TOWARDS SUSTAINABLE FREEPORTS: A NOVEL ASSESSMENT FRAMEWORK AND NEW ENHANCEMENT SOLUTIONS

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Abbreviations

AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
AM	Arithmetic Mean
ANP	Analytic Network Process
BN	Bayesian Network
BWM	Best-Worst Method
CC	Consolidation Centre
CPT	Conditional Probability Table
CSC	Container Supply Chain
CSI	Container Security Initiative
DEA	Data Envelopment Analysis
DEMATEL	Decision-Making Trial and Evaluation Laboratory
DID	Difference-in-Differences
ER	Evidential Reasoning
ESG	Environmental, Social and Governance
FDI	Foreign Direct Investment
FMEA	Failure Mode and Effects Analysis
FTP	Free Trade Port
FTPA	Free Trade Port Area
FTPZ	Free Trade Port Zone
FTZ	Free Trade Zone
GHSOM	Growing Hierarchical Self-Organising Map
GRA	Grey Relational Analysis
GRI	Global Reporting Initiative
GTFP	Green Total Factor Productivity
GTIE	Green Technology Innovation Efficiency
HRI	High-Risk Inference
IPM	Interface Public Member
ISM	Interpretive Structural Modelling

KPI	Key Performance Indicator
LRI	Low-Risk Inference
MCDM	Multiple Criteria Decision-Making
MCSC	Maritime Container Supply Chain
MO	Modus Operandi
MSC	Maritime Supply Chain
OC	Ocean Carrier
PFTZ	Pilot Free Trade Zone
PMC	Policy Modelling Consistency
POD	Port of Discharging
POL	Port of Loading
PPE	Personal Protection Equipment
PPP	Public-Private Partnerships
RIF	Risk Influencing Factor
SBM	Slack-Based Measure
SCM	Supply Chain Management
SCOT	Social Construction of Technology
SD	Standard Deviation
SEM	Structural Equation Modelling
SEZ	Special Economic Zone
TAN	Tree Augmented Naive Bayes
TAPA	Transported Asset Protection Association
TNormal	Doubly Truncated Normal Distribution
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TRI	True Risk Influence
WH	Warehouse
WMEAN	Weighted Mean
WoS	Web of Science

Abstract

Freeports and their equivalents, such as free trade zones, play a pivotal role in fostering economic development by driving regional growth, attracting investment, and enhancing trade facilitation. They are designed to create employment opportunities, reduce poverty, and integrate domestic economies into the global market through the adoption of advanced technology and management practices. However, the long-term success of freeports is contingent upon addressing challenges related to environmental issues, cargo theft, illicit trade, and technological innovation and integration. This research aims to develop a new, comprehensive framework for assessing freeport sustainability, allowing authorities to track progress and identify challenges in freeport development. Additionally, it explores cost-effective security measures and reliable, technology-driven solutions to enhance sustainability practices within freeports.

The thesis begins with a literature review focusing on the impacts of freeports and methods for sustainability assessments in related fields. It highlights key research gaps and outlines applicable theories and methods to address these gaps. This is followed by four detailed studies. The first study develops a novel framework for quantitatively assessing the sustainability of freeports. This framework integrates Key Performance Indicators (KPIs) across multiple dimensions and various data types into a unified structure using the Evidential Reasoning (ER) algorithm. A case study in a UK freeport demonstrates the model's validity and practical applicability. Additionally, the framework incorporates KPIs within both hierarchical and network structures, with the latter requiring methods beyond the ER approach for evaluation. To address this challenge, the second study introduces a data-driven Bayesian Network (BN) model to predict cargo theft incidents (a network-driven KPI) in freight supply

chains by analysing critical Risk Influencing Factors (RIFs) from historical data. This model is validated through multiple methods, offering new methodological insights for future research in risk prediction. Consequently, the first two studies collaboratively establish a comprehensive and flexible sustainability assessment framework for freeports, employing a hybrid Bayesian Network and Evidential Reasoning (BNER) model.

Furthermore, this thesis promotes innovative solutions that address key challenges in developing sustainable freeports, with a focus on achieving a balance between security, operational efficiency, and cost-effectiveness. In recognition of the critical roles of customs inspection efficiency and information technology in fostering sustainable freeports, the third study addresses container inspection strategies under resource constraints using a two-stage methodology that combines risk assessment and optimisation models. This approach translates risk-based container inspection theories into practical solutions, enabling efficient allocation of inspection resources in freeports. Concurrently, the final study attempts to underscore the blockchain's potential to enhance the security and efficiency of freeport operations by analysing the barriers to its adoption. It analyses probabilistic causal relationships among these barriers using a hybrid Decision-making Trial and Evaluation Laboratory and Bayesian Network (DEMATEL-BN) methodology. This study provides critical insights for facilitating the digital transformation of freeports.

This research makes significant contributions to advancing the sustainability of freeports, with implications that extend to the broader maritime and supply chain sectors. The findings deepen the understanding of critical concerns surrounding freeport sustainability and offer actionable insights for industry practitioners and policymakers. They support the development of cost-effective strategies to mitigate freeport risks associated with cargo theft and illicit trade, as well as the formulation of practical digital transformation plans. By addressing these critical challenges, the thesis supports the sustainable and secure growth of freeports, enhancing their role as key facilitators of global trade and economic development.

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CHAPTER 1 INTRODUCTION

Summary

This chapter begins with the research background, offering an overview of the concept of freeports and their challenges. It then outlines the research aim and objectives, followed by the research questions, and the scope and structure of the thesis.

1.1 Research Background

Originally established as government-designated areas exempt from certain customs regulations and taxes, freeports in the UK have evolved into multifaceted zones aimed at stimulating trade, creating jobs, and attracting investments. They are typically situated near seaports or airports, serving as hubs for international trade and industrial growth. The notion of a freeport is often derived from a broader concept of Special Economic Zones (SEZs), including export processing zones, free trade zones (FTZs), and freeports, each differing in size, location, and primary activities, as illustrated in Table 1.1. As of recent estimates, there are approximately 3,500 to 4,000 such zones worldwide, each tailored to local economic conditions and objectives (World Bank, 2023).

Table 1.1 Distinctions between types of SEZs (source: World Bank).

Type	Objective	Size	Typical location	Typical activities	Markets
Export Processing Zone	Export manufacturing	<100 hectares	None	Manufacturing, processing	Mostly export
FTZ	Support trade	<50 hectares	Port of entry	Transit and trade-related	Domestic
Freeport/SEZ	Integrated development	>1000 hectares	None	Multi-use	Internal, domestic, export

Historically, freeports have been instrumental in supporting economic development in both developed and developing nations. By encouraging the importation of technology, management expertise, and capital, these zones facilitate the integration of domestic industries into the global economy (Akbari et al., 2019). They function as centres for manufacturing, raw material processing, and product export, playing a vital role in fostering local employment and driving economic development (Papadopoulos, 1987).

However, the implementation of freeports is not without challenges, necessitating a close examination of various factors. The economic viability of freeports often hinges on attracting significant investment, which can be hindered by regulatory uncertainties and complex compliance requirements. The lack of clear guidelines may deter potential investors, making it essential for governments to establish coherent policies that balance business incentives with necessary oversight. While freeports promise job creation, the jobs generated often require specific skills that local labour forces may lack, necessitating targeted training and skills development programs. Without proper investment in workforce training, there is a risk of a skills gap, undermining the potential economic benefits.

Furthermore, issues such as illicit trade, cargo theft, and environmental degradation pose significant risks to the sustainable development of freeports. In recent decades, sustainability has attracted much attention from both academia and industry. The most adopted definition of sustainability is as follows (WCED, 1987): “Sustainable development is the development that meets the needs of the present without compromising the ability of future generations to meet their own needs.”

Reports indicate that freeports are vulnerable to criminal activities such as counterfeit goods trading, drug trafficking, and tax evasion (Boffey, 2020; Davidson, 2008; RUSI, 2020). The World Customs Organisation has emphasised the importance of enhancing customs controls within freeports to mitigate risks associated with low-level customs involvement, as highlighted by the OECD/EUIPO report on customs seizures of counterfeit goods (OECD, 2021).

Freeports are also susceptible to significant cargo theft risks, as they handle high-value items such as art, jewellery, and luxury goods, which makes them attractive targets for thieves. The prolonged storage of these goods without customs duties being paid further increases the risk of theft. Such incidents can severely damage the reputation and trust in freeports as secure storage facilities, potentially deterring customers and investors. Notably, figures from the Transported Asset Protection Association (TAPA) reveal that 20% of thefts in 2023 occurred directly in warehouses, factories, and similar facilities. In 2023, cargo thefts in the EMEA region (Europe, Middle East, and Africa) surged nearly 700%, escalating from 13,008 to 103,529 incidents. The total financial loss from these crimes exceeded €724 million, marking a 163% increase from 2022 and a staggering 627% rise compared to 2021 (Lysionok, 2024).

Moreover, the environmental footprint of freeports, including air pollution, habitat destruction, and traffic congestion, presents substantial concerns for local ecosystems and communities (Lam and Notteboom, 2014; Nebot et al., 2017). In response to global initiatives such as achieving net-zero emissions by 2050, freeports are under increasing pressure to adopt sustainable practices that mitigate environmental impacts while maintaining economic viability (Lirn et al., 2013). The UK and Scottish governments have collaborated to develop a green freeport model in Scotland that capitalises on the region's unique opportunities. Focused on renewable and low-carbon energy industries, the Inverness and Cromarty Firth Freeport aims to generate 25,000 jobs and attract £4.8 billion in investment, contributing to the transition to a net-zero economy (Heynes, 2023).

Additionally, the emergence of Industry 4.0 technologies, such as Artificial Intelligence (AI), blockchain technology, and 5G, offers opportunities for optimising operations within freeports but also introduces complexities and costs associated with technological integration.

Understanding and addressing these challenges are crucial for ensuring the sustainable development and effective governance of freeports in the contemporary global economy. To tackle these challenges, effective strategies demand broad stakeholder engagement and a comprehensive sustainability assessment framework. Such a framework can aid in evaluating how well freeports are addressing sustainability goals and ensuring their alignment with long-term development objectives.

1.2 Research Objectives

This thesis aims to develop a novel and comprehensive methodology for assessing freeport sustainability within an integrated framework, providing freeport authorities with an intelligent tool to track progress and challenges in freeport development. It also seeks to explore effective solutions to enhance freeport sustainability, particularly through promoting cost-effective security measures and leveraging practical technology-driven solutions. The research results will provide actionable insights for relevant stakeholders to support freeport monitoring and regulatory decisions, contributing to the broader goal of balancing economic growth with environmental and social responsibility in freeport operations.

Five objectives are developed to achieve this aim as follows:

1) To undertake a systematic literature review to analyse existing sustainability assessment frameworks and methods and explore suitable decision-making techniques, with particular

emphasis on addressing challenges such as data unavailability and uncertainty, for assessing freeport sustainability and promoting enhancement solutions. (Chapter 2)

2) To develop a novel methodology for assessing freeport sustainability that enables the quantitative assessment and integration of both quantitative and qualitative indicators, taking into account their weights from a multi-stakeholder perspective and addressing data uncertainty (Chapter 3)
3) To analyse the risk of cargo theft in freight supply chain operations using a data-driven risk analysis model, while enhancing the freeport assessment methodology to accommodate indicators with independent and interdependent influential factors. (Chapter 4)
4) To propose a practical risk prevention solution to protect freeports from illegal trade and cargo theft by analysing vulnerable nodes involved in illicit activities within Maritime Container Supply Chains (MCSCs) and developing efficient container inspection strategies. (Chapter 5)
5) To promote a technology-based solution to advance sustainable practices in freeports by assessing the challenges of integrating blockchain technology and revealing their causal relationships. (Chapter 6)

1.3 Research Questions

The critical research challenges are presented in alignment with the established objectives, focusing on data-related issues such as unavailability, incompleteness, uncertainty, and inconsistency. These challenges are further exacerbated by a limited pool of freeport professionals globally and the nascent stage of UK freeports. To address these challenges, several research questions are formulated for each objective, as outlined below.

Q1: What are the established frameworks and methods for sustainability assessments, and how to select appropriate decision-making techniques to address the aforementioned data-related issues? (Chapter 2)

Q2: How can relevant indicators be selected to assess freeport performance in alignment with the established sustainability goals? (Chapter 3)

Q3: How can indicators with different data forms and relationship structures be integrated to establish a synthesised and widely applicable framework for benchmarking freeport sustainability? (Chapters 3 and 4)

Q4: How to identify critical risk factors influencing cargo theft occurrences and analyse their interrelationships. Additionally, how to predict the probabilities of cargo theft occurrences with reliable accuracy based on historical theft data? (Chapter 4)

Q5: How can vulnerable nodes involved in illicit activities within MCSCs be evaluated, and how can their dynamic causal relationships be realised? (Chapter 5)

Q6: How can the evaluation results from Q5 be incorporated to determine the most efficient inspection strategy in freeport operations? (Chapter 5)

Q7: How can key barriers hindering blockchain adoption in the freeport context be evaluated while revealing their causal relationships in dynamic situations? (Chapter 6)

1.4 Scope and Structure of the Thesis

The research scope of this thesis centres on the urgent need for a comprehensive sustainability assessment framework for freeports and the development of innovative solutions to address key challenges in enhancing sustainable freeport operations. Accordingly, the thesis is structured into two main components: one focused on sustainability assessment, and the other on the development of innovative solutions. The assessment component incorporates global expert insights on sustainability priorities associated with freeports. A UK freeport serves as the case study to demonstrate the applicability of the assessment framework, generating real-world implications for freeport policymakers and investors.

The second component, focused on solution development, proposes strategies to enhance sustainability through risk prevention and technology integration. This includes addressing cargo theft and illicit trade, major threats to the efficiency and reputation of freeports, and evaluating the implementation of blockchain technology as a digital enabler for secure, transparent, and streamlined operations. By leveraging the collective expertise of freeport professionals worldwide, this research ensures the relevance and adaptability of these solutions across diverse contexts.

The structure of this thesis is presented in Figure 1.1. Apart from the introduction and conclusion, this research is organised into five main chapters, including a literature review and four studies to respond to the above-defined objectives; each main chapter is explained in detail below.

This research begins with the related literature review with regards to the examination and evaluation of freeport impacts on various aspects, sustainability assessment frameworks and methods in related fields, and advanced decision-making techniques for addressing critical data-related challenges.

Based on the background study, research gaps are identified, and appropriate theories and methods are explored to address these gaps.

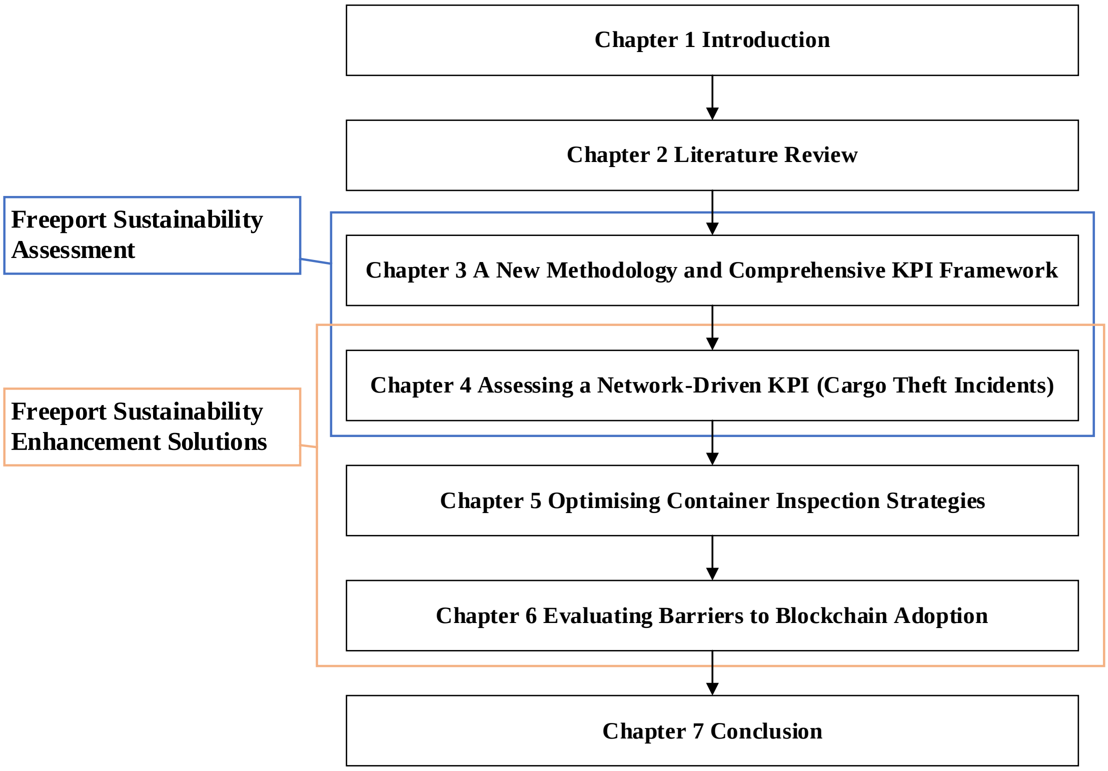

Figure 1.1 Structure of the thesis.

Chapter 3 develops a comprehensive framework to assess the sustainability level of freeports quantitatively. A hybrid Bayesian Network and Evidential Reasoning (BNER) model is built to effectively accommodate various indexes in different forms and address data uncertainty. Using the designed framework, all Key Performance Indicators (KPIs) influencing the sustainability of freeports are identified and their importance is evaluated, highlighting information technology and customs clearance efficiency as the most significant KPIs. The model is successfully applied to assess the overall sustainability of a UK freeport.

Among the KPIs identified in Chapter 3, a network-driven KPI related to cargo theft incidents cannot be evaluated using the Evidential Reasoning (ER) method alone. Chapter 4 details how this challenge is overcome through the integration of a data-driven Bayesian Network (BN) approach. This method analyses relevant Risk Influencing Factors (RIFs) to predict cargo theft occurrences within freight supply chains based on historical incident data from TAPA. Model validation and sensitivity analysis are conducted to demonstrate the model's predictive accuracy and to reveal the overall effects of multiple RIFs. Consequently, a comprehensive and highly adaptable framework for sustainability assessment is created by the integration of BN and ER, enabling the incorporation of new KPIs without altering the existing structure.

Cargo theft and illegal trade pose significant threats to the development of sustainable freeports by undermining economic efficiency, increasing security costs, and damaging the reputation of freeport operations. Addressing these challenges, information technology and efficient customs clearance emerge as critical factors for freeport sustainability. Therefore, the upcoming two chapters delve into the complexities of these factors and propose strategies to tackle them effectively.

Chapter 5 analyses the optimal container inspection strategies in freeports using a two-stage methodology combining risk assessment and optimisation models. The first stage aims to assess the risk levels of container shipments being involved in illicit activities using a Decision-Making Trial and Evaluation Laboratory and Bayesian Network (DEMATEL-BN) model. Based on the results from the first stage, the second stage determines the optimal inspection solution for container shipments arriving at a freeport within a specific timeframe, given limited inspection resources.

Building on the challenges identified in Chapters 3 to 5, particularly the need for advanced technology to enhance customs efficiency and mitigate security risks, Chapter 6 explores the role of blockchain in supporting sustainable freeport operations. Specifically, it presents a hybrid DEMATEL-BN model to evaluate barriers to blockchain adoption and to predict the influence of these barriers under dynamic conditions. Drawing on input from professionals with cross-industry expertise in both blockchain technology and freeport operations, the study provides practical insights for overcoming challenges in implementing blockchain and realising its potential to enhance sustainability in freeports.

Together, these chapters form an integrated investigation into sustainable freeport development, beginning with a comprehensive assessment, moving through specific operational risks and challenges, and culminating in the exploration of both risk-informed inspection strategies and transformative digital solutions.

CHAPTER 2 LITERATURE REVIEW

Summary

This chapter presents a literature review divided into six subsections. The first section outlines the methodology for a systematic literature review. The second section analyses the literature on freeport evaluation. Sections 2.3 and 2.4 review the literature on sustainability assessment, focusing on sustainability assessment frameworks and techniques. Section 2.5 introduces the decision-making methods used in uncertainty contexts based on a supplemented literature review. The final section highlights the research gap.

2.1 The Methodology for Literature Review

Figure 2.1 presents the methodology for a systematic literature review on topics including “freeport evaluation” and “sustainability assessment”. This process specifically selects peer-reviewed articles published in academic journals, the same as other related review-type literature (Lim et al., 2019; Yang et al., 2020). The literature search is performed using the Web of Science (WoS) Core Collection database, following the inclusion and exclusion criteria outlined in Table 2.1.

The literature on freeports and the literature on sustainability assessment are analysed separately. For the literature on freeport, two categories of key terms are applied in the search, connected by the operator “AND”. Category 1 includes “freeport”, “free trade zone”, or “free trade port”, while Category 2 contains “performance”, “assessment”, or “evaluation”. The inclusion and exclusion criteria outlined in Table 2.1 are used, yielding 188 initial results (as of August 2024). A topic search for “freeports” (and equivalents) combined with “sustainability” or “sustainable” yielded very few relevant results, which are also included in the dataset mentioned above. After a thorough review of titles and abstracts, 33 papers are identified as relevant for further analysis.

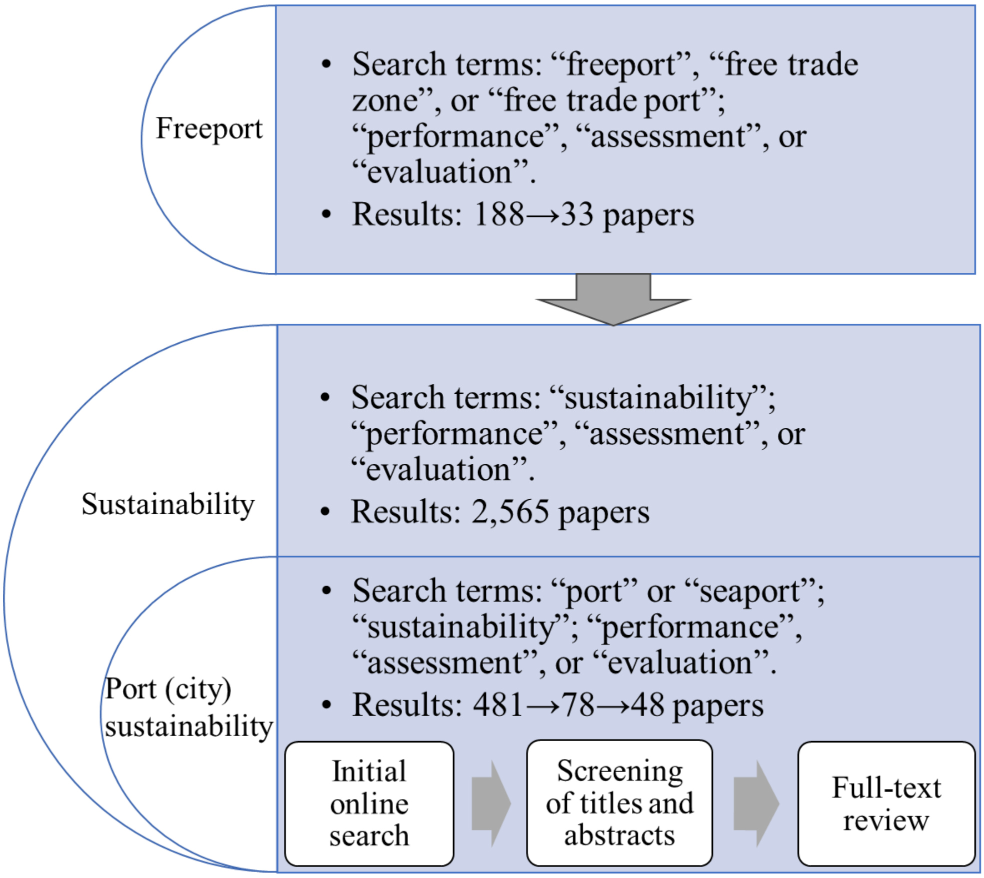

Figure 2.1 The methodology for literature review.

Table 2.1 Inclusion and exclusion criteria for the online search.

	Inclusion criteria	Exclusion criteria
WoS Index	SCI, SSCI	Other Indices
Language	English	Non-English
Doc type	Journal article, review article, early access	Proceedings paper, data paper, book chapters

2,565 papers on sustainability assessment from the past 15 years are identified using the inclusion and exclusion criteria specified in Table 2.1 (as of November 2024), forming the basis for a keyword analysis. Furthermore, to gain a comprehensive understanding of KPIs influencing freeport sustainability from multiple dimensions and the commonly used decision-support methods, this study conducts an in-depth literature review on sustainability assessments within the ports and port cities context, recognising the interconnected roles of freeports, ports, and port cities in supporting international trade, optimising logistics operations, and promoting economic development. The procedure of literature selection includes three steps as described in the following.

Step 1. Online search. Three categories of key terms are searched using the field tag “topic”, as outlined in Figure 2.1. The inclusion and exclusion criteria as shown in Table 2.1 are employed again for the initial online search, resulting in 481 articles from the last 15 years.

Step 2. Sample reduction based on the topic relevance. Given that not all results automatically retrieved in Step 1 are pertinent to the key terms used, the 481 papers are further filtered through a manual screening of titles and abstracts based on the relevance of the research topic, resulting in 78 papers with significant relevance. These 78 papers contain valuable information for this study including state-of-the-art research on port and port city sustainability, empirical studies on the sustainability performance of worldwide ports and port cities, and decision-support methods of sustainability assessment. Conversely, the excluded papers fall into two categories 1) papers that investigate other objects such as maritime, logistics, supply chain, transportation, urban city, and port infrastructure. 2) papers that focus solely on one aspect of sustainability (e.g., air pollution, climate change, technology), thereby overlooking the combined impacts of multiple factors on overall sustainability performance.

Step 3. Sample reduction based on the research depth. A thorough full-text review of the 78 papers is undertaken to identify papers that establish comprehensive and practical sustainability KPI frameworks. As a result, 30 papers are excluded from further analysis due to a lack of references to the significance of KPIs and/or their applicability. Thus, 48 papers are ultimately used for a comprehensive review of established frameworks, applied decision-making methods, and KPIs for sustainability assessment. This reduction rate of 90% is comparable to findings in other systematic review papers, showcasing that significant reduction rates are common in systematic reviews. For example, Lim et al. (2019) selected 21 papers from 704 (a 97% reduction rate) for a systematic review of port sustainability and performance. Zheng et al. (2020) reviewed 61 out of 514 articles (an 88% reduction rate) to analyse research trends on the sustainability of port cities.

2.2 Research on Freeport Evaluation

Table 2.2 summarises the 33 selected papers that focus on freeport impacts by their research aims, methodologies, and the countries or regions associated with the studied freeports. Figure 2.2 shows the distribution of the 33 papers by publication year, reflecting a significant increase in the number of papers in 2024.

Table 2.2 Summary of studies on freeport impacts.

Reference	Aim	Method	Country/Region
(Liu and Feng, 2024)	Explore the impact of Pilot Free Trade Zones (PFTZs) on urban innovation.	Difference-in-differences (DID) and mediation effect models	China
(Xia et al., 2024)	Examine the impact of PFTZ establishment on urban land use efficiency.	DID and mediation effect models	China
(Guan et al., 2024)	Examine the policy effects and transmission mechanisms of FTZs on Green Total Factor Productivity (GTFP).	DID	China

(Fan et al., 2024)	Evaluate the FTZ policy effects and mechanisms on the high-quality development of the pharmaceutical manufacturing industry.	DID	China
(Liu et al., 2024)	Examine the impact of the PFTZs' construction on the urban Green Technology Innovation Efficiency (GTIE).	DID	China
(Wang et al., 2024)	Analyse the impact of constructed FTZs on enterprise digital transformation.	DID	China
(Chang and Wang, 2024)	Verify the impact of PFTZ on high-quality economic development.	DID	China
(H. Zeng et al., 2024a)	Investigate the varied effects of FTZ strategy on agricultural trade.	DID	China
(J. Zeng et al., 2024)	Examine the impact of FTZs on firms' Environmental, Social and Governance (ESG) performance.	DID	China
(Su and Wang, 2024)	Analyse the impact of FTZs on the innovation performance of firms.	DID	China
(G. Wang et al., 2023)	Analyse the impact of PFTZs on green innovation efficiency in enterprises.	DID	China
(Cheng and Ma, 2023)	Examine the impact of PFTZ on the company's sustainability performance.	DID	China
(Shahid et al., 2023)	Analyse the impact of Shanghai PFTZ on industrial upgrading in the global value chain.	DID	China
(Lai and Chang, 2023)	Analyse the impact of PFTZs on green dual-circulation development.	DID	China
(Jiang and Zhang, 2023)	Assess whether the judiciary sacrifices justice for the sake of economic efficiency in civil cases with FTZ enterprises acting as the plaintiffs.	Hierarchical regression model	China
(X. Li et al., 2023)	Examine the impact of the establishment of FTZs on the environmental performance of enterprises.	DID	China
(Chen et al., 2022)	Verify the impact of PFTZs in promoting the transformation and upgrading of trade patterns.	DID	China
(Li and Choi, 2022)	Evaluate the economic benefits and ecological environment impact of export trade in Anhui FTZ.	Vector autoregressive model	China
(Wang and Zeng, 2022)	Develop an evaluation index system for regional policies in Free Trade Port Areas (FTPAs).	Policy Modelling Consistency (PMC) index	China, Singapore

(Arbolino et al., 2023)	Assess the impact of SEZs on regional economic growth.	Propensity score matching	Europe
(Huang et al., 2022)	Evaluate the investment environment in the Free Trade Port Zone (FTPZ) from foreign manufacturers' perspectives.	Improved Analytic Network Process (ANP)	Taiwan
(Ma et al., 2021)	Evaluate the effect of FTZs on GTFP.	DID	China
(Li et al., 2021)	Assess the impact of FTZ policy on the economic performance of port-listed companies.	DID	China
(Liu et al., 2021b)	Evaluate port efficiency and its influencing factors within the context of PFTZs.	Super- Slack-Based Measure (SBM), Tobit regression model	China
(Hsu et al., 2021)	Evaluate the overall technical efficiency, pure technical efficiency, and scale efficiency of the ports in six typical China's FTPZs.	Fuzzy Analytic Hierarchy Process (AHP)	Taiwan
(Teixeira, 2020)	Analyse the impact of the implementation of the SEZs on labour standards and social conditions.	Residuals and the stochastic frontier methods	Brazil
(Huang et al., 2020)	Assess the service quality of the FTPZ from both customer and service provider perspectives.	Multilayer quality function deployment	Taiwan
(Song et al., 2018)	Evaluate the production efficiency of environmental protection enterprises in FTZs.	Data Envelopment Analysis (DEA)	China
(Akbari et al., 2019)	Examine the role of institutional factors and resources on the performance of the firms in a FTZ.	The partial least squares	Iran
(Zhou et al., 2019)	Develop a land use performance evaluation index system tailored to the industrial economy and mixed land use in FTZs.	Delphi, entropy	China
(Chen et al., 2018)	Evaluate and compare the development performances of typical FTPZs in China.	AHP, Grey Relational Analysis (GRA)	China
(Deng et al., 2017)	Investigate the determinants of investment in FTPAs from an enterprise perspective.	Delphi, fuzzy AHP and fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)	China
(Yao and Whalley, 2016)	Analyse the Shanghai PFTZ's role in China's reform, its differences from other zones, and its impact on capital account and financial liberalisation.	Statistics	China

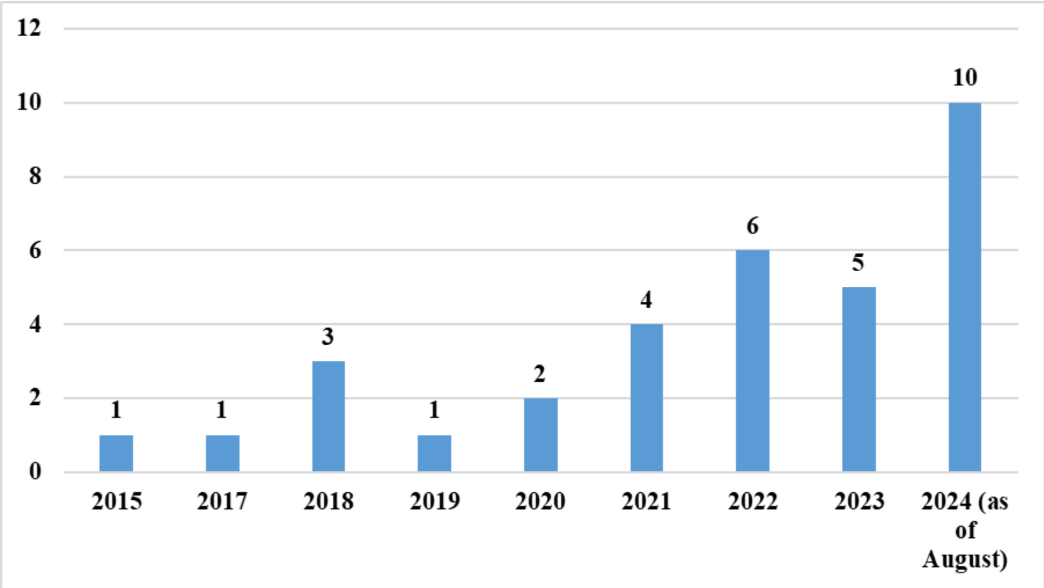

Figure 2.2 Annual number of studies on freeport impacts.

In terms of the evaluation scales, the existing studies include macro-level evaluations (urban or regional performance evaluations) and micro-level evaluations (enterprise performance evaluations). Many papers have examined the impact of freeports or their equivalents using indices at the urban or regional level. For instance, Liu and Feng (2024) examined the impact of PFTZs on the innovation performance of geographically adjacent cities with economic ties and the innovation level of the region. Xia et al. (2024) demonstrated that PFTZs can significantly enhance urban land use efficiency, with the policy effects being more pronounced in central cities, inland cities, and those with higher urbanisation rates. Two studies (Chen et al., 2022; Li and Choi, 2022) used provincial-level panel data to analyse the impact of FTZs on the transformation and upgradation of trade patterns, and economic benefits and ecological environment Impact of export trade, respectively. A study by Teixeira (2020) confirmed that the establishment of the Manaus FTZ contributed to improved labour and social efficiency in the region compared to other major industrial municipalities in Brazil, using residuals and stochastic frontier techniques to estimate performance. Other used indexes include GTFP (Guan et al., 2024; Ma et al., 2021), the efficiency of urban green technology innovation (Liu et al., 2024), high-quality economic development (Chang and Wang, 2024), and green dual-circulation development (Lai and Chang, 2023).

Many other papers have examined the impact of freeports or their equivalents at the enterprise level. The applied performance indexes include the economic performance development of port-listed companies (Li et al., 2021), enterprise digital transformation (Wang et al., 2024), firms' ESG performance (J. Zeng et al., 2024), innovation performance of firms (Su and Wang, 2024), green innovation efficiency (G. Wang et al., 2023), production efficiency of environmental protection enterprises (Song et al., 2018), environmental performance (X. Li et al., 2023), and sustainability performance of companies (Cheng and Ma, 2023). Jiang and Zhang (2023) found that in civil cases involving Chinese FTZ enterprises as plaintiffs, judicial justice was not compromised for economic efficiency, such as attracting foreign investment.

Several papers have explored the impact of freeports or their equivalents on specific industries. For instance, Fan et al. (2024) empirically examined the impact of FTZ policies on the high-quality development of the pharmaceutical manufacturing industry. The establishment of PFTZs can significantly boost the high-quality development of the pharmaceutical industry. In terms of spatial effects, these zones also create a spillover effect that enhances the industry's development in neighbouring regions. Zeng et al. (2024) revealed that establishing FTZs with partner countries had boosted China’s agricultural trade.

Unlike most studies that assess freeport performance through regional, urban, or enterprise-level indices, often focusing on a single aspect, only a limited number of papers have integrated multiple performance indexes for evaluating the overall impact of freeports or their equivalents. Huang et al., (2020) evaluated the service quality of the FTPZ based on customer and service provider requirements. These requirements were identified through a literature review and expert interviews. The evaluation considered 16 customer requirements (e.g., access to highways and ports, local market capabilities, and infrastructure completeness) and 16 service provider requirements (e.g., high shipping service frequency, lower operating costs, and access to highways and ports). Deng et al. (2017) investigated the determinants of investment in FTPAs in China from an enterprise perspective, using 13 indicators across four categories. Chen et al. (2018) developed a multi-dimensional evaluation system with 23 indicators across five categories to assess the development performance of China's FTPZs, using quantitative data from statistics and qualitative data from expert scoring. Although providing valuable insights, these studies primarily focused on economic indicators and overlooked sustainability. Moreover, they did not adequately address uncertainty and incomplete data in expert judgment. For example, experts may rate unfamiliar indicators based on limited or incorrect understanding, introducing biases, as they cannot express uncertainty. This limitation can reduce data quality and undermine the reliability of the research outcomes.

Additionally, most existing studies develop the assessment index applicable to a single country, lacking implications from a global perspective. Only a few studies have demonstrated the use of the developed framework as a benchmark for comparing practices of cross-country freeports. For instance, Arbolino et al. (2023) evaluated the economic effects of 51 European incentive zones using a propensity score matching method. The developed policy assessment framework included 14 indicators across six macro areas but relied solely on quantitative indicators. Wang and Zeng (2022) introduced the PMC index model and constructed a national park policy evaluation index system to analyse 14 representative national park policies in the Hainan rainforest, Hong Kong, and Singapore, while they only used qualitative indicators.

Based on the listed literature, freeports and their equivalents have emerged as pivotal instruments in advancing economic and technological development. Moreover, existing literature has extensively explored the mechanisms through which freeports exert their influence, revealing several key pathways and mediating effects that drive these outcomes.

Some studies highlighted the significance of talent concentration, foreign direct investment (FDI), and technological innovation as critical drivers within freeports. The concentration of talent and the attraction of FDI are often cited as essential components that facilitate innovation by providing the necessary human and financial capital (Liu and Feng, 2024; Liu et al., 2024). Additionally, the fostering of technological innovation within freeports is not only a direct outcome but also serves as a crucial mediator that amplifies the overall impact of these zones on economic performance and GTIE (Guan et al., 2024; Shahid et al., 2023). In addition, freeports play a crucial role in industrial upgrading within the global value chain. The ability of freeports to promote industrial upgrading is closely linked to their capacity to attract FDI and stimulate technological innovation (Shahid et al., 2023).

Furthermore, the literature points to specific transmission mechanisms, including cost reduction, tax incentives, and reverse technology spillover, that enable enterprises within freeports to achieve higher efficiency in green innovation (G. Wang et al., 2023). Lai and Chang (2023) observed the positive impact of freeports on regional green dual circulation, particularly through the mediating effects of green finance and technological progress.

The collective insights from these studies highlight the multifaceted role of freeports in driving economic and technological progress. The mediating effects of trade openness, technological innovation, and financial support emerge as critical components that amplify the benefits of freeports across different domains. Moreover, the focus on green technology and sustainable practices indicates a broader shift towards integrating environmental considerations into the economic agendas of freeports. This integration is essential for achieving long-term sustainable development and underscores the evolving nature of freeports as dynamic tools for economic and technological advancement.

Despite the multifaceted role of freeports in promoting economic and technological progress, as highlighted in the literature, there remains a significant gap in understanding how these impacts intersect with broader sustainability goals. According to Table 2.2 and the preceding analysis, existing studies evaluating freeport impacts are largely fragmented, primarily concentrating on isolated indices while neglecting the overall sustainability effects (Chang and Wang, 2024; Chen et al., 2018; Hsu et al., 2023a; Huang et al., 2020; Liu et al., 2024). Moreover, current methodologies exhibit limitations, such as insufficient integration of quantitative and qualitative indicators, as well as inadequate handling of uncertainty and incomplete data in expert judgment. Geographically, most studies have predominantly focused on freeports in China, highlighting the need for broader evidence from other economies to provide a more holistic understanding.

Furthermore, insufficient attention and effort have been devoted to addressing the emerging risks associated with freeports, as discussed in the research background. While freeports offer many advantages, the potential for misuse, including the facilitation of illicit trade and cargo theft, remains underexplored in the existing literature. These risks underscore the need for advanced monitoring mechanisms, such as efficient customs inspection strategies, and the digitalisation of freeport processes through technologies like blockchain and AI to mitigate vulnerabilities and enhance transparency, traceability, and efficiency in monitoring and management within freeport operations. Moreover, the successful development and implementation of these advanced monitoring strategies and digital solutions require the creation of innovative frameworks incorporating sophisticated decision-making techniques capable of addressing key research challenges, such as data uncertainty and inconsistency.

2.3 Sustainability Assessment Frameworks

In the past decade, there has been a noticeable increase in research dedicated to sustainability evaluation. To identify the research focuses on sustainability evaluation, a keyword density and network analysis are conducted for the identified literature on sustainability evaluation (as outlined in Section 2.1) using the VOSviewer software. Figure 2.3 highlights the concentration of frequently occurring terms within the sustainability assessment literature. Key terms such as “sustainability,” “energy,” “framework,” “indicators,” and “LCA” (Life Cycle Assessment) appear in bright yellow, indicating their prominence within the dataset. Moreover, Figure 2.4 shows how various topics within sustainability research are interrelated. This visualisation reveals several clusters of research focus areas. For instance, there is a cluster around decision-support methods, such as “AHP” and “TOPSIS”, often linked with key terms like “criteria”, “selection”, and “supply chain management”. Another cluster centres on “energy,” “emissions”, “climate change”, and “carbon footprint” likely indicating a focus on sustainability issues related to energy consumption.

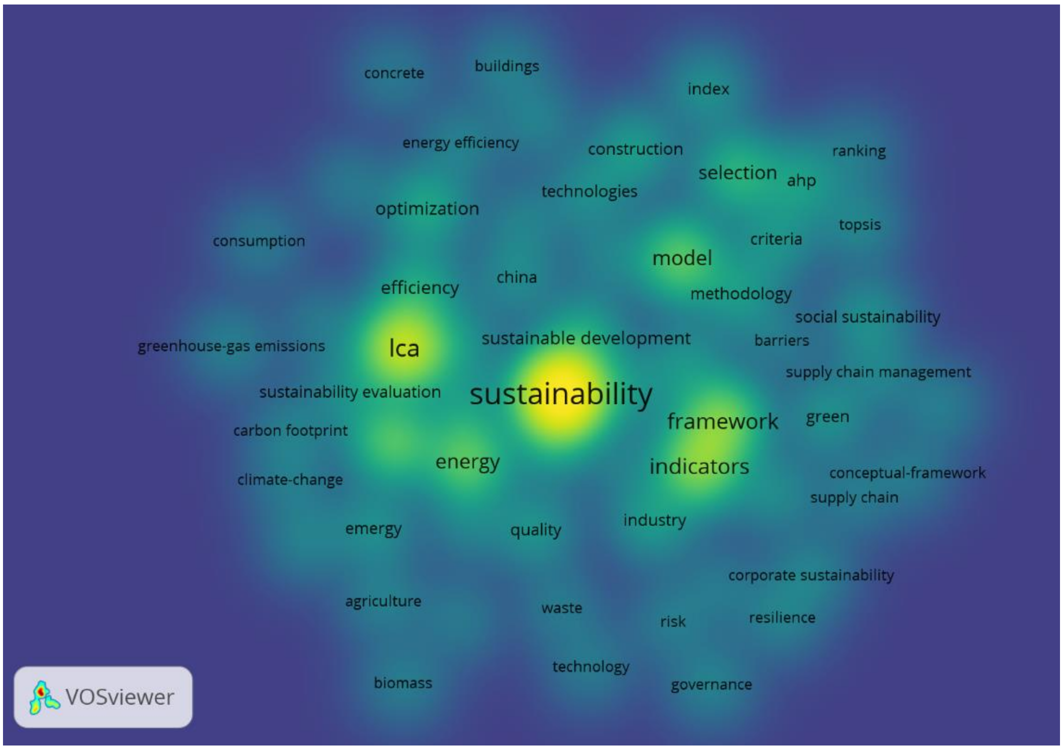

Figure 2.3 Keyword density visualisation of sustainability assessment literature.

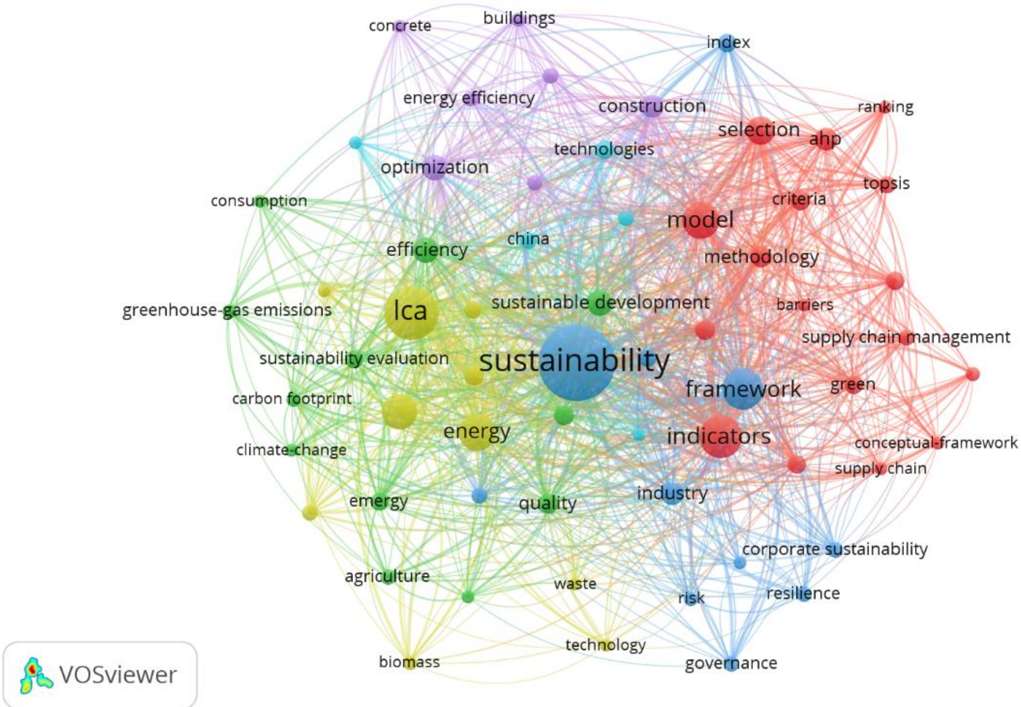

Figure 2.4 Keyword network visualisation of sustainability assessment literature.

Among the literature on sustainability evaluation within the context of ports and port cities, based on the selected literature for in-depth analysis outlined in Section 2.1. Most studies have focused on the environmental dimension of sustainability, emphasising the crucial role of economic development in line with environmental protection. Some global environmental standards already exist. For instance, there are three certifications for improving environmental performance in ports: ISO 14001, Green Ports, and Ecoports (Asgari et al., 2015). ISO 14001 establishes a group of management system standards to improve the environmental performance in organisations. It contains the most general standards that can help reduce pollution from each part of the system. Green Ports is a certification that considers both environmental protection and economic generation. Ecoports integrates effective environmental and port management, mostly applied to ports in Europe. By adhering to these certifications, ports can improve their environmental performance by monitoring issues such as air and water pollution, noise pollution, energy consumption, efficient resource utilisation, waste management, and the adoption of clean technologies. In addition, two universities (Yale/New Haven and Columbia/New York) undertook a research project known as the Environmental Performance Index (EPI) aiming at establishing an international composite environment index, which has been commissioned by the World Economic Forum/Davos. The latest edition of the EPI contains a total of 58 indicators distributed across 11 environmental issue categories and structured around three key policy objectives: climate change, ecosystem vitality, and environmental health (EPI, 2024).

Lu et al. (2016) argued that the distinction between sustainability and the concept of "green" is notable as sustainability encompasses a broader spectrum of concerns, including economic, environmental, and social aspects, whereas the concept of "green" focuses solely on the exploitation of the environment. In other words, the “green” does not encompass the prosperity or well-being of a society (Zervas, 2012). However, fewer studies have evaluated the balance among economic, environmental, and social aspects of sustainability. Among those studies that did consider additional sustainability aspects beyond the economic and environmental aspects in ports and port cities, the hierarchical framework in the Global Reporting Initiative (GRI) has been most widely used (Cavallo et al., 2015; Liu et al., 2021a; MacNeil et al., 2021; Majidi et al., 2021; Oh et al., 2018; Roh et al., 2021; Schipper et al., 2017; Shiau and Chuang, 2015; Stanković et al., 2021). 78% of the world's top 250 companies – known as the G250 companies have adopted the GRI Standards for sustainability reporting (GRI, 2022). The GRI uses a Triple Bottom Line method to build an index system from social, economic, and environmental dimensions. The Triple Bottom Line approach evaluates the business performance by considering not only the traditional bottom line of financial performance, such as net income, but also two additional bottom lines. These additional bottom lines are evaluated based on the impact of a company's social responsibility and its environmental stewardship efforts (Roh et al., 2021). There are also other sustainability frameworks, such as the Driving Force-State-Response and Pressure-State-Response frameworks (Dai et al., 2013), the Global Synthetic Index (Laxe et al., 2017), Capital frameworks, the System of Integrated Environmental and Economic Accounting framework, and Systems Analytical framework, whereas they expose various practical limitations comparing with the GRI framework concluded by Lam and Yap (2019). The GRI hierarchical framework enables the comparison of the three sustainability dimensions on their importance. It takes advantage of flexible indicator sets and clear indicator categories, which helps prevent ambiguity and overlap among different indicator categories. Consequently, the study utilises the GRI hierarchical framework to identify specific KPIs for freeport assessment.

2.4 Sustainability Assessment Methods

Several decision-making techniques have been applied in previous studies concerning sustainability evaluation. Figure 2.5 illustrates the distribution of papers using different methods. The most popular methods are the AHP, DEA, Importance-Performance Analysis (IPA), PROMETHEE, and TOPSIS. Other established methods include the SBM, DEMATEL, Structural Equation Modelling (SEM), Social Construction of Technology (SCOT), and GRA. The strengths and weaknesses of the commonly used methods are summarised, and the relevant references in port and port city sustainability evaluation are given in Table 2.3.

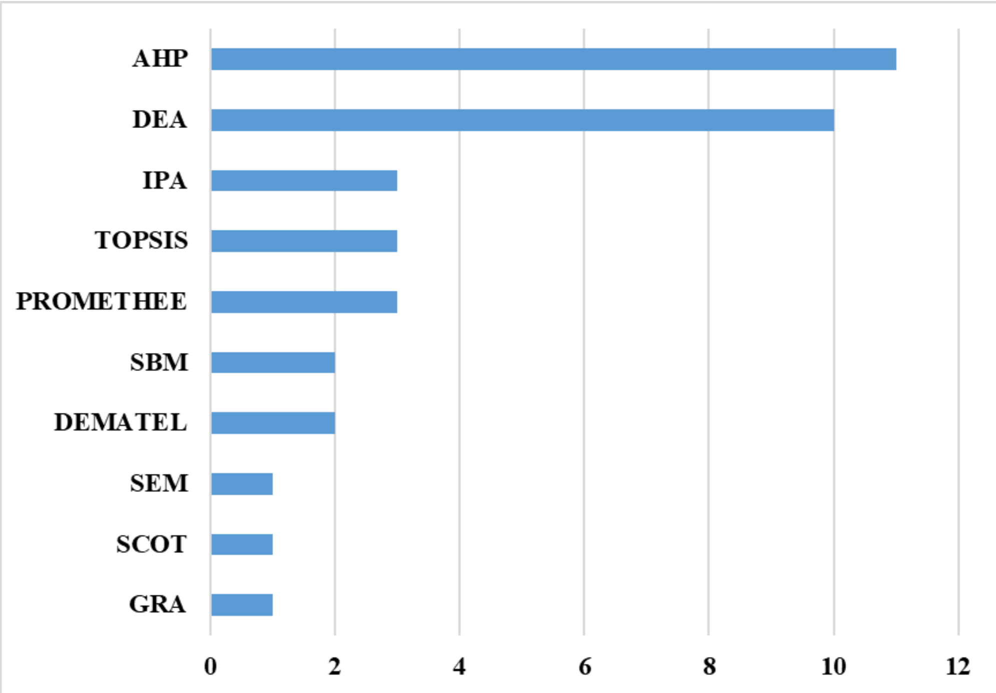

Figure 2.5 Methods used in sustainability assessments.

Table 2.3 Strengths and weaknesses of the methods used in sustainability assessments.

Methods	Strengths	Weaknesses	References
AHP	Priorities multiple criteria.	Sensitive to inconsistent data; time-consuming and complex to collect data.	Asgari et al., 2015; Cavallo et al., 2015; Chiu et al., 2014; Dai et al., 2013; Garg et al., 2022; Hsu et al., 2023; Jeevan et

			al., 2022; Kovačič Lukman et al., 2022; Lirn et al., 2013; Pourebrahim and Mokhtar, 2016; Roh et al., 2021
DEA	Considers multiple inputs and outputs.	Requires complete and accurate data.	Castellano et al., 2020; Cheon et al., 2017; Dong et al., 2019; Jiang et al., 2020; Kong and Liu, 2021; Li et al., 2018; Lin et al., 2019; Liu et al., 2021a; Puig et al., 2017; Quintano et al., 2021
IPA	Easy to understand and implement.	Not capable of analysing multiple criteria.	Hua et al., 2020; Lirn et al., 2013; Oh et al., 2018
PROMETHEE	Does not require the assumption that criteria are proportionate.	Difficult to weigh; difficult to aggregate indices of different types.	Argyriou et al., 2022; Cerreta et al., 2020; Stanković et al., 2021
TOPSIS	Easy to understand and implement.	Difficult to weigh; difficult to aggregate indices of different types.	Li et al., 2018; Majidi et al., 2021; Pourebrahim and Mokhtar, 2016
SBM	Incorporates desirable and undesirable outputs.	Requires precise and reliable data; sensitive to outliers and extreme values.	Dong et al., 2019; Kong and Liu, 2021
DEMATEL	Reflects causal structure among multiple criteria.	Time-consuming and complex to collect data.	Hsu et al., 2023; Liu et al., 2021a

Although the literature offers valuable insights into KPI selection for sustainability evaluation, the methods used in these studies have inherent limitations, particularly concerning index weighting, data collection, and the integration of indices in various forms.

(1) Index weighting. Methods like PROMETHEE and TOPSIS often struggle with assigning appropriate weights (Stanković et al., 2021; Majidi et al., 2021), leading to oversimplified or biased evaluations.

(2) Data quality and collection. Methods such as AHP, DEA, SBM, and DEMATEL rely on precise, complete, and consistent data, making them impractical for cases with incomplete or uncertain data. Additionally, methods like AHP or DEMATEL become cumbersome as the number of KPIs increases (Hsu et al., 2023; Kong and Liu, 2021).

(3) Integration of multiple indices. Simpler methods like IPA fail to handle multiple criteria effectively, and methods such as TOPSIS and PROMETHEE are often restricted to aggregating indices of similar types or formats, making it difficult to integrate quantitative and qualitative data (Pandey et al., 2023; Wu et al., 2020).

Given these constraints, this thesis will contribute by developing an innovative method for evaluating sustainability performance that effectively overcomes these limitations. From the applied research perspective, it also stands as one of the pioneering efforts in assessing freeport sustainability.

2.5 Decision-Making Methods under Uncertainty

The review of the existing sustainability assessment methods highlights significant data uncertainty when evaluating the freeport performance against identified KPIs. Similar research challenges also exist when developing security and technology-based strategies for fostering sustainable freeport operations, as discussed in Chapter 1. This section outlines the mainstream decision-making methods, such as BN and ER, which are well-suited to address these challenges.

2.5.1 BN

BN theory was introduced by Pearl (1988). It employs a probabilistic graphical model that utilises a Directed Acyclic Graph (DAG) to represent variables and their conditional dependencies. This framework combines principles from graph theory and probability theory, facilitating the modelling of complex systems with inherent uncertainties. The structure of a BN consists of nodes and directed edges, where nodes represent random variables and edges denote the dependencies between them. Each node is associated with a Conditional Probability Table (CPT) that quantifies the likelihood of each outcome based on its parent nodes' states. This design allows BNs to effectively model causal relationships, which is essential for reasoning under uncertainty.

BNs have gained attraction as a risk assessment tool due to their ability to handle incomplete data, incorporate expert knowledge, and provide clear visualisations of complex interrelationships. They excel in learning and inference, demonstrating robust data tolerance while enabling both backward and forward risk diagnosis and predictive analysis (Fan et al., 2022; H. Li et al., 2023; Liang et al., 2022). One key strength is their capacity for inference, allowing users to calculate the posterior probabilities of unknown variables given observed evidence. This feature is particularly useful in dynamic and uncertain environments, where new data can be iteratively integrated to refine predictions. Moreover, BNs present a transparent view of interdependencies, facilitating expert interpretation and communication of complex probabilistic relationships. The advancements in computational techniques and machine learning have broadened the applicability of BNs. For example, the integration of machine learning enables automatic structure learning, where algorithms determine the optimal network structure from data, enhancing the scalability of BNs for large datasets (Friedman et al., 1999).

Despite their advantages, BNs face notable limitations. Constructing an expert-driven BN for large-scale problems can be challenging. As the number of parent nodes increases, the size of the CPT can grow exponentially, potentially exceeding the limits of accurate expert assessment and computational efficiency. This exponential increase poses significant challenges for the practical application of BNs. Various strategies, such as Noisy-OR and symmetric models, seek to address this issue by simplifying CPTs, although they may not fully capture the complexity of dependencies. Furthermore, BNs, which do not incorporate utility theory, are unable to address decision problems involving multiple risk attributes (Yang, 2006).

2.5.2 ER and Its Combination with BN

The ER approach is developed based on the Dempster-Shafer theory of evidence (D-S theory) which was initially generated by Dempster (1967) and further developed by Shafer (1976). It offers a novel method for aggregating multiple criteria using the distributed assessment framework and the evidence combination rule of the D-S theory (Yang, 2001). Unlike most conventional multiple-criteria decision-making techniques, it utilises a belief degree structure to assess an attribute based on a set of mutually exclusive assessment grades (Pathak et al., 2021). The belief function enables the measurement of an attribute with uncertainties such as ignorance, fuzziness, and incomplete information. Moreover, the ER approach can effectively model both precise data and subjective judgments with uncertainties under the unified framework.

Due to its numerous advantages, the ER approach has been successfully applied in security and risk assessment in marine engineering (Liu et al., 2008; Ren et al., 2008; Sii et al., 2004), port and Maritime Supply Chains (MSCs) (Ha et al., 2017; Jiang et al., 2023; Poo et al., 2021; Wan et al., 2018; Yang et al., 2009). Although there have been a few attempts to incorporate the ER approach in sustainability performance assessment, such as in engine production lines (Zhou et al., 2017), maritime tourism (Gao, 2019), freight transportation systems (Fulzele and Shankar, 2023; Pathak et al., 2021), assurance services for sustainability reporting (Srivastava et al., 2013), and supply chains (Wan et al., 2021), only one was in alignment with the GRI (Srivastava et al., 2013). Additionally, the advantages of the ER algorithm have not been thoroughly substantiated in empirical studies. To date, only Wan et al. (2021) employed both qualitative and quantitative indicators within a unified framework. Therefore, this research stands as one of the pioneering works in sustainability assessment, showcasing a comprehensive application of the ER approach by integrating objective and subjective data with uncertainties.

While the advantages mentioned above are notable, the ER approach falls short in assessing KPIs influenced by factors that exist beyond the confines of an independent hierarchical structure and operate within an interconnected network framework. This limitation could compromise the comprehensiveness of the selected KPIs from a sustainability perspective, thereby diminishing the benchmark value of the sustainability assessment results. To overcome this limitation, this thesis proposes a novel solution to handling KPIs influenced by network-based factors by incorporating BN into ER. Existing studies that integrate both BN and ER are limited, focusing primarily on the field of risk analysis (Chang et al., 2021; X. Wang et al., 2023; Yang et al., 2019; Zhou et al., 2023), requiring more empirical evidence from a wider range of applications across different sectors. Moreover, these studies fail to demonstrate the significance of BN in overcoming the limitations of ER in combining results from interdependent attributes.

2.5.3 DEMATEL and Its Combination with BN

As a kind of MCDM tool, DEMATEL was first proposed by the Battelle Memorial Institute at the Geneva Research Center (Gabus and Fontela, 1972). DEMATEL visualises complicated, structural, and causal relationships with matrix and graph and can convert a relationship between causes and effects of criteria into a unique structural model (Falatoonitoosi et al., 2013). It has been widely applied in evaluating key success factors or challenges in many emerging issues (Hsu et al., 2023b; Zhou et al., 2011). However, compared to BN, DEMATEL has limited analytical capabilities, as it does not accommodate probabilistic assessments and uncertainties in the relationships between elements.

On the other hand, constructing a BN network based on decision-makers' opinions presents significant challenges, especially when a large converging connection of multiple parent nodes exists, as previously discussed. This convergence results in an exponential increase in the size of the CPT, exceeding expert capacity. Often, these decision-makers struggle to differentiate between direct and indirect causal relationships, which can result in inconsistencies and the formation of cycles in the BN model. Moreover, when multiple decision-makers are involved, their opinions may conflict, leading to divergent and contradictory inputs. This issue becomes particularly problematic when attempting to amalgamate these varying opinions into a cohesive decision-making support model. To address these complexities, it is crucial to adopt a systematic approach like DEMATEL. This method leverages the knowledge of decision-makers in a structured manner, enabling the effective identification and integration of their insights into the BN construction process (Yazdi et al., 2020).

Although some studies have applied the combination of DEMATEL and BN across various fields, such as safety management in the high-tech industry (Yazdi et al., 2020), smart product service system (PSS) design (Feng et al., 2023), supplier selection for a large automobile manufacturer (Kaya and Yet, 2019), and marine ranching risk management (Qin et al., 2022), the applications are highly context-specific and there are no relevant studies in the context of freeport to the author's best knowledge.

Additionally, the ranked nodes method, originally introduced by Fenton et al., (2007), is incorporated into the DEMATEL-BN approach to address the complexity of configuring CPTs based on expert opinions. This method relies on minimal expert elicitation to construct CPTs, reducing the need for significant subjective judgment. Other methods sharing this characteristic, such as the symmetric model (Feng et al., 2023; Riahi et al., 2014) and the noisy-or approach (Qin et al., 2022), are limited to Boolean nodes with binary states. In contrast, the ranked nodes approach stands out by enabling analysis across multiple states, which better aligns with real-world scenarios.

2.6 Research Gaps

The literature review identifies several critical research gaps surrounding the need for a novel sustainability assessment framework and practical solutions for enhancing sustainable freeport operations.

1) Current research on freeport impacts primarily focuses on isolated indicators. The few studies that do assess freeport performance using multiple indices tend to emphasise economic metrics, with limited attention to the environmental and social dimensions essential for sustainable development. Addressing this gap requires the development of an integrated methodology that encompasses economic, environmental, and social dimensions, aligning with the Sustainable Development Goals (SDGs).
2) Although the importance of sustainability in maritime sectors has gained attention in the past decade, existing studies fall short of developing comprehensive methodologies that integrate

KPIs in different forms within a unique framework. Specifically, there is a lack of advanced frameworks that integrate quantitative and qualitative indicators for effective overall sustainability assessment. Current evaluation methods are primarily focused on quantitative indicators, which limits their ability to comprehensively assess the multifaceted nature of sustainability, overlooking crucial factors, such as technological innovation, climate change mitigation, and social equity, that cannot be adequately measured through direct metrics. Moreover, limited efforts have been made to address data uncertainty and interactions among KPIs, as commonly used methods often rely on strong assumptions.

3) The existing research on freeport impacts is geographically limited and fails to adequately address the perspectives of multiple stakeholders in evaluating their impacts. Limited involvement of diverse stakeholders results in an incomplete and less targeted understanding of the complex impacts associated with freeports, highlighting the need for more inclusive assessment frameworks that capture a broader range of perspectives.

4) There is a significant gap in the risk analysis of freeports, as most studies focus predominantly on their positive economic contributions. However, fully realising these benefits is intrinsically linked to addressing the associated risks, including vulnerabilities to crimes such as cargo theft, smuggling, and illicit trade, which threaten the sustainability of freeport operations. This highlights the urgent need for more focused research on developing effective strategies to mitigate these emerging risks, ensuring the long-term sustainability and security of freeports.

Despite the notable advantages of BN, ER, and DEMATEL methods, each method has inherent limitations in its standalone application. BNs struggle with computational efficiency when dealing with complex interdependencies, particularly using subjective data. Additionally, BNs do not incorporate utility theory, limiting their effectiveness in decision-making scenarios that involve multiple attributes. ER approach is limited in assessing attributes influenced by network-based factors, as it assumes an independent hierarchical structure that may not capture interconnected relationships. DEMATEL cannot analyse dependencies in dynamic situations, making it less effective in contexts where uncertainty plays a significant role. Integrating these methods could effectively overcome the limitations of each approach, offering a more comprehensive solution for addressing complex, real-world problems.

This thesis develops several innovative hybrid models to address these research questions, as detailed in the following chapters.

CHAPTER 3 A NEW SUSTAINABILITY ASSESSMENT METHODOLOGY FOR FREEPORTS[1]

Summary

This chapter introduces a novel methodology for holistic sustainability assessment tailored to freeports. The study develops a new sustainability framework across economic, environmental, and social dimensions, including both qualitative and quantitative KPIs, and synthesises them into a singular index. These KPIs are prioritised from multiple stakeholder perspectives. It proposes a novel BNER model to deal with data uncertainty and interdependent factors in the performance assessment. The findings of this study highlight information technology and customs clearance efficiency as the highest-prioritised KPIs for freeport stakeholders.

3.1 Introduction

Although showing appealing economic benefits, freeports face certain issues and challenges in their implementation. Given the myriad of concerns and emerging challenges, it becomes clear that assessing the performance of freeports exclusively from an economic standpoint is inadequate. It is imperative to also take into account the environmental and social dimensions. However, the crucial task of monitoring and evaluating the sustainable development of freeports in coping with environmental and social challenges has been largely overlooked in existing studies, as revealed in Section 2.2. Therefore, it is necessary to develop a new index for evaluating the freeport performance, which integrates sustainability into their overarching development objectives and policies. Despite the increasing number of studies on maritime and port sustainability development over recent years (Shin

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[1] The findings from this technical chapter have been published in the following journal paper. Liang, X., Fan, S., Lucy, J., Chen, J., Coleman, J., Li, Y., Qu, Z., Li, H., Yang, Z., 2025. Quantitative sustainability assessment of freeports: Hybrid model evidence from the UK. J. Clean Prod. 487, 144521. https://doi.org/10.1016/j.jclepro.2024.144521

et al., 2018), the current state-of-the-art studies fail to employ advanced methods for sustainability assessment, that can integrate diverse KPIs within a unified framework, address data uncertainty and interdependent KPIs, and engage diverse stakeholders at the early stage. These research gaps are discussed in detail in Sections 2.4 and 2.6. In conclusion, current studies reveal a notable research gap to be addressed from both methodological and empirical perspectives.

Drawing upon the existing sustainability frameworks and decision-support methodologies, this study creates an innovative approach to identifying KPIs influencing the sustainability of freeports and engages a diverse range of stakeholders in evaluating the significance of KPIs through a global survey. The study employs a hybrid BNER approach, acknowledging its advantages as outlined in Section 2.5, to synthesise the overall sustainability performance of a freeport based on the integrated information across multiple criteria, particularly addressing the challenge of the KPIs interconnected in a network structure through BN's learning and inference ability. The applicability of the developed model is demonstrated through a case study of a UK freeport, subjected to a consistency test through sensitivity analysis. Building on the research gaps outlined in Chapter 2, the novelties of this study are highlighted as follows:

1) This study creates a three-tier hierarchical KPI index for freeports. This index is designed following the framework of the GRI, which encompasses three sustainability dimensions. Furthermore, this study integrates top-down and bottom-up methods to select KPIs from an extensive literature review and a real case.
2) The significance of all KPIs is assessed through a global survey that engages multiple stakeholders including researchers, policymakers, practitioners, service users, and public

residents. Moreover, this diverse engagement draws upon the collective knowledge and experience of respondents across 10 countries.

3) It develops a groundbreaking hybrid BNER methodology that, for the first time, allows for the inclusion of KPIs in both network and hierarchical structures within the same framework. This makes it possible to comprehensively evaluate the sustainability of freeports. This methodology also employs a belief structure that helps merge assessments with uncertainties, resulting in more accurate outcomes that are closer to reality when compared to other techniques.
4) A real case study is carried out to illustrate the practical applicability of the proposed model and provide valuable managerial insights towards freeport sustainability. Wherein, a sensitivity analysis is performed to examine the consistency regarding the impact of minor input changes on the outputs.

The rest of the chapter is structured as follows. Section 3.2 introduces the designed methodology and corresponding steps including KPI identification and purification, KPI importance evaluation, performance assessment and aggregation, and model validation. The practical application of these steps is illustrated in Section 3.3. The implications of this study are discussed in Section 3.4. Section 3.5 is the conclusion of this chapter.

3.2 A BNER Method for the Assessment of Freeport Sustainability

3.2.1 The Proposed Framework

Figure 3.1 illustrates the proposed framework in this study, highlighting its novel aspects. First, this study develops a three-tier KPI index in alignment with the GRI sustainability framework and identifies specific KPIs influencing freeport sustainability by combining literature review and real case analysis. The identified KPIs are purified through expert interviews in terms of their relevance and comprehensiveness in evaluating freeport sustainability. Second, the importance of KPIs is evaluated

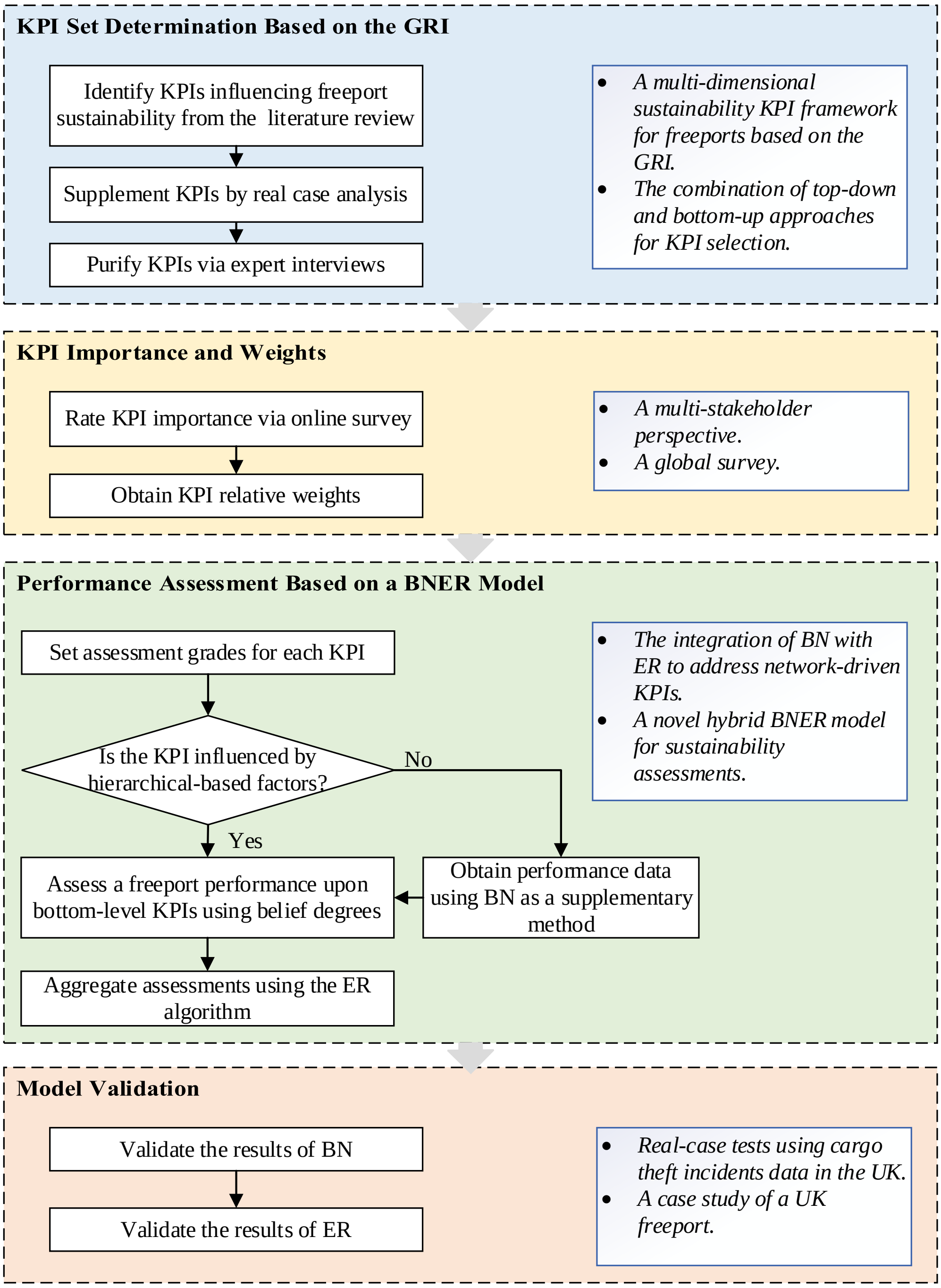

Figure 3.1 The proposed framework for freeport sustainability assessment.

using a global online survey involving multiple freeport stakeholders, providing relative weightings for the KPIs. Third, using a BNER model, the performance data of a freeport for KPIs with hierarchical or network characteristics are appropriately obtained and assessed according to their respective assessment grades. The performance results of top-level KPIs are derived by aggregating the assessments of bottom-level KPIs. Finally, the developed model is validated through various methods using real-case data, ensuring its reliability and applicability.

3.2.2 KPI Identification

It is a challenging task to identify indicators aligned with sustainability goals, and this complexity increases when assessments must consider multiple dimensions and be aggregated into a single value (Kuik and Verbruggen, 2012). The criteria used for selecting indicators encompass aspects such as significance, policy relevance, measurability, and representativeness (Shiau and Chuang, 2015). Chamaret et al. (2007) outlined two primary indicator selection approaches: the top-down and bottom-up methods. In the top-down approach, indicators are initially identified through a literature review, including publications, reports, and standards. These are then refined to establish a mutually agreed-upon set of indicators. Conversely, the bottom-up approach entails compiling the final set of indicators by gathering proposals from sector stakeholders, considering their perceptions of issues and their significance. However, this study cannot rely solely on a single method due to specific considerations. In the top-down approach, the existing literature on the performance evaluation of freeports predominantly focuses on the economic dimension, offering little reference for environmental and social dimensions. Conversely, the bottom-up approach, as observed in practices in the UK and China (selected as examples due to data accessibility), primarily utilises quantitative indicators that can be assessed through objective numerical data. Therefore, this study integrates both approaches to develop a comprehensive and balanced KPI framework for assessing freeport sustainability. In other words, it utilises both field studies and literature review methods to gather a more comprehensive array of indicators. The literature selection process is explained in Section 2.1. Additionally, the identified KPIs from the abovementioned procedure undergo a refinement process guided by expert knowledge.

3.2.3 KPI Importance Evaluation from Multiple Stakeholder Perspectives

Following the refinement of the KPI framework, the importance of KPIs is evaluated by experts using the Linkert Scale method through a global survey. Compared to other commonly used methods in criteria evaluation such as AHP, DEMATEL, and PROMETHEE, the Linkert scale shows its competitive advantage as it is easy to understand and implement, particularly valuable in scenarios involving numerous KPIs and limited availability of professionals. Researchers commonly use 5, 7, or 10-point scales to obtain importance ratings. The low end of the rating scale is usually noted as ‘not important at all’ and the high end of the scale is identified as ‘extremely important’ or ‘very important’ (Fontenot et al., 2007). This study uses a 7-point scale (1 indicates not important at all, 7 means extremely important). Subsequently, the relative weights of the KPIs are determined by normalising the importance ratings.

The sustainability assessment requires effective approaches to enhance its legitimacy and relevance. It should engage early with assessment users, incorporating public perspectives while providing active leadership (Sala et al., 2015). Stakeholders’ engagement is a specific requirement of sustainability assessment. However, previous studies on sustainability assessment within the context of ports, port cities, and freeports show limitations in analysing multiple stakeholders' perspectives, especially in terms of the engagement of service users and public residents. Participants of this survey involve multiple freeport stakeholders, including researchers (who have related studies on freeports), policymakers, practitioners (who are experts directly involved in the day-to-day operations and management of freeports), service users (who make use of the infrastructure, incentives, and trade facilitation services offered by freeports e.g., businesses, traders, importers, exporters, and manufacturers), and public residents.

3.2.4 Freeport Performance Assessment upon Bottom-Level KPIs

1) Assessment of KPIs with independent influential factors.

This study uses five exclusive assessment grades uniformly for the assessment of all KPIs across all levels. This approach eliminates the necessity for establishing complex transformation rules and fosters improved communication between academia and industry by providing a clear and transparent aggregation process (Poo et al., 2021).

According to the methodology framework depicted in Figure 3.1, prior to evaluating the performance of a freeport using individual bottom-level KPIs, it is imperative to determine the structure of influential factors relevant to each respective KPI. If the influential factors of a specific KPI are independent in a hierarchical structure, direct assessment of this KPI becomes feasible using the ER algorithm. In this case, the freeport performance data could be obtained from direct statistics for quantitative KPIs, and expert judgements for qualitative KPIs. Conversely, if the influential factors of a particular KPI are interdependent within a network structure, supplementary methods, such as BN, must be employed to acquire the essential performance data for this KPI in freeports.

2) Assessment of KPIs with interdependent influential factors.

In this study, a data-driven BN method is employed for handling KPIs influenced by interdependent factors in a network structure. Chapter 4 will provide a detailed introduction to the method. In summary, this study develops a BN model through the steps including BN structure learning, CPTs learning, and model validation. The structure of the BN can be developed through either subjective methods, objective methods, or a combination of both. In this study, we adopt an objective approach to design the BN structure, leveraging the Tree Augmented Naive Bayes (TAN) algorithm. TAN amends the naive Bayes' independence assumption but maintains its straightforward computation and stability (Friedman et al., 1997). By considering the interrelationships among multiple influential factors, it effectively overcomes the limitation of ER in handling network-based interconnected factors.

3.2.5 Freeport Performance Aggregation Using the ER Algorithm

After obtaining assessments of all bottom-level KPIs, the ER algorithm is employed to aggregate assessments of multiple KPIs. The current widely used ER algorithm for evidence aggregation is presented by Yang and Xu (2002) and applied in many studies (Akhoundi and Nazif, 2018; Poo et al., 2021; Zhang et al., 2020). This study employs it in the freeport context for the first time. The ER approach can be implemented for the sustainability assessment of freeports as follows, for instance, to aggregate all assessments related to a level-2 KPI 'service quality' (see Table 3.1 in Section 3.3.1).

$$R = \{R_k, k = 1, \ldots, L\} \qquad \text{3-1}$$

Equation 3-1 represents a set of level-3 KPIs (KPIs 12-15) influencing the assessment of 'service quality', thus, L=4 in this case.

$$G = \{G_j, j = 1, \dots, N\} \quad \text{3-2}$$

The set of assessment grades for each KPI can be represented as Equation 3-2, where G_j is the j^{th} assessment grade, $j+1$ is preferred to j, and N=5 because five grades are used in this study, as explained in Section 3.2.4.

$$\beta_{j,k} \geq 0 \text{ and } \sum_{j=1}^{N} \beta_{j,k} \ll 1 \quad \text{3-3}$$

$$\theta_k \geq 0 \text{ and } \sum_{k=1}^{L} \theta_k = 1 \quad \text{3-4}$$

In equations 3-3 and 3-4, $\beta_{j,k}$ represents the belief degree for the j^{th} assessment grade of R_k, and θ_k is the normalised weight of R_k.

$$m_{j,k} = \theta_k \beta_{j,k} \quad \text{3-5}$$

$$M_k = \bar{M}_k + \widetilde{M}_k \quad \text{3-6}$$

$$\bar{M}_k = 1 - \theta_k \quad \text{3-7}$$

$$\widetilde{M}_k = \theta_k (1 - \sum_{j=1}^{N} \beta_{j,k}) \quad \text{3-8}$$

The belief degree is transformed into basic probability masses as outlined in Equations 3-5 to 3-8. $m_{j,k}$ signifies the probability mass associated with R_k when evaluated at grade G_j. The residual probability mass, M_k, unallocated to any individual grade, is divided into $\bar{M}_k$ and $\widetilde{M}_k$. Here $\bar{M}_k$ represents the extent to which other KPIs may influence the assessment, and $\widetilde{M}_k$ arises from the incompleteness of the belief degree assessment.

{Gj} $m_{j,I(k+1)} = K_{I(k+1)}\left[m_{j,I(k)}m_{j,k+1} + m_{j,k+1}M_{I(k)} + m_{j,I(k)}M_{k+1}\right], k = 1, \cdots, L-1$ 3-9

{G}: $M_{I(k+1)} = \bar{M}_{I(k+1)} + \tilde{M}_{I(k+1)}$ 3-10

{G}: $\bar{M}_{I(k+1)} = K_{I(k+1)}\left[\bar{M}_{I(k)}\bar{M}_{k+1}\right]$ 3-11

{G}: $\tilde{M}_{I(k+1)} = K_{I(k+1)}\left[\tilde{M}_{I(k)}\tilde{M}_{k+1} + \tilde{M}_{I(k)}\bar{M}_{k+1} + \bar{M}_{I(k)}\tilde{M}_{k+1}\right]$ 3-12

$$K_{I(k+1)} = \left[1 - \sum_{j=1}^{N}\sum_{t=1 \neq j}^{N} m_{j,I(k)}m_{t,k+1}\right]^{-1}, k = 1, \cdots, L-1$$ 3-13

Next, it is ready to aggregate assessments of the four level-3 KPIs. Equation 3-9 represents the combined probability masses by aggregating the output from R_k and R_{k+1}. Equations 3-10 to 3-12 represent the combined remaining belief degree unassigned to any individual grade. Note that $m_{j,I(1)} = m_{j,1}$, $\tilde{M}_{I(1)} = \tilde{M}_1$, $\bar{M}_{I(1)} = \bar{M}_1$, and $M_{I(1)} = M_1$.

After aggregating the four assessments, the cumulative belief degree is calculated as follows. β_j represents the aggregated belief degree allocated to the j^{th} assessment grade of service quality, while β_H stands for the residual belief degree unallocated to any individual grade of service quality.

{Gj}: $\beta_j = \frac{m_{j,I(L)}}{1-\bar{M}_{I(L)}}, j = 1, \cdots, N$ 3-14

{G}: $\beta_H = \frac{\tilde{M}_{I(L)}}{1-\bar{M}_{I(L)}}$ 3-15

The overall sustainability performance of a freeport can be obtained by repeating the above ER algorithm to aggregate assessments of other KPIs in the proposed index system from the bottom level to the top level. The aggregation process is conducted through an ER-based software Intelligent Decision System developed by Xu and Yang (2005).

Furthermore, the theory of expected utility (Yang, 2001) is used to obtain a numerical performance score in a crisp value for each KPI, which makes it easy to compare results in different scenarios.

3.2.6 Model Validation Methods

The validation of the hybrid model comprises two distinct phases. First, real cases are used to evaluate the constructed BN model by comparing predicted outcomes with the actual results observed in these cases, and the model's consistency is verified using the kappa statistic (Cohen, 1960). Subsequently, to validate the consistency of the results of ER, a sensitivity analysis is performed to examine the impact of minor input changes on the corresponding outputs. For the methodology to be deemed robust with logical inference reasoning, the sensitivity analysis should meet at least the following two axioms (Poo et al., 2021; Yang et al., 2009).

- Axiom 1. A minor increase or decrease in the belief degrees related to the linguistic variables of the bottom-level KPIs will inevitably lead to a corresponding rise or fall in the belief degree of the linguistic variables and the values of the freeport sustainability indexes.
- Axiom 2. For the same change in belief degree distributions of the bottom-level KPIs, the impact on the values of freeport sustainability indexes will remain consistent with their weight distributions.

3.3 Case Studies and Analysis

3.3.1 KPIs for the Sustainability Assessment of Freeports

This study identified KPIs for assessing freeport sustainability based on a combination of top-down and bottom-up approaches. First, 40 KPIs were chosen from the literature review based on the top-down approach, while eight additional KPIs were selected from the real case of UK freeports based on the bottom-up approach. This created an index with 48 level-3 KPIs, 13 level-2 KPIs, and three top-level KPIs. Next, three experts were interviewed independently to verify the relevance and comprehensiveness of the KPIs selected from the first round. The three interviewees comprise a UK Freeport director boasting three decades of industry expertise in both strategy and execution in the UK and Morocco, along with two distinguished professors who have authored extensively cited articles in top-tier journals pertinent to the subject matter focusing on freeports in the UK and China, respectively. As a result, three new KPIs were created based on expert opinions, as depicted in Table 3.1. Nine level-3 KPIs were considered to have no direct influence on freeport development goals nor are they impacted by the freeport construction. Thus, they were assigned zero weight in this case analysis and are not included in Table 3.1. These nine KPIs include four economic KPIs (port infrastructure capacity, labour productivity, electricity cost, and fuel cost), three environmental KPIs (electricity consumption, fuel consumption, and contingency plans for pollution accidents), and two social KPIs (employment of collective bargaining agreements, and employee retention rates). A level-2 KPI (productivity and cost efficiency) was eliminated along with its three sub-KPIs (labour productivity, electricity cost, and fuel cost).

These KPIs were excluded mainly due to their lack of relevance to the freeport context. For instance, while port infrastructure capacity is a critical factor in traditional port operations, it is not directly applicable to assessing freeport sustainability. Freeports encompass a broader scope that extends beyond port operations alone. KPIs related to labour productivity, electricity consumption, fuel consumption, and their associated costs are influenced by national or regional energy policies and market conditions, beyond the control of any individual freeport. Conversely, KPIs such as employment of collective bargaining agreements and employee retention rates were excluded as they pertain to individual businesses within the freeport rather than the freeport as a whole. Furthermore, such data is unlikely to be disclosed due to its commercial sensitivity. Eventually, the purified index consists of 42 level-3 KPIs, 12 level-2 KPIs, and three level-1 KPIs, as presented in Table 3.1. The 42 level-3 KPIs include 22 quantitative ones and 20 qualitative ones, while all level-1 and level-2 KPIs are qualitative. Please see Table A.1 in Appendix A for descriptions of these KPIs.

Table 3.1 The KPI framework.

Level 1	Level 2	No.	Level 3	QT/ QL	References
Economic	Freeport size	1	Development area of freeport	QT	Chen et al., 2018; Huang et al., 2020; Liu et al., 2021a
		2	Port cargo tonnage	QT	Li et al., 2018; Liu et al., 2021b; Molavi et al., 2020; Pourebrahim and Mokhtar, 2016
		3	Port container throughput	QT	Li et al., 2018; Liu et al., 2021b; Molavi et al., 2020; Papaefthimiou et al., 2017
		4	Movement of rail freight in/out of the freeport	QT	Case study
		5	Movement of road freight in/out of the freeport	QT	Case study
	Freeport infrastructure	6	Number of new infrastructure projects	QT	Case study
		7	Information technology	QL	Chen et al., 2018; Garg et al., 2022; Hsu et al., 2023; Liu et al., 2021b
		8	Facility availability	QL	Huang et al., 2020; Majidi et al., 2021
		9	Number of customs sites	QT	Case study
		10	Number of tax sites	QT	Case study
		11	Tax policy	QL	Chen et al., 2018; Huang et al., 2020
	Service quality	12	Cargo traffic congestion	QL	Expert interview
		13	The efficiency of customs clearance	QL	Chen et al., 2018; Hsu et al., 2023; Huang et al., 2020

		14	Diversity of logistics services	QL	Chen et al., 2018; Hsu et al., 2023; Huang et al., 2020
		15	Operational accuracy	QL	Expert interview
	Economic aggregate	16	GDP change rate	QT	Jugović et al., 2022; Liu et al., 2021a; Pourebrahim and Mokhtar, 2016
		17	GDP per capita	QT	Jugović et al., 2022; Liu et al., 2021a; Pourebrahim and Mokhtar, 2016
		18	Total import and export of foreign trade change rate	QT	Cerreta et al., 2020; Liu et al., 2021a
		19	Foreign direct investment	QT	Kovačič Lukman et al., 2022; Shiau and Chuang, 2015
		20	Number of businesses operating at freeport development sites	QT	Case study
Environmental	Environmental pollution	21	Air pollution	QL	Burskyte et al., 2011; Garg et al., 2022; Jeevan et al., 2022; MacNeil et al., 2021; Papaefthimiou et al., 2017
		22	Water pollution	QL	Garg et al., 2022; Jeevan et al., 2022; Jugović et al., 2022; Leal Junior et al., 2022
		23	Noise pollution	QL	Castellano et al., 2020; Jeevan et al., 2022; Leal Junior et al., 2022; Peris-Mora et al., 2005
		24	Soil pollution	QL	Jugović et al., 2022; Leal Junior et al., 2022; MacNeil et al., 2021; Peris-Mora et al., 2005
	Waste management	25	Hazardous waste handling	QL	Chiu et al., 2014; Hua et al., 2020; Molavi et al., 2020
		26	General waste management	QL	Castellano et al., 2020; Chiu et al., 2014; Garg et al., 2022; Jeevan et al., 2022; Kovačič Lukman et al., 2022
		27	Centralised sewage treatment percentage	QT	Jeevan et al., 2022; Li et al., 2018; Liu et al., 2021a
	Energy and resource usage	28	Water consumption management	QL	Chiu et al., 2014; Leal Junior et al., 2022; Molavi et al., 2020
		29	Clean energy sources	QL	Jeevan et al., 2022; Lirn et al., 2013; Shiau and Chuang, 2015
	Environmental protection	30	Environmental training	QL	Laxe et al., 2017; Lirn et al., 2013
		31	Ecosystem and habitat protection	QL	Burskyte et al., 2011; Castellano et al., 2020; Dai et al., 2013; Lirn et al., 2013; Peris-Mora et al., 2005
		32	Climate change adaptation and mitigation	QL	Burskyte et al., 2011; MacNeil et al., 2021
		33	Environmental protection policy	QL	Expert interview

Social	Job generation	34	Number of new jobs due to the freeport development	QT	Jugović et al., 2022; Kovačič Lukman et al., 2022; Majidi et al., 2021
		35	Employment in high-tech and knowledge-oriented sectors	QT	Cerreta et al., 2020; Pourebrahim and Mokhtar, 2016; Stanković et al., 2021
	Workforce development and diversity	36	Gender equality	QL	Laxe et al., 2017; Leal Junior et al., 2022; Stanković et al., 2021
		37	Number and level of skills training	QT	Laxe et al., 2017; Roh et al., 2021
		38	Participation in skills training	QT	Pourebrahim and Mokhtar, 2016; Stanković et al., 2021
	Safety and security	39	Fatal injuries	QT	Hua et al., 2020; Jugović et al., 2022; Leal Junior et al., 2022; Roh et al., 2021
		40	Non-fatal injuries	QT	Hua et al., 2020; Jugović et al., 2022; Leal Junior et al., 2022; Roh et al., 2021
		41	Cargo theft incidents	QT	Case study
	Innovation and collaboration	42	The number of projects between firms and research innovation organisations within the Freeport area	QT	Case study

*Qualitative (QL);Quantitative (QT).

3.3.2 KPI Weights from Multiple Stakeholder Perspectives

1) Survey.

Subjective data was collected for rating the importance of KPIs using the Jisc online survey platform. The survey of this research consisted of two main parts. The first part aimed to gather information about the experience and background of participants. The second part aimed to evaluate the relative importance of KPIs using the 7-point Linkert scale.

Recognising the scarcity of professionals within the freeport industry, deliberate efforts were made to engage a diverse array of stakeholders from around the world. The survey was distributed from July to November 2022 both individually (via phone calls, emails, LinkedIn, etc.) and publicly such as at the Mersey Maritime face-to-face networking session (LBN, 2022). Ultimately, 21 completed responses were received, of which, four were unsuitable due to the respondents' knowledge primarily focusing on other sectors within the maritime industry such as naval architecture and maritime transportation rather than freeport. The collective experience and knowledge of the remaining 17 participants contributed to a comprehensive global perspective, encompassing 10 countries: the UK, China, Morocco, Germany, Russia, Dubai, Ghana, Canada, Brazil, and Iran (see Table A.2 in Appendix A). Among them, three freeport researchers are professors recognised by their publications on freeports, indexed in the WoS Core Collection, with expertise representing freeports in Russia, Taiwan, and Brazil. Additionally, each of the policymakers and practitioners has 10 to 30 years of experience in this field. The three service users represent key stakeholders from a port, a shipping company, and a forwarding company, respectively.

2) KPI importance.

Given the importance ratings (1-7) assigned to each level-3 KPI by all 17 respondents, the Arithmetic Mean (AM) and Standard Deviation (SD) values were calculated. Subsequently, the importance score of an upper-level KPI was obtained by the average of its child KPIs, as presented in Table 3.2. The results of Table 3.2 reveal the most significant KPIs on each level of the framework. This procedure was then replicated using data from each of the five stakeholder types, allowing for the comparison of different scenarios when determining KPI weights using different stakeholder perspectives.

Among level-3 KPIs, the most significant ones are information technology and efficiency of customs clearance, both scoring 6.12. There are 13 KPIs ranked in the top 10, of which 12 KPIs are under the economic dimension, one KPI belongs to the environmental dimension (environmental protection policy), and none falls within the social dimension. Under the social dimension, the most important KPIs are the number of new jobs due to the freeport development, employment in high-tech and knowledge-oriented sectors, and the number of skill training, all ranking at 17th place. At the 2nd level of the framework, service quality is the most important KPI scoring 5.74, followed by freeport size (5.66) and freeport infrastructure (5.60). Among the three level-1 dimensions, the economic dimension has the highest importance score at 5.45, followed by the environmental dimension (5.08) and the social dimension (5.02).

Table 3.2 KPI importance ratings and rankings.

Level 1	Level 2	No.	Level 3	AM (1-7)	SD	Rank
Economic dimension (5.45)	Freeport size (5.66)	1	Development area of freeport	5.59	1.66	10
		2	Port cargo tonnage	5.65	1.41	9
		3	Port container throughput	5.71	1.31	6
		4	Movement of rail freight in/out of the freeport	5.59	1.66	10
		5	Movement of road freight in/out of the freeport	5.76	1.68	5
	Freeport infrastructure (5.60)	6	Number of new infrastructure projects	5.59	1.06	10
		7	**Information technology**	**6.12**	1.36	**1**
		8	Facility availability	5.94	1.48	3
		9	Number of customs sites	5.12	1.83	25
		10	Number of tax sites	5.00	1.87	31
		11	Tax policy	5.82	1.74	4
	Service quality	12	Cargo traffic congestion	5.71	1.53	6
	(5.74)	13	**The efficiency of customs clearance**	**6.12**	**1.32**	**1**
		14	Diversity of logistics services	5.71	1.49	6
		15	Operational accuracy	5.41	1.42	15
	Economic aggregate (4.84)	16	GDP change rate	4.18	1.70	42
		17	GDP per capita	4.41	1.87	40
		18	Total import and export of foreign trade change rate	5.12	1.65	25
		19	Foreign direct investment	5.00	1.70	31
		20	Number of businesses operating at freeport development sites	5.47	1.37	14
Environmental dimension (5.08)	Environmental pollution (5.10)	21	Air pollution	5.24	1.86	17
		22	Water pollution	5.24	1.86	17
		23	Noise pollution	4.82	1.91	37

		24	Soil pollution	5.12	1.80	25
	Waste management (5.20)	25	Hazardous waste handling	5.29	1.61	16
		26	General waste management	5.24	1.60	17
		27	Centralised sewage treatment	5.06	1.64	29
	Energy and resource usage (5.00)	28	Water consumption management	5.00	1.97	31
		29	Clean energy sources	5.00	1.90	31
	Environmental protection (5.01)	30	Environmental training	4.59	1.66	39
		31	Ecosystem and habitat protection	5.18	1.94	23
		32	Climate change adaptation and mitigation	4.71	2.17	38
		33	Environmental protection policy	5.59	1.33	10
Social dimension (5.02)	Job generation (5.24)	34	Number of new jobs due to the freeport development	5.24	1.82	17
		35	Employment in high-tech and knowledge-oriented sectors	5.24	1.30	17
	Workforce development and diversity (4.88)	36	Gender equality	4.29	1.96	41
		37	Number and level of skills training	5.24	1.35	17
		38	Participation in skills training	5.12	1.45	25
	Safety and security (5.04)	39	Fatal injuries	5.18	1.98	23
		40	Non-fatal injuries	5.06	2.08	29
		41	Cargo theft incidents	4.88	1.96	36
	Innovation and collaboration (4.94)	42	The number of projects between firms and research innovation organisations within the freeport area	4.94	1.82	35

3) KPI weights from multiple stakeholders' perspectives.

Based on the KPI importance ratings, KPI weights at each level were obtained through normalisation. This was performed from different stakeholder perspectives. The global weights of these KPIs illustrate their influence on the overall framework and are presented in the following. For instance, Figure 3.2 illustrates the global weight distribution of level-2 KPIs based on the combined stakeholder perspective, with economic, environmental, and social KPIs represented in orange, green, and blue colours, respectively. Each KPI's weight was calculated by dividing its rating by the total sum of the

12 ratings. Within the framework, service quality has the greatest weight (9.21%), followed by freeport size (9.09%) and freeport infrastructure (8.99%). Table 3.3 provides the outcomes corresponding to each stakeholder viewpoint, highlighting both the similarities and discrepancies in their respective priorities. For example, it shows that, in comparison to other stakeholders, service users value the safety and security of the freeport more than its size.

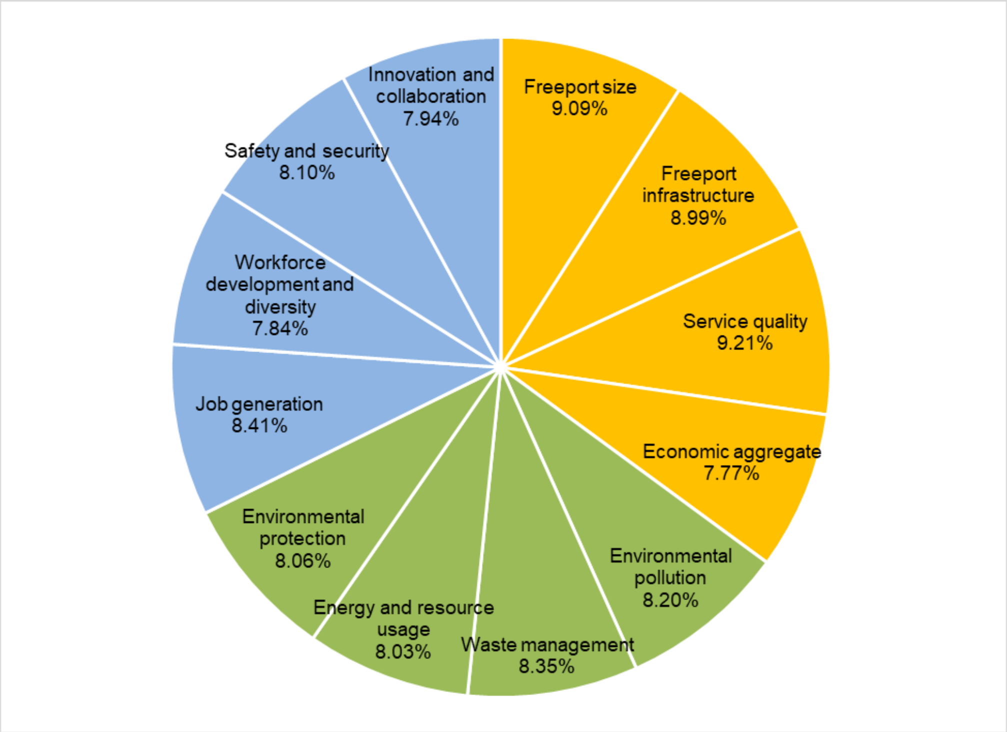

Figure 3.2 Weight distribution on Level-2 KPIs by combined stakeholders.

Table 3.3 Weight distribution on Level-2 KPIs by different stakeholders.

	Researchers	Policymakers	Practitioners	Service users	Public residents
Freeport size	10.05%	9.23%	10.15%	6.83%	8.70%
Freeport infrastructure	8.47%	9.68%	8.11%	10.88%	8.36%
Service quality	10.14%	9.43%	9.20%	9.88%	7.93%
Economic aggregate	6.92%	8.73%	8.29%	6.35%	7.96%
Environmental pollution	9.33%	7.19%	7.72%	7.19%	9.13%
Waste management	9.55%	7.28%	8.32%	7.98%	8.48%
Energy and resource usage	7.84%	7.69%	8.46%	7.49%	8.30%

Environmental protection	8.24%	8.44%	7.09%	7.49%	8.39%
Job generation	7.84%	9.68%	9.52%	8.38%	7.93%
Workforce development and diversity	6.67%	7.94%	8.60%	8.58%	7.62%
Safety and security	7.93%	7.77%	7.33%	9.98%	8.36%
Innovation and collaboration	7.03%	6.95%	7.19%	8.98%	8.85%

Figure 3.3 shows the weight distribution among three sustainability dimensions from each respective stakeholder perspective and the combined one. The results show that policymakers and practitioners have similar preferences, both prioritising the economic dimension, followed by the social and environmental dimensions. Whereas researchers and public residents prefer the environmental dimension first, followed by the economic and social dimensions. Service users uniquely exhibit the highest focus on the social dimension. In the combined scenario, the economic dimension has a higher weight than the environmental and social dimensions.

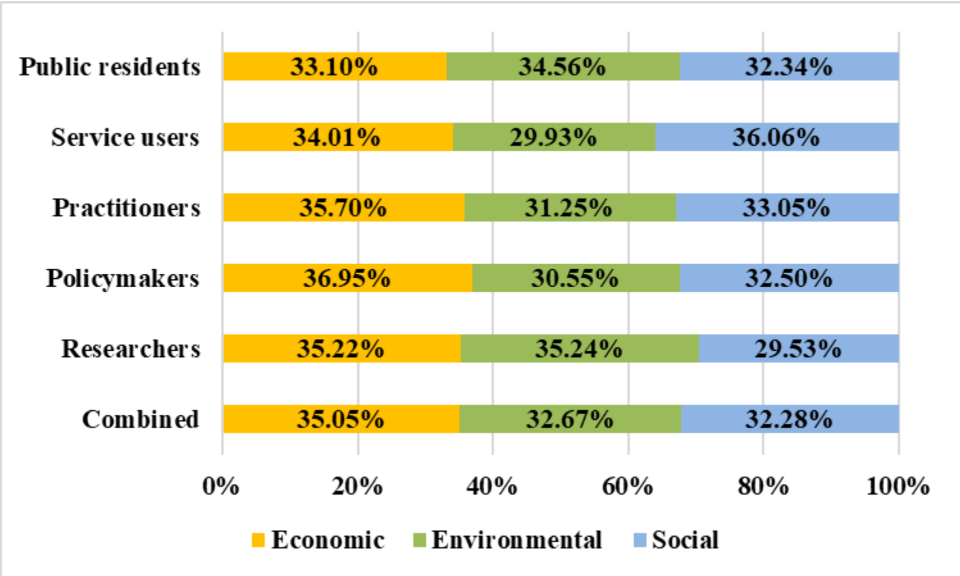

Figure 3.3 Weight distribution on level-1 KPIs by different stakeholders.

3.3.3 Performance Assessment of a UK Freeport upon Bottom-Level KPIs

1) Assessment of KPIs with independent influential factors

As explained in section 3.2.4, this study used five exclusive assessment grades uniformly for all KPIs across all levels. To be specific, five numerical grades (1=the worst, 5=the best) were used for all qualitative KPIs, and five assessment grades for quantitative KPIs were determined based on literature review and freeport inputs. For example, five assessment grades were assigned to KPI No. 10 (number of tax sites), with values {0, 1, 2, 3, 4}.

Out of the 42 bottom-level KPIs within the constructed framework, 41 are hierarchical-driven KPIs, including 21 quantitative KPIs and 20 qualitative ones. The remaining single KPI with a network structure is explained in the following section. In the subsequent steps of this case study, a freeport in the UK was used anonymously. The freeport performance data for individual quantitative KPIs was obtained from online statistics and freeport inputs, and the performance was assessed directly. For example, belief degrees {0%, 0%, 0%, 100%, 0%} were assigned to grades {0, 1, 2, 3, 4} if a freeport has three tax sites. To assess the freeport performance against individual qualitative KPIs, four senior managers at the investigated freeport were interviewed independently, each lasting about 30 minutes. During these interviews, each interviewee was asked to select one or multiple grades for each of the 20 qualitative KPIs based on the performance of the investigated freeport. As a result, the belief degree of each grade was obtained by the percentage of experts selecting that grade.

The interviewees were not required to select a grade if they felt uncertain about a specific KPI. This flexibility is due to the ER algorithm's capacity to incorporate belief degrees, even when uncertainties are present, to accurately reflect the real-world situation. For instance, belief degrees for KPI No. 30 (environmental training) were assigned as {0%, 0%, 50%, 25%, 0%}, with the remaining 25% representing the unknown category. In this study, the KPIs were identified from a wide range of references covering comprehensive aspects. As a result, some KPIs may be relatively new to domain experts.

2) Assessment of KPIs with interdependent influential factors

Within the constructed framework, one network-driven KPI associated with cargo theft incidents cannot be directly evaluated like the other KPIs. This is because online statistics and reports only contain detected and reported incidents, failing to capture all actual occurrences. Furthermore, this KPI is influenced by multiple interdependent factors within a network structure. Therefore, evaluating this KPI requires additional data collection for each influential factor and an analysis of their relationships. To address this challenge, we used a data-driven BN model to forecast the probability of cargo theft incidents in the investigated freeport region. The results of the model will be presented and thoroughly discussed in Chapter 4. In summary, 9,316 historical cargo theft incidents in the UK were used to construct the BN structure based on the TAN algorithm. Using this structure, the CPTs for the relevant nodes were learned, and the significant factors influencing cargo theft were assessed. It was able to predict the likelihood of cargo theft incidents across various regions and transform it into a vital input metric for ER. Figure 3.4 illustrates the results of TAN. The probability value for the selected UK region was converted into belief degrees (0%, 0%, 54%, 46%, 0%) across the five defined grades (0%, 5%, 10%, 15%, 20%), resulting in a numerical performance score of 0.3850. More details of the results are documented in Chapter 4.

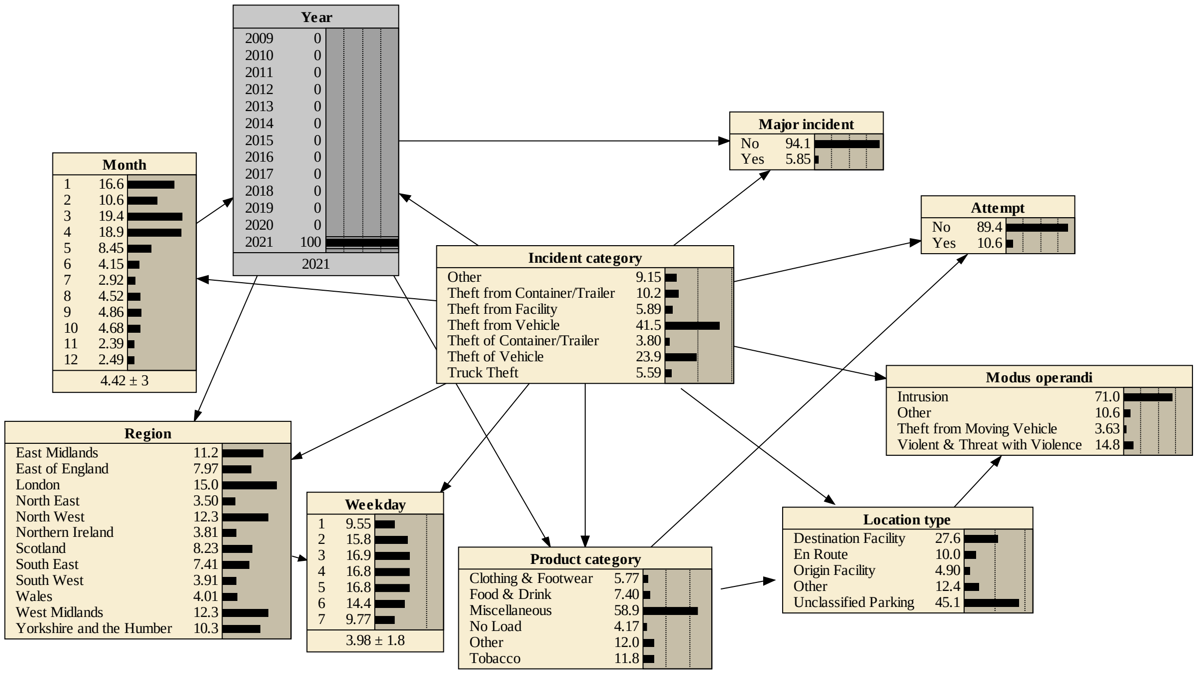

Figure 3.4 TAN results as the input for KPI cargo theft incidents.

3) Presentation of assessment results

Due to commercial sensitivity, this case study presents a partial view of the bottom-level KPIs, omitting the display of their assessment results against the five respective grades. Following the assessment against each respective KPI, a numerical performance score (ranging from 0 to 1) was obtained using the expected utility theory. The results of the investigated case are shown in Table 3.4. KPI local weights indicate the relative importance of each KPI within its corresponding upper-level category. For example, KPIs. 1-5 at level 3 all fall under the level 2 KPI category of freeport size, with KPI No. 5 accounting for a weight of 20.37% among these five KPIs.

Table 3.4 Weights and performance on bottom-level KPIs.

No	Level-3 KPI	Global weight	Local weight	Score (0-1)	Data source
1	Development area of freeport	2.54%	19.75 %	0.5175	Freeport website
2	Port cargo tonnage	2.56%	19.96 %	0.5525	GOV.UK

3	Port container throughput	2.59%	20.17 %	0.3000	GOV.UK
4	Movement of rail freight in/out of the freeport	2.54%	19.75 %	0.0000	Freeport input
5	Movement of road freight in/out of the freeport	2.62%	20.37 %	1.0000	Freeport input
6	Number of new infrastructure projects	2.54%	16.64 %	1.0000	Freeport input
7	Information technology	2.78%	18.21 %	0.6875	Expert judgement
8	Facility availability	2.70%	17.69 %	0.6875	Expert judgement
9	Number of customs sites	2.32%	15.24 %	1.0000	Freeport website
10	Number of tax sites	2.27%	14.89 %	0.7500	Freeport website
11	Tax policy	2.64%	17.34 %	0.8750	Expert judgement
12	Cargo traffic congestion	2.59%	24.87 %	0.6250	Expert judgement
13	The efficiency of customs clearance	2.78%	26.67 %	0.8750	Expert judgement
14	Diversity of logistics services	2.59%	24.87 %	0.9063	Expert judgement
15	Operational accuracy	2.46%	23.59 %	0.8750	Expert judgement
16	GDP change rate	1.90%	17.27 %	0.3450	UK Parliament
17	GDP per capita	2.00%	18.25 %	0.6075	Council website
18	Total import and export of foreign trade change rate	2.32%	21.17 %	0.0000	OEC.World
19	Foreign direct investment	2.27%	20.68 %	0.2000	Freeport website
20	Number of businesses operating at freeport development sites	2.48%	22.63 %	0.2500	Freeport input
21	Air pollution	2.38%	25.65 %	0.7500	Expert judgement
22	Water pollution	2.38%	25.65 %	0.7500	Expert judgement
23	Noise pollution	2.19%	23.63 %	0.6250	Expert judgement
24	Soil pollution	2.32%	25.07 %	0.7500	Expert judgement
25	Hazardous waste handling	2.40%	33.96 %	0.9375	Expert judgement
26	General waste management	2.38%	33.58 %	0.9375	Expert judgement
27	Centralised sewage treatment	2.30%	32.45 %	1.0000	GOV.UK
28	Water consumption management	2.27%	50.00 %	0.6875	Expert judgement
29	Clean energy sources	2.27%	50.00 %	0.8125	Expert judgement
30	Environmental training	2.08%	22.87 %	0.5625	Expert judgement
31	Ecosystem and habitat protection	2.35%	25.81 %	0.8125	Expert judgement

32	Climate change adaptation and mitigation	2.14%	23.46 %	0.8125	Expert judgement
33	Environmental protection policy	2.54%	27.86 %	0.9375	Expert judgement
34	Number of new jobs due to the freeport development	2.38%	50.00 %	0.7000	Freeport website
35	Employment in high-tech and knowledge-oriented sectors	2.38%	50.00 %	1.0000	Freeport input
36	Gender equality	1.95%	29.32 %	0.5625	Expert judgement
37	Number and level of skill training	2.38%	35.74 %	1.0000	Freeport input
38	Participation in skill training	2.32%	34.94 %	0.9000	Freeport input
39	Fatal injuries	2.35%	34.24 %	0.1800	Freeport input
40	Non-fatal injuries	2.30%	33.46 %	0.2275	Freeport input
41	Cargo theft incidents	2.22%	32.30 %	0.3850	The BN model
42	The number of projects between firms and research innovation organisations within the freeport area	2.24%	100.00 %	0.7500	Freeport input

3.3.4 Performance Aggregation of a UK Freeport Using the ER Algorithm

Finally, the performance aggregation was conducted using Equations 3-1 to 3-15 and implemented via the Intelligent Decision System software, based on six different weighting scenarios that assign weights by researchers, policymakers, practitioners, service users, public residents, and all combined, respectively. Table 3.5 presents the results of aggregated assessments for level-2 KPIs in the combined scenario (Scenario 6). It indicates that the freeport attained the highest performance score in waste management (0.9677) and the lowest score in safety and security (0.2579). Table 3.6 presents the results for level-1 KPIs and overall freeport sustainability in the six scenarios. Across Scenarios 1, 2, 3, 5, and 6, the highest performance score was observed in the environmental dimension, while the economic dimension, as the most significant dimension, recorded the lowest performance score. Overall sustainability performance scores of the six scenarios are 0.7259, 0.7270, 0.7228, 0.7350, 0.7252, and 0.7318, respectively. Figure 3.5 provides a visual representation of overall freeport sustainability in Scenario 1 as an example.

Table 3.5 Performance on level-2 KPIs based on weights given by combined stakeholders.

Level-2 KPI	Belief degrees across different grades 1	2	3	4	5	Unknown	Score
Freeport size	18.65%	15.31%	41.32%	5.43%	19.38%	0.00%	0.4787
Freeport infrastructure	0.00%	3.98%	7.68%	26.88%	57.90%	3.56%	0.8467
Service quality	0.00%	5.14%	5.14%	41.06%	48.66%	0.00%	0.8331
Economic aggregate	23.71%	54.14%	15.35%	6.80%	0.00%	0.00%	0.2631
Environmental pollution	0.00%	0.00%	32.38%	25.00%	32.00%	10.63%	0.7225
Waste management	0.00%	0.00%	0.00%	12.91%	87.09%	0.00%	0.9677
Energy and resource usage	0.00%	0.00%	10.00%	55.00%	25.00%	10.00%	0.7625
Environmental protection	0.00%	0.00%	15.46%	24.92%	49.77%	9.85%	0.8112
Job generation	0.00%	0.00%	10.00%	40.00%	50.00%	0.00%	0.8500
Workforce development and diversity	0.00%	5.77%	11.54%	11.95%	70.73%	0.00%	0.8691
Safety and security	10.41%	76.03%	13.56%	0.00%	0.00%	0.00%	0.2579
Innovation and collaboration	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.7500

Table 3.6 Performance on level-1 KPIs and the overall freeport sustainability based on weights given by different stakeholders.

Level-1 KPI	Belief degrees across different grades 1	2	3	4	5	Unknown	Score
Researchers (scenario 1)							
Economic	9.39%	17.52%	16.66%	20.89%	34.97%	0.58%	0.6363
Environmental	0.00%	0.00%	13.40%	27.43%	52.79%	6.38%	0.8325
Social	2.33%	21.79%	11.15%	41.18%	23.55%	0.00%	0.6546
Overall sustainability	**3.64%**	**11.62%**	**13.21%**	**29.42%**	**39.92%**	**2.18%**	**0.7259**
Policymakers (scenario 2)							
Economic	8.79%	18.60%	17.48%	20.50%	33.74%	0.89%	0.6295
Environmental	0.00%	0.00%	12.42%	29.22%	52.22%	6.15%	0.8341
Social	2.36%	18.95%	9.90%	35.33%	33.45%	0.00%	0.6964
Overall sustainability	**3.73%**	**12.37%**	**12.74%**	**27.97%**	**41.33%**	**1.85%**	**0.7270**
Practitioners (Scenario 3)							
Economic	12.03%	18.21%	17.71%	18.28%	32.86%	0.92%	0.6043
Environmental	0.00%	0.00%	13.00%	29.05%	51.61%	6.34%	0.8307
Social	2.42%	17.47%	9.19%	37.31%	33.62%	0.00%	0.7056
Overall sustainability	**4.70%**	**11.61%**	**12.68%**	**27.98%**	**41.08%**	**1.96%**	**0.7228**
Service users (Scenario 4)							

Economic	6.24%	14.63%	14.26%	24.62%	39.33%	0.92%	0.6904
Environmental	0.00%	0.00%	12.18%	26.75%	54.71%	6.36%	0.8404
Social	2.58%	21.78%	9.61%	42.25%	23.78%	0.00%	0.6572
Overall sustainability	**2.77%**	**12.21%**	**11.12%**	**32.41%**	**39.67%**	**1.83%**	**0.7350**
Public residents (Scenario 5)							
Economic	9.86%	17.83%	18.37%	20.19%	32.90%	0.84%	0.6211
Environmental	0.00%	0.00%	13.65%	29.18%	51.04%	6.13%	0.8281
Social	2.14%	19.62%	9.38%	43.11%	25.76%	0.00%	0.6769
Overall sustainability	**3.54%**	**11.34%**	**13.08%**	**31.31%**	**38.60%**	**2.12%**	**0.7252**
Combined (Scenario 6)							
Economic	9.44%	17.56%	17.10%	20.61%	34.44%	0.84%	0.6326
Environmental	0.00%	0.00%	12.95%	28.45%	52.38%	6.23%	0.8330
Social	2.40%	19.16%	8.44%	39.41%	30.58%	0.00%	0.6915
Overall sustainability	**3.73%**	**11.53%**	**12.17%**	**29.45%**	**41.12%**	**2.00%**	**0.7318**

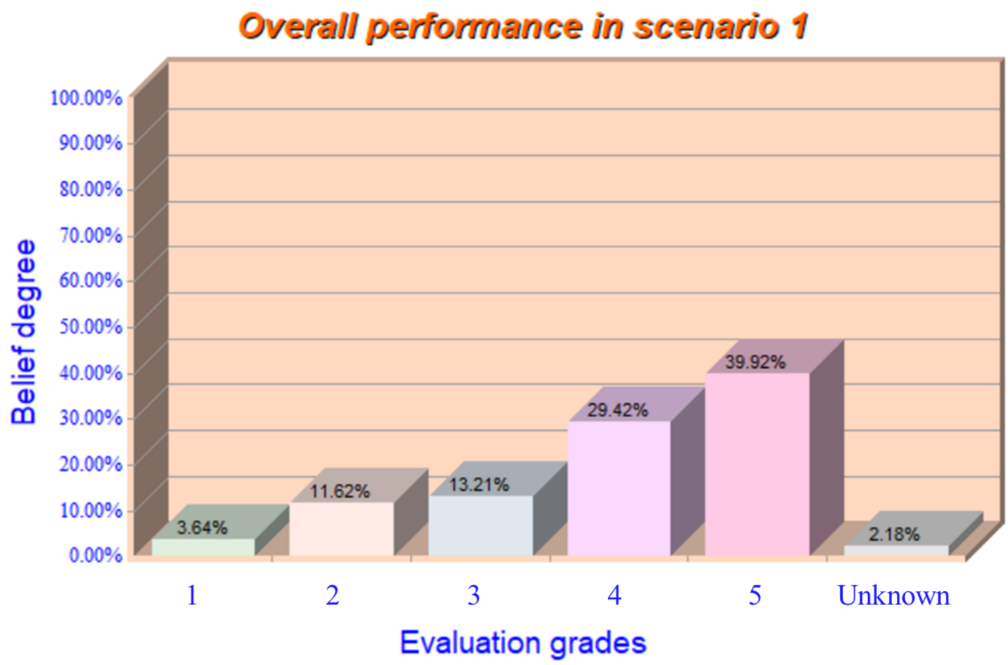

Figure 3.5 Overall sustainability performance of the investigated freeport based on researcher-assigned weights.

3.3.5 Model Validation Results

The BN validation results are detailed in Chapter 4. 930 real incidents were employed to validate the BN model yielding an accuracy of 89.14%. Additionally, the computed Kappa coefficient stands at

0.7896. Compared to previous studies, these results indicate that the model is robust in terms of accuracy (Song et al., 2020) and consistency (Altman, 1990).

The two axioms in sensitivity analysis outlined in section 3.2.6 were achieved by the following procedure. Firstly, a belief degree of 10% was reallocated in each bottom-level KPI from the least preferred grade to the most preferred grade (+10%), or conversely (-10%) if the belief degree assigned to the most preferred grade is 1. The change in the overall index was calculated, as shown in Table 3.7. It was observed that the new index value increased or decreased with the increase or decrease in the input of each bottom-level KPI. Thus, Axiom 1 was achieved.

Second, using the same belief degree variations for the bottom-level KPIs as detailed in Table 3.7, the change in the new index was compared between two weighting scenarios, Scenario 6 and Scenario 4. The 22 most important bottom-level KPIs were selected to unveil outcomes (see Table 4.8). These outcomes align with Axiom 2. For instance, the influence of KPIs.1-5 on the index value in Scenario 6 surpasses that in Scenario 4, as these KPIs carry greater weights in the former scenario than in the latter.

Table 3.7 Sustainability index sensitivity by belief degrees.

No	Level-3 KPI	Belief degrees variation	New sustainability index	Index change
1	Development area of freeport	+10%	0.7333	0.0015
2	Port cargo tonnage	+10%	0.7333	0.0015
3	Port container throughput	+10%	0.7338	0.0020
4	Movement of rail freight in/out of the freeport	+10%	0.734	0.0022
5	Movement of road freight in/out of the freeport	-10%	0.7295	-0.0023
6	Number of new infrastructure projects	-10%	0.7302	-0.0016
7	Information technology	+10%	0.7333	0.0015
8	Facility availability	+10%	0.7329	0.0011
9	Number of customs sites	-10%	0.7303	-0.0015
10	Number of tax sites	+10%	0.7324	0.0006
11	Tax policy	+10%	0.7333	0.0015

12	Cargo traffic congestion	+10%	0.7339	0.0021
13	The efficiency of customs clearance	+10%	0.733	0.0012
14	Diversity of logistics services	+10%	0.7329	0.0011
15	Operational accuracy	+10%	0.7328	0.001
16	GDP change rate	+10%	0.7329	0.0011
17	GDP per capita	+10%	0.7326	0.0008
18	Total import and export of foreign trade change rate	+10%	0.7334	0.0016
19	Foreign direct investment	+10%	0.7335	0.0017
20	Number of businesses operating at freeport development sites	+10%	0.7333	0.0015
21	Air pollution	+10%	0.7333	0.0015
22	Water pollution	+10%	0.7332	0.0014
23	Noise pollution	+10%	0.7332	0.0014
24	Soil pollution	+10%	0.7331	0.0013
25	Hazardous waste handling	+10%	0.7326	0.0008
26	General waste management	+10%	0.7326	0.0008
27	Centralised sewage treatment	-10%	0.7298	-0.002
28	Water consumption management	+10%	0.734	0.0022
29	Clean energy sources	+10%	0.7336	0.0018
30	Environmental training	+10%	0.733	0.0012
31	Ecosystem and habitat protection	+10%	0.7327	0.0009
32	Climate change adaptation and mitigation	+10%	0.7331	0.0013
33	Environmental protection policy	+10%	0.7328	0.001
34	Number of new jobs due to the freeport development	+10%	0.7352	0.0034
35	Employment in high-tech and knowledge-oriented sectors	-10%	0.7273	-0.0045
36	Gender equality	+10%	0.7337	0.0019
37	Number and level of skill training	-10%	0.7291	-0.0027
38	Participation in skill training	+10%	0.7328	0.001
39	Fatal injuries	+10%	0.7342	0.0024
40	Non-fatal injuries	+10%	0.7341	0.0023
41	Cargo theft incidents	+10%	0.7337	0.0019
42	The number of projects between firms and research innovation organisations within the freeport area	+10%	0.7352	0.0034

Table 3.8 Sustainability index sensitivity by weights.

			Global weights		Index change	
No.	Level-3 KPI	Belief degrees variation	Scenario 6	Scenario 4	Scenario 6	Scenario 4
1	Development area of freeport	+10%	2.54%	2.23%	0.0015	0.0012
2	Port cargo tonnage	+10%	2.56%	2.05%	0.0015	0.0011
3	Port container throughput	+10%	2.59%	2.05%	0.0020	0.0014
4	Movement of rail freight in/out of the freeport	+10%	2.54%	1.37%	0.0022	0.0009
5	Movement of road freight in/out of the freeport	-10%	2.62%	2.05%	-0.0023	-0.0015
6	Number of new infrastructure projects	-10%	2.54%	2.91%	-0.0016	-0.0018

7	Information technology	+10%	2.78%	3.25%	0.0015	0.0018
8	Facility availability	+10%	2.70%	3.25%	0.0011	0.0013
11	Tax policy	+10%	2.64%	2.74%	0.0015	0.0011
12	Cargo traffic congestion	+10%	2.59%	2.74%	0.0021	0.0021
13	The efficiency of customs clearance	+10%	2.78%	3.25%	0.0012	0.0014
14	Diversity of logistics services	+10%	2.59%	2.40%	0.0011	0.0010
15	Operational accuracy	+10%	2.46%	2.91%	0.0010	0.0012
20	Number of businesses operating at freeport development sites	+10%	2.48%	2.57%	0.0015	0.0015
21	Air pollution	+10%	2.38%	2.05%	0.0015	0.0012
22	Water pollution	+10%	2.38%	2.05%	0.0014	0.0011
25	Hazardous waste handling	+10%	2.40%	2.23%	0.0008	0.0007
26	General waste management	+10%	2.38%	2.23%	0.0008	0.0007
33	Environmental protection policy	+10%	2.54%	2.91%	0.0010	0.0011
34	Number of new jobs due to the freeport development	+10%	2.38%	2.74%	0.0034	0.0043
35	Employment in high-tech and knowledge-oriented sectors	-10%	2.38%	2.05%	-0.0045	-0.0032
37	Number and level of skills training	-10%	2.38%	2.23%	-0.0027	-0.0024

3.4 Implications

The findings from this research offer substantial insights into the sustainability assessment of freeports, shedding light on significant KPIs and aggregate performance indexes. In general, it reveals the prominent influence of the economic dimension among the three sustainability dimensions in enhancing the attractiveness of freeports based on the overall perspective of multiple stakeholders in the freeport sector. However, perceptions vary among different stakeholders concerning the value of each sustainability dimension. For instance, researchers and public residents have a higher preference for the environmental dimension compared to policymakers, practitioners, and particularly service users.

This disparity makes the examined freeport's overall performance reveal mild fluctuations across diverse weighting scenarios. These variations, which ranged from scores of 0.7228 (assessed by practitioners) to 0.7350 (evaluated by service users), underline the importance of understanding stakeholders' unique viewpoints. Such variations in scores, especially in distinct sustainability dimensions, can guide more personalised and effective engagement strategies with stakeholders, ensuring their expectations are met and addressed.

A solution to this disparity involves fostering improved communication among stakeholders and promoting collaborations. Additionally, policy measures that incentivise and inform service users to opt for eco-friendly choices are essential. By fostering collaboration among stakeholders and aligning policy measures with sustainable practices, freeports can deliver long-term benefits to local communities, promoting shared prosperity. Beyond enhancing trade efficiency, freeports also minimise environmental impacts, aligning with public expectations for sustainability.

This study aligns with prior research in terms of the prioritisation of KPIs. Historically, KPIs like freeport development areas, information technology capabilities, tax policies, customs clearance efficiency, and logistics have been pivotal in gauging freeport performance. The results of this study serve to reinforce the significance of these indicators in freeport sustainability evaluation, as they are consistently ranked among the top 10 KPIs. It indicates that the overall freeport sustainability can be improved by allocating more funds to develop intelligent e-commerce and digital trade, advanced information technology, effective tax policies, efficient customs systems, and convenient logistics services. By focusing on these aspects, freeports can achieve sustainable success in a rapidly evolving global trade landscape. Furthermore, the results of this study highlight that information technology and the efficiency of customs clearance are the most pivotal KPIs out of the 42 bottom-level KPIs in evaluating freeport sustainability. This observation echoes Huang et al. (2020), who emphasised the role of tech applications in shaping the service quality of FTZs. In a parallel sentiment, Gerber (2021) asserted that information technology is a key driver for international trade as it promotes cross-border value chains and further integrates manufacturing systems.

To fully capitalise on technological advancements and customs efficiencies, freeports must overcome several key challenges. First, infrastructure must be capable of supporting advanced technologies, as outdated systems can impede the integration of new solutions. Additionally, freeports need to cultivate a skilled workforce that is proficient in emerging technologies, which may require substantial investment in training and development programs.

Moreover, freeports must navigate complex and often inconsistent regulations that vary significantly between regions and countries. These regulatory discrepancies can complicate operations and slow progress. Another critical concern is the ongoing maintenance and security of technological systems. Heavy reliance on advanced technologies increases vulnerability to cyber threats and system failures, which can disrupt operations and compromise data integrity.

Lastly, enhancing customs efficiency while maintaining a high level of security presents a delicate balancing act. Streamlined customs processes must ensure thorough inspections to prevent illicit activities, as rapid clearance may sometimes compromise security. Developing comprehensive risk management strategies is vital for distinguishing between low-risk and high-risk shipments, enabling efficient operations without sacrificing safety and security.

A novel framework for sustainability assessment of freeport performance is introduced in this study. This multi-dimensional framework presents a holistic picture of freeport performance, identifying strengths and areas of improvement. As demonstrated in our case study, the investigated freeport exposes specific areas for improvement, including the freeport size (KPIs. 1- 5), economic aggregate (KPIs 16-20), and safety and security (KPIs 39-41). By adopting this novel framework, stakeholders can gain deeper insights into freeport operations, enabling targeted enhancements and fostering overall progress.

The synthesised performance index serves as a benchmark for tracking the evolution of a freeport's overall performance, identifying potential areas of concern, and ensuring continuous monitoring and improvement of sustainability efforts. Auditing and monitoring of implemented measures can be efficiently conducted at the KPI level, with best practices from leading freeports providing benchmarks to accelerate sustainability across other freeports.

3.5 Conclusion

This chapter presents a novel hybrid methodology for assessing the sustainability of freeports, offering significant contributions both methodologically and practically. It combines top-down and bottom-up approaches to selecting KPIs within the freeport-specific context and engages diverse stakeholders from around the globe to evaluate the importance of these KPIs. Utilising the BNER model, the developed framework effectively addresses data uncertainty and network-based KPIs and is successfully applied in a UK freeport. The developed framework is comprehensive and highly adaptable, as it encompasses KPIs from multiple dimensions in both quantitative and qualitative forms within hierarchical and network structures and accommodates data uncertainties. Therefore, it allows the incorporation of new KPIs without modifying the existing structure as relevant data becomes available.

The findings of this study provide important implications for the development of sustainable freeports. 1) This study provides a comprehensive KPI framework consisting of 42 bottom-level KPIs for the sustainability assessment of freeports, where the most significant KPIs are identified as the information technology, efficiency of customs clearance, facility availability, tax policy, and road freight in/out of freeport. 2) Different stakeholders' perceptions regarding the preferences on the economic, environmental, and social dimensions of freeport sustainability are varying. Accordingly, several measures are recommended to bridge the gap and foster sustainable development, such as building more partnerships and subsidising sustainable service options. 3) The developed model helps stakeholders understand a freeport's strengths and weaknesses. It provides a benchmark to assess the sustainability of a freeport over time and allows underperforming freeports to learn from the best practices of top performers.

As discussed in the current chapter, during the process of the investigation, it is found that some KPIs suffer from a highly interdependent sub-factors influencing their performance. Simple hierarchical structures fail to model such interdependency among the factors. The next chapter, aiming to address this challenge, explains how performance data related to the network-based KPI 'cargo theft incidents' can be assessed and advocates for a data-driven approach to cargo theft risk analysis.

CHAPTER 4 RISK ANALYSIS OF CARGO THEFT IN FREIGHT SUPPLY CHAINS USING A DATA-DRIVEN BN APPROACH[2]

Summary

This chapter introduces a data-driven method to analyse the RIFs of cargo theft and predict the occurrence of different types of cargo theft incidents. It offers valuable insights for preventing cargo theft in freight supply chain operations while addressing the issue of network-driven KPIs within the freeport sustainability assessment framework, as discussed in Chapter 3. A data-driven BN model is utilised to interpret the interdependencies among RIFs and their combined impact on the occurrence of various types of cargo theft incidents. The findings show that the most influential RIFs for the occurrence of cargo theft incidents are product category, year, location type, Modus Operandi (MO), and region. The findings also reveal the combined risk contributions of the RIFs, hence providing useful insights for cost-effective theft risk control in practice.

4.1 Introduction

Cargo theft risk is a critical issue for freeports because they handle high-value goods like art, jewellery, and luxury items, making them prime targets for thieves. Additionally, the international jurisdiction of freeports complicates legal recourse and coordination with law enforcement, exacerbating the problem. Among all emerging supply chain risks, the statistic shows that cargo theft has caused increasing concerns. According to CargoNet, there were 925 documented incidents in the first quarter of 2024, marking a significant 46% increase compared to the same period in 2023 and a 10% rise from the fourth quarter of 2023, and cargo theft incidents saw a 57% increase in 2023 compared to

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[2] The findings from this technical chapter have been published in the following journal paper. Liang, X., Fan, S., Lucy, J., Yang, Z., 2022. Risk analysis of cargo theft from freight supply chains using a data-driven Bayesian network. Reliab. Eng. Syst. Saf. 226, 108702. https://doi.org/10.1016/j.ress.2022.108702

the previous year. Cargo theft is becoming a global problem that must be well addressed to avoid financial loss and disruptions in supply chain operations (Casella, 2011). When a single cargo theft incident occurs, the involved supply chain costs six times the cargo value because the incident affects the costs of product replacement, incident handling, increased insurance premiums, loss of sales, and negative impact on the business reputation (Burges, 2013). Along with financial consequences, re-transporting the lost goods can increase CO_2 emissions. Furthermore, cargo theft involving hazardous materials or violent operations can cause injuries, fatalities, and environmental damage. Given such a high-risk stake, the relevant research in cargo theft risk analysis has not been undertaken sufficiently and in a good proportion to the risk level.

Within the context of cargo theft, the risks are diversified, involving classical and nonclassical events. For instance, the spread of COVID-19 in 2020 brought increased and more specific theft targets on cargo such as personal protection equipment (PPE) and medicines (*BSI Supply Chain Risk Insights Report*, 2021). For other types of cargo, cargo theft trends stayed stable in 2020 compared to the volatile records in previous years, despite the implementation of many preventive measures in practice. Although real-time monitoring devices attached to the cargo are used in practice, it is revealed not to be effective enough to reduce the interest and attempts of thieves targeting the cargo. Drone monitoring has been seen as a new solution to cargo security, but its applicability is arguable for certain types of shipments due to the high cost (Lorenc et al., 2020). The literature related to the risk analysis of cargo theft is little in general and less in supply chains. Most studies focused on the countermeasures against cargo theft, while not many studies investigated the characteristics of cargo theft, such as the main causes, hot spots, and seasonal patterns. However, without understanding the influential factors of cargo theft, preventative measures against theft and the related resources to support the preventative measures will not be allocated systematically and efficiently (Tang et al., 2010).

Typically, cargo thieves seek the opportunity to steal depending on time, location, and objective (cargo type). Besides, they may choose different methods to commit a crime in different scenarios, such as breaking and entering a vehicle/truck/warehouse, forcing a vehicle to stop. In addition, the occurrence of cargo theft from supply chains is complicated to understand because it involves various uncertainties such as transportation modes, product types, locations, and facility types. Hence, the occurrence of cargo theft incidents is dynamic depending on the situations in which the relevant risk factors are present in an interactive way.

To fill the research gap, this study aims to develop a data-driven risk analysis model for the diagnosis of the effect of relevant RIFs on cargo theft and the prediction of the occurrence of different types of theft incidents. To achieve this aim, this chapter first describes the identification of the RIFs influencing cargo theft from both the relevant literature and the historical database. Secondly, it uses a data-driven BN approach to evaluate the effects of the identified RIFs on the occurrence of different categories of cargo theft incidents. Furthermore, the model is verified using multiple methods, including a test using real cases, sensitivity analysis, and scenario analysis.

The rest of the chapter is structured as follows. Section 4.2 reviews the current studies on cargo theft and the literature-based risk factors influencing cargo theft. Section 4.3 describes the development and application of a new methodology. Section 4.4 presents the model validation results through various methods. The analysis and results are presented and discussed for insightful implications in Section 4.5, while the conclusion is drawn in Section 4.6.

4.2 Literature Review on Cargo Theft

This literature review consists of two subsections: a comprehensive review of existing cargo theft literature and a detailed analysis of the risk factors that influence cargo theft.

4.2.1 Studies on Cargo Theft

Among the limited studies on cargo theft in the current literature, most have focused on the countermeasures against different types of cargo theft incidents, while relatively few have explored the nature of cargo theft, including the probabilities of the incidents and the relevant influential factors. Specifically, the majority of research has addressed prevention strategies (Gastón Cedillo-Campos et al., 2024; Hawkes and Lydia, 2023; Toth, 1998) as well as communication and monitoring systems (Fokum et al., 2009; Harvey, 2004; Islam et al., 2023; Klodzinski and Kerr, 2007; Oranye et al., 2004; Yuan and Huang, 2008).

In 2009, Ekwall analysed and explained why cargo theft continued to occur despite all the implemented countermeasures. Since then, the awareness of the significance of investigating the nature of cargo theft has been growing. Although most subsequent studies have continued to focus on developing technologies, tools, and systems to combat cargo theft, a few have aimed to capture the risk characteristics of cargo theft incidents. These studies often appear within the broader context of supply chain security and examine issues such as: the impact of low-wage labor on supply chain security (Belzer and Swan, 2011), seasonality of cargo theft (Ekwall and Lantz, 2013), the effects of Modus Operandi (MO) and location type on cargo theft (Ekwall and Lantz, 2015a, 2015b), risk assessment of cargo theft (Ekwall and Lantz, 2016), key factors behind cargo loss severity in logistics systems (Wu et al., 2017), geography of cargo theft (Aransiola et al., 2023; Hernández Ramírez, 2024; Justus et al., 2017), and prediction of the cargo theft probability in rail transport (Lorenc et al., 2020; Lorenc and Kuźnar, 2018a).

Despite the evolution of themes in cargo theft research, the state-of-the-art methodologies in the field are mainly based on qualitative and/or basic statistical methods to investigate cargo theft factors. In other words, very few studies involve quantitative methods, and from the applied research perspective, the cases in such studies often represent a single component of a whole supply chain. As a result, the current cargo theft risk studies have revealed significant limitations from empirical and methodological perspectives. For instance, Silva and Sampaio (2023) studied cargo robbery in last-mile e-commerce deliveries in developing countries. Using real data from a major Brazilian e-commerce company, they applied regression and cluster analysis to identify key factors, such as shipment value, quantity, time of day, third-party services, and escort presence, that affect the insured value of stolen goods. They recommended improved security and tracking systems. While their findings offer valuable insights for e-commerce logistics, the focus on last-mile delivery may limit their relevance to other parts of the supply chain. Tang et al. (2010) used a hierarchical structure of criteria to evaluate the security levels against theft in a port storage area in Container Supply Chain (CSC). Based on the structure, a belief Rule-based Inference Methodology using the ER algorithm was applied to handle the various kinds of uncertainties involved during the evaluation process and generate the evaluation result. Using a hierarchical structure to model the risk factors/variables of cargo theft can easily overlook the interdependency among the factors/variables and hence affect the model's validity. Wu et al. (2017) utilised data-driven business analytics involving descriptive, predictive, and prescriptive analysis to investigate cargo loss severity in logistics systems based on the data from an electronics company. Again, it overlooked the interdependency among the factors/variables, and thus, the reflection of the result to reality became questionable. Song et al. (2020) used a data-driven approach to predict the theft risk of bulk cargo in ports based on the data from Guangzhou Port Group and Guangzhou Port Security Bureau in China. Various binary classifiers, including OneR, Decision Tree, Random Forest, Naïve Bayesian, and BN, were compared, and the results showed that BN was a suitable predictive model. However, the BN structures derived from two different structure-learning algorithms were different, requiring subjective knowledge to configure the final structure. In addition, the results could not reflect the effects of multiple states of the identified risk factors. Lorenc et al. (2020) used Artificial Neural Networks and Machine Learning methods to predict the probability of cargo theft in railway transport, respectively. Although showing some attractiveness, the methods failed to disclose the joint significance of multiple risk factors and their interdependency, leading to limited insights on prevention measures.

Clearly, previous studies have revealed some theoretical implications on quantitative cargo theft risk analysis that have not been well addressed in the current literature, and they could not be achieved without the analysis of the interdependency of the RIFs from a whole supply chain perspective. To fill this gap, this study aims to develop an advanced quantitative method to analyse the interdependence among the RIFs of cargo theft and pioneer a risk analysis model to realise the cargo theft risk prediction and diagnosis.

4.2.2 RIFs Influencing Cargo Theft Identified in the Literature Review

A cargo theft incident could occur in any part of a freight supply chain along with the cargo flows. However, the occurrence of cargo theft incidents in terms of time, place, MO, and some other factors follows certain rules to be explored. It is therefore crucial to identify and analyse the relevant RIFs. To do so, 92 relevant papers published from 1970 to 2021 were first found by searching the keyword "cargo theft" on the WoS. Secondly, book chapters were excluded. By the screen of titles, abstracts, and conclusions, we also excluded the papers 1) that addressed the development of security means and systems against cargo theft and 2) that focused on the evaluation of logistics performance without discussing the causes of cargo theft. As a result, 28 papers are finally selected, among which 22 risk factors appear frequently and are chosen for further analysis. These factors and their appearance frequencies are shown in Figure 4.1. Moreover, such factors are analysed at different levels in the selected literature. We use class I to represent the factors if their impacts are evidentially evaluated using mathematical methods, and class II to represent the factors that appear in the selected literature just to support the research background or used in a specialised segment (i.e., bulk cargo). For example, studies in the former context focus on RIFs as the central research question, systematically addressing their influence on cargo theft occurrences through data collection and analysis. Conversely, in the latter case, some studies analyse cargo theft within a specific transportation mode, such as trucking or rail, indicating transportation mode as a potential RIF. However, these studies leave the precise variability of cargo theft occurrences across different transportation modes unclear. With reference to this classification, Table 4.1 illustrates the extent to which the 22 risk factors are analysed across the 28 references, and numbers 1 to 22 are used to represent the 22 risk factors in the front row. Obviously, some factors appear in both class I and class II because they receive different levels of analysis in different literature. There are eight factors out of the 22 factors that are analysed at the level of class I, and these eight factors and their appearance frequencies as class I factors are shown in Figure 4.2. The rest of this section summarises how these important RIFs are described in the selected literature.

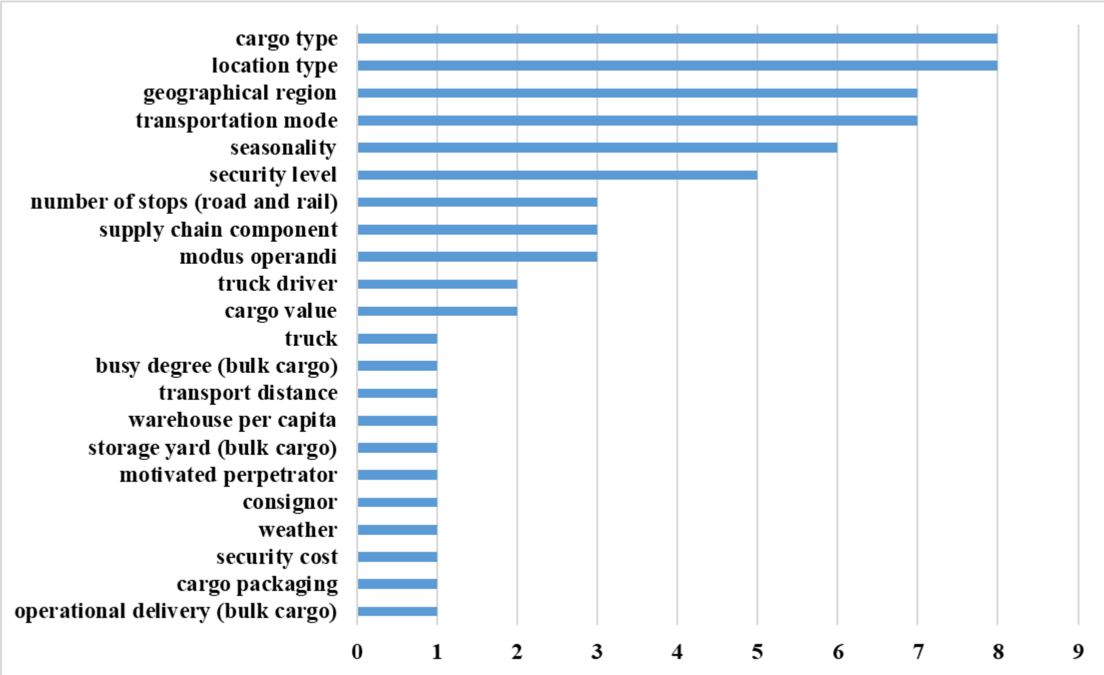

Figure 4.1 All the identified RIFs in the reviewed literature.

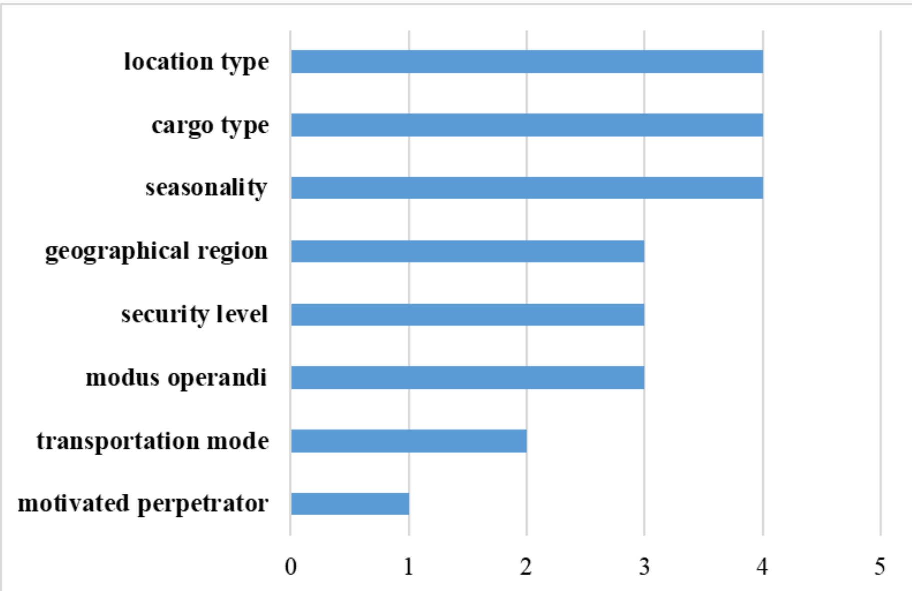

Figure 4.2 The in-depth investigated RIFs in the reviewed literature.

Table 4.1 References to the identified risk factors of cargo theft.

Reference	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
(Belzer and Swan, 2011)											II											
(Boone et al., 2016)								II														
(Burges, 2013)		II																				
(da Silva et al., 2018)																				II		
(Ekwall and Lantz, 2013)		I			I		I															
(Ekwall and Lantz, 2015b)		I			I																	
(Ekwall and Lantz, 2015a)					I		I															
(Ekwall and Lantz, 2016)		I																				
(Ekwall and Lantz, 2018)	I	I		I			I															
(Ekwall et al., 2016)			I			I																
(Ekwall, 2009)	I					I																I
(Guerin et al., 2021)																		II				
(Justus et al., 2017)	I		I		I																	
(Kit et al., 2019)				II																		

(Kubanova and Kubasakova, 2020)				II																	
(Kubanova and Poliaková, 2016)		II																			
(Lorenc and Kuźnar, 2018a)	II								II	II									II		
(Lorenc and Kuźnar, 2021)				II																	
(Lorenc and Kuźnar, 2018b)	II	II	II	II	II	II			II												
(Lorenc et al., 2020)	II	II	II	II	II	II			II												
(Orfanus, 2011)			II																		
(Repolho et al., 2019)			II					II													
(Shoukry, 2015)										II											
(Song et al., 2020)											II	II	II	II	II	II	II				II
(Tang et al., 2010)						I															
(Toth, 1998)	II																				
(Kuo-Yu et al., 2019)								II													
(Wu et al., 2017)	I		I	I																	

Note: I presents class I, and II presents class II. In the list below, * indicates factors that are present in class I but not exclusive to it, while ** denotes factors that are exclusive to class II.

1. cargo type*, 2. location type*, 3. geographical region*, 4. transportation mode*, 5. Seasonality*, 6. security level*, 7. MO*,

8. supply chain component**, 9. number of stops (road and rail)**, 10. cargo value**, 11. truck driver**, 12. cargo packaging**, 13. Weather**, 14. Truck**, 15. operational delivery (bulk cargo)**, 16. Consignor**, 17. busy degree (bulk cargo)**, 18. warehouse per capita**, 19. transport distance**, 20. security cost**, 21. storage yard (bulk cargo)**, 22. motivated perpetrator*.

Cargo type. Cargo type is one of the most frequently observed influential factors influencing cargo theft in terms of the likelihood of incidents and consequences (e.g. stolen value). Ekwall (2009) found that the thieves target the type of goods more than anything else, such as those relating to the theft opportunities exposed in a transport network. In other words, perpetrators tend to change different MOs to target the same product that they are interested in. According to 2021 data from CargoNet, the prime targets of thieves are electronics amid the chip shortage in the world and refrigerated food. BSI-recorded cargo thefts of medical devices and supplies, including PPE, jumped by over 5,000 percent in 2020 compared to 2019 due to the COVID-19 pandemic.

Location type. Location type is one of the two most frequently used risk factors in cargo theft studies. Cargo can be stolen when it takes a stop in some places such as warehouses, terminals, equipment, and truck stops. Besides, trailers and containers have become virtual warehouses on wheels and easy targets for thieves, with the Just-In-Time delivery replacing the on-hand inventory of most businesses (Toth, 1998). 97% of all attacks during a stop occur at non-secure parking locations (Ekwall and Lantz, 2015b). Cargo thefts at these locations are more of a volume crime than high-value thefts, according to the TAPA EMEA data. The risk levels of different combinations of location types and incident categories in terms of both impact and probability were examined (Ekwall and Lantz, 2016). According to the BSI and NMU cargo theft report of Q1 2021, a wide variety of tactics were involved in cargo thefts throughout Europe. The United Kingdom, Germany, Russia, Italy and France generally record some of the greatest numbers of thefts in the region. As noted at the beginning of the outbreak of the COVID-19 pandemic, a higher-than-usual number of thefts continue to occur from warehouses and facilities. As a result of disruptions to movement caused by the pandemic, stockpiled goods and trucks parked outside of warehouses and facilities became more accessible targets for thieves.

Seasonality. The seasonal variation in theft incidents was observed during particular months of the year and days of the week for many location types along transport chains (Ekwall and Lantz, 2013) and MOs (Ekwall and Lantz, 2015). The seasonal effect was also observed in cargo theft incidents that occurred in the São Paulo State of Brazil (Justus et al., 2017). Nevertheless, the patterns depend on different categories, e.g., the variation over a year is approximately the same for all location types, while the variation over a week is different (Ekwall and Lantz, 2013); the seasonal effect on violent cargo thefts is evident to be small (Ekwall and Lantz, 2018).

Geographical region. There is ample evidence that the nature of cargo theft differs among geographical regions. Cargo theft involving violence is rare in the United States, however, violence (such as intrusion, pilferage, and hijackings) is more common in Europe. In Mexico, cargo theft is an extremely violent crime committed by gangs (Burges, 2013). In Brazil, it mainly occurs in the most economically dynamic regions, such as the states of São Paulo, Minas Gerais, and Rio de Janeiro. Although São Paulo's capital shows the highest levels of cargo theft, it is in non-metropolitan areas that records of this offence are on the rise (Justus et al., 2017). Based on the data from a case company, the research by Wu et al. (2017) found that when products were shipped using sea transport to Australia or the Middle East, cargo loss of medium severity was likely to occur.

Transportation mode. Cargo theft occurs while it is in the logistical cycle of being transported by a mode of transportation (Toth, 1998). Among the critical logistics factors (transit types, product categories, and shipping destinations) influencing the severity of cargo loss, transit type was determined to be the most influential factor in the severity model (Wu et al., 2017). The case company investigated by Wu et al. (2017) suffered cargo loss (claim payments) during air, sea, and land transportation. The primary cargo loss in terms of loss value was correlated with sea transport, followed by air transport and truck transport. However, the occurrence of cargo loss incidents by air transport was much higher than that by sea transport.

Security level. Transport security means the measures to prevent both terrorist attacks and ordinary crime, especially theft (European Union, 2006). Tang et al. (2010) studied on security evaluation of a port storage area against theft in CSC, stating that security analysis is critical in CSC operation as CSC is a dominant way to transport cargo worldwide and at the same time it is also subject to many threats.

Other factors. Previous studies have also identified other factors influencing the occurrence of cargo theft incidents. Based on the theory of crime displacement, Ekwall (2009) identified the three elements of cargo theft, including the motivated perpetrators, transported goods (object), and preventive measures. Furthermore, MOs for cargo theft exhibit seasonal patterns by time of the year and day of the week (Ekwall and Lantz, 2015). Song et al. (2020) identified the influential factors of bulk cargo theft, such as truck driver, truck type, weather, cargo packaging, storage yard type, consignor, and operational setting.

4.3 A Data-Driven BN Model for Cargo Theft Risk Analysis

4.3.1 The proposed framework

To identify the RIFs influencing cargo theft occurrences and assess the importance rankings of RIFs, this study uses a data-driven BN method to train and learn from the big cargo theft data from TAPA. The proposed framework is presented in Figure 4.3. Firstly, the data on cargo theft incidents that happened in the UK is collected from TAPA, and a necessary process of data management and purification is conducted. Secondly, the identified RIFs of cargo theft, extracted from the cleaned TAPA incident reports, are verified against insights obtained from the literature. Thirdly, the cleaned dataset is used as input to construct the model using the data-driven BN approach. Next, the model is validated in terms of its predictive ability and consistency. In this process, a real case test and sensitivity analysis are conducted. The sensitivity analysis provides results on the importance of RIFs, their interrelationships, and the effects of their various states, offering valuable insights for research implications. Finally, the results are presented and discussed thoroughly.

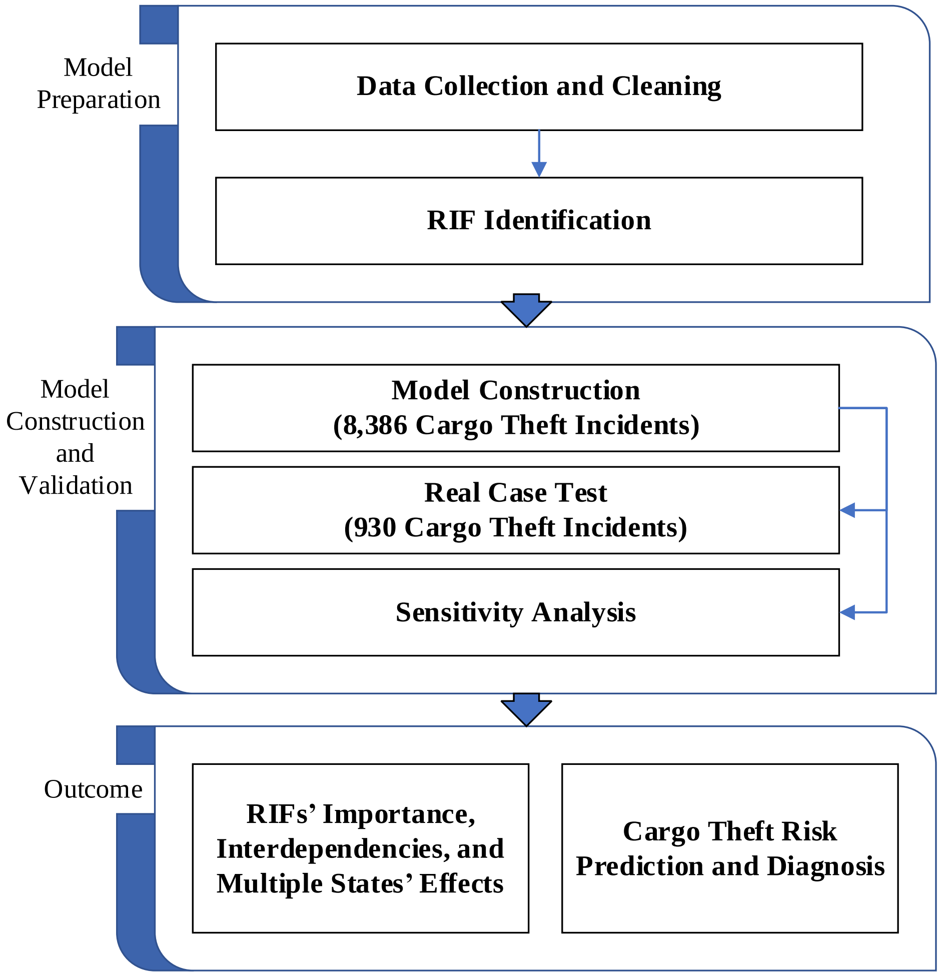

Figure 4.3 The proposed framework for cargo theft risk assessment.

4.3.2 Data Collection and Cleaning

Compared to the one-year incident data used to support most of the previous studies in the field, however, 20,270 reported cargo theft incidents in the UK, ranging from 2009 to 2021, were collected from TAPA EMEA IIS to support the analysis in this study. For each reported incident, entries can be made for the date of the incident, geographical location (including region, town, and district), location type (e.g., destination facility), type of incident (e.g., truck theft), type of MO, product category, loss value, major incident (by yes or no), attempt (by yes or no), last-mile delivery (by yes or no), and incident description. Given the fact that many incidents contain incomplete information, such as unspecified products and unknown incident categories, a data cleaning process is conducted to ensure the data completeness and the accuracy of the developed model. Finally, 9,316 incidents containing all complete data are used in this study. 8,386 incidents (90%) are randomly chosen and used to build the model, while the other 930 incidents are reserved to test the model for its validation.

4.3.3 RIF Identification

In the process of data purification, one variable, 'last mile delivery', is removed because the character has been recognised and the relevant data has only been available since 2019. As a result, nine RIFs influencing 'incident category' are identified, including major incident, attempt, MO, location type, product category, weekday, region, month, and year, among which weekday, month, and year are derived from the date column in the incident report.

There is a significant alignment between the RIFs investigated in the previous literature and those identified from real incidents, as shown in Figure 4.2. To be specific, seasonality is related to month and weekday; the transportation mode is associated with the incident categories; the security level investigated in the previous literature is not incorporated in this study because of the lack of a well-established definition and globally acceptable standards. Attempts and major incidents are additional RIFs identified from the incident reports. According to TAPA's explanation, an attempt is the act of trying to steal cargo/load/shipment unsuccessfully, while a major incident is defined as one causing a loss value of over €100k.

Moreover, each RIF has various states. Table 4.2 shows the states of the 'incident category' and the nine RIFs. This study uses the same definitions of states adopted by TAPA (https://tapaemea.org/iis-key-glossary). The states with very low percentages among the 9,316 incidents are combined and categorised under a new state, 'Other,' as they lack sufficient statistical significance.

Table 4.2 States of cargo theft variables.

Variable	States	State - 'Other'
Incident category	Theft from Container/Trailer, Theft from Facility, Theft from Vehicle, Theft of Container/Trailer, Theft of Vehicle, Truck Theft, Other	Clandestine, Fraud, Hijacking, Robbery, Theft, Theft from Train
Year	13 years from 2009 to 2021	

Month	12 months	
Weekday	7 days	
Region	East Midlands, East of England, London, North East, North West, Northern Ireland, Scotland, South East, South West, Wales, West Midlands, Yorkshire and the Humber	
Product category	Clothing & Footwear, Food & Drink, Miscellaneous, No Load, Tobacco, Other	Agricultural Materials, Bicycles, Car parts, Cash, Computers/Laptops, Cosmetics & Hygiene, Furniture/Household Appliances, Jewellery/Precious Metals, Metal, Pharmaceuticals, Phones, Sports Equipment, Tools/Building Materials, Toys/Games, Tyres
Location type	Destination Facility, En Route, Origin Facility, Unclassified Parking, Other	Authorized 3rd Party Facility, Aviation Transportation Facility, Maritime Transportation Facility, Railway Operation Facility, Road Transportation Facility, Secured Parking, Services 3rd Party Facility,
MO	Intrusion, Theft from Moving Vehicles, Violent & Threat with Violence, Other	Internal, Forced Stop, Deceptive Stop, Deceptive Pick-up, Deception Other
Attempt	No, Yes	
Major incident	No, Yes	

4.3.4 Model Construction of BN

As introduced in Section 2.5, due to it many advantages, BNs have been widely used in the maritime and transportation sectors for risk factors analysis and have gained increasing popularity in recent years, as evidenced by various studies (Fan et al., 2020; Li et al., 2014; Trucco et al., 2008; Xie et al., 2007; Yang et al., 2018; Dindar et al., 2022; Liu et al., 2022; Nguyen et al., 2021; Ung, 2021; Wu et al., 2021; Yin et al., 2022; Yu and Gardoni, 2022; Zhang and Mahadevan, 2021). The BN structure can be constructed based on subjective and/or objective methods. This study utilises a data-driven method to build the BN structure using TAN. Let A_1, $\ldots A_n$ be the risk variables, where n stands for the number of variables, TAN structure learning is the procedure of finding a tree-defining function π over A_1, $\ldots A_n$ to maximise the log-likelihood. This procedure follows the general outline proposed by Chow and Liu (1968). Among various forms of Bayes network classifiers, Naive Bayes is the simplest and is competitive with other classifiers such as C4.5 (Friedman et al., 1997). However, its conditional independence assumption among features cannot well reflect reality, which makes a severe limitation on its application in empirical studies. TAN relaxes the independence assumption of naive Bayes, yet at the same time maintains the computational simplicity and robustness of naive Bayes (Friedman et al., 1997). One characteristic that differentiates the TAN model from the traditional BN lies in the class variables. Each class variable in the BN model must have at least one parent node. However, the links can go in either direction using Bayesian inference on the results to reflect reality (Yang et al., 2021). Because of this superiority, TAN has been increasingly used to train big data to formulate BN risk models in transport (Fan et al., 2020; Zaili Yang et al., 2021; Zhisen Yang et al., 2021; Yu et al., 2021).

Once the data is obtained and cleaned, the structure of BN can be generated through the process of TAN learning with the assistance of the Netica software. As a result, a new cargo theft risk BN model containing 10 nodes is formulated. The originally obtained structure is shown in Figure 4.4, the links can go in either direction to fit the result in reality.

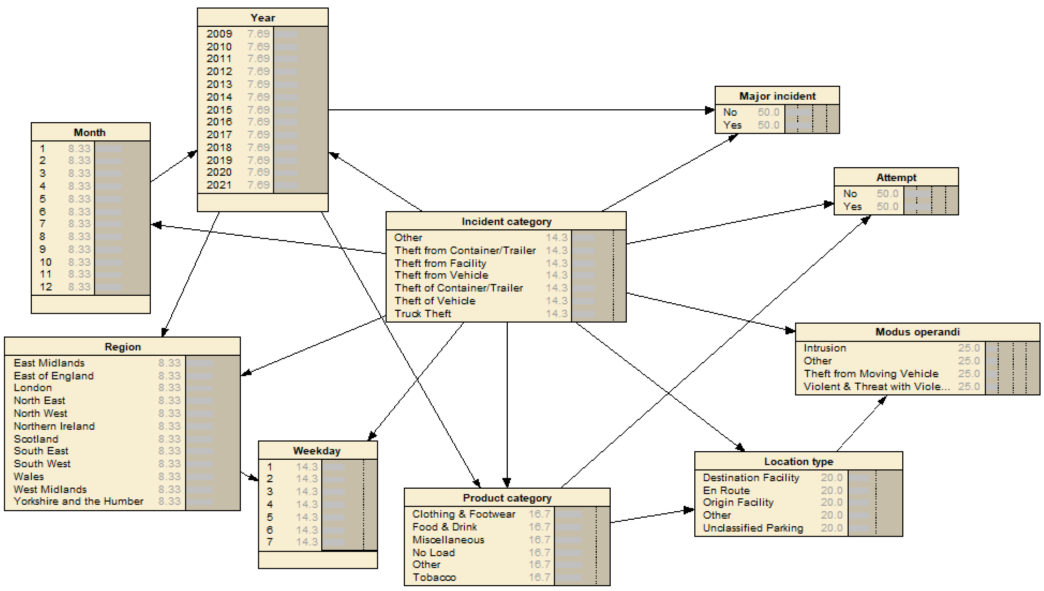

Figure 4.4 TAN structure for theft incident category.

Based on the TAN model, the CPTs of the involved nodes are then learned. Figure 4.5 presents the results of TAN. It indicates that ‘theft from vehicle’ is the most frequent incident type, accounting for

64.2% of all incident categories, followed by truck theft and theft of vehicles, accounting for 20.3% and 6.26%, respectively.

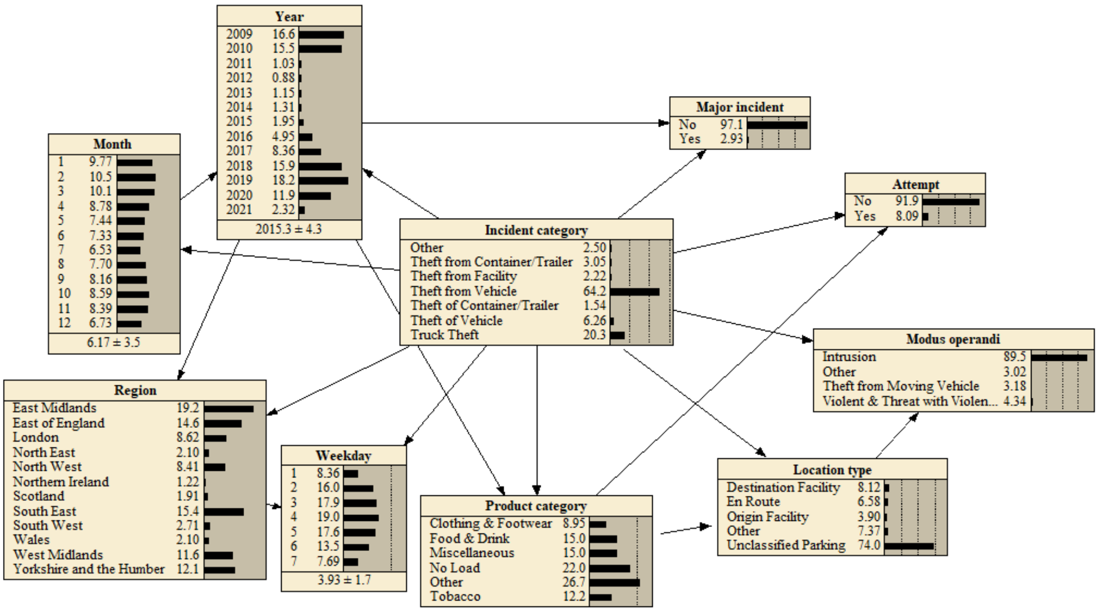

Figure 4.5 Results of TAN for theft incident category.

4.4 Model Validation

The developed model is validated by three means, including 1) the comparative analysis of the historical statistics and the predicted results learned through 8,386 cargo theft incidents; 2) the real case tests using the reserved 930 cargo theft incidents; and 3) the logic inference validation by sensitivity analysis to see if the risk prediction results reflect the reality within the context of cargo theft.

4.4.1 Comparative Analysis

The results of TAN have shown a very high reliability when compared to the historical statistics as shown in Table 4.3. To be specific, the predicted probability of ‘truck theft’ is the same with historical data (20.27%); the differences are 0.04% in ‘theft from vehicle’, and 0.01% in each other incident category. The very small variations are possibly caused by the introduction of the new state ‘other’. It proves the prediction accuracy of the built model.

Table 4.3 Comparative results of the historical data and TAN.

Incident category	Historical data (%)	Results of TAN (%)
Other	2.49	2.50
Theft from Container/Trailer	3.04	3.05
Theft from Facility	2.21	2.22
Theft from Vehicle	64.21	64.17
Theft of Container/Trailer	1.53	1.54
Theft of Vehicle	6.25	6.26
Truck Theft	20.27	20.27
Grand Total	100	100

4.4.2 Real Case Tests

This study uses real cases to test the proposed model. A confusion matrix (see Appendix B) is generated to compare the prediction results with the true values of incident categories of real cases. Moreover, the kappa statistic is used to test the model's consistency.

1) Prediction ability

930 incidents (10%) were reserved by random selection from the original database and used to test the prediction ability of the model, resulting in an overall accuracy rate of 89.14%. According to the confusion matrix in Appendix B, the prediction accuracy rates are 96.33% in ‘theft from vehicles’, and 97.91% in ‘truck theft’ by counting the number of correctly predicted incidents out of the actual incidents. Compared to the previous studies using BN in risk prediction (Yang et al., 2021; Song et al., 2020), our result indicates that the model is robust for predicting the incident category of a cargo theft incident.

2) Kappa statistic for model consistency test

Kappa coefficient (*k*) was introduced by Cohen (1960) as a statistic to measure the agreement between two raters. It has been applied in many fields and has been used in this study to measure the agreement between the predicted results and the real results. The definition of *k* is:

$$k = \frac{p_0 - p_e}{1 - p_e} \qquad 4\text{-}1$$

Where p_o is the relative observed agreement between raters, and p_e is the hypothetical probability of chance agreement, using the observed data to calculate the probabilities of each observer randomly seeing each category. To calculate the *k* value for our confusion matrix, p_o is the sum of the correctly classified incidents divided by the total number of incidents. There are four steps to calculate p_e, including 1) multiplication of the marginal frequency for a certain incident type by the classifier (the sum of the predicted 'Other' incidents) and the marginal frequency for the same incident type by the true value (the sum of the actual 'Other' incidents), 2) division of the multiplied result from Step 1 by the total number of incidents, 3) repetition of the calculations in Steps 1 and 2 for each other incident type, and 4) division of the sum of values from the first three steps by the total number of incidents.

Therefore, the *k* value for the confusion matrix in Appendix A is calculated as follows:

$p_e = (19 \times 25 + 16 \times 37 + \cdots + 190 \times 191)/930 \times 930 = 0.4839, p_0 = 0.8914$

$$k = (0.8914 - 0.4839)/(1 - 0.4839) = 0.7896$$

Although there is no standardised interpretation of the kappa statistic, a kappa (k) of 0.7896 indicates a strong strength of agreement according to Altman (1990). Landis and Koch (1977) consider 0-0.20 as slight, 0.21-0.40 as fair, 0.41-0.60 as moderate, 0.61-0.80 as substantial, and 0.81-1 as almost perfect. Further, according to Fleiss (1971), 0.7896 (>0.75) is excellent.

4.4.3 Sensitivity Analysis

To measure the dependence between incident category and RIFs and validate the model, the sensitivity analysis in this study is conducted based on mutual information, True Risk Influence (TRI) (Alyami et al., 2019), and a joint probability. Besides, a sensitivity analysis can also help validate the model (Jones et al., 2010; Yang et al., 2009).

Mutual information. The concept of mutual information is intimately linked to that of entropy. The entropy of a random variable represents the average level of "information", "surprise", or "uncertainty" of its possible outcomes. The concept of information entropy was introduced by Shannon (1948). Mutual information is the reduction of uncertainty about a variable, quantifying the amount of information obtained about one random variable based on the other variables. Therefore, mutual information is used in this study to measure the mutual dependence between the ‘incident category’ and RIFs, it can be defined as:

$$I(S,\beta) = -\sum_{s,i} P(s,\beta_i) \log_b \frac{P(s,\beta_i)}{P(s)P(\beta_i)} \tag{4-2}$$

where *S* represents the ‘incident category’ of cargo theft, β represents a random RIF (e.g. location type), β_i represents the *i*th state of β, $I(S,\beta)$ represents the mutual information between the incident category and RIFs. The RIFs having higher values of mutual information with the incident category are considered more essential RIFs influencing the incident category of cargo theft. Thus, the overall importance ranking of RIFs can be obtained (see Table 4.4). When ‘incident category’ is the target node, the ‘percentage’ column in the table indicates the extent to which each RIF influences the ‘incident type’. For instance, the influence level of the ‘incident category’ on itself is 100%. It can be seen from the ‘mutual info’ column, that the most essential factor among all RIFs influencing the ‘incident category’ is the ‘product category’.

Table 4.4 Mutual information of ‘incident category’.

Node	Mutual Info	Percentage (%)	Variance of Belief
Incident category	1.6286	100	0.3547
Product category	0.5504	33.80	0.1096
Year	0.3810	23.40	0.0632
Location type	0.1844	11.30	0.0090
MO	0.1289	7.91	0.0069
Region	0.0933	5.73	0.0148
Month	0.0429	2.63	0.0043
Major incident	0.0303	1.86	0.0014
Weekday	0.0260	1.60	0.0043
Attempt	0.0072	0.44	0.0001

TRI. TRI, as a new method of sensitivity analysis, was proposed by Alyami et al. (2019). In nature, the index is generated by the average of the highest and lowest possible influence of a variable on the target node in the investigated risk-oriented BN. It is used in this study because of its ability to evaluate the risk impacts of RIFs in multiple states. Specifically speaking, there are four steps to calculate the value of TRI of a random RIF (e.g., product category) with respect to an incident category (e.g., truck theft). Firstly, it is to increase the probability of each state of a selected RIF (e.g. each product category) to 100%, respectively. Secondly, it is to identify the two states (product types) generating the highest and the lowest probabilities of truck theft, respectively. Thirdly, it is to calculate the absolute difference value between the highest probability (86.60) generated from the second step and the original probability (20.3) of truck theft to obtain the High-Risk Inference (HRI) value; and calculate the absolute difference value between the lowest probability (0.92) generated from the second step and the original probability (20.3) of truck theft to obtain the Low-Risk Inference (LRI) value. Lastly, it calculates the TRI (42.84) of the product category for truck theft by taking the average value of HRI (66.30) and LRI (19.38). The RIFs with higher TRI values have stronger impacts on the investigated incident category. Therefore, the importance rankings of RIFs for different incident categories can be generated. According to the above procedure, the TRI values of the 'product category' for seven different incident categories are calculated by adjusting the probability of each product type to 100%, respectively, as displayed in Table 4.5. Scenarios 1-6 represent the results of adjusting the probabilities of the six product types to 100%, respectively. A similar procedure is then applied to other RIFs. Eventually, TRI values of all RIFs for the seven incident categories are obtained and displayed in Table 4.6. Accordingly, Table 4.7 shows the importance rankings of RIFs in each investigated incident category, it is obvious that the influence of a RIF on cargo theft varies with the incident type. For instance, the 'product category' is the most important RIF for theft from vehicles and truck theft, it is less important for other incident types though.

Furthermore, the network joint probability is generated (as presented in Table 4.8) to reflect the states' effects of RIFs and enable the analysis of the joint effect of multiple RIFs on incident categories. Let *X and Y* represent a random RIF and incident category, respectively, X_i represents the i^{th} state of *X,* Y_j represents the j^{th} state of *Y*. The joint probability that events X_i and Y_j both occur is calculated by:

$$P(X = X_i, Y = Y_j) = P(X = X_i)P(Y = Y_j | X = X_i) \quad \text{4-3}$$

where $P(X=X_i)$ is the prior probability of the i^{th} state of a random RIF X, and $P(Y=Y_j|X=X_i)$ is the conditional probability that the j^{th} state of incident category Y occurs given that the i^{th} state of X has already occurred. The highest joint probability value in each column indicates the most influential state for a particular incident category. For instance, for theft from vehicles, 'tobacco' is the most targeted product (88.2%) and 'en route' is the most influential location type. In each column, both the highest and the lowest values are highlighted as bold and italic values. Thus, it helps understand the influence level of each state on various incident types compared to other states. More analytical results are to be found in the next section.

Table 4.5 TRI of product category for all incident categories.

	Scenario									
Product category	Original	1	2	3	4	5	6			
Clothing & Footwear	8.95	100.00	0.00	0.00	0.00	0.00	0.00			
Food & Drink	15.00	0.00	100.00	0.00	0.00	0.00	0.00			
Miscellaneous	15.00	0.00	0.00	100.00	0.00	0.00	0.00			
No Load	22.00	0.00	0.00	0.00	100.00	0.00	0.00			
Other	26.70	0.00	0.00	0.00	0.00	100.00	0.00			
Tobacco	12.20	0.00	0.00	0.00	0.00	0.00	100.00			
Incident category								HRI	LRI	TRI
Other	2.50	2.86	3.15	3.15	0.89	2.72	3.08	0.65	1.61	1.13
Theft from Container/Trailer	3.05	3.74	2.79	6.07	1.04	3.28	2.27	3.02	2.01	2.52
Theft from Facility	2.22	3.19	2.40	2.48	0.52	3.53	1.14	1.31	1.70	1.51
Theft from Vehicle	64.20	82.60	82.60	67.40	7.20	81.80	88.20	24.00	57.00	40.50
Theft of Container/Trailer	1.54	2.09	2.30	1.37	1.26	1.47	1.04	0.76	0.50	0.63
Theft of Vehicle	6.26	2.86	5.21	18.00	2.54	6.26	2.35	11.74	3.91	7.83
Truck Theft	20.30	2.64	1.57	1.58	86.60	0.92	1.94	66.30	19.38	42.84

Table 4.6 TRI of all RIFs for all incident categories.

	Product category	Year	Location type	MO	Region	Month	Major incident	Weekday	Attempt
Other	1.13	5.13	3.13	15.06	3.48	1.00	7.42	0.46	0.14
Theft from Container/Trailer	2.52	10.09	4.19	0.69	3.12	2.18	4.20	0.66	3.46
Theft from Facility	1.51	7.02	10.05	1.93	3.96	0.98	4.53	1.48	0.25
Theft from Vehicle	40.50	31.90	32.40	33.80	31.16	12.45	23.90	12.65	0.00

Theft of Container/Trailer	0.63	3.44	4.91	1.39	2.71	0.97	3.74	1.47	0.11
Theft of Vehicle	7.83	10.77	12.86	13.53	6.47	7.02	3.99	3.50	1.00
Truck Theft	42.84	32.41	15.62	9.27	16.40	10.22	0.05	7.70	3.00

Table 4.7 The importance rankings of RIFs for the incident categories.

	Product category	Year	Location type	MO	Region	Month	Major incident	Weekday	Attempt
Other	6	3	5	1	4	7	2	8	9
Theft from Container/Trailer	6	1	3	8	5	7	2	9	4
Theft from Facility	6	2	1	5	4	8	3	7	9
Theft from Vehicle	1	4	3	2	5	8	6	7	9
Theft of Container/Trailer	8	3	1	6	4	7	2	5	9
Theft of Vehicle	4	3	2	1	6	5	7	8	9
Truck Theft	1	2	4	6	3	5	9	7	8

Table 4.8 The joint probability.

Product category							
	Other	Theft from Container/ Trailer	Theft from Facility	Theft from Vehicle	Theft of Container/ Trailer	Theft of Vehicle	Truck Theft
Clothing & Footwear	2.86	3.74	3.19	82.60	***2.09***	2.86	2.64
Food & Drink	*3.149*	2.79	2.40	82.60	2.30	5.21	1.57
Miscellaneous	**3.15**	***6.07***	2.48	67.40	1.37	***18.00***	1.58
No Load	***0.89***	***1.04***	***0.52***	***7.20***	1.26	2.54	***86.60***
Other	2.72	3.28	***3.53***	81.80	1.47	6.26	***0.92***
Tobacco	3.08	2.27	1.14	***88.20***	***1.04***	***2.35***	1.94
Year							
	Other	Theft from Container/ Trailer	Theft from Facility	Theft from Vehicle	Theft of Container/ Trailer	Theft of Vehicle	Truck Theft
2009	2.05	***0.52***	1.40	39.70	***0.38***	6.13	49.80
2010	1.67	0.56	***0.77***	***27.80***	0.41	3.12	***65.70***
2011	11.5	8.44	12.00	31.60	6.21	12.30	18.00
2012	9.17	9.85	11.50	31.60	***7.25***	15.80	14.80
2013	8.35	7.56	***14.80***	40.50	5.56	11.90	11.30
2014	***9.51***	9.08	12.70	39.00	4.88	14.90	9.94
2015	5.94	***20.70***	8.89	44.00	4.38	9.46	6.67
2016	3.35	12.30	4.95	69.80	2.28	4.62	2.63
2017	2.27	2.63	1.14	87.00	2.03	3.26	1.69
2018	***1.24***	1.29	0.94	***91.60***	1.66	***2.37***	***0.88***
2019	1.63	3.54	1.59	81.40	1.21	8.93	1.71
2020	2.58	1.50	1.82	82.00	1.80	7.70	2.56
2021	9.15	10.20	5.89	41.50	3.80	***23.90***	5.59

Location type	Other	Theft from Container/ Trailer	Theft from Facility	Theft from Vehicle	Theft of Container/ Trailer	Theft of Vehicle	Truck Theft
Destination Facility	***7.53***	***1.01***	2.52	56.10	0.83	***27.90***	4.07
En Route	3.61	2.72	1.22	***80.30***	1.02	7.49	***3.67***
Origin Facility	5.19	2.24	***20.40***	***15.50***	3.34	18.40	***34.90***
Other	6.79	***9.39***	12.40	35.70	***10.50***	15.70	9.50
Unclassified Parking	***1.28***	2.71	***0.30***	69.00	***0.68***	***2.19***	23.80

MO	Other	Theft from Container/ Trailer	Theft from Facility	Theft from Vehicle	Theft of Container/ Trailer	Theft of Vehicle	Truck Theft
Intrusion	***0.28***	3.13	***2.05***	66.50	***1.41***	4.64	***22.00***
Other	***30.40***	***3.30***	***5.91***	***18.10***	***4.18***	***28.9***	9.15
Theft from Moving Vehicles	2.10	2.19	2.07	***85.70***	2.05	***1.84***	4.02
Violent & Threat with Violence	29.20	***1.92***	3.17	33.10	1.96	27.10	***3.47***

Region	Other	Theft from Container/ Trailer	Theft from Facility	Theft from Vehicle	Theft of Container/ Trailer	Theft of Vehicle	Truck Theft
East Midlands	***1.46***	2.54	***1.29***	***82.30***	1.10	***2.47***	***8.80***
East of England	2.02	4.54	1.34	73.90	1.04	3.65	13.60
London	3.75	1.71	1.73	63.10	0.93	9.09	19.60
North East	5.20	4.89	4.62	45.70	3.85	11.40	24.40
North West	3.83	2.38	3.57	39.80	2.27	9.95	***38.20***
Northern Ireland	***8.42***	***7.83***	9.04	***19.98***	***6.16***	***15.40***	33.10
Scotland	5.39	6.16	***9.21***	34.00	5.09	15.00	25.10
South East	1.56	4.09	1.65	72.30	***0.74***	3.54	16.10
South West	3.78	3.80	5.98	41.50	4.18	11.80	29.00
Wales	5.57	4.90	5.23	26.50	3.59	12.60	41.60
West Midlands	2.60	***1.60***	1.96	54.60	1.73	10.40	27.20
Yorkshire and the Humber	1.64	1.77	1.55	64.20	1.20	4.79	24.80

Month	Other	Theft from Container/ Trailer	Theft from Facility	Theft from Vehicle	Theft of Container/ Trailer	Theft of Vehicle	Truck Theft
1	2.67	3.39	2.19	68.60	1.57	10.75	***10.76***
2	2.70	3.48	2.25	61.90	***0.84***	8.31	20.50
3	2.36	2.72	2.12	61.10	1.41	9.48	20.80
4	2.97	2.73	2.44	61.40	1.00	4.52	25.00
5	***3.65***	***5.99***	1.51	***51.60***	1.18	6.28	29.80
6	3.09	3.74	2.61	63.80	1.95	***2.07***	22.80

	Other	Theft from Container/ Trailer	Theft from Facility	Theft from Vehicle	Theft of Container/ Trailer	Theft of Vehicle	Truck Theft
7	1.73	2.45	2.76	61.90	1.51	4.11	25.60
8	2.06	2.37	2.05	56.40	2.28	3.64	***31.20***
9	***1.66***	2.66	***1.38***	68.00	1.21	2.86	22.20
10	1.71	3.19	1.70	76.40	1.28	2.72	13.00
11	2.83	***1.63***	2.55	***76.50***	1.96	3.06	11.40
12	2.52	2.21	***3.34***	59.20	***2.77***	***16.10***	13.90
Major incident							
	Other	Theft from Container/ Trailer	Theft from Facility	Theft from Vehicle	Theft of Container/ Trailer	Theft of Vehicle	Truck Theft
No	***2.07***	***2.80***	***1.95***	***65.60***	***1.32***	***6.02***	***20.30***
Yes	***16.90***	***11.20***	***11.00***	***17.80***	***8.80***	***14.00***	***20.40***
Weekday							
	Other	Theft from Container/ Trailer	Theft from Facility	Theft from Vehicle	Theft of Container/ Trailer	Theft of Vehicle	Truck Theft
1	2.41	2.63	3.08	48.10	3.56	***11.40***	28.90
2	2.21	***2.35***	2.41	66.10	1.18	6.05	19.70
3	2.49	3.17	***1.51***	67.60	1.13	5.25	18.80
4	***2.02***	2.83	1.58	70.40	***0.86***	4.87	17.50
5	2.9375	3.63	1.6	***71.30***	1.23	***4.41***	***14.90***
6	***2.9434***	3.16	2.81	59.60	1.31	7.39	22.80
7	2.66	***3.66***	***4.46***	***46.00***	***3.80***	9.16	***30.30***
Attempt							
	Other	Theft from Container/ Trailer	Theft from Facility	Theft from Vehicle	Theft of Container/ Trailer	Theft of Vehicle	Truck Theft
No	***2.48***	***2.49***	***2.18***	***64.17***	***1.52***	***6.42***	***20.80***
Yes	***2.76***	***9.40***	***2.67***	***64.20***	***1.74***	***4.42***	***14.80***

4.5 Result Discussion and Implications

4.5.1 Analytical Results

The overall ranking of risk impacts of RIFs on cargo theft incident category shows that ‘product category’ is the most important RIF out of the nine RIFs, followed by ‘year’, ‘location type’, ‘MO’, ‘region’, and the other four RIFs (‘month’, ‘major incident’, ‘weekday’, ‘attempt’). Furthermore, the essential RIFs and their significant states with respect to each incident type are evaluated. The product category is the most important RIF for the overall incident category, mainly because of its significant effects on theft from vehicles and truck theft. Furthermore, ‘tobacco’ is the most targeted product in theft from vehicles, with a joint probability of 88.2% being the highest among all product categories. Besides, a ‘no-load’ truck is more attractive (86.6%) than a ‘no-load’ vehicle/container/trailer/facility.

Location type has significant impacts on many incident types, including theft from facility, theft of container/trailer and vehicle, and theft from container/trailer and vehicle. Regarding the significant states of location type, the most contributing location type of theft from facilities, for example, is 'origin facility'. The most influential location types of theft of vehicles and theft from vehicles are 'destination facility' and 'en route' respectively, which indicates that it is most likely for vehicles to be stolen at destination facilities, and for cargoes to be stolen in motion. However, direct statistics show that 'unclassified parking' is the riskiest location type, accounting for around 75% of all the investigated cargo theft incidents. A possible explanation is that the correlations between location type and other RIFs (i.e., product category, MO) have more contributions compared to its direct contribution to each incident category. A similarity applies to the states' effects of MO, although 90% of the incidents use 'intrusion' according to direct statistics, 'intrusion' is not the most effective MO for the investigated incident types, except truck theft.

The region is the fifth most important RIF influencing the occurrence likelihood of cargo theft incidents, but it still reveals some useful information. For example, in 'East Midlands', the probabilities of theft from facility (1.29%), theft of vehicle (2.47%), and truck theft (8.8%) are the lowest among all regions in the UK, while the risk of theft from vehicle (82.3%) is the highest. On the contrary, in 'Northern Ireland', the risk of theft from vehicles is the lowest in the UK, while the risks of other incident types are higher than those in most of the other regions. Previous studies have also discussed the dynamic character of cargo theft occurrences in geographical regions (Burges, 2013; Justus et al., 2018). This study further investigates this character by differentiating the incident categories of cargo theft.

Month, major incident, weekday, and attempt are less significant RIFs than the other five RIFs. Overall, the seasonal pattern in terms of the month of the year and the day of the week is insignificant. Figure 4.6 displays the trends of probabilities of different cargo theft incident categories in months and weekdays. Looking at the most frequent incident category, i.e., theft from vehicle, the riskiest months are 'October' and 'November', and the peak days during the week are 'Tuesday to Friday'. For other incident categories, e.g., theft from/of container/trailer, theft from facility, and truck theft, 'Sunday' tends to be the peak day during the week. Another finding is that even though direct statistics show that the overall probability of truck theft incidents (20.3%) is much lower than that of theft from vehicles (64.2%), truck theft is the most likely incident type to cause a major incident with a loss value over €100k.

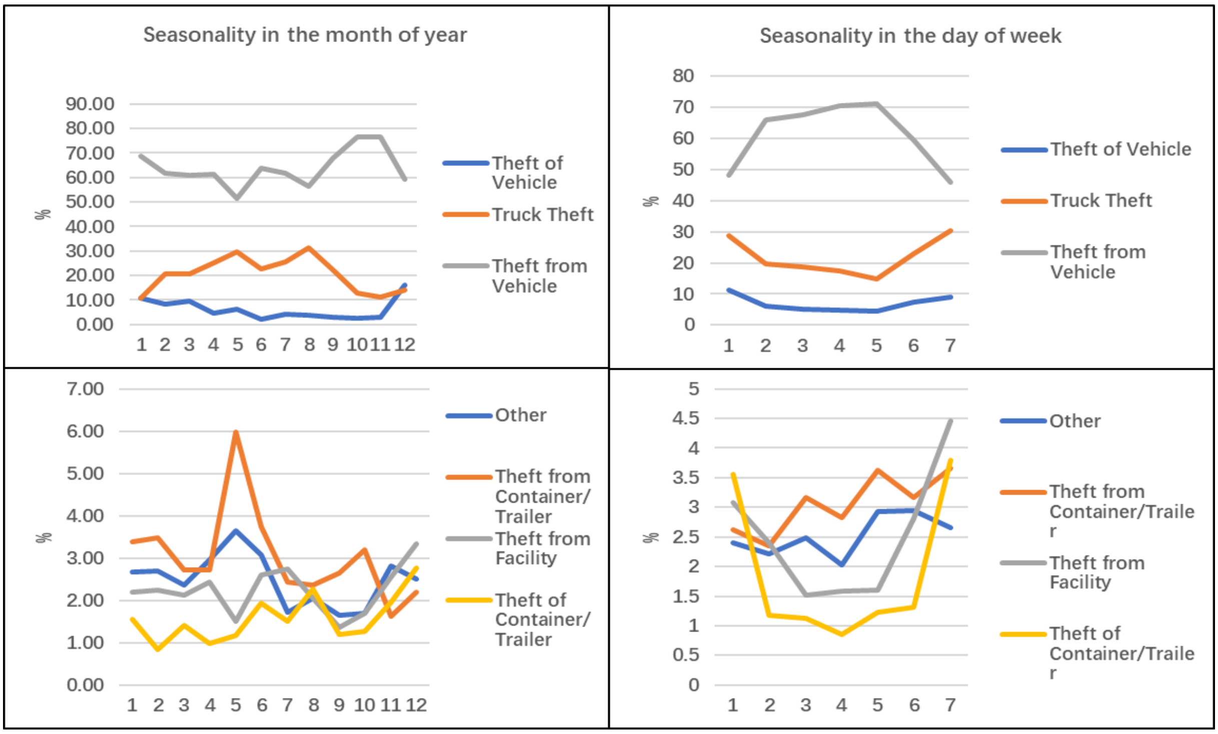

Figure 4.6 Seasonality in incident categories.

In addition to the correlations between incident category and each RIF, BN can reflect the combined effects of multiple RIFs in each incident category to simulate reality. Figure 4.7 illustrates the scenario when 'Tobacco' is 'in transit' in 'East Midlands' in 'May' on a 'Monday', predicting a very high risk for 'Theft from Vehicle' (94.6%). If knowing the probability of a cargo theft incident is such high in advance, freight owners would not deliver their cargoes in that scenario without taking special protection measures. Such high-level risks could be avoided in the future with the availability of our proposed risk prediction and diagnosis model in this study. Figure 4.8 and Figure 4.9 illustrate two other scenarios where the transported product categories are 'Food & Drink' and 'Miscellaneous'. When comparing the risk probabilities of 'Theft from Container/Trailer' in these scenarios, it is found that the most significant state of each RIF for each incident category varies depending on the specific scenarios. For instance, although 'Miscellaneous' is the most targeted product for 'Theft from

Container/Trailer' without knowing the states of other RIFs (see Table 4.8), it is less targeted than 'Food & Drink' in this specific scenario.

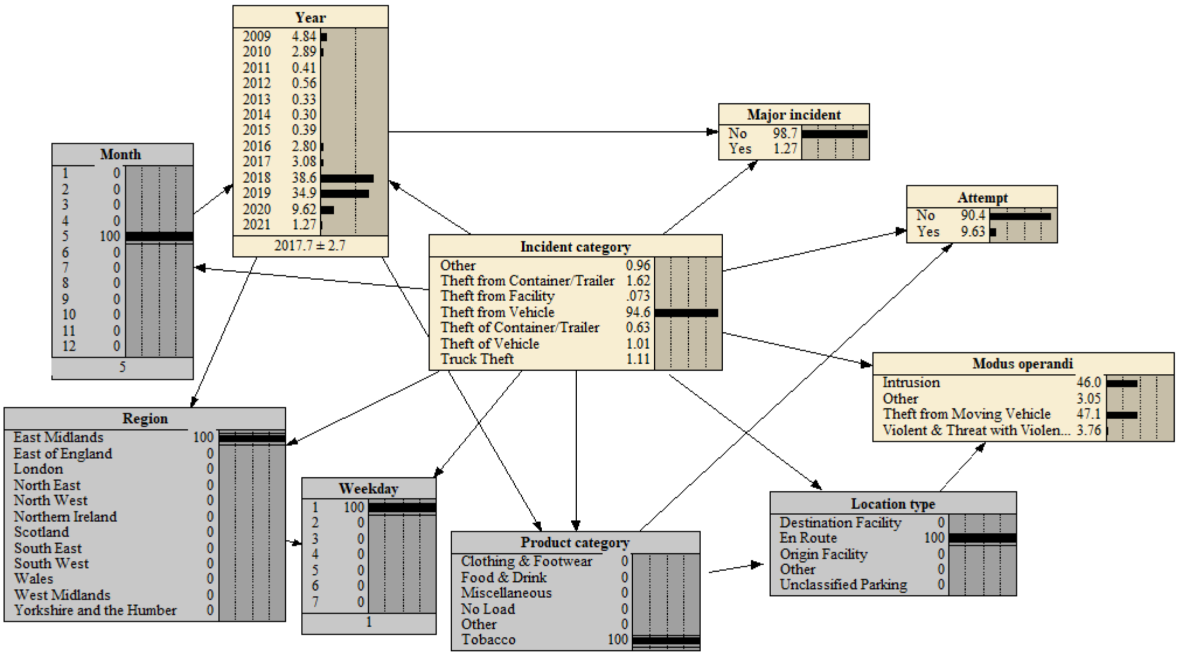

Figure 4.7 Scenario analysis (tobacco).

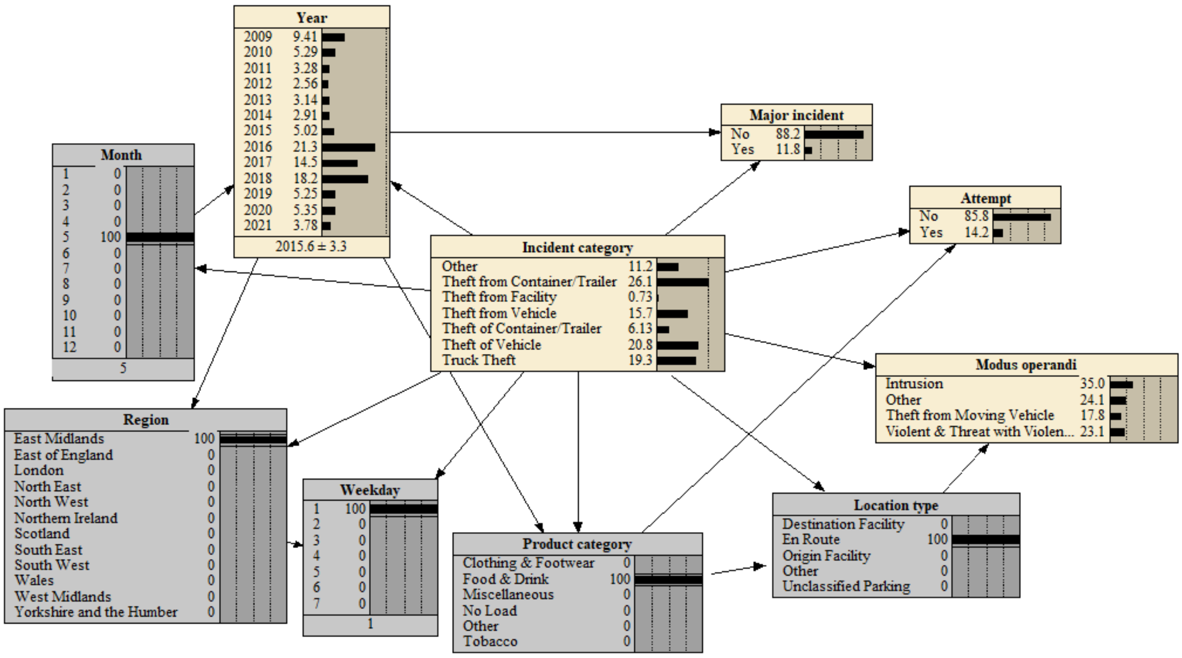

Figure 4.8 Scenario analysis (food & drink).

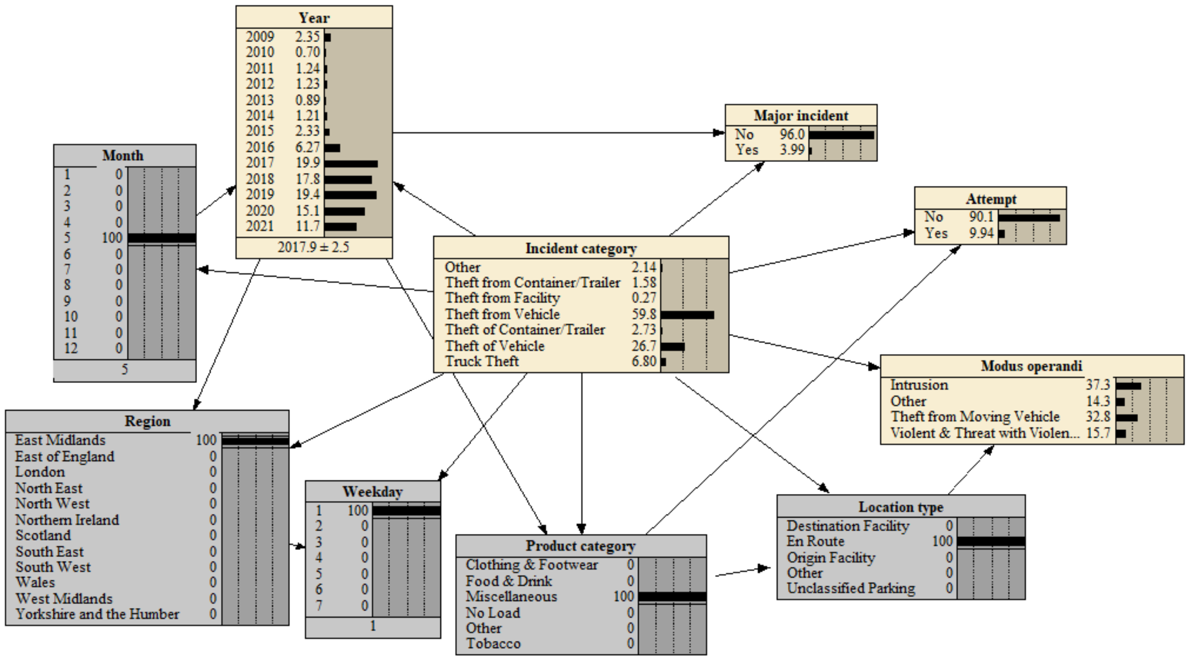

Figure 4.9 Scenario analysis (miscellaneous).

4.5.2 Implications

From the above analytical results, the most important factors and their significant states influencing the occurrence likelihood of cargo theft incidents from freight supply chains have been identified. Accordingly, decision-makers in supply chains can gain useful insights on how to prioritise the resource allocations for various products, location types, and regions where the cargo security level is relatively low. For instance, the highest security setting should be allocated to moving cargoes (e.g., tobacco, clothing & footwear, food & drink) from vehicles to use high-tech real-time monitoring equipment such as drones, considering the significantly high probability of tobacco theft incidents from vehicles. Besides, the highest types of cargo theft incidents in different regions vary, indicating cargo protection associations should enhance cooperation with local transport authorities to develop different safety policies for cargo transportation with respect to the major incident types in different regions.

Based on the known information on cargo type, conveyance mode, location type, and destination region, multiple supply chain stakeholders can use the developed model of this study to make optimised decisions against cargo theft. Logistics companies, for the first time, can evaluate their logistics solutions made for the shippers and/or consignees from a safety perspective beyond the traditional cost and transit time aspects. Insurance companies can make diversified pricing strategies considering not only the cargo value factor but also the risk level of theft crimes derived from the model, simultaneously, freight owners and carriers can select the best-fitted insurance product for their shipped cargo.

This is a pioneering study advising supply chain stakeholders to not only pay attention to the high-valued product, location type, MO, and region contributing to the occurrence of cargo theft incidents but also give special consideration to the direct causal relationships between the states of the essential RIFs and each incident type.

4.6 Conclusion

This chapter describes a new cargo theft risk analysis from both empirical and methodological perspectives. It develops an advanced quantitative risk analysis method to analyse the interdependency of the RIFs influencing cargo theft from a whole supply chain perspective. First, the cargo theft RIFs are identified from the literature and incident records. Second, a data-driven BN is proposed to construct the model with uncertainty to realise cargo theft risk prediction and diagnosis. Despite BN's popularity in such sectors as transportation and energy for incident investigation, its application in freight supply chains is new. Third, the critical RIFs contributing to cargo theft are evaluated to predict the occurrence of possible cargo theft incidents. Lastly, the real incidents are investigated to test and verify the model with an accuracy rate of 89.14%. Furthermore, the model is validated using sensitivity analysis and scenario analysis.

The findings of this study provide the most significant implications for the prevention of cargo theft in freight supply chains.

1) This study pioneers the development of an advanced model to predict the risk level of cargo theft incidents. The most influential RIFs of cargo theft incidents are identified as product category, year, location type, MO, and region from a UK case study.
2) This study reveals the combined effects of multiple RIFs and differentiates the states' effects of each RIF, which enables the scenario simulation of reality.

3) This study recommends that supply chain stakeholders move beyond solely addressing the high-risk states of individual factors contributing to cargo theft incidents and instead focus on understanding the dynamic interactions among the RIFs.
4) The developed model can benefit multiple supply chain stakeholders in prioritising resource allocation and optimising the decisions for cost-effective theft risk control in practice.

Building on the valuable insights gained from this study regarding targeted risk control measures and resource allocation, the next chapter expands the investigation by exploring risk-based inspection strategies to address crimes associated with freeports, such as cargo theft and illicit trade.

CHAPTER 5 A RISK-BASED CONTAINER INSPECTION SOLUTION IN FREEPORT OPERATIONS

Summary

The study develops a novel two-stage decision-making approach for container inspection optimisation in the context of freeport-centric supply chains targeting high-risk containers. The first stage employs a DEMATEL-BN model to assess and predict container risk by analysing the impact of vulnerable nodes within the MCSC. The obtained risk values from the first stage are used as inputs for an optimisation model for effective inspection resource allocation. The study identifies the most critical risk nodes within the MCSC, such as consolidation centres and ports of loading. It makes methodological contributions by addressing uncertainties in operational research. It offers practical solutions for enhancing freeport security without compromising operational efficiency, providing a comprehensive framework for addressing the challenges of illicit trade in a globalised trading environment.

5.1 Introduction

The World Customs Organisation emphasises that customs should oversee freeport operators and tenants to ensure compliance with security standards and requirements, while also carrying out necessary customs surveillance, including inspection, detection, and seizure of illicit goods in freeports. Customs administration often has the authority to detect and seize illicitly traded goods in a freeport. For instance, in the UK, goods must be cleared by customs before they can be moved to a freeport customs site, and containers arriving at a freeport customs site must be opened, and goods checked (HMRC, 2022).

Although container inspection can help secure a freeport against illicit shipments, it increases the customs clearance time for containers moving in and out of freeports. As the simpler customs procedure features one of the benefits of freeports, customs monitoring at freeports requires a scientific solution to realise a balancing act between stringent security measures and trade facilitation. The need for an optimal inspection strategy that ensures effective resource allocation without compromising security or causing excessive delays has become increasingly critical.

With the emergence of FTZs in the world, the service level of the CSC plays an important role in the efficiency, quality and cost of the world trade (He et al., 2015). While some literature proposes optimal container inspection models, a significant research gap persists in developing comprehensive models that evaluate container risk levels by analysing the impact of vulnerable stages within the supply chain, particularly in the context of freeports, where unique challenges and opportunities for illicit trade exist. A comprehensive approach is needed to address this gap and facilitate practical and efficient inspection strategies.

The majority of the world's non-bulk cargo is transported in standard marine shipping containers, which move through multiple transfer points along the supply chain. This journey typically begins at the factory, followed by consolidation and intermodal exchange at a warehouse, transport to a port, sea shipment to another port, and finally, deconsolidation at a warehouse before reaching the buyer. Each of these stages introduces potential vulnerabilities that can be exploited for illegal activities (Kumar and Verruso, 2008). To implement effective container inspection practices, it is crucial to thoroughly understand the underlying risks associated with container movements and develop an effective approach to identifying high-risk containers and quantifying their risks.

To bridge the research gap, this study aims to develop a novel model for optimising container inspection strategies in the context of freeport-centric supply chains. Initially, it invites professionals with expertise in MCSCs and freeports to evaluate the causal relationships among various container transfer points influencing the risk of containers' involvement in illicit activities such as smuggling and trafficking. This evaluation employs a DEMATEL approach, recognising its strength in analysing causal relationships and successful applications across various industries. Based on the output from DEMATEL, a BN is constructed and parameterised using a ranked nodes method to facilitate dynamic container risk assessment. The container risk levels assessed by the DEMATEL-BN model then serve as inputs for an optimisation model designed to determine the most effective inspection strategy given limited inspection resources. Finally, the proposed model is validated and demonstrated through a numerical example to illustrate its practical applicability.

Accordingly, the novelties of this study are highlighted as follows:

1) This study pioneers the use of a BN model to comprehensively evaluate container risks across diverse nodes within the freeport-centric supply chains, providing a dynamic assessment of container risk within a new context.
2) By integrating risk assessment and optimisation models, this study translates risk-based inspection optimisation theory into practical solutions, offering a robust framework to support customs inspection decisions in real-world scenarios.
3) By integrating DEMATEL and ranked nodes approaches to enhance the BN model, this study significantly reduces the uncertainty and high demand associated with expert evaluation. The method effectively preserves the BN model's multi-state capabilities, enabling the assessment of severity-linked probabilities associated with container risk.

The rest of the chapter is structured as follows: Section 5.2 reviews the current container inspection strategies. Section 5.3 outlines the methodology designed for this study. Section 5.4 demonstrates the practical implementation of the methodology, while Section 5.5 discusses the implications of this research. Finally, Section 5.6 concludes this chapter.

5.2 Literature Review on Container Security

5.2.1 Research Themes in Container Security Literature

A systematic literature review was conducted using the WoS database, searching for the topics “container security” or “container inspection” in conjunction with “maritime” or “supply chain” or “port”. Out of an initial 245 results retrieved through the SCI and SSCI indexes (as of March 2025), 79 papers were identified as relevant to the search topics based on title and abstract screening. These papers cover various themes, as detailed in Table 5.1, with the majority of focus on cargo inspection: from demand prediction to strategy development, followed by technology applications for improving cargo container security (e.g., X-ray detectors, wireless sensor networks, and blockchain). In addition, some papers specifically address issues such as container risk assessment, container security initiatives, and resource allocation. Figure 5.1 presents the year distribution of papers across the two primary research themes. The inspection category has the highest number of papers overall, with peaks between 2010 and 2013 and again in 2017. Technology-focused research also has a significant presence, particularly in 2014 and 2021. To align with the focus of this research, the next section will further analyse papers on cargo inspection strategies.

Table 5.1 Research themes in container security literature.

Themes	Number of papers
Review of container security operations	1
Recovery strategies for the disruptions in liner shipping networks	1
Inland terminal layout design for railway safety	1
Implementation of cargo containers control program	1
Container security resource allocation	1
Qualitative studies on container security initiatives	4
Cargo container risk assessment	11
Cargo inspection demand forecasting	3
Cargo inspection strategy development	27
Technology applications for cargo container security	29

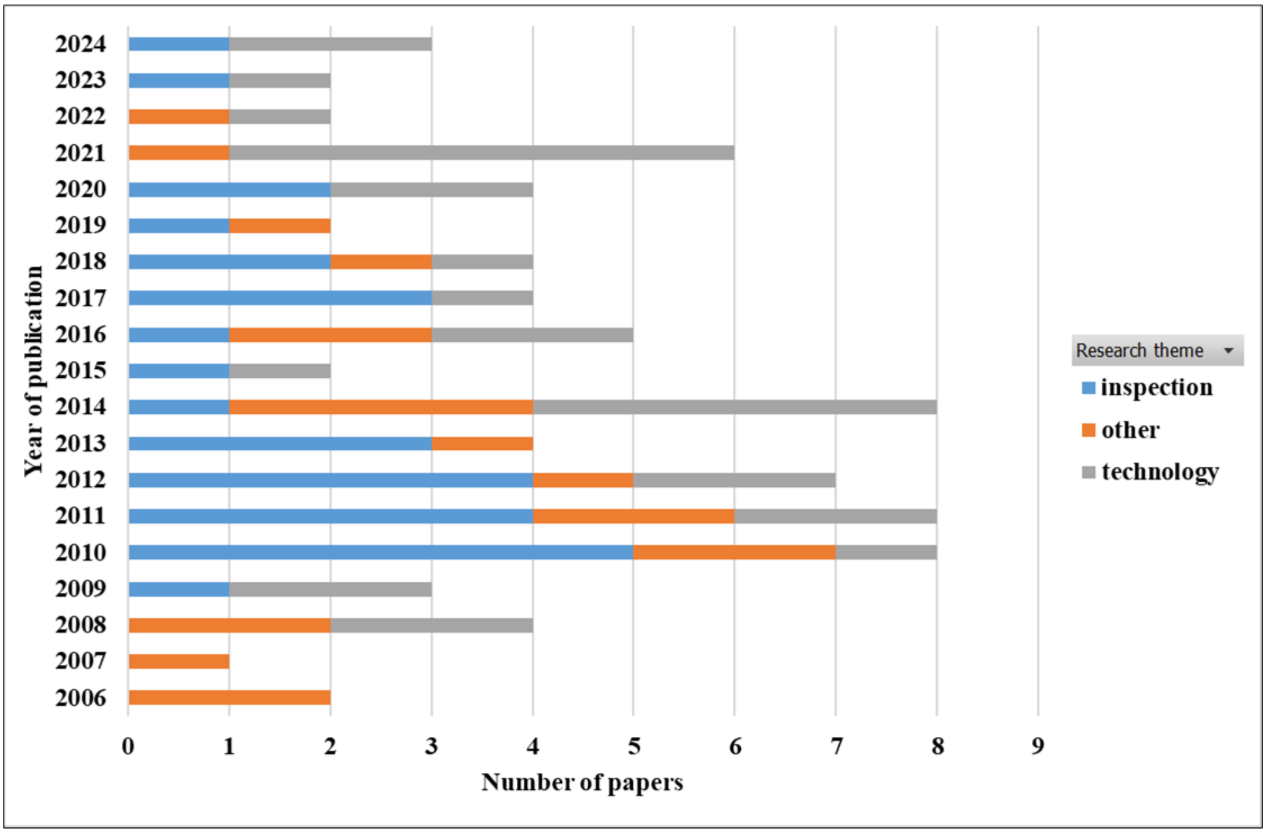

Figure 5.1 The year distribution of papers by major research themes.

5.2.2 Container Inspection Strategy

For the container inspection problem, the literature addressed multiple issues, including optimisation of inspection processes, Public-Private Partnerships (PPP) for security, and the integration of inspection activities within container terminal operations.

The primary challenge in container inspection is achieving a high level of security without causing excessive costs, delays or disruptions to supply chains. Many researchers have addressed this issue. For example, the study by Guan and Yang (2010) analysed how the allocation of berths and inspection operations interact to prevent bottlenecks. By determining the optimal service rate for inspection centres, they ensured that inspection processes did not slow down the overall operations of a container terminal. Similarly, Longo (2010) used a simulation-based approach to model how inspection procedures can be designed to minimise disruption to terminal operations. Longo demonstrated that the flow of containers towards inspection areas can be managed through optimised policies, balancing security demands with operational efficiency. Concho and Ramirez-Marquez (2010) focused on optimising the configuration of the inspection strategy itself by introducing a holistic evolutionary algorithm. They minimised total inspection costs while maintaining a high detection rate for suspicious containers through the optimisation of sensor thresholds. Further, Bichou (2011) conducted an empirical analysis of how security regulations affect the operational efficiency of container terminals. Using a Malmquist DEA, Bichou demonstrated that security regulations can enhance productivity through targeted inspections, especially when complemented by pre-screening and reporting measures. The model developed by Pourakbar and Zuidwijk (2018) proposed an optimal inspection policy that balances security risks and inspection costs by targeting high-risk containers without imposing unnecessary delays on the entire system. Morales et al. (2020) compared fuzzy logic and growing hierarchical self-organising map (GHSOM) techniques for container inspection, incorporating technologies like RFID and X-ray scanning. Their findings suggest GHSOM is especially effective in enhancing security while reducing costs, highlighting the value of advanced technologies in streamlining inspections. Zhou et al. (2020) explored the spatial integration of inspection areas within container terminals, addressing the importance of site selection for inspection centres. They argued that the placement of inspection areas directly affects terminal traffic flow, which in turn influences overall efficiency. In a recent study, Ma et al. (2024) developed an optimisation model to minimise the mean squared error of container-level pest probability estimates produced by the Agricultural Quarantine Inspection Monitoring (AQIM) program in the United States. The model explores the strategic trade-off between sampling more containers with fewer box inspections and sampling fewer containers with more box inspections.

PPP plays a crucial role in enhancing container security while maintaining operational efficiency. Bagchi and Paul (2017) explored the concept of PPP in their examination of the U.S. Customs-Trade Partnership Against Terrorism (C-TPAT). Their model highlighted how the government could shift some security responsibilities to private firms through incentive structures, such as reduced inspections for compliant members. Pourakbar and Zuidwijk (2018) argued that customs authorities rely heavily on information provided by private firms to assess container risks. They suggested that a well-structured PPP can facilitate smoother inspections by sharing data and leveraging private sector investments in inspection facilities. A significant example is the global anti-counterfeiting tool Interface Public Member (IPM), which facilitates information sharing between customs and private firms (Pourakbar and Zuidwijk, 2018). By providing customs officers access to valuable data on counterfeit products, IPM enhances the capacity of customs administrations to target counterfeit goods, while private firms benefit from the protection of their intellectual property. Nikoofal et al. (2023) developed a sequential game involving the government, firms, and an adversary to explore the optimal inspection capacity and incentives. They summarised two key benefits of PPP: reduced inspection rates as an operational advantage and lower infiltration risks as a security benefit.

Several studies have explored how container inspections can be integrated into the everyday operations of container terminals without causing inefficiencies. Longo (2010) used a simulation-based approach to model how inspection procedures can be designed to minimise disruption to terminal operations. Longo demonstrated that the flow of containers towards inspection areas can be managed through optimised policies, balancing security demands with operational efficiency. Zhou et al. (2020) explored the spatial integration of inspection areas within container terminals, addressing the importance of site selection for inspection centres. They argued that the placement of inspection areas directly affects terminal traffic flow, which in turn influences overall efficiency.

Although the developed models in the literature offer theoretical insights into finding optimal inspection strategies, their practical implementation is often constrained by strong assumptions, such as the known information of containers' risk scores and the adversary's decision to infiltrate (Bagchi and Paul, 2017; Nikoofal et al., 2023; Pourakbar and Zuidwijk, 2018). However, such information is usually unavailable or highly uncertain in reality, thereby restricting the practical applicability of these models in real-world scenarios. To overcome this limitation, it is imperative to develop a complementary approach for evaluating container risks. Accordingly, the subsequent literature review will critically examine existing research on container risk assessment.

5.2.3 Container Security or Risk Assessment

In addition to the 11 papers focusing on container risk assessment listed in Table 5.1, a supplementary search using the keywords "container risk assessment" combined with "port," "maritime," or "supply chain" identified two additional studies by Nguyen et al. (2022) and Cao et al. (2025). In particular, Nguyen et al. (2022) reviewed literature on container shipping operational risks from both managerial and methodological aspects and established a framework to distinguish and categorise container shipping operational risk studies using six criteria, including risk bearer/taker, analysis scale, risk coverage, risk approach, concepts and parameters, and applied methodologies. Cao et al. (2025) focused on the cascading failures triggered by extreme events (e.g., natural disasters, geopolitical conflict events, and pandemics). They developed a novel resilience analysis framework using two novel redistribution rules for modelling cascading failures to investigate the impact of port disruptions on the shipping network resilience.

In general, the literature on container security or risk assessment reveals the complex and multi-faceted nature of risks associated with CSCs. A key area of focus is the impact of various risk factors on the CSCs. Studies by Yang (2010) and Chang et al. (2016) explored how risk factors such as physical breaches, financial instability, and operational inefficiencies influence the overall security of the supply chain. Chang et al. (2016) delved into the human element by investigating how employee perceptions of risk vary based on factors like work experience and company size. It highlights the subjective nature of risk perception and underscores the importance of considering human factors in risk management. Some studies identified and classified risks within container shipping to create a more structured understanding of potential vulnerabilities. For instance, Chang et al. (2014) examined three primary risk categories (risks related to information flow, physical flow, and payment flow) and calculated the risk scale of each risk factor by multiplying risk likelihood and risk consequence. Wan et al. (2019) proposed a framework that categorises risks into various aspects, including society, natural environment, management, infrastructure and technology, and operations, and evaluated these factors in terms of their occurrence likelihood and consequence severity.

Several studies have attempted to develop effective risk management strategies. For instance, Yang (2011) and Alyami et al. (2014) focused on tools like risk matrices and Failure Mode and Effects Analysis (FMEA) to assess and manage risks. The use of FMEA, particularly when combined with advanced techniques like FRBN as discussed by Alyami et al. (2014), provides a dynamic approach to evaluate and mitigate risks in container terminals. Riahi et al. (2014) and Kumar and Verruso (2008) emphasised the need for advanced decision support systems that leverage mathematical models and technological tools to assess and mitigate risks in real time. The proposed models aim to enhance the reliability of cargo shipment systems by identifying high-risk containers and operators, thereby improving overall supply chain security. Yang (2010) and Yang and Wei (2013) analysed the trade-offs between implementing stringent security protocols and maintaining the efficiency of maritime logistics. They argued that while security is paramount, it must be balanced against cost, time, and competition factors to avoid imposing excessive burdens on supply chain stakeholders.

However, only a few studies (Kumar and Verruso, 2008; Riahi et al., 2014; Yang et al., 2010) particularly investigated effective strategies to address the risks related to illicit trade involving containers. Moreover, the literature provides limited insights into quantitative methods for assessing container security or risk levels, with studies by Riahi et al. (2014) and Kumar and Verruso (2008) focusing solely on the risk probability in container risk assessments, neglecting to evaluate the risk severity. On the other hand, although Yang (2011, 2010) assessed the impact of risk factors from the CSI on Taiwan's MSC using a loss exposure matrix to identify risk severity and frequency and a bowtie diagram for risk management strategies, the loss exposure matrix may oversimplify complex risks with interdependent effects or cascading consequences, limiting the depth of the analysis.

Container movements span multiple transfer points across the supply chain, each introducing potential security vulnerabilities. Given the dynamic and multifaceted nature of interdependent variables influencing container risk and compromising container security, a key challenge is to develop a holistic risk assessment framework that adapts to these complexities. Furthermore, since all existing studies rely on subjective data for container risk measurement due to the absence of objective data, a novel methodology is essential for effective subjective data collection by addressing uncertainty, inconsistency, and the high demand for expert input.

5.2.4 Research Gaps

Consequently, the following research gaps are identified:

1) A research gap exists in container security research in the unique context of freeports, where the potential for illicit trade demands practical and efficient inspection strategies. Although freeports and the CSC play a critical interconnected role in enhancing global trade efficiency, there is a notable lack of studies that comprehensively assess container risk by accounting for freeports' involvement across multiple supply chain stages.

2) The theoretical models in the literature on optimal container inspection strategies face limited practical implementation due to strong assumptions stemming from the inherent uncertainty of variables in real-world scenarios. This limitation underscores the need for a novel approach capable of quantitatively assessing these variables.

3) The literature highlights another significant gap in container risk assessments, specifically the lack of a dynamic approach for assessing the likelihood of risks associated with different severity levels at

various CSC nodes with cascading effects. Implementing such an approach can help avoid the need for redundant data collection for these two risk dimensions in each new scenario.

To address these gaps, this study investigates container security in a new context of freeport-centric supply chains. It introduces a novel approach utilising BN to manage uncertain variables in container inspection optimisation. BN facilitates the dynamic evaluation of risk variables associated with cargo containers, including the severity and its corresponding probability. To mitigate the inefficiencies of BN in constructing causal networks based on subjective data, DEMATEL and ranked nodes methods are integrated as enhancements. The advantages of this combination are detailed in Section 2.5.

5.3 A Two-Stage Decision-Making Approach for Optimal Container Inspection Strategies

5.3.1 Methodology Overview

The introduction and literature review of this chapter illustrate the need for an optimal container inspection strategy within the freeport context that ensures effective resource allocation while maintaining security and avoiding excessive delays in the face of uncertain demand for inspections. Moreover, addressing the challenge of uncertain variables in existing research is of utmost importance. To mitigate these uncertainties, this study proposes a novel two-stage methodology for decision-making in container inspections, combining risk assessment and optimisation models. Figure 5.2 provides an overview of the methodology flow, highlighting the risk variables that connect the two stages, i.e., container risk severity and the corresponding container risk probability. In the first stage, the proposed methodology enables the assessment of the two variables for a group of containers potentially involved in illicit activities, using a hybrid DEMATEL-BN model. In the second stage, it utilises the outputs derived from the first stage to model optimal inspection strategies for containers arriving at a freeport within a specific time unit. Subsections 5.3.2 and 5.3.3 elaborate on the detailed steps of these two stages, respectively.

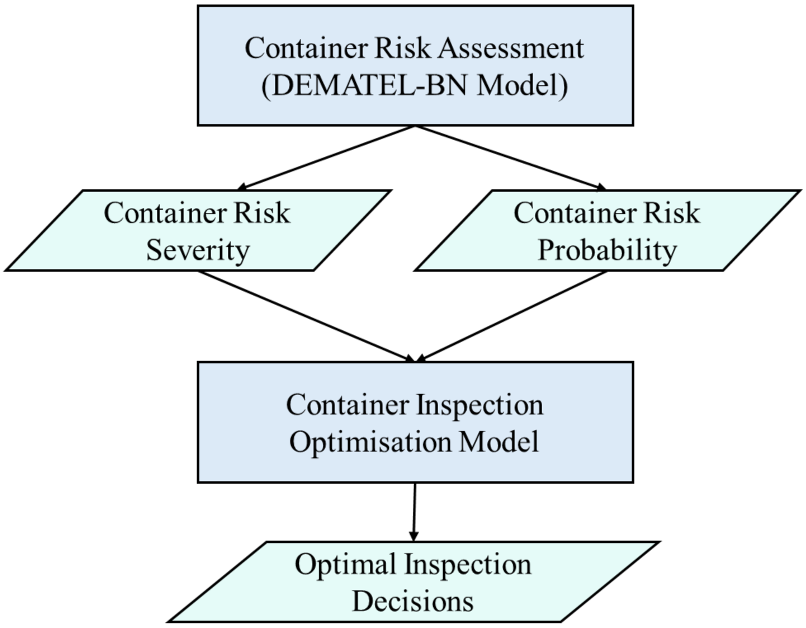

Figure 5.2 The two stages of container inspection decision-making.

5.3.2 Container Risk Assessment

This stage assesses container risk by examining the critical nodes within freeport-centric supply chains that are involved in handling and transporting the container shipment. Based on research by Kumar and Verruso (2008) and Riahi et al. (2014), the most significant nodes in MCSCs are identified as the container Consolidation Centre (CC), Warehouse (WH), Port of Loading (POL), Ocean Carrier (OC), and Port of Discharging (POD). Building on their findings, this study examines these specific nodes to understand their interactions with Freeport and identify vulnerabilities that may facilitate illegal activities. These nodes, whether functioning independently or interdependently, can heighten the risk of illicit activities by increasing opportunities for physical contact with containers. The interdependency of these nodes means that risks at one point in the supply chain can propagate and amplify vulnerabilities across all connected nodes. For instance, inadequate security at the CC can allow tampered containers to pass undetected to the POL. The following hypothesis is proposed to clarify the above statement: these nodes interdependently influence the risk associated with cargo containers.

Subsequently, the DEMATEL-BN model for assessing container risk is implemented by the following steps. For a detailed illustration of this process, please refer to Section 5.4.1.

Step 1. Evaluating causal relationships among the nodes

This step analyses interdependencies among the nodes using DEMATEL, referring to relevant literature on DEMATEL (Gabus and Fontela, 1972; Govindan, 2022; Govindan and Chaudhuri, 2016; Hsu et al., 2023a). Specifically, a DEMATEL-based survey is conducted to rate direct causal relationships among these nodes using expert opinions. *A* scale from 0 to 4 is used to indicate the influence level of one node on another (a_{ij}), where "0" stands for no influence and "4" stands for extreme influence. Equations 5-1 to 5-4 are used to compute the direct relation matrix and total relation matrix in DEMATEL.

$$A = \begin{bmatrix} 0 & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & 0 \end{bmatrix} \tag{5-1}$$

$$K = 1\Big/max_{1 \ll i \ll n} \sum_{j=1}^{n} a_{ij} \tag{5-2}$$

$$N = K \times A \tag{5-3}$$

$$T = N \times (I - N)^{-1} \tag{5-4}$$

In particular, the initial relationship matrix *A* is established for a total of *n* nodes, as shown in Equation 5-1. The normalising factor *K* and the normalised matrix *N* are calculated according to Equations 5-2 and 5-3, and the total influence matrix *T* ($T = [t_{ij}]$) is calculated according to Equation 5-4, where "*I*" signifies the unit (identity) matrix.

Based on the total influence matrix, the DEMATEL causal influence graph can be set up with "*R*+*C*" on the x-axis and "*R*-*C*" on the y-axis, where *R* is the sum of rows and *C* is the sum of columns for each node, as depicted in Equations 5-5 and 5-6. *R*+*C* represents the degree of central role and *R*-*C* indicates the degree of relation.

$$R = [r_i]_{n\times 1} = [\sum_{j=1}^{n} t_{ij}]_{n\times 1} \quad (5\text{-}5)$$

$$C = [c_j]_{1\times n} = [\sum_{i}^{n} t_{ij}]_{1\times n} \quad (5\text{-}6)$$

Step 2. DAG Construction

In this step, the total influence matrix of DEMATEL is utilised to establish a basis for constructing a DAG as a preparatory step for building a BN model. With t_{ij} representing the strength of total influence that one node has on another, this process involves linking all causal relations where t_{ij} exceeds a threshold value and refining the network by eliminating cycles (Chang et al., 2011; Yazdi et al., 2020). This threshold is determined to ensure that the network connects the identified nodes as extensively as possible while minimising the occurrence of cycles and reverse arcs. It preserves the network's logical consistency and focuses on significant interactions.

Step 3. Defining states

Unlike the noisy-or and symmetric models, which are typically constrained to two states ('yes' and 'no'), the ranked nodes approach can accommodate multiple states. This study defines five states that are mutually exclusive and collectively exhaustive: Very High (VH), High (H), Moderate (M), Low (L), and Very Low (VL). This classification aligns with previous BN-based risk studies (Chang et al., 2021; Yazdi et al., 2020; Zhou et al., 2023). Each state is assigned a numerical value: 0.2 for VL, 0.4 for L, 0.6 for M, 0.8 for H, and 1 for VH.

Step 4. Parameterising the BN

The ranked nodes method, as introduced in Section 2.5, is employed here to parameterise the BN causal network of critical nodes affecting container risk. This method determines the probabilities of a child node utilising a weighted function derived from the values of its parent nodes. Ranked nodes represent discrete variables with states expressed on an ordinal scale, which can be translated into a continuous and monotonically ordered bounded numerical scale.

In this study, the doubly truncated normal distribution (TNormal) is applied to model ranked causes using the weighted mean (WMEAN). Unlike the standard Normal distribution, which extends from negative to positive infinity, the TNormal distribution is bounded by specific endpoints. It is denoted as TNormal (mu, sigma, lower, upper), where 'mu' represents the WMEAN based on the parent nodes' values, and 'sigma' determines the central tendency and uncertainty for the child node's conditional probability distribution. The 'lower' and 'upper' parameters are used to set the finite range of the child node's value, for instance, between [0,1].

This study parameterises the TNormal distribution using output from DEMATEL, a method proven effective in previous research (Kaya et al., 2023; Kaya and Yet, 2019; Yazdi et al., 2020). Specifically, the initial average matrix from the DEMATEL approach is used to derive the weights of parent nodes for each child node. SD values are calculated based on the initial relationship matrices from the experts. The parameter 'sigma' is calculated by normalising the summed SD values for the parent nodes.

Equation 5-7 computes the probability distribution of *Y* given a set of causes *X*, which contains ranked nodes $X_i (i = 1,2,\cdots,n)$,

$$p(Y|X) = TNormal[WMEAN(X), sigma, 0,1] \quad \text{5-7}$$

where X_i are the parent nodes of *Y*.

By following the steps outlined above, severity-linked probabilities of container risk can be assessed, serving as key inputs for the optimisation stage.

5.3.3 Container Inspection Strategy Optimisation

Once the initial stage of container risk assessment is complete, the inspection optimisation process can proceed using the following model.

Table 5.2 shows the notation and definition for all variables used in this model. This study considers a set of container shipments imported into a freeport within a specific time frame. Each shipment *i* has an arrival rate a_i. However, due to limited capacity *c,* with a service rate μ, not all containers can be inspected. Under this limitation, an inspection rate βi should be assigned to each shipment based on its risk level. Consequently, upon arrival, freeport operators need to perform a risk assessment to obtain the severity S_i and corresponding probability P_i that each shipment contains illicit or mis-declared goods, using the risk assessment model in Section 5.3.2.

Table 5.2 Table of notation.

Notation	Variable type	Definition
i	Index variable	Shipment's serial number, $i \in \{1,2,\dots,N\}$.
β_i	Decision variable	Inspection rate for shipment *i*.
Z	Value of the objective function	The total expected loss.
c	Parameter	Inspection capacity, i.e. the number of staff conducting inspections, or the number of machines used in the process.
P_i	Parameter	Risk probability that shipment *i*'s containers are involved in illicit activities.
S_i	Parameter	Risk severity (the magnitude of harm, disruption, or financial loss) if an illicit container escapes detection.
θ	Parameter	A threshold value of $P_i S_i$.
a_i	Parameter	Arrival rate at the freeport (the number of containers in shipment *i*).
μ	Parameter	Service rate (the number of containers that each facility can inspect within a specific time unit).
γ	Parameter	Inspection error rate of each inspection facility.
λ	Parameter	Arrival rate at the inspection site that complies with the maximum allowable waiting time requirement.

1) Assumptions

Assumption 1: Each inspection facility can only inspect one container at a time.

Assumption 2: Each container needs to be inspected only once by a single inspection facility upon each arrival if it is selected for inspection.

Assumption 3: In this study, the queueing rule is based on the M/D/c model (Kleinrock, 1975), which describes a system with c inspection servers where arrivals are determined by a Poisson process (in line with prior research (Pourakbar and Zuidwijk, 2018)), and inspection service times are fixed (deterministic).

2) The objective

The objective of this optimisation model is to minimise the total expected loss if any illicit container escapes inspection or is released after inspection. According to the definition of risk (i.e. Risk = Likelihood * Consequence), the objective function is defined in Equation 5-8:

$$\min Z = min \sum S_i P_i a_i \left[\left(\beta_i \gamma + (1 - \beta_i) \right) \right] \quad \text{5-8}$$

Here the likelihood associated with container risk is given by $P_i\left[\left(\beta_i\gamma + (1-\beta_i)\right)\right]$. $\beta_i\gamma$ represents the probability that an illicit container is mistakenly released after inspection, and $(1-\beta_i)$ represents the probability that an illicit container bypasses inspection entirely.

3) Constraints

$$\sum_i \beta_i a_i \ll c\mu < \sum_i a_i \quad (1)$$

$$\sum_i \beta_i a_i \ll \lambda < \sum_i a_i \quad (2)$$

$$\beta_i \in [0,1] \quad (3)$$

$$P_i S_i > \theta \quad (4)$$

$$\gamma > 0 \quad (5)$$

Constraints (1) and (2) indicate that the inspection rate must satisfy both the maximum waiting time constraint and the inspection capacity utilisation constraint. Constraint (1) ensures that the expected arrival rate of containers to the inspection site does not exceed the total inspection service rate ($c\mu$). Whereas the total inspection service rate is lower than the overall expected arrival rate of containers to the freeport. In addition, according to the M/D/c queueing rule, the maximum allowable waiting time allows for the calculation of the corresponding arrival rate (λ). Therefore, the condition in Constraint (2) $\sum_i \beta_i a_i \ll \lambda$ ensures that the inspection strategy aligns with the waiting time requirement. Constraint (3) defines the value range of the inspection rate. Constraint (4) suggests that an inspection-free lane may be implemented for containers with a risk level at or below a threshold value θ, which can be determined from historical inspection records by identifying a threshold below which no seizures have ever occurred. In cases where there are insufficient inspection records, θ can be set to 0. However, determining this threshold based solely on a balance between inspection effectiveness and cost may not be advisable, as it would compromise security standards for economic benefit and potentially provide more opportunities for criminals to engage in illicit trade. Constraint (5) suggests that achieving a zero error rate in the inspection process is practically unattainable.

By solving the model, customs can determine the optimal inspection rate to assign to each imported shipment.

5.4 Case Study

This section showcases the application of the designed methodology framework through an illustrative example.

5.4.1 Illustrative Example for Container Risk Assessment

In the step of identifying causal relationships using the DEMATEL survey, experts with experience in both freeport and supply chain operations were targeted, resulting in responses from a total of nine experts. Table 5.3 provides details about their relevant backgrounds. The initial matrices from these nine experts for evaluating MCSC risk can be found in Appendix C. These experts bring extensive experience and knowledge in freeports and container supply chains, with an average of seven years of professional expertise. Their collective experience spans several countries, including the UK, China, Germany, Nigeria, India, Bangladesh, Malaysia, and Singapore.

Table 5.3 Survey participants on container risk evaluation.

Expert No.	Job position	Years of experience	Experienced countries
1	Logistics supervisor	8	UK
2	Associate professor	15	China
3	PhD researcher	5	UK, China, and Germany
4	Freeport terminal senior gate supervisor	7	Nigeria
5	Logistics customer care supervisor	3	India
6	Shipping service senior sales support	3	India
7	Global logistics analyst	3	India
8	Associate logistics analyst	1	India
9	Head of research and innovation (port terminal operator) and postdoc researcher	20	Bangladesh, Malaysia, and Singapore

Table 5.4 presents the initial average matrix, which reflects the experts' average perceptions of how an increase or decrease in the risk level of one node may directly affect the risk level of another. According to Equation 5-2, the value of *K* is 0.069231. Table 5.5 displays the SD values of their perceptions. Table 5.6 presents the total influence matrix, which captures both the direct and indirect influences among the nodes. These tables were used to parameterise the BN model based on the ranked nodes approach, as described in the following section.

Table 5.4 Initial average matrix for MCSC nodes.

	CC	WH	POL	OC	POD	Freeport	Container
CC	0.0000	3.0000	2.0000	1.7778	2.0000	2.3333	3.3333
WH	2.3333	0.0000	2.3333	1.5556	2.0000	2.1111	2.4444
POL	2.1111	2.0000	0.0000	2.5556	1.4444	2.2222	3.1111
OC	1.2222	2.0000	2.6667	0.0000	2.6667	1.7778	2.2222
POD	1.8889	2.2222	1.8889	2.1111	0.0000	2.3333	2.7778
Freeport	1.7778	2.0000	2.0000	2.1111	2.6667	0.0000	2.1111
Container	2.5556	2.1111	2.2222	2.2222	2.6667	2.3333	0.0000

Table 5.5 SD values of expert evaluations for vulnerable MCSC nodes.

	CC	WH	POL	OC	POD	Freeport	Container
CC	0.0000	0.8660	1.2247	0.9718	1.1180	1.2247	0.5000
WH	1.2247	0.0000	1.0000	0.8819	0.8660	1.2693	0.5270
POL	1.0541	1.0000	0.0000	1.1304	1.1304	1.2019	1.0541
OC	0.8333	1.0000	1.0000	0.0000	1.0000	1.2019	1.3944
POD	1.4530	0.8333	1.0541	1.2693	0.0000	1.4142	0.9718
Freeport	1.3017	1.2247	0.7071	1.0541	1.2247	0.0000	1.1667
Container	0.7265	0.9280	1.3944	1.5635	1.2247	1.2247	0.0000

Table 5.6 Total influence matrix of MCSC nodes.

	CC	WH	POL	OC	POD	Freeport	Container
CC	1.5701	1.8821	1.8105	1.7159	1.8574	1.8337	2.1908
WH	1.5507	1.5378	1.658	1.5444	1.6817	1.6526	1.9470
POL	1.598	1.7241	1.5863	1.6598	1.7226	1.7225	2.0560
OC	1.4591	1.6229	1.6435	1.4166	1.6826	1.6009	1.8946
POD	1.5628	1.7097	1.6753	1.6114	1.6034	1.7032	2.0083
Freeport	1.5003	1.6378	1.6211	1.555	1.6976	1.5042	1.9043
Container	1.6823	1.7989	1.7843	1.7049	1.8529	1.796	1.9581

To construct the DEMATEL causal influence graph, several indicators were computed based on Equations 5-5 and 5-6, as presented in Table 5.7. Figure 5.3 illustrates the causal and effect graph. According to the *R-C* axis in the causal diagram, the causal factors include CC, OC, and POL, while the effect factors comprise POD, WH, Freeport, and Container. Additionally, the causal diagram uses the *R+C* axis to represent the varying central roles of factors. Those positioned further along this axis have a more central role, influencing and being influenced by many other factors, such as 'Container'.

Table 5.7 The degree of central role and the degree of relation of MCSC nodes.

	R	*C*	*R+C*	*R-C*
CC	12.8605	10.9233	23.7838	1.9372
WH	11.5722	11.9133	23.4855	-0.3411
POL	12.0693	11.7790	23.8483	0.2903
OC	11.3202	11.2080	22.5282	0.1122
POD	11.8741	12.0982	23.9723	-0.2241
Freeport	11.4203	11.8131	23.2334	-0.3928
Container	12.5774	13.9591	26.5365	-1.3817

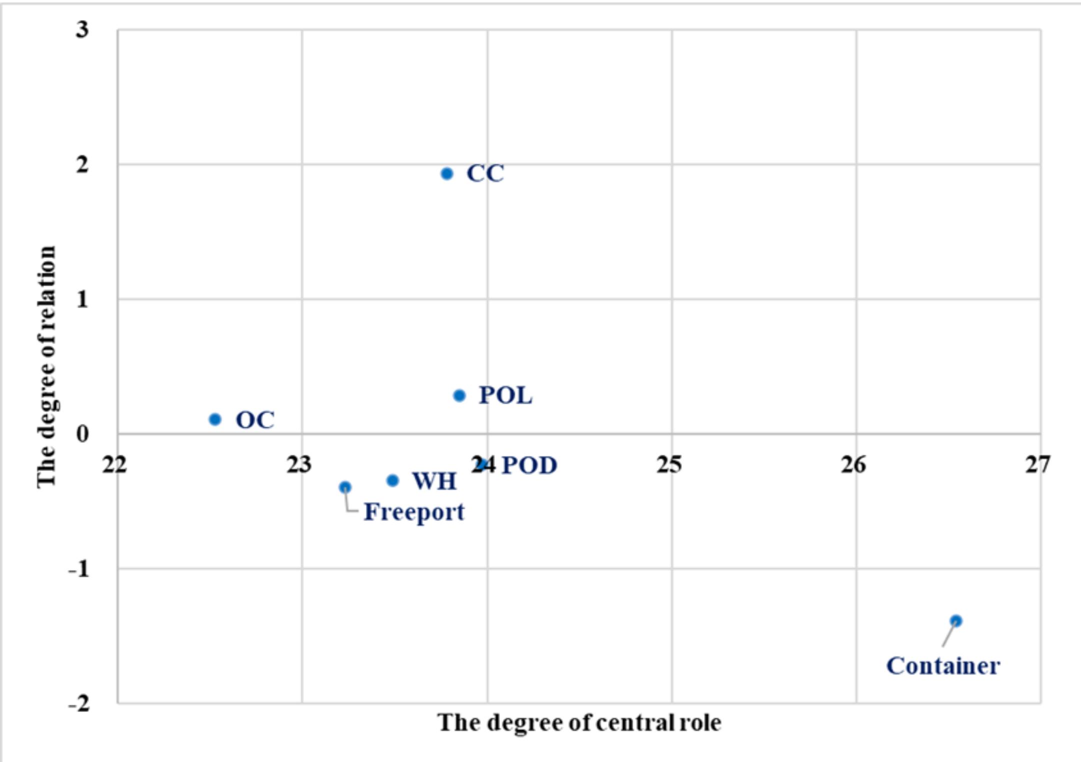

Figure 5.3 Container risk assessment causal diagram with the degree of central role and the degree of relation.

Next, based on Step 2 in Section 5.3.2, the total influence matrix from DEMATEL was used to establish the BN structure by linking all causal relations that exceeded a threshold. This threshold was determined through a probing approach to achieve an optimal balance between maintaining network connectivity and reducing cycles. In this case, a threshold value of 1.8 was identified as optimal, as it connects all nodes while minimising the occurrence of cycles and reverse arcs. As illustrated in Figure

5.4, this directed graph has two cycles: POD→Container→POD and a self-loop at 'Container'. It was refined by removing the self-loop at 'Container' and the reverse arc (Container→POD) with a lower influence value. Subsequently, it was converted into a DAG to serve as the foundation for building a BN model, as shown in Figure 5.5. The identified nodes interdependently influence the risk associated with moving containers, supporting the hypothesis outlined in Section 5.3.2.

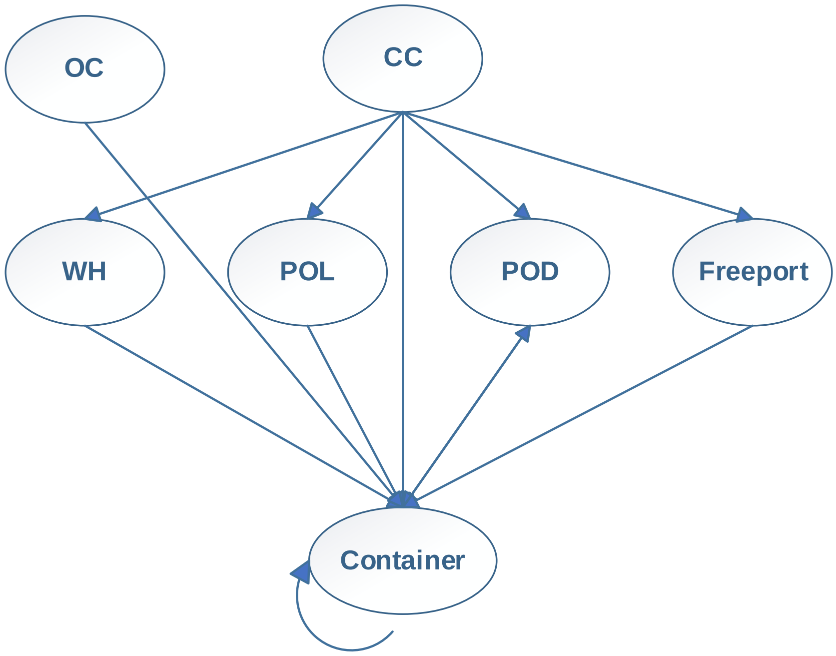

Figure 5.4 Directed graph of MCSC nodes for threshold 1.8.

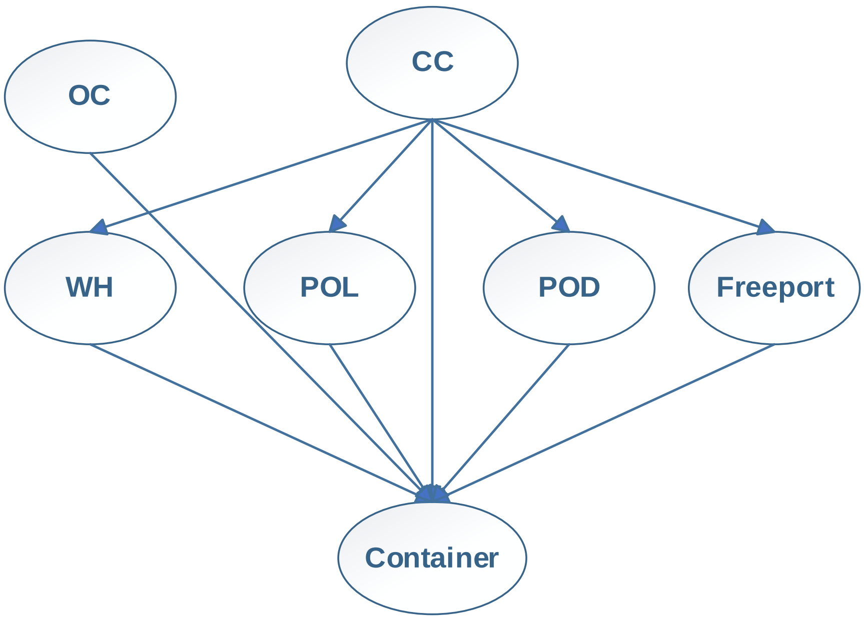

Figure 5.5 DAG of MCSC nodes for building the BN model.

Using the TNormal (*mu, sigma, lower, upper*) to model ranked causes for parameterising the BN requires two key parameters: *mu* (weights of the parent nodes) and *sigma* (the normalised-summed SD values) for each child node. In this study, the initial average matrix from DEMATEL was used to derive the weights of the parent nodes for each child node. For instance, in the case 'Container', the weights of its parents (CC, WH, POL, OC, POD, Freeport) were determined based on the numerical set (3.3333, 2.4444, 3.1111, 2.2222, 2.7778, 2.1111). As a result, *mu* is expressed as: $(0.2083 \times CC + 0.1528 \times WH + 0.1944 \times POL + 0.1389 \times OC + 0.1736 \times POD + 0.1319 \times Freeport)$. The SD values from Table 5.5 were summed and normalised to be used as *sigma*. For example, the SD values of the parent nodes of 'Container' are (0.5000, 0.5270, 1.0541, 1.3944, 0.9718, and 1.1667). The value of *sigma* was calculated by dividing their sum by the total of (3.3333, 2.4444, 3.1111, 2.2222, 2.7778, and 2.1111), yielding 0.3509. Thus, the probability function for 'Container' is $TNormal(0.2083 \times CC + 0.1528 \times WH + 0.1944 \times POL + 0.1389 \times OC + 0.1736 \times POD + 0.1319 \times Freeport, 0.3509, 0, 1)$. The GeNIe 4.1 academic software (https://www.bayesfusion.com) was used for parameter configuration. As a result, the parameterised BN structure using the ranked nodes method is illustrated in Figure 5.6. This structure illustrates the corresponding probability for each potential severity level (ranging from VL to VH) that a container shipment is involved in illicit activities.

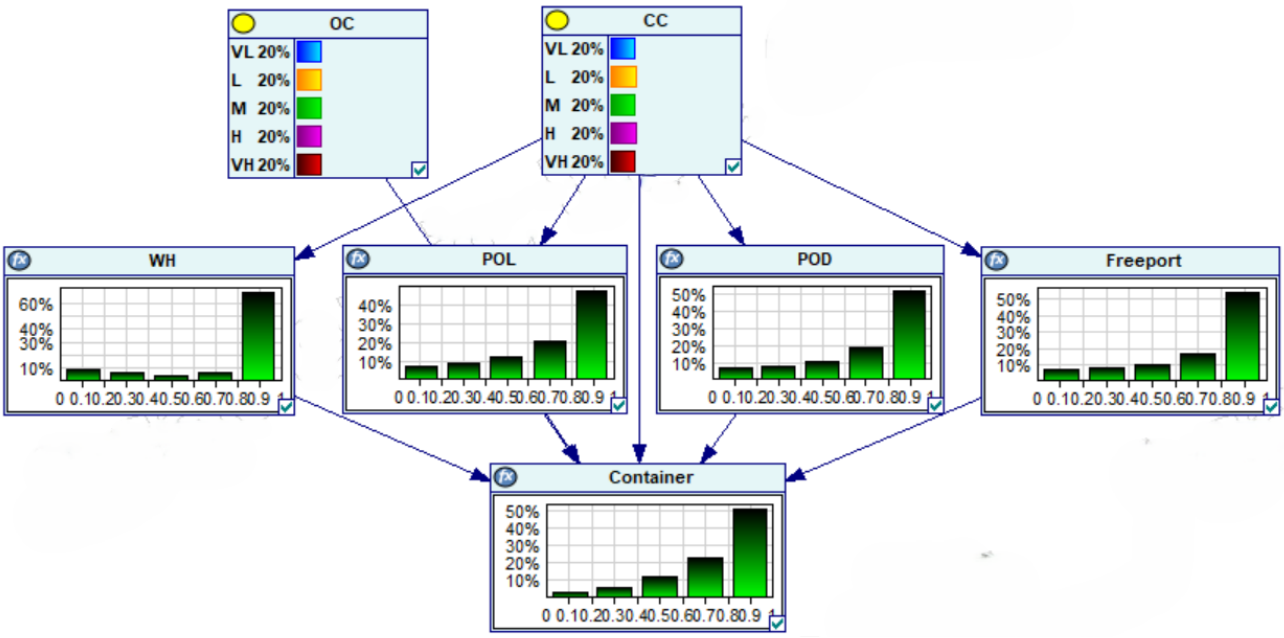

Figure 5.6 The parameterised BN structure of MCSC nodes.

A numerical example was performed to demonstrate the effectiveness of the proposed model. In this case, a random sample of 10 shipments (*N*=10) arrived at a freeport within a specific time period. Table 5.8 presents the results of container risk assessment based on varying input values of CC, where the risk probabilities of OC from VL to VH are set at 20% each (prior research by Riahi et al. (2014) has introduced how to assess risk scores of container consolidation centres and ocean carriers). Taking shipment 1 as an example, if the risk assessment result derived from the audit score for the parent node CC is 100% VH, the estimated probabilities (P_1) of its containers' risk severity across various levels (VL, L, M, H, and VH) are (0%, 1%, 5%, 21%, and 73%). Consequently, P_iS_i can be obtained and used as input for the subsequent optimisation stage, e.g., $PS_{(i=1)} = (0\%, 1\%, 5\%, 21\%, 73\%) \times (0.2, 0.4, 0.6, 0.8, 1) = 0.9320$.

Table 5.8 Container risk assessment results of the 10 shipments.

Shipment No.	CC risk probabilities (input)	Container risk probabilities (output)
1	(0%, 0%, 0%, 0%, 100%)	(0%, 1%, 5%, 21%, 73%)
2	(0%, 25%, 25%, 20%, 30%)	(1%, 4%, 10%, 24%, 61%)
3	(0%, 0%, 0%, 5%, 95%)	(0.1%, 0.5%, 3.9%, 18.9%, 76.6%)
4	(30%, 0%, 10%, 30%, 30%)	(5%, 7.7%, 11.1%, 21.6%, 54.6%)
5	(0%, 0%, 0%, 10%, 90%)	(0.1%, 0.6%, 3.3%, 19.4%, 76.6%)
6	(5%, 25%, 20%, 15%, 35%)	(2.2%, 4.9%, 10.3%, 24.7%, 57.9%)
7	(0%, 0%, 0%, 14%, 86%)	(0.2%, 1.3%, 5%, 21.9%, 71.6%)
8	(23%, 35%, 0%, 18%, 24%)	(5%, 8.9%, 14.2%, 23.9%, 48%)
9	(0%, 0%, 0%, 20%, 80%)	(0.1%, 0.8%, 4.1%, 19.5%, 75.5%)
10	(30%, 20%, 20%, 30%, 0%)	(5.9%, 9.8%, 15.3%, 24.8%, 44.2%)

5.4.2 Illustrative Example for Container Inspection Strategy Optimisation

Table 5.9 outlines the expected risk severity value (P_iS_i) derived from the first stage and the parameter settings for the number of containers in each shipment (a_i). Additional parameter settings include an error rate (γ) of 5% and a service rate (μ) of 50 for each inspection facility. Consequently, $\sum_i a_i$=2,800. According to Constraint (1), this model is employed to determine a solution when inspection resources are limited and cannot accommodate all arriving containers, leading to the conditions $c\mu$<2,800 and c<56. To demonstrate the model's applicability, it is solved for $\lambda = c\mu$ with values of c set to 30, 40, 50, and 55, respectively.

Table 5.9 Values of parameters ai and PiSi.

Shipment No.	P_iS_i	a_i
1	0.9320	400
2	0.8800	400
3	0.9428	300
4	0.8262	200
5	0.9436	50
6	0.8624	150
7	0.9268	300
8	0.8020	200
9	0.9390	350
10	0.7832	450

Substituting the above values into the objective function and constraints can find the optimal solution for β_i using a simple linear programming approach. Table 5.10 displays the optimal solutions for c=30, 40, 50, and 55, as examples.

Table 5.10 The optimal container inspection solutions.

c	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9	β_{10}	z
30	1	0.25	1	0	1	0	1	0	1	0	1141.32
40	1	1	1	0.25	1	1	1	0	1	0	728.38
50	1	1	1	1	1	1	1	1	1	0.33	346.66
55	1	1	1	1	1	1	1	1	1	0.89	160.65

Figure 5.7 illustrates the relationship between error rates (γ) and total expected loss (z) across various inspection capacities (c). It shows that as error rates increase, the minimised total expected loss tends to rise, while the extent of this impact is significantly influenced by the level of inspection capacity. Freeports with higher inspection capacities are better positioned to manage the risks associated with increasing error rates. Freeport policymakers and practitioners can use this graph to evaluate the trade-offs between inspection capacity investments and the potential financial risks associated with varying error rates, enabling more informed resource allocation.

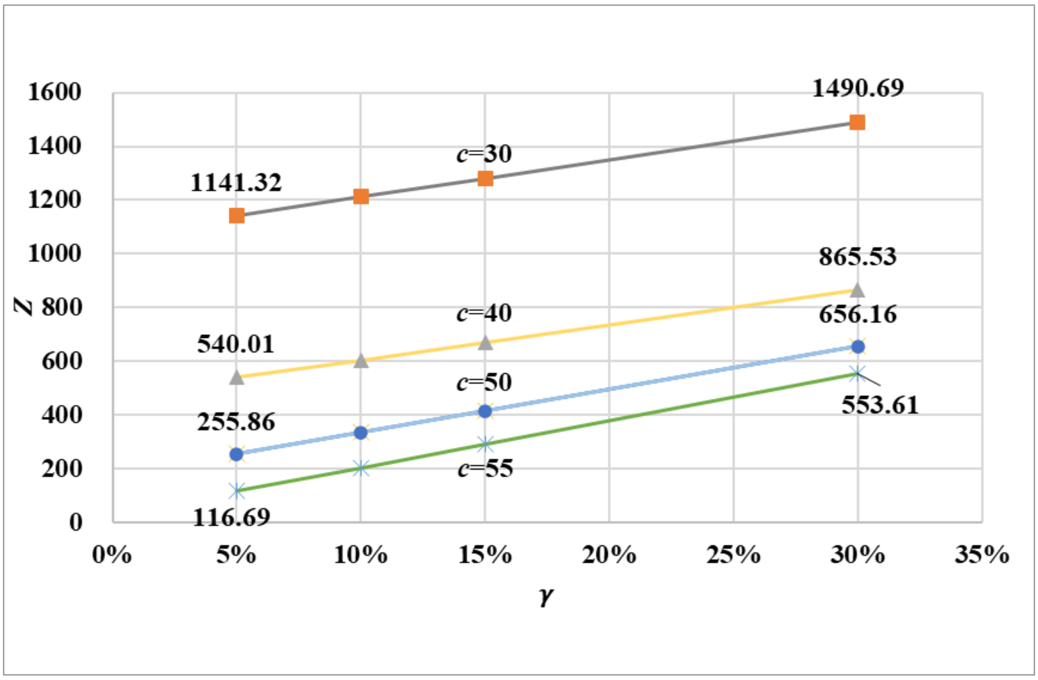

Figure 5.7 The effect of error rate on the total expected loss across various inspection capacities.

5.5 Implications

In practice, the research findings offer valuable insights for fostering a more secure and efficient environment within MCSCs. By enabling a balance between security and operational efficiency, the model enhances the sustainability of freeports, making them more attractive for international trade. This, in turn, contributes to the standardisation of security protocols across global freeports, thereby strengthening the resilience of the MCSC network against illicit activities.

Through the DEMATEL causal graph, this study has identified key causal and effect factors in the supply chain for container risk assessment. CC, OC, and POL are identified as causal factors. It indicates that disruptions in these nodes can significantly impact the entire supply chain. For example, risks at the consolidation centre can propagate through the supply chain, affecting other components. Therefore, these nodes require special careful monitoring. Conversely, nodes such as the WH, POD, and Freeport are more reactive, being influenced by other factors in the supply chain.

Stakeholders are recommended to prioritise investment in technologies and practices that enhance the reliability and security of consolidation centres, ocean carriers, and ports of loading.

Simultaneously, adaptive measures should be developed to manage vulnerabilities at the port of discharging, warehouse, and Freeport.

When considering centrality, the node ‘Container’ is positioned highest on the *R+C* axis, indicating that it is both significantly influenced by and has a strong influence on other factors. According to the total influence matrix, its most influential factors are CC, POL, and POD, while the factors most impacted by it include POD, WH, and Freeport. Therefore, containers should be strategically inspected upon arrival at nodes such as POD, WH, and Freeport. In addition, strategies focused on reducing container risk severity, such as enhanced inspection protocols or improved tracking systems, could have a beneficial ripple effect on the entire supply chain network.

The causal relationships between various supply chain components are visualised through the BN, supporting the evaluation of probabilities for different levels of container risk severity. The BN causal network reveals that all the investigated supply chain components directly contribute to the risks of containers being involved in illicit activities. The detailed probability mapping enables a nuanced understanding of the likelihood that a container shipment is involved in illicit activities. Such a predictive model aids in optimising inspection processes by identifying high-risk containers.

Therefore, unlike other studies that only propose theoretical approaches to optimise customs inspection processes by identifying high-risk containers, this research translates theory into practical solutions by integrating risk assessment and optimisation models.

The proposed optimisation model offers practical implications for enhancing customs inspection efficiency and security at freeports. By incorporating constraints that balance inspection capacity with container arrival rates, the model ensures that resources are allocated effectively to maximise inspection coverage and meet the waiting time requirement.

The implications of this research extend beyond the immediate context of freeport operations. The proposed model can serve as a blueprint for freeport policymakers worldwide, guiding them in implementing more effective security measures without impeding trade flow.

5.6 Conclusion

This Chapter presents a comprehensive model for optimising container inspection strategies within freeport-centric supply chains, addressing the critical need to balance security and operational efficiency. By using a DEMATEL approach and engaging experts in MCSCs and freeports, this study finds key causal factors, such as CC, OC, and POL, that significantly influence the risk of containers being involved in illicit activities. A BN is employed to reveal the dynamic interrelationships among these factors and conduct a risk assessment of containers' involvement in illicit activities. The ranked nodes approach is applied to parameterise the model, offering the advantage of minimising reliance on subjective probabilities assigned by experts. Based on these results, an optimisation model is developed to determine the most effective inspection strategy, given limited inspection resources. Finally, the proposed model is validated and demonstrated through numerical analysis to showcase its practical applicability.

The findings of this study offer practical insights for enhancing the security and sustainability of freeports and MCSCs in several ways:

(1) By identifying and prioritising high-risk nodes such as consolidation centres and ports of loading, the model enables targeted investment in technologies and practices that strengthen the security of these critical points, thereby reducing the overall risk of illicit activities within the MCSC.
(2) The integration of predictive risk assessment with the optimisation model ensures that inspection strategies are not only theoretically sound but also feasible for real-world application, enabling more effective and efficient deployment of inspection resources.
(3) It offers a data-driven approach to balancing security with trade facilitation, helping freeports become more resilient and attractive to international trade while maintaining compliance with global security standards.

Recognising the potential of blockchain technology to enhance transparency and further improve inspection efficiency and security in freeport operations, the next chapter explores the conditions and challenges surrounding its adoption.

CHAPTER 6 TOWARDS FREEPORT DIGITALISATION: A NOVEL FRAMEWORK FOR ASSESSING BARRIERS TO BLOCKCHAIN ADOPTION IN FREEPORT OPERATIONS[3]

Summary

This chapter introduces a novel hybrid approach to assessing blockchain adoption barriers within the freeport context. This study makes methodological contributions by introducing a DEMATEL-BN model to identify complex interrelationships and facilitate probabilistic estimations regarding the significance of these barriers. This study leverages primary data gathered from experts experienced in both blockchain technology and freeport operations to ground the analysis in real-world insights. It identifies high investment cost as the most interactive barrier and lack of trust among stakeholders as the most essential barrier. Additionally, by evaluating the overall impact of barriers, the study enables targeted strategies for freeport operators to implement the blockchain application.

6.1 Introduction

The increasing volume of global trade, coupled with rising expectations for efficiency and security, necessitates a paradigm shift in the operational modalities of freeports. This shift is towards digitalisation, a transformative process that integrates digital technologies into all areas of freeport operations, thereby fundamentally changing how they operate and deliver value. The digital transformation of freeport operations signifies a monumental leap towards achieving unprecedented levels of operational efficiency. Moreover, the adoption of digital technologies equips freeports with robust security protocols and surveillance systems (Wang et al., 2022). The safety implications of digitalising freeport operations cannot be overstated in an era where cyber and physical security threats loom large (Liu and Wu, 2020; Shi and Fan, 2021; Stevens, 2021; Tian et al., 2023).

While the digital transformation of freeports signals a new era of operational efficiency and security, the integration of blockchain technology stands out as a promising development. Blockchain technology, first introduced by Nakamoto (2008), with its inherent features of decentralisation,

[3] The findings of this technical chapter have been published in the following journal paper. Liang, X., Fan, S., Li, H., Jones, G., Yang, Z., 2025. Navigating Uncertainty: A Novel Framework for Assessing Barriers to Blockchain Adoption in Freeport Operations. J. Mar. Sci. Eng. 13, 249. https://doi.org/10.3390/jmse13020249

transparency, and immutability, offers remarkable benefits for enhancing the efficiency and safety of freeport operations. This potential is underscored in various industry and academic publications (Liu and Wu, 2020; MCD, 2023; Shi and Fan, 2021; Stevens, 2021; Tian et al., 2023). For instance, the Malta Freeport and Hainan FTZ are among the freeports that have implemented blockchain technology in practice. Despite its potential to transform freeport operations, its widespread adoption remains limited, facing numerous barriers and challenges that have to be addressed. For instance, the challenges faced by TradeLens, a blockchain-based platform developed by IBM and Maersk, reflect such key obstacles as the lack of full global industry collaboration and difficulties in convincing stakeholders, including shippers and freight forwarders, of its value. These issues, along with high costs and limited incentives, exemplify the organisational and economic barriers that can hinder blockchain adoption in complex ecosystems (PierNext, 2023). Moreover, a literature review, coupled with expert consultations conducted for this study, highlights several barriers, including technological barriers, such as difficulties in integrating blockchain with existing IT systems, and organisational hurdles, e.g., resistance to change and a general lack of understanding about blockchain among employees. Additionally, regulatory and legal ambiguities related to blockchain technology present significant impediments, deterring its broad implementation in freeports. Yet, the literature has not adequately assessed these critical obstacles to blockchain adoption, especially their interrelationships. Without a comprehensive understanding of how these obstacles interact and influence blockchain adoption, efforts to promote implementation and allocate resources will remain unsystematic and ineffective.

To bridge the research gap, this study aims to develop an innovative methodology for evaluating the barriers to blockchain adoption in freeports. Initially, it undertakes a comprehensive literature review within freeports, maritime operations, and supply chains to identify common barriers to blockchain adoption. Subsequently, it involves professionals with expertise in both blockchain technology and freeport operations to assess the causal relationships among identified barriers through a semi-structured survey based on DEMATEL. Furthermore, the study integrates the findings from the DEMATEL analysis with the capabilities of BN for learning and inference to construct a causal network and probabilistic model, with the BN structure parameterised using ranked nodes. Finally, a sensitivity analysis is conducted to ensure the consistency of the model.

Accordingly, the novelties of this study are highlighted as follows:

1) Analysing the blockchain application in the freeport context.

From an applied research perspective, this study pioneers the exploration of blockchain application in the freeport context, offering actionable managerial insights into the most interactive and essential barriers to blockchain application and the combined effects of these barriers.

2) Pioneering BN for blockchain adoption analysis.

This study introduces the use of a BN inference mechanism in analysing blockchain adoption, presenting a novel quantitative model that enables probabilistic risk prediction of the significance of barriers to blockchain adoption in freeports under uncertainty.

3) Integrating DEMATEL and BN.

By integrating the DEMATEL and BN methods, the study offers a systematic approach to identifying and quantifying the interrelationships among blockchain adoption barriers. This integrated model makes a valuable contribution to systems analysis by offering a robust framework for understanding and addressing the multifaceted nature of factors within complex systems.

4) Applying the ranked nodes approach.

The ranked nodes approach is applied to configure Conditional Probability Tables (CPTs) within the DEMATEL-BN model. This innovation minimises reliance on expert-assigned probabilities, reducing uncertainty while maintaining the BN model's capacity to account for multistate effects.

The rest of the chapter is structured as follows: Section 6.2 provides a literature review on blockchain adoption in the related industries to freeports and methods for assessing barriers to blockchain adoption to define the state-of-the-art of the study. Section 6.3 outlines the methodology designed for this study, including the steps for barrier identification, assessment, and sensitivity analysis. Section 6.4 demonstrates the practical application of these steps, while Section 6.5 discusses the implications of this research. Finally, Section 6.6 concludes the chapter.

6.2 Literature Review on Blockchain Adoptions

This literature review is divided into two subsections. It provides an overview of research on blockchain adoption in industries relevant to freeports, along with the methods used to analyse its adoption barriers.

6.2.1 Blockchain Adoptions in Related Industries

Although digital transformation in freeports is gaining attention, academic investigation in this area is very limited, particularly research focusing on the potential of blockchain to enhance efficiency and security in freeport operations. Wang et al. (2022) formulated an innovative conceptual framework illustrating a generic freeport model supported by 5G technology. Several studies have examined blockchain's transformative role in the Hainan Free Trade Port (FTP). For instance, Shi and Fan (2021) focused on the rapid development of cross-border ecommerce within the Hainan FTP, identifying blockchain as a solution to challenges such as information service inefficiencies and payment security. They proposed a blockchain-based supply chain information service platform tailored to Hainan's local needs and free trade policies. Tian et al. (2023) explored the strategic implications of incorporating blockchain in the Hainan FTP's supply chain network, suggesting that its adoption significantly influenced global supply chain redesign and pricing strategies. Liu and Wu (2020) examined blockchain's application in Hainan's intelligent port logistics, offering insights into how blockchain technology can revolutionise logistics and trade in FTZs. Collectively, these studies underscore blockchain's transformative potential in freeports, advocating for its strategic integration to bolster trade efficiency and security.

Given the scarcity of research on freeport operations, the literature review broadens its scope to include maritime and supply chain studies. Blockchain technology is increasingly recognised as a transformative force in both the maritime industry and supply chain management (SCM), offering unparalleled transparency, efficiency, and security. It enhances logistics and supply chains by enabling secure, real-time information exchanges and automating transactions via smart contracts. Key applications include tracking product origins, managing product flow, forecasting demand, reducing fraud, providing open access to supply chain data, minimising environmental impact, and streamlining transactions. These applications often intersect, offering comprehensive improvements in SCM (Dujak and Sajter, 2019). According to the study by Han and Fang (2024), blockchain technology transformed supply chain finance by modernising traditional methods and fostering new models, enhancing green practices and risk management, and promoting transparent, efficient, and sustainable operations across different industries. Despite its potential, technological, organisational, and environmental challenges hinder its broad adoption in SCM, keeping blockchain in SCM at an early stage of development. For example, adopting blockchain technology may reduce the demand from privacy-sensitive customers, even if they do not use blockchain traceability services, despite the increase in the product's retail price due to blockchain adoption (Fang et al., 2024).

Blockchain use cases have been steadily developed and tested in the maritime industry since 2017, particularly in documents, operations, finance, and insurance, while also pointing to its synergy with Internet of Things and smart grids for more secure and efficient maritime operations (Pu and Lam, 2021). Shin et al. (2023) delved into blockchain's specific applications within the maritime and shipping sectors, pinpointing document management, transaction oversight, and operational enhancements as key areas of implementation. Kapidani et al. (2021) analysed expert opinions from two developing countries, Montenegro and South Africa, to highlight the benefits, uncertainties, and knowledge gaps associated with blockchain implementation in emerging maritime economies. In recent studies, Zhang et al. (2024) proposed an improved blockchain-based cold chain traceability system for marine fishery vessels, using the Node-grouped and Reputation-evaluated Practical Byzantine Fault Tolerance consensus algorithm to enhance the reliability and efficiency of the blockchain system. Li et al. (2024) used a Hotelling model to examine the pricing strategies and blockchain technology investment preferences of two competitive shipping platforms across three scenarios: neither platform invests, only one platform invests, and both platforms invest. Meanwhile, Li et al. (2024) used a game model to analyse the investment and subsidy strategy for low-carbon port operations, considering the effectiveness of blockchain in enhancing cargo owners' low-carbon trust.

Current research outlines a promising yet challenging path ahead for blockchain in enhancing the transparency, efficiency, and sustainability of freeport operations, as well as the relevant supply chains and maritime transport. The exploration of blockchain's potential, coupled with strategies to overcome its adoption barriers, is crucial in realising its full benefits across these sectors. However, the existing literature within the maritime sector lacks a thorough quantitative analysis of the risks and obstacles associated with blockchain applications. As an exploratory study, Nguyen et al. (2022) assessed potential risks in container shipping blockchain information systems with inputs from the industry, using a network model and a quantitative analysis with probabilistic indexes for multi-event risk scenarios. Yet, their study presupposed blockchain's adoption, neglecting the pre-adoption phase barriers. Additionally, their methodology relied on expert-provided probabilities to assess the likelihood of causal connections between different risk events and overlooked the magnitude of the risks themselves. A more thorough approach is required to address these limitations. This study enriches the discourse by proposing a new method to identify and evaluate critical obstacles to blockchain adoption, specifically within the freeport context, offering valuable insights into facilitating its broader integration.

6.2.2 Methods for Assessing Barriers to Blockchain Adoptions

Existing research on blockchain application barriers employs both qualitative and quantitative methodologies. Qualitative approaches, such as literature reviews, case studies, and thematic analyses, are prevalent. For instance, Mohammed et al. (2023) utilised a systematic literature review of 52 articles from 2016 to 2021 to craft a conceptual framework that outlines the enablers, benefits, and challenges of adopting blockchain in food supply chains. Similarly, Sargent and Breese (2023) conducted a structured literature review of 76 articles to identify major barriers to blockchain adoption in supply chains, while Moretto and Macchion (2022) engaged with blockchain providers and companies in the fashion sector to evaluate perspectives on adoption influencers and obstacles, as well as the effects on supply chain variables. Nonetheless, these qualitative methods fall short in evaluating the importance of various criteria and their interrelationships.

Some studies resort to more sophisticated Multiple Criteria Decision-Making (MCDM) techniques. Table 6.1 showcases the MCDM methods used in the referenced literature, highlighting their respective benefits and drawbacks. Although these methods offer valuable insights for identifying and prioritising key barriers against the implementation of blockchain technology, each has inherent limitations. For example, the AHP and Delphi are inadequate for analysing interdependencies among the influential factors. Interpretive Structural Modelling (ISM) identifies relationships between the factors but is restricted to transitive relationships, lacks the ability to quantify the strength of these relationships, and does not classify them into cause-and-effect groups. In contrast, DEMATEL effectively analyses complex systems with interdependencies and causal relationships. However, as with other MCDM methods discussed above, it does not address uncertainty or variability in these interrelationships and lacks adaptability for dynamic scenario analysis, limiting its applicability in formulating actionable strategies.

Table 6.1 MCDM methods used in the assessment of barriers to blockchain applications.

Methods	References	Advantages	Limitations
AHP	(Kaur et al., 2022; Mangla et al., 2022; Naseem et al., 2023; Nazam et al., 2022)	Priorities multiple criteria.	Sensitive to inconsistent data; time-consuming and complex to collect data; cannot reflect interrelationships among multiple criteria.
DEMATEL	(Govindan, 2022; Kaur et al., 2022; Khan et al., 2023; Kumar et al., 2022)	Reflects causal structure among multiple criteria.	Time-consuming and complex to collect data.
Delphi	(Khan et al., 2023; Nazam et al., 2022; Sahebi et al., 2020)	Consensus-driven; helps to gather expert opinions systematically; can be conducted remotely.	Time-consuming; results can be influenced by dominant individuals; may not reach consensus.
ISM	(Balci and Surucu-Balci, 2021; Kumar et al., 2022)	Analyses relationships between system elements.	Time-consuming and complex to collect data; limited to transitive relationships and unable to quantify their strength; cannot classify factors into cause-and-effect groups.
Best-Worst method (BWM)	(Heidary-Dahooie et al., 2022; Sahebi et al., 2020)	Efficient data collection; fewer comparisons; easy to use.	Cannot reflect interrelationships among multiple criteria.

6.3 A DEMATEL-BN Method for the Evaluation of Blockchain Adoption Barriers

This section comprises four subsections, outlining the interactive steps to formulate its logic flow. The first subsection introduces the methodology of this study, the second presents the most commonly examined barriers identified from the literature review, and the last two sections elaborate on the detailed steps of barrier assessment and sensitivity analysis, respectively.

6.3.1 The Proposed Framework for Evaluating Barriers to Blockchain Adoption

Recognising the limitations of traditional MCDM methodologies, hybrid emerging models have been proposed to overcome these challenges by integrating advanced quantitative methods, such as BNs. The combination of DEMATEL and BN is selected for its superior capacity, as outlined in Section 2.5, to delineate and quantify the complex interdependencies and uncertainties that characterise blockchain adoption scenarios. Compared to the traditional DEMATEL approach, the BN component offers a significant advantage by effectively addressing uncertainty and variability in the interrelationships among barriers.

This study pioneers the application of a hybrid approach to formulating a comprehensive framework for assessing barriers to blockchain applications in freeports. It also enriches the limited research that integrates DEMATEL and BN with a clear and cohesive model. It specifically elaborates on the processes of causal network construction and refinement, BN parameterisation, and the model's consistency test. In doing so, it establishes best practices that can be applied to similar research challenges. Such benefits can be achieved through the development of the proposed new framework, as presented in Figure 6.1. First, key barriers to the adoption of blockchain in supply chains and maritime scenarios are identified through a systematic literature review. In the barrier assessment stage, the DEMATEL approach is employed to evaluate the causal relationship among the identified barriers. It leverages expert insights with interdisciplinary knowledge in freeports and blockchain. The total influence matrix derived from DEMATEL forms the basis for constructing the causal network of the following BN model, thereby enhancing BN with a systematic approach to gathering expert judgment. Additionally, CPTs are generated using the ranked nodes approach, which further advances the DEMATEL-BN model by addressing the uncertainty of expert-assigned probabilities. The consistency of the model is subsequently verified through a sensitivity analysis.

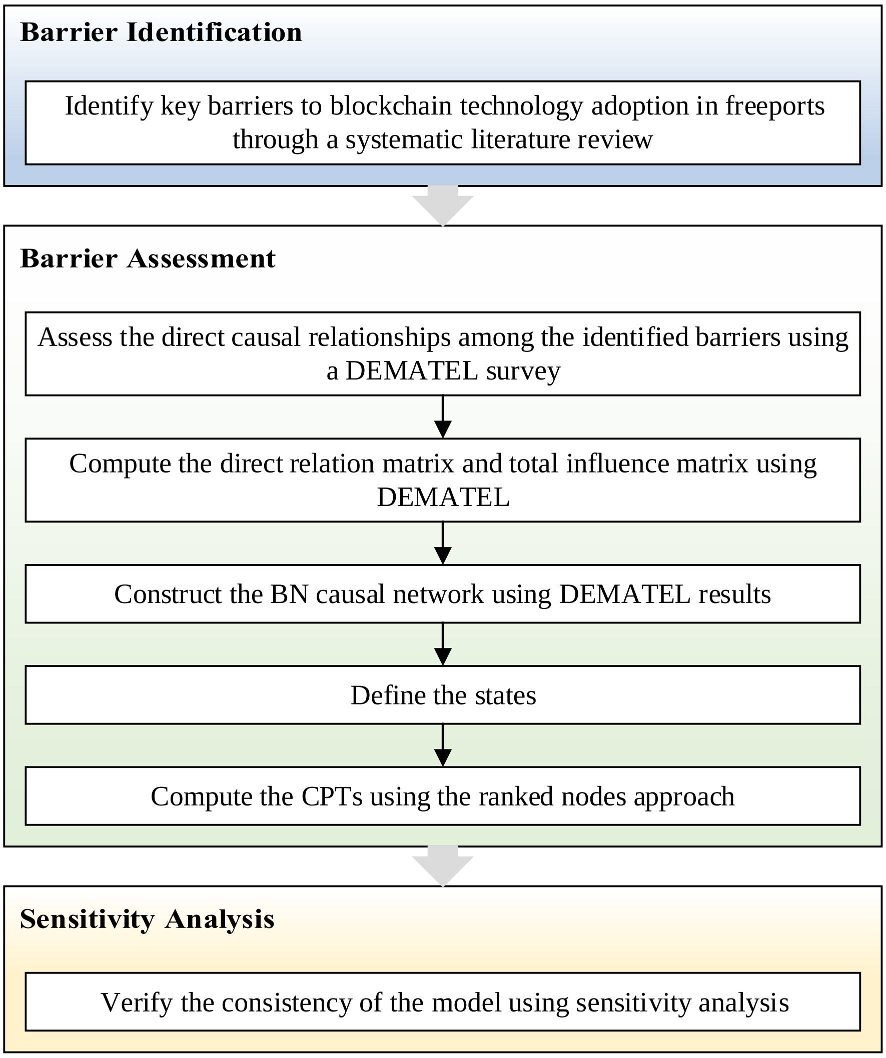

Figure 6.1 The proposed framework for evaluating barriers to blockchain adoption in freeports.

6.3.2 Barrier Identification

To identify critical barriers to blockchain adoption in freeports, this study broadens the literature review to include related contexts, such as ports, maritime, and supply chains, given the limited research specifically focused on freeports. Initially, it reviewed all barriers to blockchain implementation that have been examined in relevant research across various sectors, including manufacturing, e-commerce, container shipping, and diverse supply chain types. However, the frequency of occurrence of these barriers varies, and some have not been explicitly defined in the existing literature, highlighting the need for further refinement. Consequently, this study selected the 10 most frequently examined and well-defined barriers (B1 to B10), as presented in Table 6.2, to analyse their interrelationships.

Table 6.2 The examined barriers in the existing literature.

References for the barriers	B1 Legal and regulatory challenges	B2 Lack of industry standard	B3 Lack of scalability	B4 Concerns about data security and privacy	B5 Lack of trust	B6 Lack of stakeholder collaboration	B7 Lack of technology capacity resources	B8 Lack of knowledge and expertise	B9 High investment cost	B10 Lack of interoperability
(Govindan, 2022)	Y	Y	Y	Y	Y	Y	Y	Y		
(Heidary-Dahooie et al., 2022)	Y	Y	Y					Y		
(Kaur et al., 2022)	Y	Y	Y	Y		Y	Y	Y	Y	Y
(Kazancoglu et al., 2023)		Y		Y				Y	Y	
(Khan et al., 2023)		Y		Y	Y	Y	Y	Y	Y	
(Kumar et al., 2022)	Y	Y	Y	Y	Y		Y	Y	Y	Y
(Kumar and Barua, 2023)	Y	Y	Y		Y	Y	Y	Y	Y	
(Mangla et al., 2022)		Y	Y	Y		Y		Y	Y	
(Mohammed et al., 2023)	Y	Y	Y					Y	Y	Y
(Sargent and Breese, 2023)	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

(Moretto and Macchion, 2022)		Y				Y	Y	Y	Y	
(Naseem et al., 2023)		Y		Y		Y	Y	Y	Y	
(Nazam et al., 2022)	Y	Y			Y	Y		Y	Y	
(Nguyen et al., 2023)	Y			Y	Y	Y	Y		Y	
(Balci and Surucu-Balci, 2021)	Y			Y	Y	Y		Y	Y	

Other barriers were excluded due to their low frequency of appearance in the literature, occurring no more than twice, and vague definitions, such as business model and road map, operational challenges, lack of management support, framework complexity, the majority attack, culture of an organisation, management, social, or cultural issues, and market competition and uncertainty. The number of selected barriers aligns with the majority of existing studies on interrelationship analysis of barriers to blockchain adoption. For instance, Govindan (2022), Khan et al. (2023), and Nguyen et al. (2023) analysed 10 barriers, while Balci and Surucu-Balci (2021) examined 8. Table 6.3 provides descriptions of the 10 identified barriers.

Table 6.3 Descriptions of the barriers to blockchain adoption.

No.	Barriers	Descriptions
B1	Legal and regulatory challenges	Users and operators of blockchain face uncertainty due to the absence of established legal frameworks, resulting in regulatory challenges.
B2	Lack of industry standard	Varied global practices regarding product standards, taxation, and customs regulations make integrating these rules into blockchain networks challenging across different jurisdictions.

B3	Lack of scalability	The restricted block size and increasing transaction volumes strain the network, requiring more nodes for processing. This limitation can lead to network slowdowns as transaction volumes surge.
B4	Concerns about data security and privacy	Cyber threats pose risks of unauthorised data access and dissemination. Moreover, businesses may hesitate to disclose sensitive information due to concerns about competitive advantage and privacy breaches.
B5	Lack of trust	Industry stakeholders exhibit a lack of confidence in blockchain technology, undermining its widespread adoption.
B6	Lack of stakeholder collaboration	Bringing together relevant parties to establish private distributed networks proves challenging in many instances.
B7	Lack of technology capacity resources	Limited internet speed, storage capacity, and digital platform availability impede blockchain adoption.
B8	Lack of knowledge and expertise	Blockchain technology is nascent, leaving many stakeholders unaware of its implications. Organisations struggle with the complexities of implementation, requiring specialised technical expertise and infrastructure.
B9	High investment cost	The substantial costs associated with building the blockchain infrastructure and management capabilities deter adoption, particularly for small and medium-sized enterprises.
B10	Lack of interoperability	Interoperability refers to the ability of different blockchains to communicate and share in-formation effectively. Incompatibility among various blockchain projects written in different languages and on diverse platforms leads to network isolation and information asymmetry, hindering seamless communication and collaboration.

6.3.3 Barrier Assessment

A DEMATEL-BN model is used to evaluate the causal relationships among the identified barriers using the following steps. For a detailed illustration of this process, please refer to Section 6.4.2.

1) A DEMATEL-based survey is conducted to rate direct causal relationships among *n* identified barriers using expert opinions. A 0-4 scale indicates the influence level (a_{ij}) of the i^{th} identified barrier on the j^{th}, with "0" meaning no influence and "4" indicating very high influence.
2) Equations 5-1 to 5-4, as detailed in Section 5.3.2, are used to compute the direct relation matrix and total relation matrix. Using the total influence matrix, the DEMATEL causal influence graph is constructed, as defined in Equations 5-5 and 5-6.
3) In this step, the total influence matrix of DEMATEL is utilised to establish a basis for the BN causal network. With t_{ij} representing the strength of total influence that one barrier has on another, this process consists of connecting all causal relations where t_{ij} exceeds a certain threshold value and refining the network by removing cycles. Please refer to Sections 5.3.2 for the rule of threshold setting.
4) In this study, five mutually exclusive and collectively exhaustive states are defined for the degree of all barriers within the constructed network: very high (VH), high (H), moderate (M), low (L), and very low (VL).
5) CPTs are generated using the ranked nodes method. The TNormal distribution is applied to model the ranked causes, as defined by Equations 5-7 and explained in detail in Section 5.3.2.

6.3.4 Sensitivity Analysis for Model Verification

A sensitivity analysis is performed to examine the impact of minor input changes on the corresponding outputs. This analysis is crucial to establish the robustness of the methodology and its capacity for logical inference. To be considered robust, the sensitivity analysis has to satisfy the following two axioms (Fan et al., 2022; H. Li et al., 2023). Specifically, the process involves systematically adjusting the prior probabilities of each parent node and computing the updated expected utility of the corresponding child node. These utility values are evaluated in relation to anticipated changes or trends, guided by the established axioms.

- Axiom 1. A nominal increase or decrease in the prior probabilities of each parent node should correspondingly lead to an increase or decrease in the posterior probability of each child node.
- Axiom 2. The cumulative impact of probability changes in a set of evidence should not be less than the impact derived from any of its subsets.

6.4 Model Application and Results Analysis

This section demonstrates the application of the designed framework in real-world freeport operations in the subsequent three subsections.

6.4.1 Survey Participants

The survey targeted industrial experts with cross-disciplinary experience in blockchain technology and freeport operations. However, professionals with dual expertise in blockchain and specific industries, particularly freeports, are rare due to the nascent stage of blockchain applications in this domain. Consequently, three experts who fulfilled these criteria participated in the survey. Despite the small sample size, their extensive experience and specialised knowledge add significant value and credibility to the findings. This reflects the good practices of existing studies in the field regarding the number of experts used to support a DEMATEL analysis. For instance, Feng et al. (2023), Kaya et al. (2023), and Yazdi et al. (2020) collected data from three experts, while Gan et al. (2022) obtained data from four experts. The credentials of these experts are presented in Table 6.4. In the first section of the survey, open-ended questions were used to gather experts' perspectives on the reasons behind freeports' reluctance to adopt blockchain technology. Their insights provided specific clarifications on some of the identified barriers, as detailed in Table 6.5.

Table 6.4 Expert credentials for evaluating barriers to blockchain adoption in freeports.

Expert No.	Role/Involvement with freeports	Years of experience in freeports	Role/Involvement with blockchain technology or IT system development	Years of experience with blockchain technology or IT system development
1	Involved in a UK Freeport bid, emphasising digitalisation.	1 year	Involved in strategy development, facilitating blockchain applications and an	10 years

			Oracle platform development in maritime.	
2	Involved in the informatisation construction of a Chinese Freeport, formulating import and export business system rules, organising research and development of related systems.	12 years	Minister of Digital Industry. Involved in several blockchain application projects, understanding blockchain applications in various industries, e.g., digital assets, supply chain, and certificate storage, familiar with public chain consensus, security standards, and development tools.	5 years
3	Working in an African Freeport.	5 years	Information and Communication Technology (ICT) Engineer.	5 years

Table 6.5 Expert interpretations of the identified barriers.

No.	Barriers	Freeport expert interpretations
B1	Legal and regulatory challenges	Blockchain risks include potential disruptions to existing management and regulatory frameworks (Expert 2).
B4	Concerns about data security and privacy	Blockchain comes with risks, necessitating robust data protection supported by stringent security measures (Expert 1).
B7	Lack of technology capacity resources	Obstacles to blockchain adoption include technical complexities (Expert 2).
B8	Lack of knowledge and expertise	Technical complexities require specialised expertise (Expert 2); challenges of adopting blockchain include limited technical professionals and a lack of established applications (Expert 3).
B9	High investment cost	Obstacles to blockchain adoption include high development costs (Expert 2); businesses prioritise return on investment, yet few have demonstrated substantial profitability from blockchain applications (Expert 3).

6.4.2 Assessing Barriers to Blockchain Adoption in Freeport Operations

The implementation of the designed process to assess the interrelationships among the barriers, along with the results, is outlined as follows:

1) The total influence matrix. Appendix D displays the initial matrices from the three experts and their average initial matrix. The total influence matrix was derived using Equations 5-1 to 5-4 with the value of *K* being 0.040541, as illustrated in Table 6.6. As outlined in Equations 5-5 and 5-6, several indicators were calculated and are presented in Table 6.7. Consequently, Figure 6.2 illustrates the causal and effect graph. All causal barriers (B4, B5, B7, and B10) are positioned above the horizontal axis, while the effect barriers (B1, B2, B3, B6, B8, and B9) are located below it. The *R+C* axis represents the varying central roles of barriers. Those

positioned farther along the axis have a more central role, such as B9, interacting with many other barriers.

Table 6.6 Total influence matrix of blockchain adoption barriers.

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
B1	0.7234	0.8582	0.7387	0.667	0.5224	0.858	0.6825	0.7781	0.9546	0.5992
B2	0.9102	0.8308	0.8222	0.7423	0.5732	0.9295	0.7956	0.8653	1.0476	0.6704
B3	0.8313	0.8466	0.6734	0.6638	0.5174	0.8796	0.7132	0.7884	0.9678	0.607
B4	0.9576	0.9907	0.8651	0.7055	0.6474	1.0261	0.8365	0.921	1.1066	0.7402
B5	0.9612	1.016	0.8897	0.8147	0.5702	1.0416	0.8483	0.901	1.1441	0.7499
B6	0.9686	1.0122	0.8867	0.7999	0.6531	0.9181	0.8346	0.9202	1.1502	0.7574
B7	0.9807	1.0129	0.9093	0.809	0.6377	1.0162	0.7701	0.9547	1.1754	0.7546
B8	0.9136	0.955	0.8467	0.7523	0.6013	0.9569	0.8301	0.7927	1.0889	0.713
B9	1.0301	1.0526	0.9551	0.8319	0.6668	1.0774	0.8901	0.9796	1.0678	0.7535
B10	0.8542	0.9055	0.8023	0.7016	0.5588	0.9283	0.7662	0.8441	1.0112	0.5911

Table 6.7 The degree of central role and the degree of relation of blockchain adoption barriers.

	R	*C*	*R+C*	*R-C*
B1	7.3821	9.1309	16.513	-1.7488
B2	8.1871	9.4805	17.6676	-1.2934
B3	7.4885	8.3892	15.8777	-0.9007
B4	8.7967	7.488	16.2847	1.3087
B5	8.9367	5.9483	14.885	2.9884
B6	8.901	9.6317	18.5327	-0.7307
B7	9.0206	7.9672	16.9878	1.0534
B8	8.4505	8.7451	17.1956	-0.2946
B9	9.3049	10.7142	20.0191	-1.4093
B10	7.9633	6.9363	14.8996	1.0270

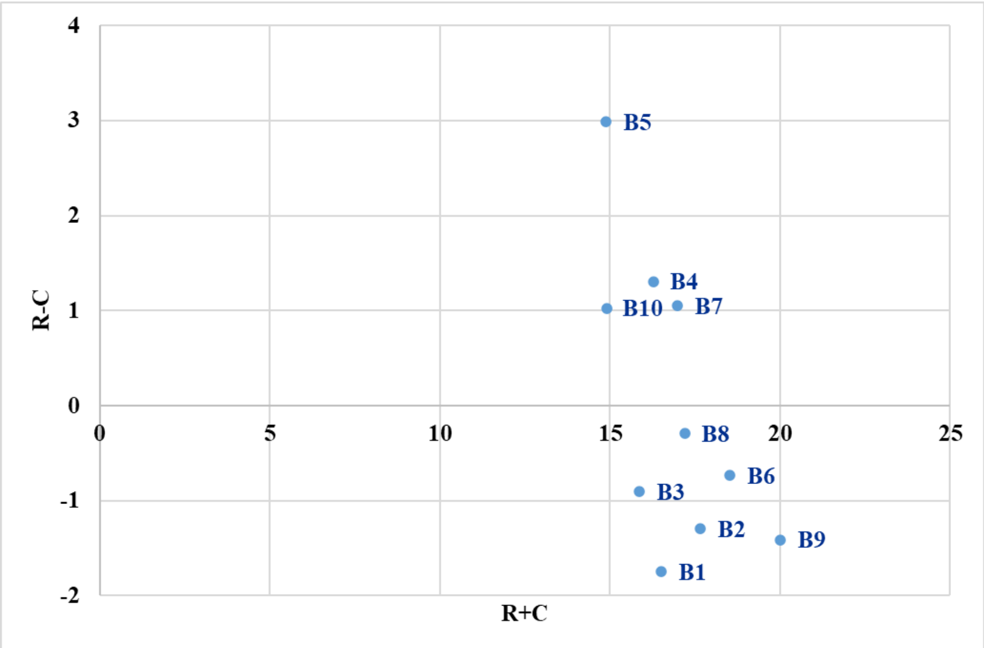

Figure 6.2 Blockchain adoption barriers causal graph with the degree of central role and the degree of relation.

2) The causal network. The total influence matrix from Table 6.6 was utilised to develop the causal network for BN. After incrementally testing all possible values (0.8, 0.9, and 1) using a probing approach, a threshold of 1 was found to be the most effective, as it results in a structural network that connected the majority of the identified barriers while minimising the occurrence of cycles and reverse arcs. Figures 6.3 and 6.4 present the directed graphs for thresholds 0.9 and 1, respectively. Notably, although connecting all identified barriers, a significant number of cycles emerge when the threshold is set at 0.9 or lower, making it ineffective for constructing a DAG. Specifically, the directed graph for threshold 0.9 consists of 31 cycles, including two self-loops. In contrast, applying threshold 1 reduces the cycles to just 4: B9→B6→B9, B9→B2→B9, B9→B6→B2→B9, and a self-loop B9.

   Subsequently, the initial network, established with a threshold of 1, was refined and converted into a DAG to serve as the foundation for building a BN model. Aside from the self-loop at B9, the refinement involved removing two reverse arcs with relatively lower influence values: one from “B2 Lack of Industry Standard” to “B9 High Investment Cost” (1.0476), and the other from “B9 High Investment Cost” to “B6 Lack of Stakeholder Collaboration” (1.0774). The revised causal network is depicted in Figure 6.5. This revised network consists of nine factors, excluding the 'Lack of Scalability' barrier due to its absence of any causal relationships exceeding the threshold of 1.

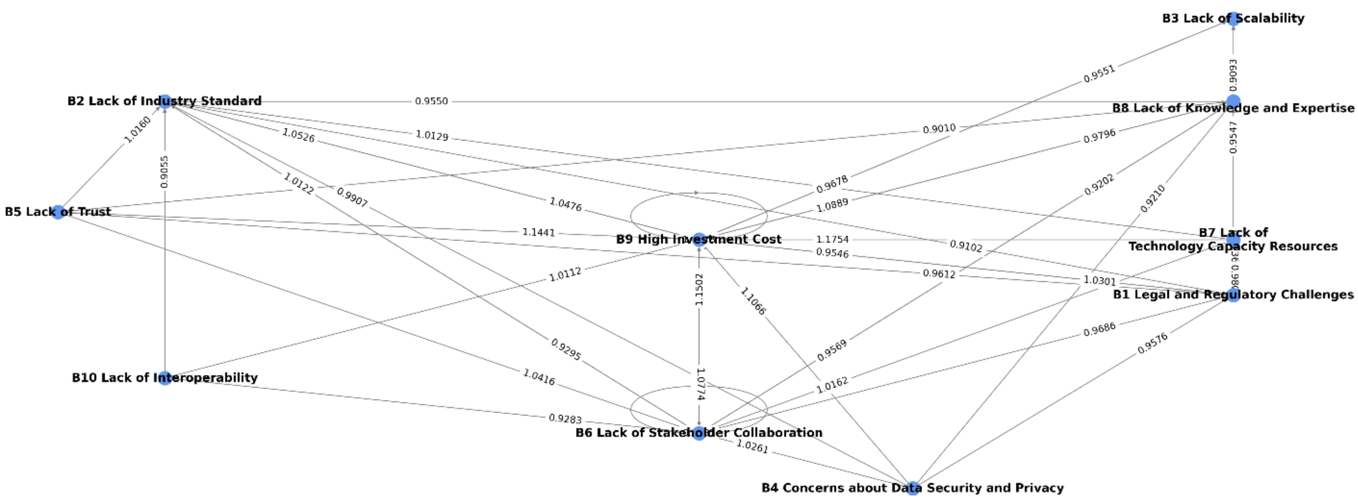

Figure 6.3 Directed graph of blockchain adoption barriers for threshold 0.9.

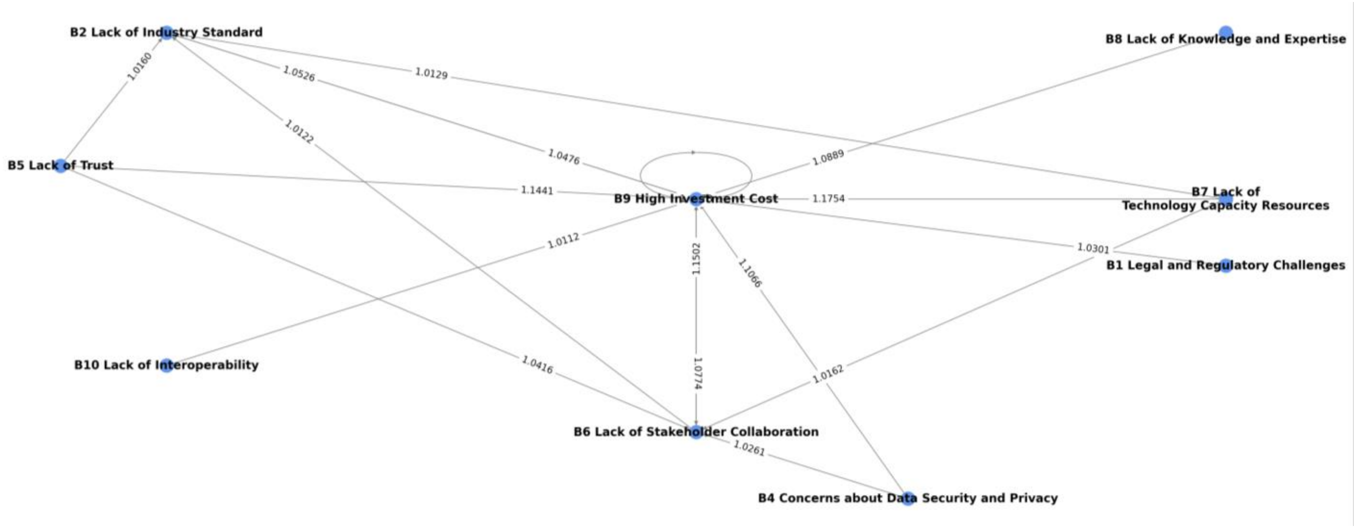

Figure 6.4 Directed graph of blockchain adoption barriers for threshold 1.

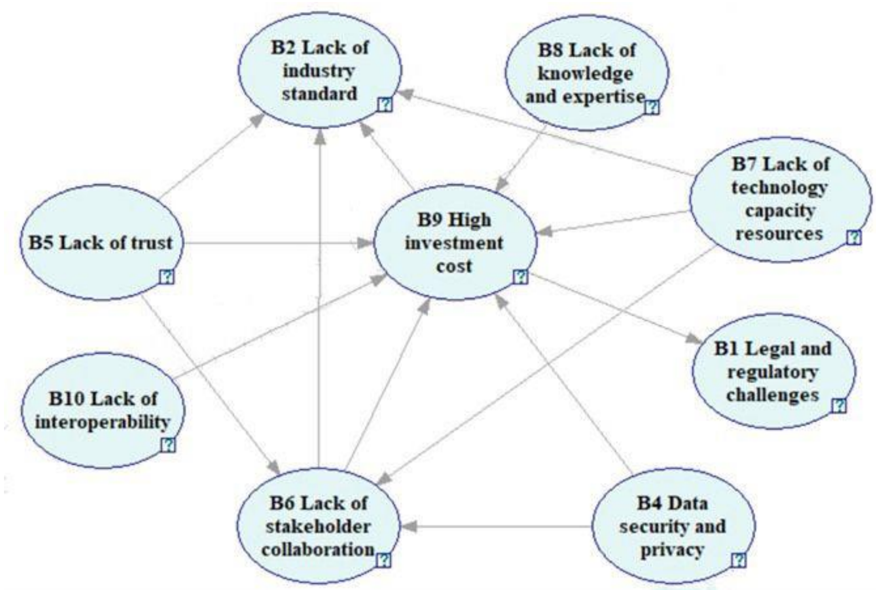

Figure 6.5 The refined causal network of blockchain adoption barriers.

3) The CPT configuration. To parameterise the BN structure based on TNormal (mu, sigma, lower, upper), the initial average matrix from the DEMATEL approach was used to derive weights of the parent nodes for each child node (see Table D.4 in Appendix D). Taking the barrier "Lack of industry standard (B2)" as an example, the weights of its four parents (B5, B6, B7, and B9) were deduced from a numerical set (3.0000, 3.0000, 2.6667, 3.0000), resulting in normalised weights of (0.2571, 0.2571, 0.2286, 0.2571). On the other hand, the SD values were calculated and added up for each child node, as presented in Table 6.8. The summed SD values were further normalised to be used as an input (sigma) for the TNormal distribution. For instance,

the SD values of parent nodes of B2 are (0.0000, 0.0000, 0.5774, 1.0000). The normalisation, achieved by dividing their sum by the total of (3.0000, 3.0000, 2.6667, 3.0000), resulted in a value of 0.1352.

Thus, B2=TNormal (0.2571*B5+0.2571*B6+0.2286*B7+0.2571*B9, 0.1352, 0, 1).

The GeNIe academic software (https://www.bayesfusion.com) was used to configure the BN parameters as this software supports the TNormal function natively. The BN structure, configured through the ranked nodes method, is illustrated in Figure 6.6. This figure illustrates the predictive probabilities for each state of the child nodes (B1, B2, B6, and B9) when all causal barriers (B4, B5, B7, B8, and B10) are set to 100% very-low severity.

Table 6.8 SD values of expert evaluations for blockchain adoption barriers.

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
B1	0.0000	0.0000	1.0000	2.0000	1.1547	1.1547	0.5774	0.5774	1.0000	0.5774
B2	0.0000	0.0000	1.1547	2.0817	1.1547	0.5774	0.5774	0.5774	0.0000	1.1547
B3	1.5275	0.5774	0.0000	2.0817	1.0000	1.0000	0.0000	0.5774	1.0000	0.5774
B4	1.5275	1.1547	1.7321	0.0000	2.0817	**0.5774**	1.5275	1.5275	**1.5275**	1.1547
B5	1.1547	**0.0000**	0.5774	2.3094	0.0000	**0.5774**	1.1547	1.1547	**1.1547**	1.1547
B6	1.1547	**0.0000**	0.5774	2.0817	2.0817	0.0000	1.0000	1.1547	**0.5774**	1.5275
B7	1.5275	**0.5774**	0.5774	2.0817	1.5275	**1.1547**	0.0000	0.0000	**0.0000**	1.1547
B8	1.1547	0.5774	0.5774	2.0000	1.5275	1.1547	0.0000	0.0000	**0.5774**	1.1547
B9	**0.5774**	**1.0000**	0.5774	2.0817	2.0000	0.5774	0.5774	1.0000	0.0000	1.1547
B10	1.0000	0.5774	0.5774	2.0817	1.1547	0.0000	1.1547	1.5275	**1.5275**	0.0000

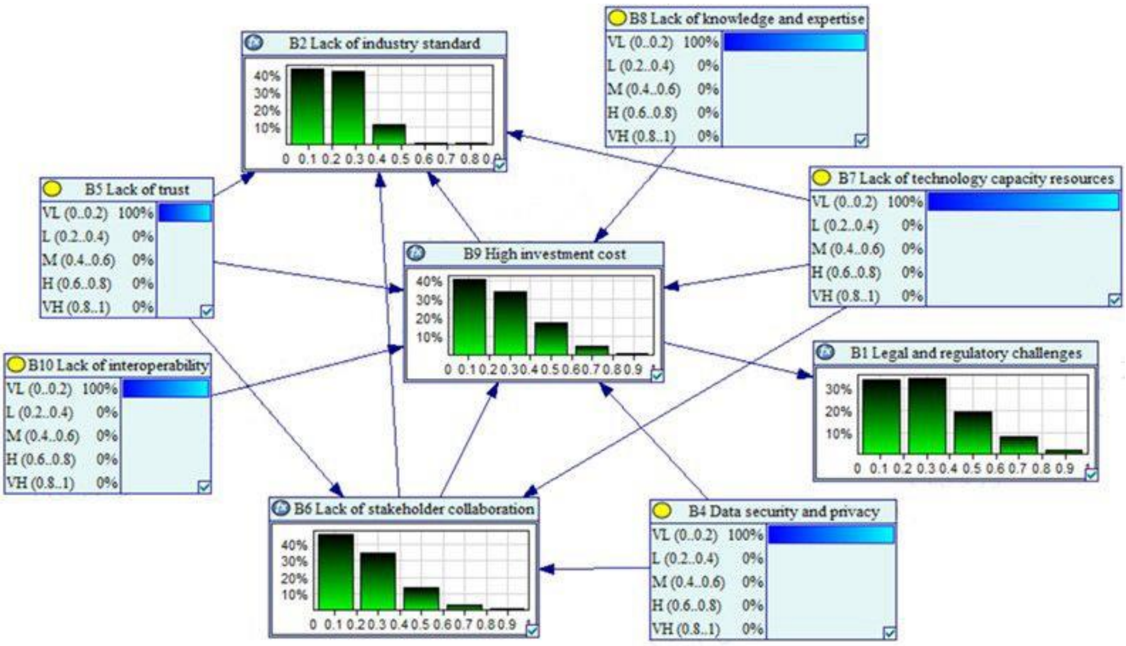

Figure 6.6 The parameterised BN structure of blockchain adoption barriers.

6.4.3 Sensitivity Analysis Results

The fulfilment of the two Axioms was demonstrated through the following process, with Table 6.9 providing an example of B9. Initially, each parent node experienced a minor adjustment of 10%, redistributed from VL (-10%) to the VH (+10%). The consequent change in the expected utility of the corresponding child node was computed. This calculation revealed that the value of a child node varied in direct proportion to the changes in its parent nodes' values. Specifically, the values 0.2831, 0.2850, 0.2893, 0.2819, and 0.2825 are all greater than the original value of 0.2777, thereby satisfying Axiom 1. Subsequently, for Axiom 2, the expected utility values of the child node were recalculated with a 10% reallocation in multiple parent nodes. This process confirmed the attainment of Axiom 2, as the values follow the progression 0.2777<0.2947<0.3012<0.3160<0.3162.

Table 6.9 Barrier severity sensitivity demonstrated by B9.

B4	B5	B7	B8	B10	B9
/	/	/	/	/	0.2777
10%	/	/	/	/	0.2831
/	10%	/	/	/	0.2850
/	/	10%	/	/	0.2893
/	/	/	10%	/	0.2819
/	/	/	/	10%	0.2825
10%	10%	/	/	/	0.2947
10%	10%	10%	/	/	0.3012
10%	10%	10%	10%	/	0.3160
10%	10%	10%	10%	10%	0.3162

6.5 Implications

The implications of the developed model are manifold and significant for decision-makers and practitioners. Although existing research has identified many challenges in integrating blockchain technology across various contexts, the methodologies applied have intrinsic limitations, with only a few studies successfully addressing the interrelationships among these challenges (Balci and Surucu-Balci, 2021; Govindan, 2022; Kaur et al., 2022; Khan et al., 2023; Kumar et al., 2022; Nguyen et al., 2023). Understanding these interrelationships is essential for developing integrated solutions to address these challenges effectively. Moreover, no prior studies have specifically explored the emerging context of freeports, which is distinct due to its regulatory frameworks, handling of luxury goods, and complex stakeholder interactions.

This study addresses this gap by providing a strategic tool to evaluate the complex interrelationships among various barriers to blockchain implementation within a freeport system. First, by identifying the barriers that hold a central role within a freeport system, attention and funding can be efficiently directed to the most influential factors for substantial improvements. For instance, high investment costs (B9) emerge as the primary barrier requiring attention due to its central position in the system. Given businesses' focus on return on investment, demonstrating the tangible financial benefits of blockchain applications becomes crucial. A recommended strategy involves developing a phased implementation plan, starting with pilot projects to showcase immediate value and scalability potential, thereby attracting further investment and support for broader integration.

Second, the ability to differentiate between causal and effect barriers allows for a targeted approach to managing systemic challenges. To be specific, addressing causal barriers with the most significant influence may lead to a cascading positive effect on other barriers, optimising the efficacy of interventions. For example, addressing the lack of trust (B5) among partners in freeport supply chains might not only resolve that specific issue but also help mitigate the lack of industry standard (B2), the lack of stakeholder collaboration (B6), and high investment costs (B9). Conversely, addressing effect barriers, even those with a central position such as high investment costs (B9), requires implementing mitigation measures to address their underlying causes.

Moreover, the influence of barriers on one another is not fixed but can vary across different combinations. Therefore, freeport policymakers should avoid evaluating each factor's influence in isolation and instead consider it within specific scenarios. However, this variability has not been addressed in current research, as highlighted in Section 6.2.2. In this light, the model holds significant implications for advancing factor analysis in blockchain applications by accommodating this uncertainty. It enables a more nuanced understanding of complex systems and promotes the use of integrated approaches, such as network analysis and probabilistic models, to examine interdependent factors and capture their dynamic, combined effects across scenarios. In contrast, existing frameworks based on MCDM methods can evaluate the influence between barriers but are limited in their ability to infer the likelihood of a barrier occurring based on the presence of its influential factors.

Finally, the developed model is applicable not just for the blockchain adoption scenarios but also catalyses the strategic planning and implementation of broader digitalisation initiatives within freeports and other special economic zones. It fosters economic growth while maintaining a balance between operational efficiency and security.

6.6 Conclusion

This chapter presents a novel hybrid methodology for assessing the barriers to blockchain adoption in freeports, offering significant contributions both methodologically and practically. Although numerous studies have examined the adoption of blockchain technology across industries, the associated challenges and causal relationships remain insufficiently addressed. Furthermore, little research has explored its implementation in freeports. This study begins with a comprehensive literature review on blockchain adoption in maritime and supply chain activities, providing a foundation for defining the current state-of-the-art practices in freeport operations while highlighting the advantages and limitations of existing methods. Through the literature review, key barriers are identified. Subsequently, a hybrid DEMATEL-BN model is employed to analyse the probabilistic causal relationships of these barriers, effectively addressing variability across different scenarios. Finally, the model's consistency is verified through sensitivity analysis.

The findings of this study provide important implications for the digital transformation in freeports. First, it provides stakeholders, including freeport authorities, regulatory bodies, logistics companies, and technology providers, with a comprehensive overview of the challenges that need to be addressed to harness the full potential of blockchain technology. Second, by identifying the causal barriers and central barriers, the study can more effectively inform the development of targeted interventions and strategies to overcome the most crucial obstacles, thereby speeding up the adoption process. Furthermore, the methodology enables probabilistic inferences about the significance of individual barriers, accounting for the combined influence of other barriers, thereby enhancing its practical applicability. Lastly, assessing the barriers to blockchain adoption contributes to the broader discourse on digital transformation in freeports and various logistics hubs, offering valuable insights into how digital technologies can be effectively integrated to enhance operational efficiency and safety.

The design of this methodology for analysing factors influencing blockchain applications ensures its transferability and adaptability across various research disciplines, such as maritime transport and supply chain management. Stakeholders can utilise this model to adapt their strategies through dynamic scenario analysis, ensuring that efforts are concentrated on the most critical factors.

CHAPTER 7 CONCLUSION AND FUTURE RESEARCH

Summary

This chapter concludes the thesis by reflecting on how the objectives outlined in Section 1.2 are achieved, highlighting its contributions from both theoretical and practical perspectives in Section 7.1, and discussing research limitations and directions for future studies in Section 7.2.

7.1 New Contributions and Implications

While freeports hold significant potential to stimulate trade and drive economic development, their sustainability challenges are frequently neglected. The existing research highlights several critical gaps that require further investigation. A primary area of need is the lack of comprehensive sustainability assessment frameworks. Existing studies on freeports largely emphasise isolated economic indicators, often overlooking the environmental and social dimensions that are crucial for their sustainable development. Although these sustainability dimensions have garnered more attention in related maritime sectors like ports and port cities, existing methods for sustainability assessments lack the capability to integrate diverse KPIs, encompassing both qualitative and quantitative measures. Additionally, these methods often fail to address data uncertainties and interdependencies among factors, further restricting their practical application.

Research into the vulnerabilities of freeports, particularly to crimes such as cargo theft and illicit trade, is also limited. These risks threaten the long-term sustainability and security of freeports, highlighting the urgent need for advanced monitoring mechanisms. Effective customs inspection strategies and the integration of technologies like blockchain and AI into freeport processes are crucial for mitigating vulnerabilities. However, realising this potential depends on developing innovative frameworks that leverage advanced decision-making methods to address persistent challenges, such as data inconsistency and uncertainty, which remain inadequately explored in existing research.

To address these research gaps, this thesis presents a comprehensive framework that incorporates several innovative solutions aimed at achieving freeport sustainability. Through a series of detailed studies, it thoroughly examines the multifaceted challenges faced by freeport operations, including the absence of a comprehensive sustainability framework, risks linked to cargo theft and illicit trade, conflicts between security controls and operational efficiency, and barriers to the integration of blockchain technology.

The objectives of this thesis, as outlined in Section 1.2, are comprehensively addressed through a structured progression across previous chapters, with each corresponding research question from Section 1.3 answered in turn. This is demonstrated by the following list of applied methodologies and research outcomes.

1) Conducting a systematic literature review to explore sustainability assessment frameworks and evaluate decision-making techniques to address data-related challenges, such as unavailability, incompleteness, uncertainty, and inconsistency. (Chapter 2)
2) Integrating top-down and bottom-up methods to select KPIs for freeport sustainability based on an extensive literature review and field studies, guided by the GRI. (Chapter 3)
3) Introducing a novel hybrid BNER model for freeport sustainability assessment, effectively incorporating quantitative and qualitative KPIs within both hierarchical and network structures and addressing data uncertainty to create a comprehensive and adaptable framework. (Chapters 3 and 4)
4) Developing a data-driven BN model using historical data to analyse the RIFs of cargo theft occurrences and predict cargo theft incidents with reliable accuracy and actionable insights. (Chapter 4)
5) Employing a hybrid DEMATEL-BN approach to identify vulnerable nodes within MCSCs, analyse their causal relationships, and assess the risk of containers' involvement in illicit activities in freeport-centric supply chains. (Chapter 5)
6) Designing an effective container inspection solution by combining risk assessment and optimisation models to translate risk-based inspection theory into practice. (Chapter 5)
7) Applying a DEMATEL-BN model and leveraging interdisciplinary expertise to conduct a dynamic causal network analysis of blockchain adoption barriers in the emerging context of freeports. (Chapter 6)

The proposed methods offer significant advancements in guiding freeport authorities in sustainability monitoring and enhancement, owing to their reliability and applicability. These methods are easily adaptable to changes in data across different freeports and over time. Moreover, the proposed frameworks can be applied to address similar research challenges in the future. As a result, this thesis provides both theoretical and practical implications, as outlined in the following three aspects.

1) Monitoring freeport sustainability with a comprehensive and adaptive framework

This research creates an integrated index framework that can serve as a benchmark for evaluating the sustainability of freeports over time and enabling underperforming freeports to learn from the best practices of top performers. By identifying key KPIs, such as customs efficiency and information technology, and assessing stakeholder-specific perspectives on sustainability dimensions, the framework provides practical guidance to enhance trade efficiency, foster stakeholder collaboration, address disparities, and promote the sustainable long-term prosperity of freeports.

The proposed framework, built on the hybrid BNER model, demonstrates strong adaptability for other performance assessment needs, including other types of SEZs dealing with hierarchical and network-driven factors as well as incomplete data.

2) Enhancing freeport sustainability through robust risk mitigation strategies

This research raises awareness of the crime-related risks faced by freeports and emphasises the need for an incident or accident reporting system to facilitate risk pattern analysis. Such analysis identifies trends and varying impacts of risk factors, enabling targeted preventive measures. For instance, this research employs a data-driven approach to enabling scenario-specific predictions of cargo theft incidents, providing actionable insights for cost-effective strategies to prevent theft and address vulnerabilities in their operations. Additionally, this research introduces an innovative framework for optimising container inspection strategies in freeports, striking a balance between stringent security and operational efficiency. By identifying high-risk containers, it enhances resource allocation, strengthens supply chain security, and offers a global blueprint for resilient and trade-friendly freeports.

By demonstrating the applicability of the BN model to both objective data (Chapter 4) and subjective data (Chapters 5 and 6), this research provides future researchers with the flexibility to choose the most suitable framework for conducting risk assessments under uncertainty, based on the availability of data. For example, if data on seizures of illicit import containers in freeports becomes available, the data-driven BN model for cargo theft can be applied to identify key RIFs of illicit trade across various scenarios and to inform the development of targeted prevention strategies.

3) Enhancing freeport sustainability through blockchain integration

The digitalisation of freeport processes through technologies like blockchain and AI is vital for mitigating vulnerabilities while enhancing transparency, traceability, and efficiency. Fully realising this potential requires addressing key challenges related to the integration of these technologies. This research provides a strategic tool to analyse the complex interrelationships among barriers to blockchain adoption in freeports, offering valuable insights for stakeholders driving digital transformation. It emphasises the importance of addressing causal and central barriers to achieve cascading benefits, and considers dynamic factor influences to enable smoother blockchain integration.

7.2 Limitations and Future Research

While this research offers significant contributions, several limitations need to be addressed in future studies.

1) Future research could expand the case studies to include more freeports globally to provide robust comparative analysis, offering deeper insights into the effectiveness of sustainability practices and enabling the identification of global best practices. The model reflects the current best practices in general. In future, when the methodology is applied to other freeport systems requiring new

KPIs, the model is flexible and adaptable, allowing for the incorporation of additional metrics to enhance its generality and comprehensiveness.

2) In Chapter 4, the data-driven BN model for cargo theft risk analysis consolidates certain low-probability states, such as electronics in the product category and hijacking in the incident category, into a single state labelled ‘other.’ These categories have garnered significant industrial attention and warrant further investigation to understand their specific risk dynamics when combined with other RIFs. Moreover, the inclusion of Year as a static node in the current BN model limits the model's ability to capture temporal dependencies and evolving patterns in cargo theft. A dynamic BN could potentially address this limitation by modelling temporal transitions and dependencies, which may improve the model’s capacity for forecasting.
3) In Chapter 5, the two-stage methodology for container inspection strategy is demonstrated using a small sample of 10 shipments; however, the computational time required for the first-stage container risk assessment is expected to increase proportionally with larger sample sizes. Additionally, the second-stage container inspection optimisation could be further developed by including decision variables regarding government incentive levels and company investment levels, thereby informing public-private partnership strategies.

By addressing the identified limitations and building on the proposed methodologies, future research can further enhance the resilience, sustainability, and technological integration of freeports, ensuring their continued relevance and effectiveness in the global economy.

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APPENDICES

Appendix A. KPI Descriptions and Survey Participants

Table A.1 KPI descriptions.

No.	Level-3 KPIs	Descriptions
1	Development area of freeport (Hectare)	Land within the freeport area that has been earmarked for development.
2	Port cargo tonnage (tons)	Total volume by commodity type of freight loaded and unloaded at the port. If the freeport has more than one seaport or airport, use the total of all.
3	Port container throughput (TEUs)	It refers to containers. If the freeport has more than one seaport or airport, use the total of all.
4	Movement of rail freight in/out of the freeport (tons or TEUs)	The number of units of rail freight entering and leaving the freeport zone. Rail movements can be collected using advance plans.
5	Movement of road freight in/out of the freeport (tons or TEUs)	The number of units of road freight entering and leaving the freeport zone. Road movements can be collected through the use of traffic counters at entrances/exits.
6	Number of new infrastructure projects	Number/type of new infrastructure projects directly related to the Freeport (set up within the tax site, customs site, port area, and freeport boundary)
7	Information technology	It reflects the development of freeports in intelligent E-commerce, digital trade, and information resource sharing.
8	Facility availability	It refers to the availability of cargo handling facilities with freeport development and increasing cargo volume.
9	Number of customs sites	
10	Number of tax sites	
11	Tax policy	It refers to the coverage of relevant policy areas such as: 1)Stamp Duty Land Tax (SDLT) Relief 2)Enhanced Structures and Buildings Allowance 3)Enhanced Capital Allowances 4)Employer National Insurance Contributions Relief 5)Business rates
12	Cargo traffic congestion	It measures the timeliness of freeport services when cargoes enter the freeport zone.
13	The efficiency of customs clearance	It refers to the timeliness and simpleness of customs procedures.
14	Diversity of logistics services	It refers to the diversity of services such as intermodal transportation, storage, and on-time delivery to meet customer requirements in a timely, cost-effective manner.
15	Operational accuracy	It refers to the accuracy of business operations in the freeport.
16	GDP (change rate)	Data is to be collected within the direct area where the freeport is to have an impact. Otherwise, use the UK regional (where the freeport is located) data instead.
17	GDP per capita (thousand pounds)	Data is to be collected within the direct area where the freeport is to have an impact. Otherwise, use the UK regional (where the freeport is located) data instead.

18	Total import and export of foreign trade (change rate)	Data is to be collected within the direct area where the freeport is to have an impact. Otherwise, use the UK regional (where the freeport is located) data instead.
19	Foreign direct investment (pounds)	Foreign direct investment that is directly related to the freeports program.
20	Number of businesses and jobs operating at freeport development sites	
21	Air pollution	It refers to the air quality degradation caused by main air pollutants from freeport activities (e.g., CO_2, SO_2, NO_x, PM2.5, and PM10).
22	Water pollution	It refers to the water environmental degradation caused by spills or leaks from oil products and bulk liquids, and discharges of chemical pollutants in freeport waters.
23	Noise pollution	It refers to the disturbance (e.g., noise and vibration) to the community during cargo handling, infrastructure construction and demolishment.
24	Soil pollution	It refers to spills or leaks of dangerous liquids (HC, paints, solvents, oils) from land traffic, construction, vessel repair, and leached material from storage of stock.
25	Hazardous waste handling	It includes separating hazardous goods and poisons during construction and operation, employing licensed contractors to handle hazardous waste, sterilising and burning cargo coming from the epidemic area, etc.
26	General waste management	It includes garbage classification in the freeport area, a dedicated storage area for recycling, reducing packaging use and office waste.
27	Centralized sewage treatment	It refers to the percentage of productions and operations in freeports using the centralised sewerage service.
28	Water consumption management	It includes reducing waste of drinking water and irrigation, monitoring water leakage, on-site water treatment and reuse.
29	Clean energy sources	It refers to the ratio of freeport operation machinery, ships, and vehicles using electricity, Liquefied natural gas (LNG) and other clean energy sources.
30	Environmental training	It refers to the popularization of training sessions for workers to improve their environmental awareness.
31	Ecosystem and habitat protection	It refers to the strategies for reducing the degradation of natural habitats, halting the loss of biodiversity, and protecting threatened species.
32	Climate change adaptation and mitigation	It refers to the adaptive capacity of freeports in dealing with climate change through policy planning and operational changes.
33	Environmental protection policy	By consideration of the following principles (Wildlife and Countryside Link, July 2020): Freeport proposals must align with the UK's net-zero carbon emissions commitment, excluding airports from the scope; All environmental and animal welfare standards must take precedence over trade policy regulations; Freeports must maintain strict customs procedures to prevent facilitating illegal trade in wildlife.
34	Number of new jobs due to the freeport development	The number of new jobs to be created due to the freeport development.

35	Employment in high-tech and knowledge-oriented sectors	It refers to the percentage of employment in high-tech and knowledge-intensive sectors.
36	Gender equality	It refers to the balance between female and male employees.
37	Number and level of skills training	The number of skills programs and information on the type of program (i.e. length of the course, level of expertise) set up to meet identified Freeport workforce needs.
38	Participation in skills training	The number of people enrolled in skills programs set up to meet identified freeport workforce needs.
39	Fatal injuries	Rate of fatal injuries per 100,000 workers (the data of the UK regions is to be collected if the data within freeports is not available).
40	Non-fatal injuries	Rate of non-fatal injuries per 100,000 workers (the data of the UK regions is to be collected if the data within freeports is not available).
41	Cargo theft incidents	The occurrence probability of cargo theft incidents within the UK regions where the freeports are located.
42	The number of projects run jointly between firms and research innovation organisations within the freeport area	The number of projects featuring the collaboration between firms and research innovation organisations as a direct result of the freeport. Research innovation organisations include universities, catapult centres, research infrastructure and Public Sector Research Establishments (PSREs).

Table A.2 Participant list.

Participant No.	Role	Experienced countries
1	Researcher (Professor)	Russia
2	Researcher (Professor)	China
3	Researcher (Professor)	Brazil
4	Policymaker (Director)	The UK, Morocco
5	Policymaker (Director)	China
6	Policymaker (Investment Officer)	China
7	Practitioner (Customs Officer)	China
8	Practitioner (Administrative Officer)	China
9	Practitioner (Freeport Consultant and Adviser)	The UK, Dubai, Ghana, Canada
10	Practitioner (Infrastructure Management)	The UK
11	Freeport service user (Shipping Center Construction Office/Port)	China
12	Freeport service user (Forwarder)	China
13	Freeport service user (Shipping Company)	Germany
14	Public resident	The UK
15	Public resident	The UK
16	Public resident	China, the UK
17	Public resident	The UK, Iran

Appendix B. Confusion Matrix of Cargo Theft Prediction

Table B.1 Confusion matrix of cargo theft prediction.

Predicted	Other	Theft from Container /Trailer	Theft from Facility	Theft from Vehicles	Theft of Container /Trailer	Theft of Vehicles	Truck Theft	Actual total	Accuracy rate (%)
Actual									
Other	**14**	1	1	5	0	4	0	25	56.00
Theft from Container/Trailer	0	**13**	1	21	0	2	0	37	35.14
Theft from Facility	0	0	**4**	6	1	4	1	16	25.00
Theft from Vehicles	4	2	4	**577**	1	11	0	599	96.33
Theft of Container/Trailer	0	0	0	6	**2**	0	1	9	22.22
Theft of Vehicles	1	0	2	15	2	**32**	1	53	60.38
Truck Theft	0	0	0	1	0	3	**187**	191	97.91
Predicted total	19	16	12	631	6	56	190	930	89.14

Appendix C. Initial Matrices from DEMATEL for Container Risk Assessment

Table C.1 The initial matrix of expert 1 (MCSC nodes).

	CC	WH	POL	OC	POD	Freeport	Container
CC	0	4	0	2	3	1	3
WH	3	0	2	0	4	3	2
POL	2	3	0	1	0	3	4
OC	2	3	4	0	2	2	0
POD	4	2	3	1	0	3	3
Freeport	1	0	2	4	4	0	2
Container	2	4	0	4	2	3	0

Table C.2 The initial matrix of expert 2 (MCSC nodes).

	CC	WH	POL	OC	POD	Freeport	Container
CC	0	3	4	2	4	4	3
WH	2	0	4	1	2	3	2
POL	4	3	0	2	1	4	3
OC	1	2	3	0	4	1	1
POD	0	2	3	4	0	4	3
Freeport	1	1	2	1	4	0	1
Container	2	1	2	1	4	1	0

Table C.3 The initial matrix of expert 3 (MCSC nodes).

	CC	WH	POL	OC	POD	Freeport	Container
CC	0	3	2	1	2	3	4
WH	4	0	2	1	2	4	3
POL	1	2	0	3	1	3	2
OC	0	0	4	0	4	4	2
POD	1	2	1	3	0	3	2
Freeport	4	4	3	3	3	0	4
Container	3	2	1	0	1	4	0

Table C.4 The initial matrix of expert 4 (MCSC nodes).

	CC	WH	POL	OC	POD	Freeport	Container
CC	0	2	3	1	2	1	4
WH	3	0	3	2	2	1	2
POL	3	2	0	2	3	2	3
OC	2	3	2	0	2	1	2
POD	4	3	2	2	0	1	3
Freeport	1	2	2	1	1	0	1
Container	3	2	4	1	4	2	0

Table C.5 The initial matrix of expert 5 (MCSC nodes).

	CC	WH	POL	OC	POD	Freeport	Container
CC	0	4	1	1	1	4	4
WH	4	0	1	1	1	3	3
POL	1	1	0	1	1	1	1
OC	1	1	1	0	1	1	1
POD	1	1	1	1	0	1	1
Freeport	3	3	1	1	1	0	1
Container	1	1	1	1	1	1	0

Table C.6 The initial matrix of expert 6 (MCSC nodes).

	CC	WH	POL	OC	POD	Freeport	Container
CC	0	3	2	1	1	2	3
WH	1	0	3	2	2	1	2
POL	2	3	0	3	2	2	3
OC	1	2	3	0	3	2	4
POD	1	2	2	3	0	2	3
Freeport	2	1	2	2	2	0	2
Container	3	2	3	4	3	2	0

Table C.7 The initial matrix of expert 7 (MCSC nodes).

	CC	WH	POL	OC	POD	Freeport	Container
CC	0	2	1	4	1	2	3
WH	1	0	1	3	1	0	3

POL	2	0	0	4	0	0	4
OC	0	3	2	0	2	0	3
POD	2	4	0	0	0	0	4
Freeport	0	3	1	2	3	0	2
Container	3	2	2	2	2	1	0

Table C.8 The initial matrix of expert 8 (MCSC nodes).

	CC	WH	POL	OC	POD	Freeport	Container
CC	0	4	2	2	1	1	3
WH	1	0	3	2	2	2	3
POL	1	2	0	3	3	2	4
OC	2	2	3	0	3	2	4
POD	1	2	2	2	0	3	4
Freeport	1	2	2	2	2	0	4
Container	3	3	4	4	4	4	0

Table C.9 The initial matrix of expert 9 (MCSC nodes).

	CC	WH	POL	OC	POD	Freeport	Container
CC	0	2	3	2	3	3	3
WH	2	0	2	2	2	2	2
POL	3	2	0	4	2	3	4
OC	2	2	2	0	3	3	3
POD	3	2	3	3	0	4	2
Freeport	3	2	3	3	4	0	2
Container	3	2	3	3	3	3	0

Appendix D. Initial Matrices from DEMATEL for Evaluating Blockchain Adoption Barriers

Table D.1 The initial matrix of expert 1 (blockchain adoption).

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
B1	0	3	3	4	2	2	1	2	3	2
B2	3	0	3	4	2	2	3	2	3	3
B3	4	3	0	4	2	3	2	2	3	2
B4	4	4	4	0	4	4	4	4	4	3
B5	3	3	3	4	0	3	3	3	4	3
B6	4	3	3	4	3	0	3	3	4	3
B7	4	3	3	4	3	3	0	3	4	3
B8	3	3	2	4	3	3	3	0	3	3
B9	4	3	3	4	4	4	3	3	0	3
B10	3	2	2	4	2	3	3	4	3	0

Table D.2 The initial matrix of expert 2 (blockchain adoption).

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
B1	0	3	2	0	0	4	1	3	4	1
B2	3	0	1	0	0	3	2	3	3	1

B3	3	2	0	0	0	4	2	3	4	1
B4	3	2	1	0	0	3	2	3	3	1
B5	3	3	2	0	0	3	3	1	4	1
B6	2	3	2	0	0	0	2	3	3	1
B7	3	2	2	0	0	3	0	3	4	1
B8	3	2	2	0	0	3	3	0	3	1
B9	3	4	4	0	0	3	3	4	0	1
B10	2	3	3	0	0	3	3	3	4	0

Table D.3 The initial matrix of expert 3 (blockchain adoption).

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
B1	0	3	1	2	2	2	2	2	2	1
B2	3	0	3	3	2	2	3	3	3	1
B3	1	2	0	1	1	2	2	2	2	1
B4	1	2	1	0	3	3	1	1	1	3
B5	1	3	2	4	0	4	1	1	2	3
B6	2	3	2	3	4	0	1	1	4	4
B7	1	3	3	3	2	1	0	3	4	3
B8	1	3	3	2	2	1	3	0	4	3
B9	3	2	3	3	2	3	2	2	0	1
B10	1	3	2	1	2	3	1	1	1	0

Table D.4 The average initial matrix (blockchain adoption).

	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
B1	0.0000	3.0000	2.0000	2.0000	1.3333	2.6667	1.3333	2.3333	3.0000	1.3333
B2	3.0000	0.0000	2.3333	2.3333	1.3333	2.3333	2.6667	2.6667	3.0000	1.6667
B3	2.6667	2.3333	0.0000	1.6667	1.0000	3.0000	2.0000	2.3333	3.0000	1.3333
B4	2.6667	2.6667	2.0000	0.0000	2.3333	3.3333	2.3333	2.6667	2.6667	2.3333
B5	2.3333	3.0000	2.3333	2.6667	0.0000	3.3333	2.3333	1.6667	3.3333	2.3333
B6	2.6667	3.0000	2.3333	2.3333	2.3333	0.0000	2.0000	2.3333	3.6667	2.6667
B7	2.6667	2.6667	2.6667	2.3333	1.6667	2.3333	0.0000	3.0000	4.0000	2.3333
B8	2.3333	2.6667	2.3333	2.0000	1.6667	2.3333	3.0000	0.0000	3.3333	2.3333
B9	3.3333	3.0000	3.3333	2.3333	2.0000	3.3333	2.6667	3.0000	0.0000	1.6667
B10	2.0000	2.6667	2.3333	1.6667	1.3333	3.0000	2.3333	2.6667	2.6667	0.0000

Appendix E. Publications Arising from This Thesis

1. Liang, X., Fan, S., Lucy, J., Yang, Z., 2022. Risk analysis of cargo theft from freight supply chains using a data-driven Bayesian network. Reliab. Eng. Syst. Saf. 226, 108702. https://doi.org/10.1016/j.ress.2022.108702

2. Liang, X., Fan, S., Lucy, J., Chen, J., Coleman, J., Li, Y., Qu, Z., Li, H., Yang, Z., 2025. Quantitative sustainability assessment of freeports: Hybrid model evidence from the UK. J. Clean Prod. 487, 144521. https://doi.org/10.1016/j.jclepro.2024.144521

3. Liang, X., Fan, S., Li, H., Jones, G., Yang, Z., 2025. Navigating Uncertainty: A Novel Framework for Assessing Barriers to Blockchain Adoption in Freeport Operations. J. Mar. Sci. Eng. 13, 249. https://doi.org/10.3390/jmse13020249
4. Liang, X., Fan, S., Li, H., Yang, Z., 2025. A Risk-Based Container Inspection Solution in Freeport-Centric Supply Chains. (Unassigned)
5. Book Chapter: Liang, X., Fan, S., Yang, Z., 2025. Risk analysis and preventive strategies for cargo theft in freight supply chain operations, in: Reference Module in Social Sciences. Elsevier. https://doi.org/10.1016/B978-0-443-28993-4.00098-6