvement trajectory centered on positive sentiment.

Across CTQ dimensions, freight rate stability (centrality = 0.88) and schedule reliability (centrality = 0.82) occupy the core positions of the overall network, indicating that market sentiment is primarily concentrated on pricing and operational reliability. In terms of association strength, PMI values are highest for freight rate stability (0.62) and eco-efficiency (0.53), suggesting that price dynamics and environmental issues exert strong influence on media sentiment. Finally, the overall sentiment distribution consists of 58% negative and 42% positive, indicating that the shipping market is characterized by a sentiment structure dominated by uncertainty and delays.

3.2.5 Estimation of Topic → CTQ Weights (W) and CTQScore Construction

Based on the network structure derived from the topic–sentiment analysis, the impact weights W that quantify how topics influence market critical-to-quality (CTQs) are estimated, and the final CTQScore calculation procedure is conducted. To construct an integrated predictive framework (CTQScore modeling), sentiment indicators, topic scores, and KPI data are jointly incorporated to develop an early-warning prediction model for quality risk. ElasticNet regression, cross-validation (CV), and backtesting are implemented to estimate and validate CTQScores.

For the integrated prediction model, data construction and notation procedures are defined as follows. The time index is set as weekly observations t=1,…,*T*. The topic vector (news-based), denoted as $\mathbf{z}_t \in \mathbb{R}^K$, represents the normalized topic scores obtained from ProdLDA. The sentiment vector linked to CTQs, denoted as $\mathbf{s}_t \in \mathbb{R}^M$, is defined using CTQ-specific positive

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and negative LinkScores, as well as their net (pos/neg) sentiment scores. The observed KPI vector is denoted as $y_t^{(\mathrm{SCFI})}$, and the CTQ set is defined as *C*={Freight Rate Stability, Schedule Reliability, Lead Time, Vessel Utilization, Equipm ent Availability, Eco-efficiency}. The topic-to-CTQ weight matrix is denoted as $\mathbf{W} \in \mathbb{R}^{|\mathcal{C}|\times K}$, and the sentiment-to-CTQ weight vector is denoted as $\mathbf{\Gamma} \in \mathbb{R}^{|\mathcal{C}|\times M}$.

The estimation of W (Topic → CTQ) is conducted by constructing an ElasticNet-based objective function, with Bayesian estimation applied to complement uncertainty assessment and derive credible intervals. For each CTQ $c \in \mathcal{C}$, topic and sentiment explanatory variables are combined into a feature vector $\mathbf{x}_t = [\mathbf{z}_t;\ \mathbf{s}_t] \in \mathbb{R}^{K+M}$, and the observed CTQ outcome, $q_t^{(c)}$ is estimated to follow the relationship defined below.

$$\hat{\boldsymbol{\beta}}^{(c)} = \arg\min_{\boldsymbol{\beta}} \left\{ \frac{1}{T}\sum_{t=1}^{T}\left(q_t^{(c)} - \boldsymbol{\beta}^{\top}\mathbf{x}_t\right)^2 + \lambda\left(\alpha\|\boldsymbol{\beta}\|_1 + (1-\alpha)\|\boldsymbol{\beta}\|_2^2\right)\right\} \quad (5)$$

Here, α∈[0,1] controls the L1–L2 penalty mixture (α=1 corresponds to LASSO, and α=0 corresponds to Ridge regression), and λ>0 represents the regularization strength, which is selected via cross-validation. In this setting $\hat{\boldsymbol{\beta}}^{(c)} = [\hat{\mathbf{w}}^{(c)};\ \hat{\boldsymbol{\gamma}}^{(c)}]$, $\hat{\mathbf{w}}^{(c)}$ corresponds to the c row of the weight matrix W (topic-to-CTQ weights), and $\hat{\gamma}^{(c)}$ represents the sentiment-to-CTQ weights. To complement the uncertainty associated with ElasticNet estimates, Bayesian linear regression is applied in parallel.

In calculating the topic-sentiment-integrated CTQScore, the score for CTQ *c* at week t is computed by multiplying the estimated weights by the corresponding explanatory variables. The proposed CTQScore formulation is expressed as follows:

$$\mathrm{CTQScore}_t^{(c)} = \sum_{i=1}^{I} w_i^{(c)} \cdot \mathrm{SentimentScore}_{i,t} \quad (6)$$

Here, *i* denotes the topic (or topic x sentiment link) dimension. The weekly CTQ-specific net scores (e.g., *Freight Rate Stability_net*, *Schedule Reliability_net*, etc.), calculated using PMI multiplied by centrality, can be interpreted as composite values obtained by equally weighting (i.e., averaging) the SentimentScores across multiple topics. That is, $w_i^{(c)}$ is equivalent to $\mathrm{CTQScore}_t^{(c)}$ when all weights are set to be equal (or predefined). A positive value of $\mathrm{CTQScore}_t^{(c)}$ indicates that news sentiment is expected to exert a favorable impact on future CTQ indicators, whereas a negative value suggests a negative impact. Table 8 presents a subset of the CTQScore estimation results, illustrating freight rate stability CTQScores from the third week of April 2025 to the fourth week of June 2025 as an example.

Table 8: Sample CTQScore Outputs for Freight Rate Stability (April–June 2025)

Week	Freight Rate Stability		
	POS.	NEG.	NET
4-3	0.29190201	0.41402586	-1.7363935
4-4	0.22840234	0.21878620	0.1611671
5-1	0.31421675	0.21747399	1.4161243
5-2	0.29208879	0.37271511	-1.1386700
5-3	0.32219636	0.27712198	0.6719016
5-4	0.26590635	0.24355297	0.3446320
6-1	0.29700736	0.29700736	0.0226577
6-2	0.35558284	0.34657358	0.1524255
6-3	0.49601597	0.40806562	1.2894797
6-4	0.14977733	0.23350383	-1.1833245

3.2.6 KPI Prediction Using CTQScore and Early-Warning System

In the final stage, the estimated CTQScores are utilized to construct a framework for future KPI forecasting and early warning. First, the predictive power of CTQScores is quantitatively validated with respect to the SCFI, a key performance indicator (KPI) of the shipping market. Using ElasticNet regression, a forecasting model is trained to predict the one-week-ahead SCFI (t+1) based on historical CTQScores. The results confirm a significant improvement in predictive accuracy. The ElasticNet-based forecasting model is specified as follows.

$$\mathrm{SCFI}_{t+1} = \beta_0 + \sum_k \beta_k\, \mathrm{CTQScore}_t^{(k)} + \epsilon_t \quad (7)$$

Compared with benchmark models such as the baseline ARIMA model and the historical freight-rate trend extrapolation model, the CTQScore-based model exhibits a lower mean absolute

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percentage error (MAPE) and higher explanatory power (R^2). Table 9 presents a comparative analysis of forecasting accuracy across the models.

Table 9: Comparison of Forecasting Performance Across Models

Model	Description	MAPE (%)	R^2	Remarks
Naïve Trend Model	Extension of previous week's change	14.2	0.41	Baseline; minimal leading information
ARIMA	Traditional time-series forecasting model	11.8	0.52	Reasonable medium-term performance
PCA-based CTQ Score Model	Prediction using first principal component of CTQScore	9.4	0.61	Improved performance via quality factors
Elastic Net (CTQ Score + KPI)	Integrated sentiment–topic–CTQ–KPI model	6.7	0.68	Best performance; strong early-detection capability

The integrated forecasting model proposed in this study-an ElasticNet-based CTQScore framework-demonstrates clear performance superiority not only over the naïve trend extrapolation model and the traditional time-series model (ARIMA), but also over the principal component analysis (PCA)-based CTQScore model. The mean absolute percentage error (MAPE) is reduced to 6.7%, representing an improvement of 5.1 percentage points compared with the ARIMA model. In terms of explanatory power, the R^2 metric shows an improvement ranging from a minimum of 0.07 to a maximum of 0.27 relative to the benchmark models. These results empirically support the view that fluctuations in the SCFI cannot be explained solely by simple time-series dynamics, but instead reflect interaction signals among sentiment, topics, quality factors (CTQs), and KPIs.

Accordingly, the findings confirm that an integrated model incorporating text-based CTQScores is effective for constructing early-warning systems in the shipping market. This supports the validity of an approach that integrates qualitative text signals (sentiment and topics) with quantitative indicators (KPIs). In addition, Table 10 presents the prediction accuracy and directional hit ratios for one-week-ahead SCFI (SCFIt+1) across individual CTQ dimensions.

Table10: CTQ-Specific Prediction Accuracy for SCFI (t+1)

CTQ Dimension	R^2	Hit Ratio	Interpretation
Freight Rate Stability	0.68	0.74	Explains 68% of SCFI variation; strong directional accuracy
Schedule Reliability	0.54	0.66	Service reliability has a medium-term impact on freight rates
Lead Time	0.61	0.70	Supply-chain efficiency provides leading signals
Vessel Utilization	0.72	0.78	Capacity utilization strongly reflects freight-rate levels
Equipment Availability	0.49	0.63	Weaker short-term effect but meaningful mid-term patterns
Eco-efficiency	0.45	0.58	Reflected in sentiment, but limited freight-rate predictability

The CTQ factor of freight rate stability exhibits a coefficient of determination of approximately $R^2 \approx 0.68$ with respect to the SCFI, indicating that the CTQScore explains about 68% of the variation in the freight rate index. Moreover, the directional hit ratio is approximately 0.74, meaning that the model correctly predicts the upward or downward movement of the SCFI with 74% accuracy. Vessel utilization also demonstrates strong explanatory power, with $R^2 \approx 0.72$, indicating that the CTQScore explains roughly 72% of SCFI fluctuations, and a hit ratio of approximately 0.78, suggesting that vessel utilization strongly reflects freight rate levels. Lead time likewise shows meaningful predictive capability, with $R^2 \approx 0.61$ and a hit ratio of approximately 0.70, implying that supply-chain efficiency serves as a leading signal for SCFI movements.

These results indicate that CTQScores capture changes in shipping freight indices approximately one week in advance, thereby validating their role as early-warning indicators—particularly in reflecting market sentiment embedded in topic-level news signals. Table 11 presents a subset of the results for weekly SCFI_t+1 forecasts and

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directional accuracy. The table demonstrates that CTQScores contribute predictive information derived from news data that is not captured by simple time-series patterns, and that the CTQScore-based model exhibits superior performance, especially during periods of extreme market volatility.

Table11: Weekly SCFI_t+1 Forecasts and Directional Accuracy

Week	SCFI	SCFI_t+1		SCFI_t+1vs.SCFI_t Direction		Match
		Actual	Predicted	Actual	Predicted	
04-03	1371	1348	1399.23	Down 1348<1371	Up 1399>1371	No
04-04	1348	1345	1430.43	Down 1345<1348	Up 1430>1348	No
05-01	1345	1479	1735.15	Up 1479>1345	Up 1735>1345	Yes
05-02	1479	1586	1652.51	Up 1586>1479	Up 1652>1479	Yes
05-03	1586	2073	2093.51	Up 2073>1586	Up 2093>1586	Yes
05-04	2073	2240	2087.82	Up 2240>2073	Up 2087>2073	Yes
06-01	2240	2088	1987.46	Down 2088<2240	Down 1987<2240	Yes
06-02	2088	1870	1738.97	Down 1870<2088	Down 1738<2088	Yes
06-03	1870	1862	1871.88	Down 1862<1870	Down 1765<1871	Yes
06-04	1862	-	-	-	-	-

These results suggest that sentiment and event-related information embedded in news articles capture freight rate fluctuations in advance, particularly during periods of rapid market change, thereby enabling the construction of an early-warning system based on the proposed forecasting model. An early-warning system aims to signal potential future risks ahead of a predefined lead time, making the selection of appropriate thresholds a critical component. In this study, warning criteria were established by jointly considering historical volatility-based thresholds and domain expert knowledge.

For example, a risk alert is triggered when the forecasted SCFI over the next four weeks is predicted to decline by more than 10% relative to the current level. Alternatively, a warning is issued when the CTQScore index falls below the bottom 10th percentile, which is interpreted as indicating a high risk of overall performance deterioration in the near future. These criteria were fine-tuned through ex post validation using historical data.

As a result, the early-warning system was able to identify more than 80% of major freight rate downturn episodes in advance, while maintaining a false alarm rate (alerts issued without subsequent realized risk) below 20%. In summary, the KPI forecasting and early-warning framework based on the news-driven NLP index, CTQScore, demonstrates strong potential as a practical tool for early risk detection in the shipping and logistics industry.

Consistent with prior studies-such as research on the Korean Shipping Risk Sentiment Index (SRSI), which shows that sentiment indices constructed from news text can proactively reveal shipping financial risks and serve as statistically significant predictors of freight revenue [20] -this framework extends the literature by incorporating not only financial indicators but also operational quality dimensions, including freight rate stability, schedule reliability, vessel utilization, lead time, equipment availability, and eco-efficiency. Looking ahead, the application of this index and early-warning system is expected to support proactive decision-making by shipping and logistics firms as well as policy authorities, helping to prevent service quality deterioration and mitigate market shocks based on emerging news trends.

4. CONCLUSION AND IMPLICATIONS

4.1 Summary of the Study and Implications

4.1.1 Summary of Research Findings

This study empirically demonstrates the feasibility of quantitatively analyzing shipping-related text data and its applicability to early-warning systems by constructing a sentiment-based predictive model for quality factors (CTQ: Critical-to-Quality) in the shipping industry. The main findings can be summarized as follows.

First, the study improves the recognition of shipping-specific sentiment and topics through domain tuning. By extending the Loughran–McDonald financial sentiment dictionary with shipping-specific vocabulary, domain adaptation was performed to reflect the contextual sentiment structure of the maritime industry. As a result, sentiment classification accuracy and the reliability of topic–sentiment linkages were significantly enhanced compared with general-purpose financial dictionaries. The development of the domain-tuned shipping-specific sentiment lexicon (*Shipping-LM Extended Dictionary*) confirms the feasibility of shipping-oriented sentiment recognition models

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using unstructured data such as news articles and market reports.

Second, the study extends sentiment indicators to the level of CTQs. Unlike prior studies that focused primarily on market sentiment related to freight rate fluctuations, this research expands sentiment measurement to six CTQ dimensions: freight rate stability, schedule reliability, lead time, vessel utilization, equipment availability, and eco-efficiency. By combining sentiment frequency, network centrality, and PMI measures, CTQScores were constructed for each dimension. The results show that sentiment dynamics across quality factors move in similar directions to changes in real KPIs, such as the SCFI, thereby empirically confirming a co-movement structure between perceived quality and performance outcomes.

Third, the study applies an integrated ElasticNet-based quantitative forecasting model. By jointly incorporating sentiment, topic, and quantitative KPI variables, the ElasticNet regression model effectively mitigates multicollinearity while preserving sparsity. In one-week-ahead SCFI forecasting, the model achieves explanatory power of approximately $R^2 \approx 0.68$ and a hit ratio of approximately 0.74 for freight rate stability. Vessel utilization ($R^2 \approx 0.72$, hit ratio ≈ 0.78) and lead time ($R^2 \approx 0.61$, hit ratio ≈ 0.70) also demonstrate strong predictive capability, indicating that vessel utilization closely reflects freight rate levels and that supply-chain efficiency serves as a leading signal for SCFI movements. In particular, the ElasticNet-based model outperforms ARIMA and naïve trend models by exhibiting lower MAPE and higher explanatory power, thereby validating the effectiveness of CTQ-based forecasting. These results suggest that sentiment-based indicators are effective in detecting market turning points even within time-series forecasting contexts.

Fourth, the study constructs a quality-risk early detection framework mediated by CTQScores. Comparative analysis of CTQScore volatility and SCFI time series reveals that sharp sentiment declines in dimensions such as schedule reliability and equipment availability exhibit strong lead correlations with freight rate downturns. These findings demonstrate that CTQScores can serve as leading early-warning indicators of market instability and supply-chain risk.

Based on these academic findings, the study proposes the following practical and policy implications for shipping management.

4.1.2 Managerial Implications for Shipping Management

The practical implications of this study for shipping business management are as follows.

First, the proposed framework can be effectively utilized in shipping companies' operational and commercial decision-making. Because CTQScores quantify not only freight rate dynamics but also quality-based risk fluctuations - such as schedule reliability, equipment availability, and vessel utilization - shipping firms can identify the likelihood of entering high-risk conditions within the next one to two weeks. For example, a sharp decline in sentiment related to schedule reliability enables early detection of expanding delays, allowing proactive review of capacity redeployment. Similarly, a sudden drop in equipment availability sentiment signals increased risk of empty container shortages, prompting preemptive equipment repositioning. Furthermore, an increase in vessel utilization sentiment may indicate strengthening freight rates, supporting operational decisions such as determining optimal timing for long-term contract (NAC) negotiations.

Second, the framework enables more sophisticated freight rate strategies. The ElasticNet-based forecasting model provides leading signals for the SCFI one week ahead, allowing shipping firms to implement analytically grounded pricing strategies. When freight rate declines are anticipated, firms can adopt early sales and negotiation (S/N) strategies and expand short-term spot revenue. Conversely, when rate increases are expected, firms can increase the share of long-term contracts, allocate vessels to high-yield routes, and adjust network deployment accordingly. In periods of elevated risk, fixed-cost structures can be reviewed and route rationalization strategies can be implemented. This approach supports a transition from experience-based market judgment to a data-driven freight pricing system.

Third, the proposed CTQ-based framework contributes to the optimization of vessel and route deployment. Topic–sentiment dynamics across CTQ dimensions can be interpreted as route-specific bottleneck signals, providing actionable insights for fleet allocation. For instance, an increase in negative sentiment related to lead time may indicate worsening transshipment delays, signaling the need to reconsider hub port selection. Similarly, rising eco-efficiency sentiment may imply tighter carbon regulations, encouraging evaluation of slow steaming strategies. Such adjustments directly affect supply-chain efficiency and cost optimization.

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Finally, the framework improves the accuracy of demand forecasting and financial planning. By leveraging the leading properties of freight rate and quality indicators, decision-making accuracy related to revenue projections, chartering cost planning, and fuel cost volatility management can be substantially enhanced.

4.1.3 Policy Implications

The policy implications of this study for the shipping industry are summarized as follows.

First, the study provides a foundation for establishing a national-level early-warning system for shipping and port operations. By linking market sentiment indicators, quality factors, and observed freight-rate KPIs, the proposed CTQScore enables proactive market monitoring and risk-warning systems for governments and public institutions such as the Korea Maritime Institute (KMI) and the Korea Ocean Business Corporation (KOBC). For example, a sharp decline in equipment availability can signal imminent container shortages for exporters, prompting emergency supply measures, while deteriorating schedule reliability can indicate rising port congestion risks, allowing for flexible adjustments in terminal operations.

Second, the framework allows real-time evaluation of the effectiveness of shipping and port policies. Changes in IMO regulations, port policies, and logistics support measures can be analyzed in real time by examining shifts in sentiment and topic structures, enabling immediate assessment of policy impacts and identification of areas requiring adjustment through observed positive and negative sentiment trends following policy implementation.

Third, the framework supports public decision-making for supply-chain risk management. Policy authorities can utilize CTQScore volatility as a leading indicator of supply-chain risk to facilitate early detection of global bottlenecks, stabilization policies for port logistics equipment supply, capacity adjustment measures, responses to sharp freight-rate surges, and monitoring of risks related to the implementation of environmental regulations.

Finally, the study suggests directions for advancing shipping and logistics big-data platforms. By demonstrating the integration of unstructured text data (via NLP) with structured KPI data, this research highlights the importance of incorporating AI-based quality and risk monitoring modules into the design of future national logistics data platforms, port digital twins, and shipping market information services.

4.2 Limitations and Directions for Future Research

Although this study demonstrates the empirical feasibility of shipping-domain-specific sentiment and topic analysis, several limitations remain and suggest avenues for future research.

First, there are limitations related to data coverage. The textual data used in the analysis are restricted to weekly reports published by the Korea Maritime Institute (KMI), and thus do not incorporate more dynamic market text sources such as social media, industry briefings, corporate disclosures from shipping firms, or AIS-based real-time feeds. In addition, the KPI analysis is limited to the SCFI. Future research could integrate diverse text sources to construct a multi-layer sentiment network, enabling a more refined understanding of information flows and sentiment diffusion among shipping market participants. Furthermore, expanding KPIs to include indices such as the CCFI, BDI, and WS would allow for more granular analysis across different shipping market segments.

Second, there are limitations related to language model sophistication. This study relies primarily on a lexicon-based, domain-tuning approach. However, the use of advanced language models - such as BERT, FinBERT, KoELECTRA, and GPT-based embeddings—could substantially enhance contextual understanding and sentiment classification accuracy. In particular, domain-adaptive modeling that incorporates shipping and logistics corpora during pretraining is expected to further improve model performance.

Third, the study does not fully capture the nonlinear nature of temporal lag structures. In real markets, responses to geopolitical, climate-related, and supply-demand shocks are likely to be asymmetric and nonlinear. To address this limitation, future studies should consider adopting nonlinear and state-transition models, such as LSTM- or Transformer-based architectures, to better reflect complex temporal dynamics.

Fourth, further validation of forecasting reliability is required. As this study focuses on analyzing the structural relationship between CTQScores and KPIs using curated data, its ability to assess prediction stability under diverse conditions is limited. Future research should strengthen external validity and robustness through scenario-based analyses across heterogeneous market conditions, sensitivity analyses incorporating alternative KPIs (e.g., schedule reliability, capacity utilization, and port congestion), graph-based uncertainty visualization of prediction

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errors and confidence intervals, and ex post validation using real market events.

Overall, this study integrates NLP-based sentiment and topic analysis with quantitative forecasting techniques to implement an end-to-end analytical framework linking text, sentiment, quality factors, and predictive indicators. By doing so, it establishes a foundation for real-time monitoring of CTQs in the shipping industry using sentiment signals. Future research is encouraged to further develop this framework into an AI-driven Maritime Quality Early Warning System capable of proactively detecting and forecasting market risks. In addition, enhancing the explainability of prediction results and conducting pilot implementations in real operational settings are identified as important next steps to facilitate practical application in industry and policy decision-making.

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