Artificial Intelligence (AI)-based Multi-criteria Shipping Industry Provider Selection

by Ibraheem Abdulhafiz Q. Khan

Thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

under the supervision of Professor Farookh Hussain

University of Technology Sydney
School of Computer Science
Faculty of Engineering and Information Technology
NSW - 2007, Australia

October 2025

CERTIFICATE OF ORIGINAL AUTHORSHIP

I, *Ibraheem Abdulhafiz Q. Khan*, declare that this thesis is submitted in fulfilment of the requirements for the award of *Doctorate of Philosophy*, in the *School of Computer Science*, *Faculty of Engineering and Information Technology* at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

This research was supported by an Australian Government Research Training Program (RTP) Scholarship doi.org/10.82133/C42F-K220.

SIGNATURE: Production Note: Signature removed prior to publication.

[Ibraheem Abdulhafiz Q. Khan]

DATE: 25th October, 2025

PLACE: Sydney, Australia

DEDICATION

First and foremost, I am immensely grateful to God Almighty for granting me the strength and ability to complete this thesis, and it is only through His grace that I have reached this significant milestone.

I would also like to thank my dear family, who has been a constant source of love, support and encouragement. In particular, I am eternally grateful to my wife; your unwavering support, patience and love have been the foundation of my journey.

To my brothers and sisters who have been companions on this path—your belief in my abilities and unwavering support have bolstered and motivated me.

Finally, a special mention goes to my children—the lights of my life, who have brought me immeasurable joy and inspiration at every step of this journey. Your smiles and unconditional love have made all the hard work worthwhile while reminding me of the importance of pursuing one's dreams.

This thesis represents not only my academic journey but also acknowledges the love and sacrifices made by my family. I dedicate this work to all of you with appreciation and immense gratitude.

Ibraheem Abdulhafiz Q. Khan

ACKNOWLEDGMENTS

First, I thank the Almighty for giving me the strength and determination to complete my PhD thesis despite the challenges I faced throughout my academic journey. I would also like to express my sincere gratitude to my supervisors, Professor Farookh Hussain and Dr Firas Al Doghman, for their unwavering support, invaluable guidance and insightful mentorship, which played a crucial role in my research and writing endeavours.

Additionally, I wish to express my sincere appreciation to the Saudi Arabian Cultural Mission (SACM) in Australia for their generous support and encouragement during my PhD studies.

Last, I would like to thank my family, my wife and my kids, for their continued support and encouragement throughout my PhD journey.

Ibraheem Abdulhafiz Q. Khan

October 2025 @UTS

ABSTRACT

This thesis highlights that automating the selection of maritime shipping service providers is pivotal to supply-chain performance. By replacing fragmented and subjective practices with transparent analytics, automation reduces cost and time, improves reliability, and ensures decisions are reproducible at scale. To achieve this, the thesis introduces an intelligent multi-criteria search engine (MC-SE) that integrates artificial intelligence (AI) and multi-criteria decision-making (MCDM) to support both shippers and freight companies in identifying reliable, cost-effective providers. The objectives are to (i) develop an AI-based predictive classifier for offshore shipping decisions; (ii) systematically map provider criteria to the service quality framework (SERVQUAL); (iii) propose an AI-assisted approach for criteria weighting; (iv) conduct a SERVQUAL survey for provider-side assessment; and (v) validate the framework through an Australian case study.

Methodologically, criteria were extracted from provider websites and benchmark datasets, then clustered into decision attributes using semantic similarity techniques. These clusters were aligned with SERVQUAL dimensions to ensure construct validity. AI-based weighting and supervised learning were applied within an MCDM pipeline to calculate attribute importance, integrate cost as a complementary decision factor, and rank providers objectively. This dual use of structured datasets and unstructured textual content ensures that the framework adapts to both traditional logistics data and dynamic, web-based information sources. Provider-side service quality is structured via SERVQUAL, while cost is modelled as a complementary decision attribute within the overall MC-SE multi-criteria framework.

Validation demonstrates strong agreement between the proposed MC-SE weighting and the SERVQUAL survey (mean absolute error (MAE), MAE = 0.014), with dimension-level differences typically within 2–3%. The optimisation classifier, based on a voting ensemble, achieves 82.3% accuracy on held-out test data. These findings show that data-driven weighting, combined with supervised learning, can robustly support provider selection in practice.

Overall, this thesis develops a novel, AI-driven framework to support the automated selection of maritime shipping service providers, bridging gaps between academic models and industry practice. Future research will refine the MC-SE framework, evaluate its portability across diverse contexts, and extend the evaluation to incorporate customer-experience evidence that complements provider-side quality and explicit cost trade-offs. Importantly, providers' clusters are consistently aligned with canonical SERVQUAL dimensions to preserve theoretical and empirical coherence.

1) **Published (Conference)** — I. A. Q. Khan, F. K. Hussain, and F. Q. M. S. Al-Doghman, "Regression Analysis Using Machine Learning Approaches for Predicting Container Shipping Rates," in *Proceedings of the 36th International Conference on Advanced Information Networking and Applications (AINA-2022)*, Sydney, Australia, pp. 269–280. Springer, LNNS.
DOI: 10.1007/978-3-030-99587-4_23

2) **Accepted / In Press (Journal)** — I. A. Q. Khan, F. K. Hussain, and F. Q. M. S. Al-Doghman, "Selection of Maritime Shipping Providers based on Machine Learning and AHP," *Expert Systems with Applications*, Elsevier (2025).
Preprint DOI: 10.2139/ssrn.4310991
Final DOI: *to be assigned upon publication*

3) **Submitted (Under Review)** — I. A. Q. Khan, F. K. Hussain, and F. Q. M. S. Al-Doghman, "Enhancing Decision-Making in Shipping Service Provider Selection: A Clustering-Based AI Approach with SERVQUAL Integration," submitted to *Engineering Applications of Artificial Intelligence*.
DOI: *not applicable (under review)*

4) **Submitted (Under Review)** — I. A. Q. Khan, F. K. Hussain, and F. Q. M. S. Al-Doghman, "Selecting Maritime Shipping Providers Using Artificial Intelligence and Multi-criteria Decision-Making Practices, Considering Service Quality," submitted to *European Journal of Operational Research*.
DOI: *not applicable (under review)*

Table of Contents

List of Figures

Figure **Page**

List of Tables

Table **Page**

Chapter 1

Introduction

1.1 Introduction

Maritime transport occupies a central position in the global economy, acting as the foundation for international commerce. Maritime transport is estimated to handle 80% of global merchandise commerce by volume and 70% by value [1]. Maritime transportation offers an economical and effective method of transporting various commodities, such as raw materials, finished products, and energy resources [2]. Therefore, this primary mode of transportation supports economic expansion, encourages international collaboration, and guarantees the availability of products in global markets. Thus, the absence of the crucial role of maritime transport would significantly disrupt the worldwide supply chain, affecting economic progress and globalisation.

Transportation research has emphasised the importance of consignees' decision making in selecting maritime transport providers. Shippers consider factors such as price and service quality when choosing carriers. Shipping rates are crucial for stakeholders, as indicated by several studies

[3][4]. Service-related criteria include customs compliance, punctuality, packaging proficiency, door-to-door service, corporate responsibility, and integration with other logistics systems [5][6]. Several studies indicate that other factors, such as provider stability, adaptability, sustainability, and durability, are crucial quality factors [7][8][9]. Moreover, shipping service providers are not homogeneous, and different factors are crucial in specific geographic regions and consumer groups.

1.2 Shipping Service Provider Selection

Various decision-making models are employed to select shipping service providers, ranging from conventional multi-criteria decision-making (MCDM) methods [10][11][12] to advanced machine learning (ML) models [13][14]. MCDM involves the evaluation of alternatives based on multiple criteria to facilitate informed decision-making processes. In this context, a criterion indicates the standard factors experts use to evaluate and compare shipping providers. These criteria include cost, trustworthiness, responsibility, and reliability. Specifically, any MCDM method should consist of the names of the shipping providers (alternatives) and their respective criteria (attributes).

Conventional MCDM approaches provide systematic ways to evaluate and compare alternatives. For example, the analytical hierarchical process (AHP) [15][16][17] establishes a hierarchy of criteria and evaluates shipping providers by relative importance; the technique for order of preference by similarity to ideal solution (TOPSIS) [17] identifies the most favourable provider by distances from ideal and negative-ideal solutions; and criteria importance through intercriteria correlation (CRITIC) [18] assesses interdependencies among criteria to yield more balanced weights. While effective, these tools rely on predefined criteria and substantial expert input, and can be difficult to scale when alternatives and attributes proliferate (e.g., more than 80 providers across Australian ports).

Transition to advanced approaches. The reliance on expert judgment and the limited scalability of conventional MCDM motivate the adoption of data-driven methods. ML models such as random forest (RF), eXtreme gradient boost (XGBoost), and multilayer perception (MLP) have been used to predict freight rates and identify optimal routes [4], while fuzzy-based approaches manage imprecision and uncertainty to support multi-criteria evaluations [19]. Complementing these, service quality in logistics research is most often operationalised using the service quality (SERVQUAL) scale, which assesses tangibles, empathy, reliability, responsiveness, and assurance (TERRA) [20][21]. Reviews highlight its strengths and limitations across sectors [22][23], while applications in maritime transport and freight forwarding confirm its relevance [9][24][25]. By integrating SERVQUAL with ML models, decision-makers can achieve both conceptual rigour and data-driven robustness in evaluating shipping providers, ultimately enhancing operational efficiency and customer satisfaction [26][27].

In addition to traditional decision-making methods and machine learning approaches, SERVQUAL has comprehensive criteria for evaluating shipping service providers based on dimensions such as tangibles, empathy, reliability, responsiveness, and assurance (TERRA) [22]. SERVQUAL demonstrates its effectiveness in assessing service quality in maritime shipping and other logistics domains [9][25]. By adopting SERVQUAL or similar frameworks, decision-makers can ensure consistent evaluations across service providers, ultimately enhancing decision-making processes. Furthermore, integrating machine learning models with established frameworks like SERVQUAL enables more robust and data-driven decisions in selecting shipping service providers, leading to improved operational efficiency and customer satisfaction [26][27].

The SERVQUAL scale consists of five dimensions, providing a comprehensive evaluation framework to assess the overall quality of shipping services. These dimensions include:

1. **Tangibles**: This dimension assesses the physical and visible aspects of the service (e.g., facilities, equipment, and documentation appearance) that shape impressions of quality and professionalism. In the shipping context, this includes vessel condition, port facilities, and the quality of documentation.

2. **Empathy**: This dimension reflects individualised care and understanding of consignees' needs, emphasising tailored, attentive service. Empathetic providers adapt to customer constraints (e.g., schedule changes) and foster long-term relationships.

3. **Reliability**: The provider's ability to perform the promised service dependably and accurately (e.g., on-time delivery, correct documentation, and consistent tracking). Reliability underpins smooth logistics operations.

4. **Responsiveness**: Promptness and willingness to help customers, including timely responses to enquiries, proactive status updates, and swift issue handling, which together enhance satisfaction.

5. **Assurance**: Knowledge, competence, and professionalism that inspire confidence and trust (e.g., regulatory compliance, certifications, domain expertise, and experienced staff).

Scope and theoretical justification. While SERVQUAL structures provider-side service quality through five core dimensions: tangibles, empathy, reliability, responsiveness, and assurance [20][21] —it does not incorporate cost efficiency. In this study, cost is therefore treated not as a hidden sixth dimension but as a complementary attribute that operates alongside SERVQUAL within a multi-criteria decision-making framework. This treatment is consistent with the literature on logistics and operations research, where quality and cost are often analysed together using hybrid or integrated MCDM models [28][29][30][31][32]. Recent work further demonstrates that cost–quality trade-offs can be systematically evaluated in shipping and logistics: hybrid models have been applied to the selection of third party logistics providers [33], to the optimisation of last mile delivery performance [34], to the classification of the crowd logistics platform [35], and to the evaluation of sustainable city logistics where social cost-benefit analysis is combined with MCDM [36]. These precedents provide a strong theoretical foundation for incorporating cost explicitly as an external but decision-relevant criterion, ensuring that SERVQUAL remains intact as a service quality construct.

In parallel, this study recognises the role of the consumer-side instrument service performance (SERVPERF), which captures perceived performance outcomes directly rather than relying on expectation–perception gaps [37]. SERVPERF has been shown to align closely with value-for-money perceptions and customer satisfaction [23][38]. To strengthen this consumer perspective, future extensions of the framework can also incorporate widely adopted measures of customer voice—such as satisfaction indices, customer satisfaction score (CSAT) [39], loyalty metrics like net promoter score (NPS) [40], and sentiment signals derived from digital platforms [41][42]. By combining these consumer-oriented indicators with SERVPERF, the framework can evolve into a dual-track model: SERVQUAL continues to represent provider-side service quality, cost remains a complementary criterion within the multi-criteria structure, and SERVPERF, enriched with customer-voice inputs, reflects the consumer-side experience. This mapping not only makes the theoretical boundaries explicit but also sets a clear trajectory for broadening the framework in a balanced, rigorous way.

1.3 Approach

Multi-criteria decision-making (MCDM) methods, which typically rely on experience, pose challenges for experts. The existing maritime shipping service provider selection literature lacks a standardised model integrating diverse criteria and advanced ML approaches. While many studies identify various factors influencing selection, they remain fragmented and context-specific. Traditional methods for making decisions based on multiple criteria have been used. A unified framework could address this gap and improve transparency and effectiveness in selecting shipping service providers. Therefore, this study provides different approaches that utilise automated methods and advanced provider selection criteria.

This study adopts the SERVQUAL framework [25][43], to overcome the selection limitations of the MCDM approaches. SERVQUAL structures provider-side service quality across the five dimensions: tangibles, empathy, reliability, responsiveness, and assurance. In this thesis, *cost* is treated as a complementary decision attribute outside the SERVQUAL construct (see the scope note above), and is weighted alongside SERVQUAL dimensions within the overall MCDM setup. Throughout the thesis, all references to SERVQUAL follow the TERRA order (Tangibles, Empathy, Reliability, Responsiveness, and Assurance); cost remains a complementary, non-SERVQUAL attribute integrated at decision time via MCDM.

Compared to alternative approaches, the SERVQUAL model surpasses other models such as the NPS [40] and four components (4C). Although NPS primarily measures customer loyalty, the 4C model emphasises cost, compliance, capability, and coverage.

This study opts for the SERVQUAL framework, as it allows the construction of a set of criteria that facilitate consistent comparisons among service providers and addresses the inherent heterogeneity in carrier selection, integrating them into an AI-based model to predict the optimal shipping provider.

The combined utilisation of MCDM and AI-based models enables the ranking of shipping providers based on these criteria. Integrating these dimensions into the selection process enables decision makers to comprehensively evaluate shipping service providers and make more informed decisions based on various aspects of service quality.

1.4 Research Challenges

This study faces several challenges in exploring the selection of maritime service providers in the shipping industry. The main challenges can be summarised as follows:

1. **Optimising Maritime Shipping Provider Selection:** The research challenge involves revolutionising maritime shipping service provider selection based on current datasets. The challenge is to find a suitable dataset for shipping service providers —in this thesis, the experiments are conducted using the Australian Government's Voyage Reports dataset [44] and supported by prior ML-based optimisation studies in maritime contexts [13][14]—and identify and tune suitable machine-learning algorithms for precise provider predictions. The challenge also involves integrating outputs from machine learning models into an MCDM model, such as an analytical hierarchy pro-

cess (AHP). Therefore, the research strives to bridge the gap between industry intricacies and automated, data-driven decision-making.

2. **Identifying and Grouping Decision Criteria:** The critical challenge is to define the appropriate decision criteria (attributes) to select providers of maritime services. The existing literature lacks unified guidelines for determining these criteria or how to group them. The criteria should be easy to use and generic, considering different shipping providers, regardless of their size, scope of work, and experience. Therefore, developing a comprehensive framework that considers both strategic and operational considerations in provider selection is necessary. This study employs the SERVQUAL as a cornerstone for these criteria grouping. As previously discussed, SERVQUAL is the adopted criteria grouping approach, supported by established applications in logistics and service quality assessment [9][22][25].

3. **Integrating Decision-Maker Knowledge with AI-based Models:** A critical challenge lies in effectively combining the expertise and experience of decision makers with AI-based models in group MCDM approaches to evaluate maritime shipping service providers' performance comprehensively. Bridging the gap between expert insights and automated decision-making processes is crucial to accurately assess and compare the overall performance of service providers in the maritime industry. The SERVQUAL criteria were extracted from over 300 maritime shipping service providers' websites. The idea is to use clustering and machine learning semantic similarity to extract related criteria and group them semantically to generate adjectives and acceptable service provider criteria that could be used automatically in any MCDM technique, in line with prior work on hybrid MCDM and AI integration [10][19][30].

4. **Generalisability of Research Findings:** Ensuring the generalisability and applicability of research findings beyond the Australian shipping industry is crucial. To achieve this, contextual factors and potential variations in industry standards and preferences must be carefully considered, allowing the transferability of insights and recommendations to different geographies and market contexts, as evidenced in broader logistics and cross-industry studies [33][36].

These challenges echo broader logistics selection studies that highlight multi-criteria trade-offs and methodological needs [45][46]. Addressing these challenges is fundamental to improving decision-making processes, increasing the efficiency of the ocean freight market, and empowering the stakeholders of service providers in the Australian shipping industry to make informed decisions.

1.5 Research Questions

Aim. To develop and evaluate an AI-enabled multi-criteria search engine (MC-SE) that automates the selection of maritime shipping service providers by combining provider-side service quality with a complementary cost attribute and data-driven predictions.

Guiding research question. How can an AI-based, multi-criteria decision framework integrate SERVQUAL-derived quality dimensions with a complementary cost attribute and machine-learning outputs to automate and improve maritime shipping service provider selection?

A complete and formally enumerated set of research questions and objectives is presented in Chapter 3, Section 3.5, where each question is mapped to specific objectives and evaluation methods.

1.6 Significance of the Thesis

This thesis incorporates the widely recognised SERVQUAL framework to extract comprehensive criteria to select maritime shipping providers, address the industry's unique challenges, and provide a practical tool for evaluation and comparison. In addition, this study holds significant value for the maritime industry in Australia, which is currently struggling with overcapacity and fierce competition. The research aims to streamline decision making in selecting shipping service providers by introducing an innovative AI-based classifier model. This model uses a clustering approach to predict the most suitable providers based on various cargo shipment criteria originally extracted from shipping providers' websites. Therefore, a new model is proposed that combines artificial intelligence with multi-criteria decision-making methods. By automating the selection process, the thesis enhances the reliability and efficiency of the maritime shipping market in Australia, improving market competitiveness and operational performance. Accordingly, integrating the MCDM method with the AI-based model ensures a more accurate prediction of the optimal providers, further enhancing the decision-making process in the maritime shipping market.

This section also explains how the contributions of this thesis improve the scientific and social situation of the shipping industry. These contributions are as follows:

1.6.1 Scientific Contributions

1. The thesis makes a scientific contribution by constructing the Ship-SERVQUAL dataset, one of the first structured efforts to systematically collect and curate criteria for shipping service providers from their publicly available web content. Rigorous collection and valida-

tion methods were employed, including cross-referencing information and conducting sensitivity analyses, ensuring both credibility and reproducibility.

2. This research could be among the first to extract the provider's specific selection criteria as expected by consignees based on the contents of the provider's websites. Rigorous methods for data collection and analysis are employed to strengthen the credibility and reduce bias, such as cross-referencing information along with sensitivity analyses to assess the robustness of the extracted criteria.

3. This work utilises the SERVQUAL framework for the first time to extract criteria for selecting maritime shipping service providers.

4. This research introduces a pioneering approach that combines an AI-based model with the MCDM method to address the selection of maritime shipping service providers.

5. This research prioritises shipping service providers, simplifying and streamlining the decision-making process.

6. This thesis significantly reduces the burden on experts by providing automatic solutions to their challenges in selecting shipping service providers.

1.6.2 Social Contributions

1. **Efficiency and Sustainability:** This research improves efficiency and sustainability in maritime shipping by developing advanced decision-making models and integrating AI technologies. The proposed approach reduces costs, improves delivery timelines, and promotes environmental responsibility.

2. **Informed choices:** The study facilitates informed choices by providing an evaluation framework for selecting service providers. By leveraging AI-based models, this research study contributes to market transparency, fair competition, and inclusivity by simplifying the decision-making process.

3. **Social responsibility:** In addition to improving efficiency and sustainability in maritime shipping, the selection model developed in this research prioritises the consideration of social responsibility criteria when evaluating service providers. By incorporating aspects of social responsibility, such as ethical practices, labour rights, and community participation, into the decision-making framework, this model promotes responsible and ethical shipping practices, contributing to a more socially conscious and responsible maritime industry.

1.7 Thesis Structure

This thesis provides an intelligent methodology by developing an intelligent framework for selecting optimal maritime shipping service providers by combining the proposed AI-based model with the MCDM approach, selecting the shipping service providers' criteria by applying the SERVQUAL method. The thesis structure is shown in Fig. 1.1.

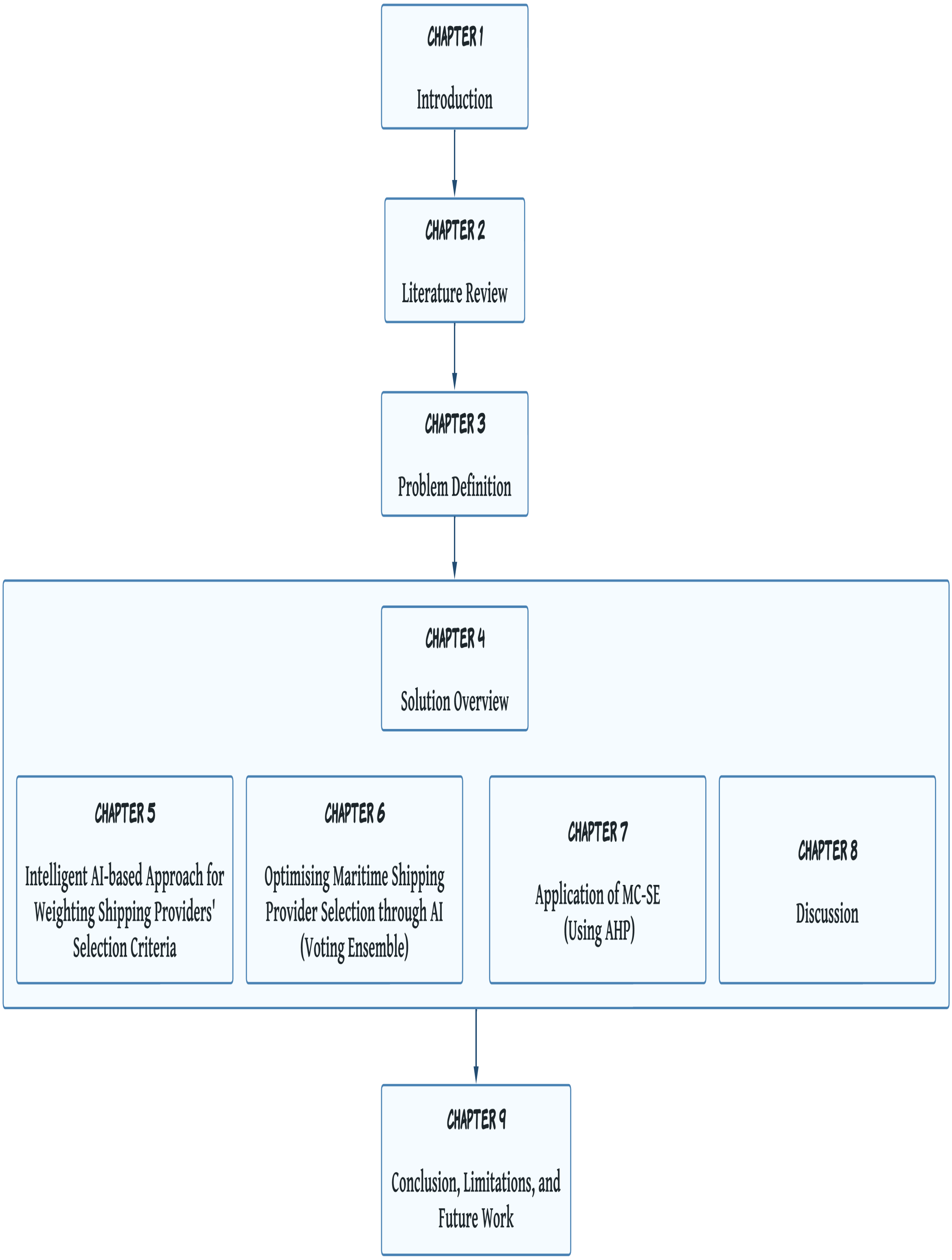


Figure 1.1: The Thesis Structure

This thesis is organised into nine chapters. The current chapter identifies the research challenges and research contributions and provides a brief overview of each chapter. The rest of the thesis is organised as follows:

- **Chapter 2:** This chapter summarises the existing literature. It explores and evaluates the current literature regarding selection criteria, selection methods, multi-criteria decision making models, and the existing literature gaps.
- **Chapter 3:** This chapter provides the formal definition of the research problems and also defines the concepts and terminology utilised in this thesis. This chapter then details the research problem, the research questions, and the research objectives.
- **Chapter 4:** This chapter overviews the proposed solutions, including identifying effective service provider selection criteria using the SERVQUAL framework, implementing an intelligent AI-based approach for weighting shipping providers' selection criteria, conducting surveys and leveraging the SERVQUAL framework in shipping service provider evaluation, and outlining the methodology for a real-case study and MCDM validation within the overall framework.
- **Chapter 5:** This chapter identifies criteria used by shipping service providers and provides details on two proposed approaches for weighting criteria from the benchmark dataset and extracting web content.
- **Chapter 6:** This chapter introduces a tailored ensemble voting classifier model for the maritime shipping industry, leveraging feature selection, weighting, and established machine learning models to enhance the selection of shipping service providers.

- **Chapter 7:** This chapter introduces a novel approach to selecting maritime shipping service providers, combining the multi-criteria search engine (MC-SE) framework with the analytic hierarchy process (AHP).
- **Chapter 8:** This chapter discusses the research questions that led to the proposed intelligent multi-criteria search engine (MC-SE). The MC-SE can be used to prioritise selection automation and simplify decision making.
- **Chapter 9:** This chapter concludes the study by highlighting limitations and proposing future work on selecting maritime service providers using the proposed MCDM and AI approach.

1.8 Conclusion

This study examines the process of selecting maritime shipping service providers in the Australian shipping industry. It emphasises the crucial role of marine transportation in facilitating international trade, fostering economic development, and supporting global supply chains. The research focuses on the difficulties encountered in choosing service providers and proposes adopting a MCDM approach. Specifically, it suggests integrating the SERVQUAL framework to assess service quality. The study derives the weights of shipping criteria from the shipping providers' websites. The key contributions of this thesis encompass advancements in decision-making processes and the integration of the SERVQUAL framework, ultimately leading to enhanced selection methodologies in the shipping industry. The literature review is discussed and analysed in the following chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter reviews and synthesises the studies on the selection of shipping service providers to frame the research questions, establish theoretical and conceptual frameworks, and inform research methodology. Furthermore, the literature review focuses on weighting shipping service providers and multi-criteria decision-making (MCDM) tools, highlighting the gap in the literature.

The maritime shipping process involves a sequential journey from the shipper to the consignee, transferring through different stages and locations. It starts with the shipper, who prepares the goods for transport and arranges their collection from the origin warehouse. After being collected, the cargo is transported to the departure port, where it undergoes the necessary procedures, including customs clearance and documentation. Subsequently, the shipment is loaded onto a vessel for sea transportation to the destination port. Once the cargo reaches the destination port, it undergoes customs procedures to ensure compliance with regulations. Then, it is transported to the destination warehouse for temporary storage and further processing. The load is sorted, organised, and prepared for final delivery to the consignee at the destination warehouse [47]. To ensure a seamless and efficient sea transport process from the shipper to the consignee, the shipper, warehouses, ports, and consignee must coordinate effectively. Figure 2.1 illustrates the sea shipping process from shipper to consignee.

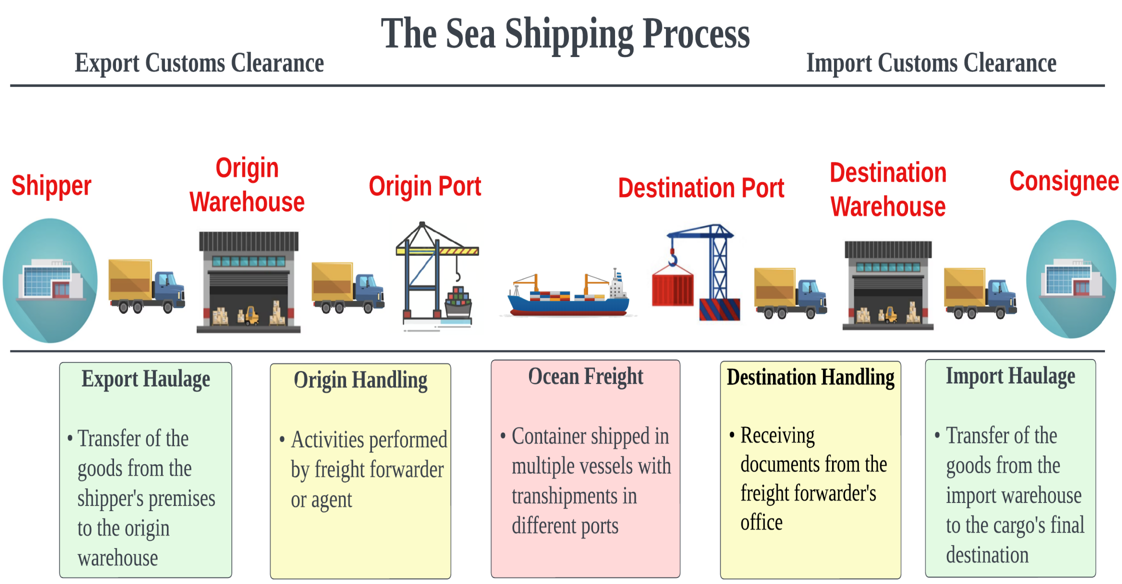


Figure 2.1: The Sea Shipping Process

Shipping service providers facilitate product transportation, storage, packaging, and delivery within logistics and supply chains. Their prominent role is represented in the collaboration with carriers, the organisation of storage and handling logistics, and the management of paperwork and documentation. Engaging a reliable and professional shipping service provider can reduce costs, improve delivery timelines, and increase customer satisfaction. Shipping service providers are essential to facilitate the safe, efficient, and affordable maritime shipping of goods for businesses

[48]. Selecting the most suitable shipping service provider is crucial to ensure business success and to be able to transport goods in a minimum of time, with lower costs and fewer risks, particularly when transporting dangerous items across the ocean.

Transportation research has paid great attention to the decision-making process consignees use when choosing among competing maritime transport providers. Shippers rely on various decision criteria, with factors based on price and service that influence their selection of an ocean carrier [3]. Multiple research studies highlight the importance of shipping rates as an essential criterion for a broader spectrum of stakeholders in shipping [3][4][49]. Service-based selection criteria comprise aspects such as compliance with customs laws [5], adherence to timetables and schedules [3][49][50][51][52], proficiency in packaging [5], provision of door-to-door service [3][6], corporate accountability [3] and integration with other transportation and logistics systems [6].

2.2 Review of Selection Criteria and Selection Methods

This section discusses the selection criteria and methods for shipping service provider selection.

2.2.1 Review of Selection Criteria

The selection criteria for maritime shipping vary worldwide. Fuel costs, freight exchange, and trade categories such as general cargo, petroleum or dry bulk influence the variations. These categories require evaluating capacity, cargo safety expenses, and specialised logistics and supply requirements. For example, a study that examines Indian container shipping services [52] emphasises flexibility and price as crucial factors in selecting container shipping providers. Similarly, countries such as Taiwan [3], Australia [53], South Korea [17], and the United States [4] [54] discuss additional criteria specific to their respective contexts, with a primary focus on schedules and quality of service. An exploratory factor analysis conducted in [3] reveals that network, schedule, and corporate social responsibility significantly influence the choice of maritime freight services.

In addition, environmental criteria are often considered significant factors in the selection process. A two-scenario experiment study [55] examined the impact of social and ecological sustainability on carrier selection. The results revealed that long-term ecological perceptions and short-term social dimensions influence shippers' decisions. Similarly, an exploratory factor analysis conducted in a survey of Ghanaian shipping carriers [49] identified service quality, document precision, freight prices, environmental concerns, schedule dependability, and fast handling as critical considerations when selecting a shipping liner.

Customer-centric or flexible services also play a crucial role in selecting container shipping providers. In their study, Balci *et al.* [6] investigated the potential for container lines to distinguish their services within strategic alliances. Using factor analysis on survey data from Turkish container lines and freight forwarders, they provided information on effective differentiation strategies. They designed an interquartile presentation to show how distinct and significant each service feature is. The findings show that good customer connections and customer service can distinguish container lines from each other. According to this study, container lines may be able to grow and maintain their competitiveness in intra-alliance competition if they adopt more customer-focused company strategies. In line with this, the study conducted in Turkey by Tepe and Gulmez [56] demonstrated that customer value and loyalty are essential selection criteria in addition to the internal capabilities of the shipping provider.

Based on the previous studies, the research by Iqbal *et al.* [50] used multiple regression tests to survey shipping lines in Pakistan and identified the most crucial factors for selecting container lines. They discovered that cost, timeliness, dependability, information technology (IT) orientation, and communication were the most significant determinants of the selection of the container shipping line. Ejem *et al.* [57] focused on using MCDM techniques to resolve the evaluation and selection of third-party logistics (3PL) in Nigeria. They considered cost, service level, financial capability, reputation, and long-term customer relationships as the most important assessment criteria for the selection process.

The work in [58] explores variations in port selection factors between trunk liners and feeder service providers in the shipping industry. The study highlights that trunk liners and feeder service providers have different operational requirements and priorities when selecting ports for their services. The researchers conducted surveys and interviews with industry professionals to gather data on the port selection factors considered by both shipping lines. The findings indicate that the trunk lines prioritise transportation factors such as port infrastructure, connectivity, and efficiency, while feeder service providers focus more on factors such as transhipment connectivity, feeder network coverage, and cost considerations. This article helps to understand port selection processes. It provides opportunities for port authorities and shipping lines to better align their strategies and services based on the specific needs and preferences of different shipping lines.

However, the literature reports that most criteria for selecting shipping service providers are fragmented and not grouped into a homogeneous criteria selection model, except for a few. The four components (4C) (i.e., customer solutions, customer cost, convenience, and communication) marine marketing framework was used to obtain relative selection criteria, which included transport dependability, cargo security, freight prices, transit duration, and on-time delivery [19]. Ho *et al.* [59] identified 12 criteria, of which integrated logistics and on-time delivery were the most relevant. Ergin *et al.* [5] concluded that the availability of equipment and the notice to consignees were the most critical considerations for shippers, based on 31 criteria collected from a survey.

From a marketing perspective, the selection of a carrier can involve communication, existing customers, financial stability, reputation, pricing structure, liability, fleet condition, and management [60]. The research in [61] combines a survey and structural equation modelling to examine the selection criteria of service provision, pricing competitiveness, corporate image, service proficiency, and sales support in the Korean maritime shipping industry. Price competition was found to be the most crucial factor, but service proficiency and sales assistance were more critical than geographical considerations. The study [52] conducted a survey and interview based on the service quality (SERVQUAL) framework to identify 45 criteria used by Indian shippers for container selection. Then, the analytical hierarchy process (AHP) was applied, showing that Indian shipping companies focus on cost, customer service, operations, reputation, infrastructure, scheduling, and IT orientation.

The study in [62] explores the key factors that influence container port competitiveness from the perspective of global shipping lines. It investigates port infrastructure, service quality, operational efficiency, and location advantages. The study emphasises the significance of these factors in determining the competitiveness of container ports in the global shipping industry. It provides insight into port authorities and stakeholders to enhance their competitive advantages and gives them insight into shipping line customers.

However, research found that the low flexibility of cost and price was the most critical aspect [24] of the triangulation of surveys and interviews to study the selection criteria in Vietnam's shipping and logistics. The essential factors were resource availability, service results, adopted logistic processes, management principles and IT usage, image and reputation, and social responsibility. Similarly, in the other study conducted in Vietnam [51], the most critical factors for selecting container shipping included service cost, operation, financial performance, and competition.

Consequently, the selection criteria for maritime shipping vary globally and are influenced by factors such as fuel costs, trade categories, and freight exchange. Studies highlight criteria such as flexibility, price, schedules, service quality, and environmental concerns. However, customer-centric services and factors such as cost, timeliness, dependability, IT orientation, and communication consistently emerge as significant determinants. Further research can develop standardised selection models that consider regional priorities. Table 2.1 summarises the criteria used to select shipping service providers in our literature review.

As distilled in Table 2.1, existing criteria syntheses foreground provider-side service quality but do not theorise cost efficiency within SERVQUAL. To preserve construct integrity, this thesis treats cost as a complementary attribute (see Table 2.2) for conceptual mapping, and formalises the scope in Chapter 3.

Table 2.1: Criteria extracted from literature following guidelines of [26].

Ref.	Criteria (Factors)	Country
Kannan *et al.* (2011) [52]	The flexibility of services offered and price	India
Fanam and Ackerly (2019) [3]	Shipping lines network, schedule, and corporate social responsibility	Australia
Davis-Sramek and Robinso (2020) [55]	Social and ecological sustainability	US
Khan and Hussain (2022) [4]	Shipping costs	US
Peter *et al.* (2016) [49]	Service quality, document accuracy, freight prices, environmental concerns, schedule dependability, and swift handling	Ghanaian
Balci *et al.* (2018) [6]	Good customer connections and customer service	Turkey
Ejem *et al.*(2021) [57]	Cost, service level, financial capability, reputation and long-term customer relationships	Nigeria
Tepe and Arabelen (2022) [56]	Customer value and loyalty	Turkey
Iqbal and Siddiqui (2017) [50]	Shipping cost, timeliness, dependability, IT orientation, and communication	Pakistan
Ho *et al.* (2017) [59]	Integrated logistics and on-time delivery	Taiwan
Ergin *et al.* (2022) [5]	Availability of equipment and the notice to consignees	Turkey
ARC MARINE (2018) [60]	Communication, existing customers, financial stability, reputation, pricing structure, liability, fleet condition, and management	US
KIM and Kim (2020) [61]	Service provision, pricing competitiveness, corporate image, service proficiency, and sales support	South Korea
Thai (2008) [24]	The availability of resources, the quality of service, the logistics methods used, the management precepts, the use of IT, the company's image and name, and its sense of social responsibility.	Vietnam
Yoon *et al.* (2018) [51]	Service cost, operation, financial performance, and competition	Vietnam

2.2.2 The Selection of Optimal Shipping Providers Using Machine Learning Models

Machine learning (ML) can help shipping service providers select the most efficient and cost-effective shipping routes. By analysing historical data, machine learning algorithms can identify patterns in the data that can be used to predict the best routes for shipments.

The work in [63] presents a new approach to selecting resilient suppliers to make decisions in digital manufacturing. The study utilises digital data to predict supplier sensitivities to disruptions and their impact on supply chain performance. The approach employs supervised machine learning algorithms, specifically k-nearest neighbours (KNN), and simulation in a digital made-to-order manufacturing environment. The results demonstrate that machine learning supports decision making in resilient supplier selection, leading to more predictable delivery and improved risk mitigation. The study highlights the importance of developing resilient supplier portfolios and achieving resilient supply chains through data-oriented relationships. Moreover, the findings provide valuable information for managers, including identifying critical suppliers, reengineering the supplier base, and optimising risk mitigation efforts.

Our published paper [4] uses machine-learning approaches and real-time data to predict container freight rates. The study explores the use of ensemble models, including random forest (RF), extreme gradient boost (XGBoost), and multilayer perception (MLP), to provide accurate forecasts. After applying these regression-based machine learning models to the North American TransBorder Freight dataset from 2006 to 2021, the study finds that MLP outperforms the ensemble models with a test precision rate of 97%. The research demonstrates the effectiveness of machine learning in predicting container shipping rates.

Our previously proposed approach [26] comprises three steps: container criteria extraction, best provider selection using machine learning models, and ranking of shipping service providers using AHP. The SERVQUAL framework is used in the container criteria extraction step, ensuring alignment with established quality dimensions in the shipping industry. For provider selection, random forest (RF), extreme gradient boost (XGBoost), support vector machine (SVM) and k-nearest neighbours (KNN) models are used, with the voting-based approach achieving the highest accuracy (0.8230), precision (0.8055) and F1 score (0.7748) of the models evaluated. Then, AHP is applied to objectively rank shipping providers based on their performance on the identified criteria. The proposed approach is applied in a real case study focused on selecting Australian shipping providers.

The work in [27] focuses on analysing and studying the logistics supply chain model using artificial intelligence (AI) and extensive data analysis based on incremental kernel fuzzy clustering algorithms. The authors aim to improve the management of transportation providers in the logistics service supply chain to improve operational efficiency and service quality. The results show that three suppliers are selected based on their performance in customer satisfaction, accuracy of logistics operations, and transportation cost. The paper concludes by emphasising the importance of integrating AI and extensive data analysis in managing the supply chain of logistics services.

The work in [64] explores the factors influencing consumers' intention to use third party logistics (3PL) services during the COVID-19 pandemic. The study uses machine learning algorithms to predict these factors: artificial neural network (ANN) and random forest (RF) classifiers. The research finds that consumers' attitude is the most significant factor affecting their behavioural intention to use 3PL services. Other contributing factors include customer satisfaction, perceived value, perceived environmental concern, assurance, responsiveness, empathy, reliability, tangibility, perceived behavioural control, subjective norms, and perceived authority support. The study demonstrates that the ANN and RF algorithms achieve high accuracy rates of 98.56% and 93%, respectively, in predicting these factors. The results suggest that consumers are more likely to choose 3PL service providers if they demonstrate availability and environmental concerns to meet customer needs. Safety and convenience also play crucial roles in ensuring the continuous patronage of consumers. The article highlights the importance of using machine learning techniques to measure behavioural intention in logistics and discusses managerial insights for service providers.

2.2.3 MCDM Selection Methods

The existing literature provides evidence of using conventional MCDM models to select shipping service providers. Of these models, the AHP has been used in studies involving Chinese shippers [15]. AHP adopts a hierarchical structure to evaluate and compare alternatives by conducting pairwise comparisons of criteria and subcriteria, thus determining the relative importance of each criterion. Another approach, the technique for order of preference by similarity to ideal solution (TOPSIS), uses a distance-based methodology to evaluate and compare alternatives [17][65]. The TOPSIS method calculates the weights of each criterion based on its relative importance and considers the concept of "closeness" to the ideal solution. Custom and fuzzy models incorporating fuzzy logic have also been used to select shipping services [32][66].

In a comprehensive study evaluating 21 third-party logistics (3PL) providers in North America, a complex MCDM model was developed [66]. This model integrates multiple decision-making methods, including criteria importance through inter-criteria correlation (CRITIC), multi-objective optimisation based on ratio analysis (MOORA), and complex proportional assessment (COPRA). The CRITIC method was used to determine the weights of each criterion according to its relative importance, and MOORA and COPRA were used to evaluate the alternatives by measuring their proximity to the ideal solution [66]. The study also incorporated sentiment analysis using machine learning to correlate model output scores with customer sentiments expressed in online reviews.

The theory of reasoned action (TRA) and the technology acceptance model (TAM) were applied to investigate the relationship between the behaviour beliefs of the shippers and their perceived usefulness, attitudes, and intention to select a Korea-China train ferry [67]. TRA and TAM are MCDM methods that use a ratio-based approach to evaluate and compare alternatives. The weights assigned to each criterion are determined based on their relative importance. Furthermore, the study [68] uses the fuzzy analytical hierarchy process (FAHP) evaluation to identify the most critical factor in transportation performance, focusing on the sustainability of logistics, environmental sustainability, and social sustainability in the context of logistics transport performance. The work in [51] builds upon a previous model developed for evaluating domestic shipping lines and extends it to assess the performance of container shipping companies in Vietnam. The FAHP method is used as a decision-making tool to handle uncertainty and vagueness in the evaluation process.

The work in [69] proposes a methodology to select 3PL providers in cold chain management. The study addresses the importance of choosing reliable 3PL providers to transport and store temperature-sensitive goods. The proposed approach combines the fuzzy analytical hierarchical process (FAHP) and the fuzzy technique for order of preference by similarity to ideal solution (FTOPSIS) methods to evaluate and rank potential 3PL providers based on multiple criteria. The FAHP is used to determine the criteria weights, while the FTOPSIS is used to calculate the closeness coefficient and identify the best 3PL provider. The methodology is applied to a case study, which shows its effectiveness in supporting decision-making processes for cold chain management.

The work in [70] proposes a logistics provider selection scheme for the healthcare industry based on a novel hierarchical clustering approach based on weighted density. The study addresses the challenge faced by healthcare providers in selecting logistics service providers that can meet their specific requirements. The scheme consists of a three-step decision-making process. In the first step, an evaluation index system is established to assess the ability of candidate providers. The weights of the indices are calculated using the AHP, which helps prioritise the importance of different criteria. Candidate providers are clustered using the proposed weighted density-based hierarchical cluster analysis (WDBHCA) method in the second step. This method incorporates the density concepts and weights obtained in Step 1 to enhance clustering performance. In the final stage, the optimal class of logistics service providers is selected based on the results of the clustering process. The proposed scheme is validated through a case study in the healthcare industry, showing its feasibility and effectiveness. The authors also suggest that this scheme can be applied to selecting providers in other fields beyond healthcare.

Consequently, the literature demonstrates the application of various MCDM models to select shipping service providers. These models employ different approaches. However, all methods require experts to assign initial weights and use the selection method.

2.2.4 Criteria Frameworks (SERVQUAL Framework)

SERVQUAL is a well-established framework for assessing service quality. It helps organisations measure and improve their service performance based on customer expectations and perceptions. This study takes advantage of the SERVQUAL framework as a foundation to extract criteria to overcome the limitations of existing methods. SERVQUAL offers a well-established approach to selecting shipping service providers based on service quality only. The framework encompasses five dimensions: Tangibles, Empathy, Reliability, Responsiveness, and Assurance (TERRA), collectively providing a comprehensive set of criteria for evaluating service quality [22]. Figure 2.2 shows the SERVQUAL dimensions when applied in shipping services to achieve the most significant goal of satisfying customers.

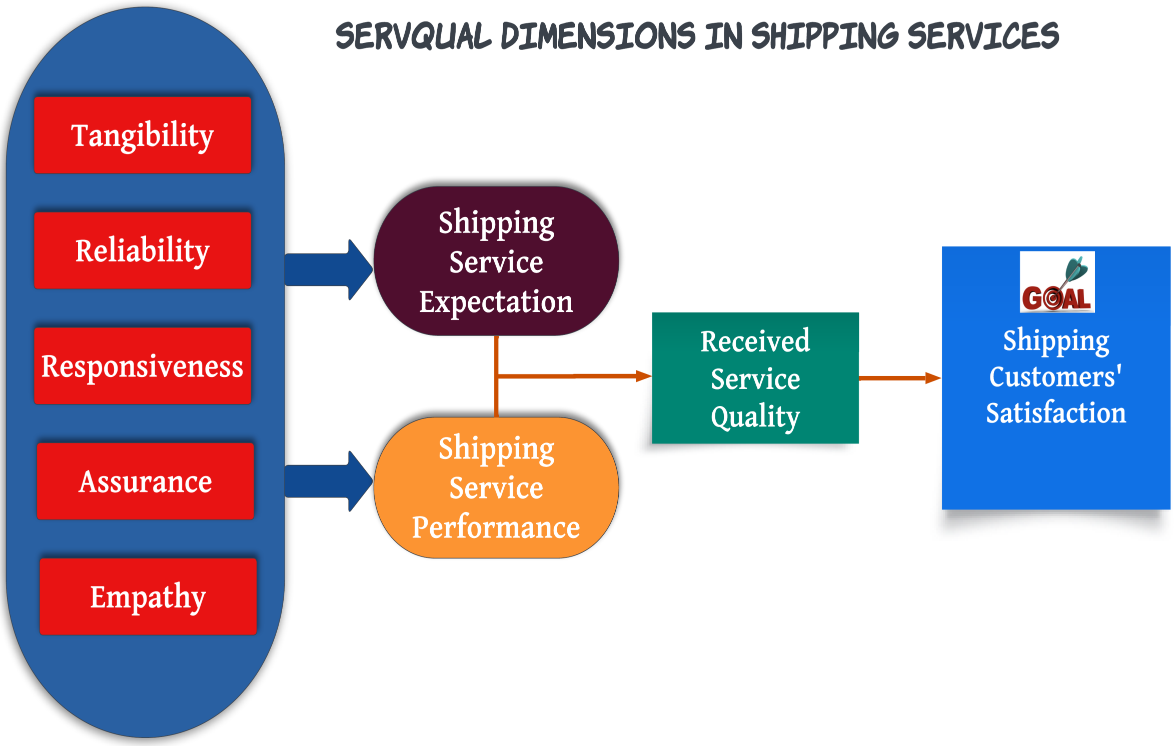


Figure 2.2: SERVQUAL Dimensions in Shipping Services

Dimensions and Relevance:

- **Tangibles**: Physical and visible artefacts of service delivery (e.g., vessel condition, port facilities, documentation, and appearance) that shape perceptions of professionalism and quality.
- **Empathy**: Individualised care, accommodation of consignee con-

straints, and tailored solutions that foster trust and long-term relationships.

- **Reliability**: Ability to perform the promised service dependably and accurately (e.g., on-time schedules, correct documentation, and consistent tracking).
- **Responsiveness**: Prompt willingness to help (e.g., timely replies, proactive status updates, and swift issue handling).
- **Assurance**: Knowledge, competence, and professionalism (e.g., certifications, regulatory compliance, and experienced staff) that inspire confidence.

Scope of SERVQUAL, SERVPERF, and complementary cost. As illustrated in Fig. 2.2 and summarised in Table 2.2, different frameworks capture service evaluation from distinct perspectives. In this thesis, SERVQUAL is retained to represent provider-side service quality through its five core dimensions (Tangibles, Empathy, Reliability, Responsiveness, and Assurance) [20][22]. Cost efficiency, while critical for decision-making, is not a SERVQUAL dimension and is therefore treated as a complementary attribute that operates alongside the SERVQUAL construct within a multi-criteria decision-making framework [28][29][30][31][32]. The consumer-side instrument service performance (SERVPERF), which evaluates performance outcomes directly [23][37][38], is acknowledged as a valuable extension for integrating customer satisfaction (CSAT) [39], customer loyalty measured by the net promoter score (NPS) [40], and sentiment-based indicators [41][42]. However, full integration of SERVPERF is marked for future research to preserve the current study's scope.

Despite earlier reservations about SERVQUAL's applicability in maritime shipping [24], recent studies have validated its efficacy across diverse applications [9][25][32][43][45][46]. SERVQUAL emerges as a reliable instrument for measuring service quality, particularly in logistics [32][45][46] and ocean freight forwarding domains [9]. Its utility extends to aiding ocean container carriers in crafting effective marketing strategies for engaging Australian shippers [52]. In contrast to frameworks like the maritime four components (4C) model [19], SERVQUAL offers a more comprehensive perspective, addressing the needs of consignees, shippers, or customers and ensuring consistent comparisons among service providers. However, traditional MCDM approaches often have limitations, particularly in balancing quality and cost considerations [25][43]. Building on SERVQUAL's foundation, this study enhances MCDM methods for shipping service selection [26] by replacing cost-based features with SERVQUAL, as discussed earlier. Table 2.2 summarises the most common alternative frameworks — such as NPS, customer effort score (CES), CSAT, 4C, delivered duty paid (DDP), SERVPERF, and SERVQUAL, for selecting criteria for shipping service providers based on the following criteria suggested by this study:

1. **Customer-Centricity**: refers to the extent to which service providers prioritise and cater to the needs and preferences of customers, placing them at the centre of their operations.
2. **Measurability**: indicates the framework's ability to be quantified or assessed using conventional scales or qualitative data.
3. **Comparability**: refers to the capacity to compare the performance of several service providers using the framework.
4. **Completeness**: indicates the framework's ability to evaluate service quality across multiple dimensions or customer experience characteristics.

Table 2.2: Comparison of criteria frameworks to SERVQUAL

Framework	Definition	Customer-Centricity	Measurability	Comparability	Completeness
Net Promoter Score (NPS)	Measures the likelihood customers will recommend a provider to others, using a 0-10 scale NPS	Not specifically designed for customer-centricity.	Measurable using NPS scale.	Allows provider comparisons.	Does not evaluate service quality across multiple dimensions.
Customer Effort Score (CES)	Measures how easily customers can do business with a provider using a scale of 1-7 CES	Not specifically designed for customer-centricity.	Measurable using CES scale.	Allows provider comparisons.	Does not evaluate service quality across multiple dimensions.
Customer Satisfaction Score (CSAT)	Measures overall customer satisfaction with a provider using a 1-7 scale CSAT	Not specifically designed for customer-centricity.	Measurable using CSAT scale.	Allows provider comparisons.	Does not evaluate service quality across multiple dimensions.
Four Components (4C)	Evaluates service quality based on customer value, cost, convenience, and communication	Does not explicitly focus on customer-centricity.	Does not provide a standardised measure of service quality. Relies on qualitative data.	Allows provider comparisons based on 4C dimensions. evaluates service quality across multiple dimensions (customer value, cost, convenience, and communication).	Does not explicitly address all service-quality dimensions; provides partial completeness through four marketing components.
Delivered Duty Paid (DDP)	DDP evaluates shipping providers based on their ability to handle shipping processes from start to finish	Does not explicitly focus on customer-centricity.	Does not provide a standardised measure of service quality. Relies on qualitative data.	Allows provider comparisons based on their ability to handle shipping processes.	Evaluates service quality across multiple dimensions of the shipping process (start to finish).
Service Performance (SERVPERF)	Measures service quality solely based on customer-perceived performance, without considering expectation–perception gaps	Consumer-side perspective; captures direct customer experiences	Post-service surveys, customer ratings, and reviews	Allows provider comparisons based on perceived performance scores	Does not evaluate expectations; complementary to SERVQUAL but noted as out-of-scope in this study
Service Quality (SERVQUAL)	SERVQUAL evaluates provider-side service quality across five dimensions (TERRA): Tangibles, Empathy, Reliability, Responsiveness, and Assurance	Does not explicitly focus on customer-centricity.	Provides a comprehensive measure of service quality across SERVQUAL dimensions.	Allows provider comparisons based on service quality.	Evaluates service quality across multiple dimensions (tangibles, empathy, reliability, responsiveness, and assurance).

In the existing studies, the methods used are either static (surveys) or machine learning models based on the specific environment. Most models are not directly related to shipping service providers except [4][26].

Mapping note. Table 2.3 consolidates the literature-derived criteria and aligns them to the five SERVQUAL dimensions used in this thesis. The second column lists studies and indicative factors reported by each source; the third column summarises why those factors belong to the given SERVQUAL dimension in the context of maritime shipping. This provides a single, transparent bridge from prior work to the SERVQUAL construct operationalised later in Chapter 5.

Table 2.3: SERVQUAL-aligned criteria for shipping service providers, derived from the literature

SERVQUAL Dimension	Studies and Factors	Explanation
Tangibles	Customer value research [56] IT orientation and communication [50][51][52] Network reliability and infrastructure [3][52] Cargo [3] Environmental sustainability [55] Accessibility [67] 12 criteria in [5]	This dimension validates the shipping provider's capability to deliver the necessary services. For example, choosing the port is of utmost importance from the customer's point of view.
Empathy	Customer relations [6] Customer loyalty strategies [56] Transport cost [50] Rate or cost (pricing of service) [3][19][50][52][51][49][59] Customer service [52] Corporate social responsibility [3] Four criteria in [5] Intention to choose the service [67] Convenience [19][59] Service quality [49]	Ensuring that services can be tailored as needed and unforeseen challenges can be managed instils greater customer confidence in the chosen services.

Continued on next page

Table 2.3 – Continued from previous page

SERVQUAL Dimension	Studies and Factors	Explanation
Reliability	Core offering [6] Door-to-door [3][6] Customer value research [56] Reliability in scheduling and timely service [3][49][50][51][52] Environmental sustainability [55] Purchase intent [55] Efficiency, quick handling [49][67] Perceived usefulness [67] Service quality [49] 13 criteria in [5]	If the service provider employs experienced staff, it reduces the risk associated with transportation for the shipping provider.
Responsiveness	Responsiveness [50][51] IT orientation and communication [19][50][51][52][59] Attitude toward the service [49]	Regular updates to consigners about the delivery schedule assist them in planning their logistics effectively.
Assurance	Customer service [6] Door-to-door [6][3] Customer value research [56] IT orientation and communication [19][50][51][52] Operation [52] Reputation [52] Environmental sustainability [55] Social sustainability [55] Trust [55] Accessibility [67] Perceived usefulness [67] Shipper needs [19][59] Service quality [49] Document precision [49] Environment issues [49] 25 criteria in [5]	The shipping provider's compliance with all prerequisites of maritime shipment is confirmed through its records, certifications and quality of customer service.

The extracted criteria and their SERVQUAL alignment are consolidated in Chapter 2, Table 2.3. Thus, the synthesis follows systematic review protocols advocated for management research, ensuring transparency and reproducibility [71].

2.3 Conclusion

Several studies emphasise criteria such as freight rate, carrier capabilities and performance, scheduling, and equipment quality. Interestingly, most of these studies prioritise quality considerations over cost. However, there is a prominent gap in the current research landscape, as studies that employ ML models to automate the selection process are scarce. To address this research gap, this study adopts the SERVQUAL framework and condenses the selection criteria into five dimensions to improve comprehensibility for decision-makers. Using the SERVQUAL framework and exploring the potential of ML models, this study contributes to improving the selection of maritime shipping service providers using MCDM approaches. This research aims to give decision makers a comprehensive understanding of the selection process, enabling them to prioritise customer-centricity, measurability, comparability, and completeness. The following chapter addresses the formal definition of the research problems.

CHAPTER 3

Problem Definition

3.1 Introduction

Chapter 2 reviewed the existing studies on the selection of shipping service providers, indicating their limitations related to the lack of an automated selection process. This chapter introduces and defines the key terms and concepts central to the thesis. It outlines the formal definition of the research problem and presents research questions and objectives. The methodology employed to address the identified problem is discussed. The chapter concludes by summarising its key points and paving the way for subsequent chapters.

3.2 Key Terms and Concepts

This section presents research keywords and their formal definitions, providing clarity and a shared understanding of the terminology used.

3.2.1 Decision Making

Decision making involves the selection of the best option, which requires information analysis, situational assessment, and rational or intuitive choices. Individual preferences, experiences, and constraints significantly impact this process, highlighting its importance. Developing critical thinking skills is essential to improve decision making [72][73].

3.2.2 Decision Makers

Decision makers are individuals or groups who make decisions based on the available information and expertise. They evaluate alternatives, consider relevant factors, and choose the most appropriate decision to achieve the desired outcomes [74][75].

3.2.3 Shipping Stakeholders

Shipping stakeholders comprise various individuals and organisations, including shippers, consignees, shipping lines, freight forwarders, port authorities, customs agencies, logistics providers, governments, and regulatory bodies [76]. These integral participants in the shipping ecosystem engage in reciprocal interactions that shape and are shaped by the flow of goods. Their collaborative efforts are essential to ensure the seamless operation and prosperity of the industry [42].

3.2.4 Maritime Shipping

Maritime shipping is the transportation of goods and commodities by sea using cargo ships, container ships, or tankers. It involves the movement of goods across oceans, seas, or other navigable waterways, linking various ports and countries [77].

3.2.5 Shipping Service Provider

For this study, the term shipping providers refers to companies or organisations that offer sea freight goods transport services. These providers may include shipping lines, freight forwarders, and logistics companies specialising in maritime transportation [78].

3.2.6 Selection Criteria

The selection criteria for services are the specific factors used to evaluate and choose a service provider. They include quality, cost, reliability, scalability, compatibility, expertise, support, compliance, security, and references [3][53].

3.2.7 Criteria Weighting

Criteria weighting refers to assigning relative importance or significance to various factors within the service selection criteria [79]. This step helps prioritise and quantify the impact of each criterion on the decision-making process, ensuring a more nuanced evaluation and ultimately aiding in selecting the most suitable service provider [80].

3.2.8 Service Selection

Service selection requires meticulous evaluation of available alternatives, considering factors such as quality, cost, dependability, scalability, and alignment with desired outcomes [55][31].

3.2.9 Multi-criteria Decision-Making Approach (MCDM)

Multi-criteria decision-making (MCDM) is a methodology utilised to evaluate and choose multiple alternatives that achieve various objectives [81]. MCDM includes different criteria and factors for decision making [82].

3.2.10 Analytic Hierarchy Process (AHP)

The analytical hierarchy process (AHP) is a multi-criteria decision-making method developed by Thomas L. Saaty in the 1970s [83], [84]. It is a widely used approach to decision making that includes breaking down a complex problem into several hierarchical levels and evaluating each alternative against multiple criteria. Using mathematical calculations, AHP helps decision makers objectively assess and prioritise options based on their importance and compatibility with the desired outcomes [85].

3.2.11 Artificial Intelligence-Based (AI-based) Models

AI-based models represent advanced decision support tools that harness complex algorithms and machine learning methodologies to meticulously analyse extensive datasets, enabling autonomous decision-making processes [86][87].

3.2.12 Artificial Intelligence-Based (AI-based) Models

AI-based models represent advanced decision support tools that harness complex algorithms and machine learning methodologies to meticulously analyse extensive datasets, enabling autonomous decision-making processes [86][87]. Several machine learning (ML) baselines were implemented with scikit-learn [88], gradient boosting with XGBoost [89], and ensemble diversity arguments follow standard theory [90]. Moreover, support vector machine (SVM) were included given their effectiveness in high-dimensional settings [91].

3.2.13 Clustering of Shipping Service Providers

Clustering is an artificial intelligence (AI) method that categorises or groups various attributes, characteristics, or factors into meaningful clusters [41][92]. Clustering of shipping service providers' [70] criteria refers to grouping the various criteria used to evaluate and select shipping service providers into distinct clusters or categories.

3.2.14 Classification of Shipping Service Providers

Classification is an artificial intelligence (AI) method used to classify data points into predefined classes or categories [41][93]. This study uses classification to categorise shipping service providers based on specific shipping service providers' criteria that help predict the most suitable provider, similar to our previous research [26].

3.2.15 Semantic Similarity

Semantic similarity is a measure that quantifies conceptual relatedness between textual elements, taking into account the meaning and interrelationships of words or phrases [94]. This measure uses computational and linguistic methodologies to determine the proximity of the meaning of two or more textual elements, allowing comparisons [95]. In this study, semantic similarity was employed to discern the semantics of the clusters of shipping service providers, facilitating the deduction of criteria weights for these providers.

3.2.16 Service Quality Framework (SERVQUAL)

The service quality framework, often referred to simply as SERVQUAL, is a comprehensive model that has been extensively used to assess and quantify service quality. SERVQUAL examines five core dimensions: Tangibles, Empathy, Reliability, Responsiveness, and Assurance (TERRA) [96]. Accordingly, the dimensions evaluate: the *physical and visible* aspects of delivery (Tangibles), *individualised care* (Empathy), *dependable* *performance* (Reliability), *prompt willingness to help* (Responsiveness), and *professional competence and compliance* (Assurance) [20].

3.2.17 Service Performance (SERVPERF)

The service performance framework, commonly referred to as SERVPERF, evaluates service quality solely on perceived performance, without modelling expectation–perception gaps [37]. In contrast to SERVQUAL's gap-based approach, SERVPERF captures the consumer-side experience directly through post-service outcomes, making it well suited to contexts where value-for-money and satisfaction are inferred from what customers actually receive. This perspective has been widely examined in service quality research, where meta-analyses confirm its strong relationship with satisfaction, attitudinal loyalty, and purchase intention [23]. In maritime shipping, this aligns with customer ratings, reviews, and post-service surveys that reflect timeliness, handling quality, and communication effectiveness as experienced by shippers. In this thesis, SERVPERF is acknowledged as a complementary consumer-side perspective to SERVQUAL, but its full integration is deferred to future work to maintain scope.

3.3 Approach Adopted to Solve the Research Problem

The design science research (DSR) methodology is used to address the main research questions in this thesis (see Chapter 1, Section 1.5 for the complete set of research questions and objectives that guide this study). DSR involves the identification of problems, the design and development of artifacts, a rigorous evaluation, and an iterative refinement [97][98].

The employment of the DSR methodology in this investigation functions as a fundamental framework for crafting an innovative solution in maritime shipping provider selection. The DSR enables the creation of an AI-driven framework specifically tailored to optimise the process of selecting maritime shipping providers. This methodological approach not only enriches decision-making capabilities for stakeholders but also significantly contributes to advancing knowledge within the scholarly realms of logistics and supply chain management.

The methodology of DSR consists of five stages: problem awareness, suggestion, development, evaluation, and conclusion. These stages are illustrated in Fig. 3.1.

Stage 1: Problem Awareness

The first step of DSR is awareness of the problem when researchers realise there is an existing problem that needs to be solved or a situation that needs to be enhanced by establishing specific artifacts [97][98]. In this study, design science research begins with a rigorous review, which uncovers significant gaps in the selection of automated freight providers in logistics, which has been plagued by subjectivity and information overload. This necessitates an avant-garde approach harmonising AI and MCDM techniques. The goal is to forge an AI-driven multicriteria selection framework tailored to shipping service providers, underpinned by artificial intelligence insights and machine learning algorithms for precise performance prediction. Therefore, implementing DSR in this study promises increased efficiency and transparency and addresses the knowledge gaps, transforming logistics and supply chain management. In essence, rigorous problem awareness heralds the development of an unprecedented framework to redefine the industry.

Stage 2: Suggestion

Following the problem awareness stage, the suggestion phase emerges when stakeholders recognise various potential solutions to the identified problem. At this juncture, a preliminary design is proposed that describes

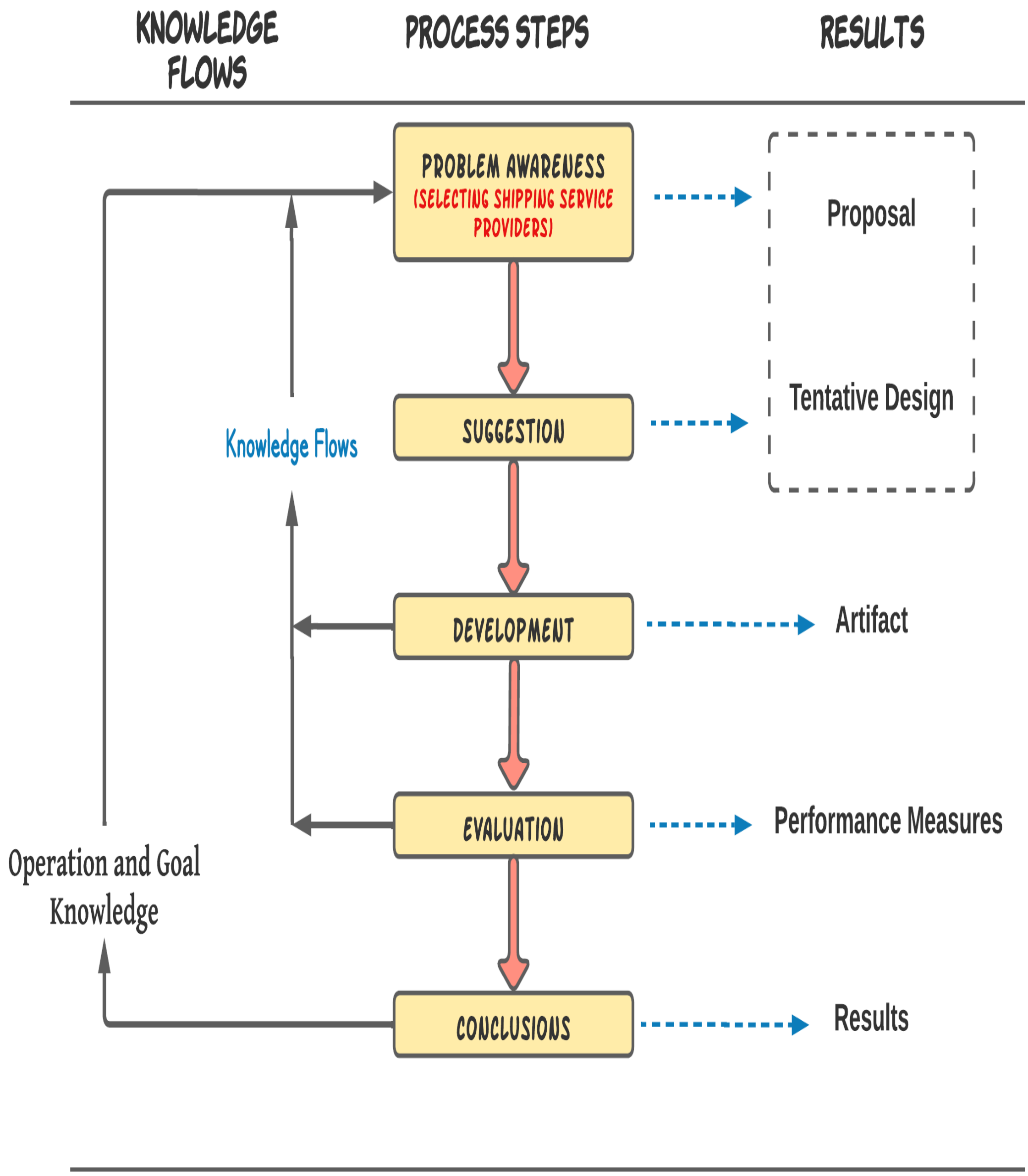


Figure 3.1: Design Science Research (DSR) Methodology (Adapted from [98])

the artifacts envisaged and their developmental pathways. It is essential to note that the output of the suggestion stage provides valuable feedback on the problem awareness phase, allowing for a refined examination of this research [97][98].

In this study, during the suggestion stage, it is evident that, while datasets were identified, they were insufficient for the envisioned AI-based model development. Additionally, while alternative criteria models beyond SERVQUAL were considered, they proved incomplete and limited in scope. Moreover, the manual MCDM approach used by experts in isolation with automation was deemed impractical. Hence, the suggestion stage outputs are further feedback on the problem awareness phase, thereby the research proposal is reviewed again, which yields an acceptable suggestion of an intelligent multi-criteria search engine (MC-SE) decision-making framework.

Stage 3: The Development

The development stage comes immediately after the suggestion stage. In this stage, the suggested artifacts are implemented to solve the problems or enhance the positions. Implementation methods at this stage depend on the artifact to be built [97][98].

The suggestion phase revealed key aspects: inadequate datasets requiring further refinement and alternative criteria models which were incomplete for maritime shipping, emphasising the need for a tailored, comprehensive model. The impracticality of manual MCDM highlights the importance of AI-based models, guiding the development of the MC-SE framework. The framework development was based on the concepts of components. The framework is equipped with the generation and weighting of the shipping criteria and is then followed by the automation of the decision-making process with an MCDM tool such as AHP. In other words, the manual assignments of criteria weights are not needed as input.

Stage 4: The Evaluation

The evaluation phase represents the penultimate step in the DSR methodology. In this phase, the artifacts created during the research process undergo a rigorous evaluation to gauge their performance and effectiveness. This evaluation follows the criteria specified in the research proposal stages and the initial design suggestions. If the results fall short of expectations, a feedback loop is initiated, looping back to the earlier stages, particularly the problem awareness, suggestion, and development phases. This iterative review process aims to improve artifacts, aligning them more closely with the objectives of the original research proposal [97][98].

Various evaluation methodologies are employed to address each research question in this study. For instance, machine learning techniques are utilised to evaluate the efficiency of the optimised shipping service provider classifier. Metrics such as precision and F1-measure are instrumental in assessing the effectiveness of these weights in optimising provider selection within the dynamic maritime shipping industry. Moreover, the evaluation critically aligns the criteria weights derived from the MC-SE framework with the survey findings. The evaluation encompasses regression performance metrics and statistical methods for addressing criteria weights concerning the survey output. In addition, the SERVQUAL survey is evaluated following its guidelines and is then used as an input to the MC-SE framework to gauge the reliability and validity of the proposed framework.

Stage 5: Conclusions

The conclusion stage is the ultimate step in the DSR. This stage occurs when final conclusions are drawn in connection with the artifacts, considering that stages 1 to 4 are iterated multiple times until the assessment gives acceptable outcomes [97][98]. In summation, this research represents a significant stride forward in the selection process of maritime shipping service providers. Creating an AI-based predictive classifier, systematically aligning criteria with the SERVQUAL framework, innovative criteria weighting, and applying MCDM techniques contribute to a transformative decision-making framework. This research addresses the challenges of subjectivity, information overload, and dynamic maritime shipping demands by providing stakeholders with a robust provider selection model. These findings, derived through the rigorous application of the DSR methodology, can revolutionise decision-making processes, enhance supply chain performance, and increase customer satisfaction.

3.4 Problem Overview and Problem Definition

This section introduces the research problem and formally defines the study's scope.

3.4.1 Problem Overview

The thorough review of the literature in Chapter 2 highlights a significant research gap, particularly in automating the selection of freight providers. This gap pertains specifically to applying AI-based intelligent models utilising MCDM techniques, aiming for an automated process requiring minimal human intervention. Although existing studies emphasise various selection criteria such as freight rate, carrier capabilities, scheduling, and equipment quality, these investigations have a notable predilection toward prioritising quality considerations over cost. Little attention was paid to the heterogeneous criteria inherent in shipping service providers. Furthermore, a distinct paucity of research efforts leverages ML models for automating the selection process. Unautomated selection methods often suffer from subjectivity, inconsistency, and information overload, exacerbated by the growing global trade landscape and intricate supply chains with many providers. Therefore, this study aims to fill these gaps using the SERVQUAL framework to develop criteria and employ ML models to improve the selection of maritime service providers, providing decision makers with a more nuanced understanding of the selection process. This study develops a new MC-SE framework that extracts criteria and adopts MCDM techniques (such as AHP).

Consequently, this research aims to develop an AI-driven, MCDM framework to automate freight provider selection based on predefined criteria extracted from benchmark datasets, addressing subjectivity and information overload challenges. First, AI-based methodologies leverage extensive datasets to distil insights and patterns, enhancing the precision and efficiency of decision making. Second, MCDM methods enable organisations to systematically assess and compare providers, accounting for performance across multiple criteria and considering their relative importance and interdependencies. These improvements are expected to improve supply chain performance and customer satisfaction, substantively addressing identified knowledge gaps and fostering advances in evaluating shipping service providers. Ultimately, this approach significantly advances logistics and supply chain management decision-making.

This study considers published datasets about shipping service providers and posted content on shipper's websites. Although published data was used to optimise and find the best provider based on machine learning classification methods, the second content was used to group the provider criteria in the SERVQUAL patterns. The MC-SE framework clusters website content into decision criteria, establishes weights based on business preferences and requirements, and aggregates the criteria scores to rank providers. Crucially, the framework offers adaptability to evolving business priorities, allowing the customisation of criteria weights and flexibility in their adjustments over time.

This formalisation directly underpins [RQ2] (criteria mapping) and [RQ4] (SERVQUAL/SERVPERF perspectives) as defined in Research Questions (Section 3.5).

Formalisation of Criteria.

This thesis adopts the SERVQUAL framework as the primary basis for provider-side service quality, while incorporating *cost* as a complementary (non-SERVQUAL) decision attribute. The consumer-side perspective, captured through SERVPERF and related customer-voice measures (e.g., CSAT, NPS, CES, sentiment), is acknowledged as an extension beyond the present scope.

Let $\mathcal{Q} = \{\text{Tangibles, Empathy, Reliability, Responsiveness, Assurance}\}$ denote the provider-side service-quality dimensions (SERVQUAL, in TERRA order). Let $\mathcal{C} = \{\text{Cost}\}$ denote the complementary cost attribute, and let $\mathcal{V}$ denote consumer-side indicators grounded in SERVPERF (e.g., CSAT, NPS, CES, sentiment features). The criterion set used in this study is therefore $\mathcal{S} = \mathcal{Q} \cup \mathcal{C}$, with weights estimated using multi-criteria decision-making methods such as AHP or TOPSIS.

For completeness, a future extension can be formalised as $\mathcal{S}^+ = \mathcal{Q} \cup \mathcal{C} \cup \mathcal{V}$, which unifies provider-side quality (SERVQUAL), cost (complementary), and consumer-side outcomes (SERVPERF/customer voice) without conflating constructs.

Rationale. Service quality (SERVQUAL) was chosen over service performance (SERVPERF) because the available benchmark dataset and provider website features align more directly with provider-side service quality dimensions. SERVPERF is nevertheless acknowledged as a valid alternative for capturing experiential, consumer-side performance and remains an important avenue for future work.

Addressing the current imbalance between quality and cost considerations, the study aims to develop a systematic approach that minimises human intervention while accommodating the diverse criteria of shipping service providers. The research seeks to revolutionise decision-making processes by creating a novel MC-SE framework, advancing academic knowledge and practical applications.

3.5 Research Questions

In light of the problem definition, the main research questions (RQ) for this thesis are as follows:

RQ1: How can an AI-based predictive classifier be developed to select the optimal maritime shipping service provider using predefined criteria from benchmark datasets, and how does it enhance decision making for offshore shipping customers?

RQ2: How does the systematic mapping of criteria to the SERVQUAL framework improve the selection decisions of maritime shipping providers?

RQ3: What methods and tools are required to create and implement an effective multi-criteria search engine (MC-SE) framework that combines AI-based models with multi-criteria decision-making techniques to improve maritime shipping service provider selection?

RQ3.1: How can innovative AI-based approaches intelligently weight the selection criteria of the maritime shipping providers, ensuring the continued relevance of the chosen criteria to optimise the selection of the providers?

RQ3.2: How can multi-criteria decision-making techniques efficiently automate the ranking of maritime shipping service providers based on AI-identified weighted criteria, specifically within the context of marine shipping service selection in Australia?

RQ4: How can a SERVQUAL survey assess service quality in the shipping service provider industry and utilise it for decision making or AI-based data-driven models?

RQ5: How to validate the effectiveness and reliability of the MC-SE framework and the AI models developed for selecting maritime shipping service providers, and which validation methodologies and criteria are suitable for this purpose?

3.6 Aims and Objectives

This research study aims to understand the maritime shipping market, enabling freight companies to have access to an intelligent MC-SE framework. It also allows customers to conduct a trusted search to select shipping service providers with more reasonable prices and reliable services. In general, the five main objectives of this research study, depicted in Fig. 3.2, can be summarised as follows:

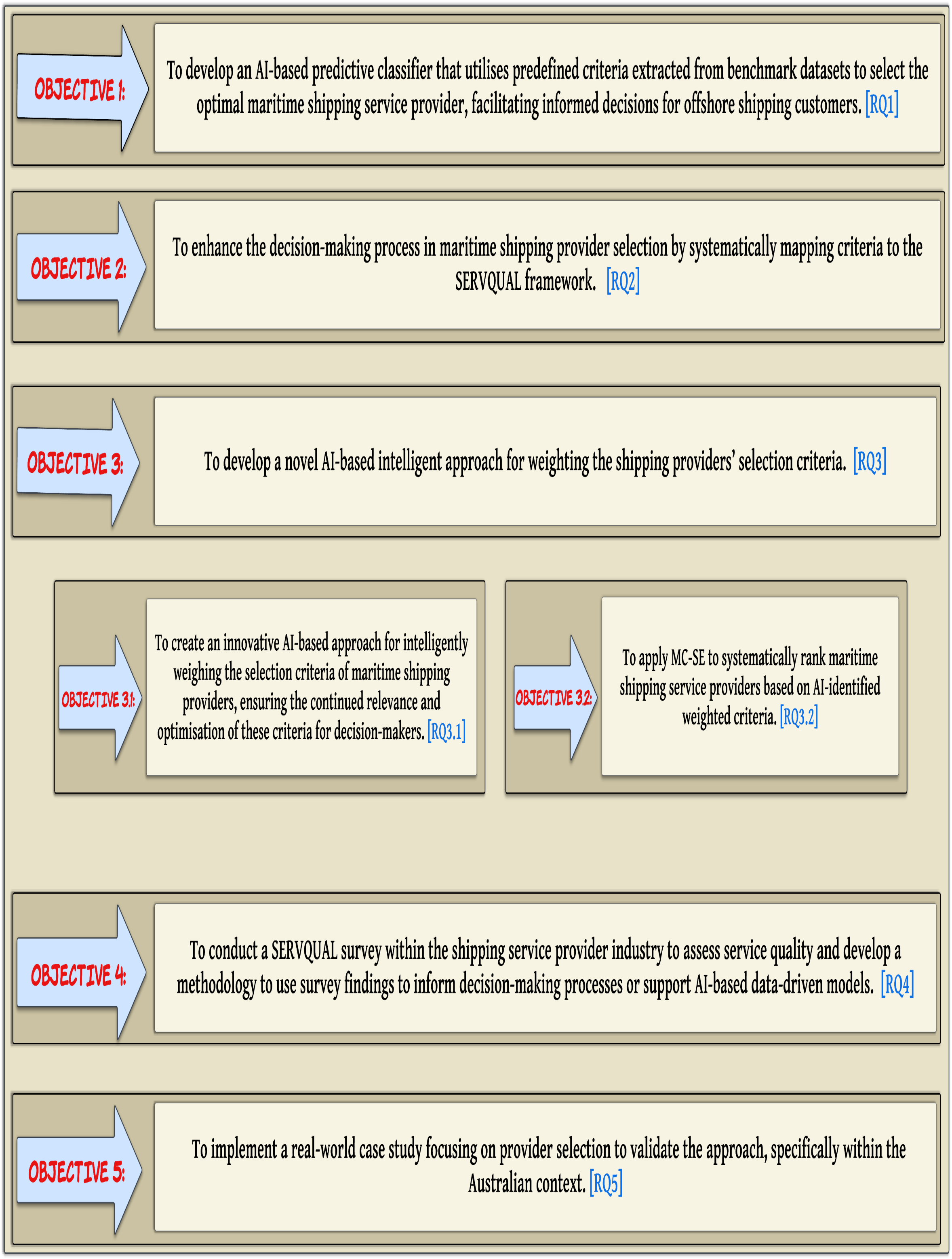


Figure 3.2: Research Objectives

Objective 1: To develop an AI-based predictive classifier that utilises predefined criteria extracted from benchmark datasets to select the optimal maritime shipping service provider, facilitating informed decision making for offshore shipping customers. [**RQ1**]

Objective 2: To enhance the decision-making process in maritime shipping provider selection by systematically mapping criteria to the SERVQUAL framework, while recognising cost efficiency as a complementary non-SERVQUAL attribute. [**RQ2**]

Objective 3: To develop a novel AI-based intelligent approach for weighting the shipping providers' selection criteria. [**RQ3**]

> **Objective 3.1:** To create an innovative AI-based approach for intelligently weighting the selection criteria of maritime shipping providers, ensuring the continued relevance and optimisation of these criteria for decision makers. [**RQ3.1**]
>
> **Objective 3.2:** To apply MC-SE to systematically rank maritime shipping service providers based on AI-identified weighted criteria. [**RQ3.2**]

Objective 4: To conduct a SERVQUAL survey in the shipping service provider industry to assess service quality and develop a methodology to use survey findings to boost decision-making processes or support AI-based data-driven models, while acknowledging SERVPERF as a potential consumer-side perspective for future integration. [**RQ4**]

Objective 5: To implement a real-world case study focusing on provider selection to validate the approach, specifically in the Australian context. [**RQ5**]

3.7 Conclusion

This chapter utilises the design science research (DSR) methodology to revolutionise the selection process of maritime shipping service providers. The multi-criteria search engine (MC-SE) framework is proposed to recognise the industry's challenges, particularly the lack of automated selection methods in multi-criteria decision making (MCDM). The research journey was detailed in five stages: awareness of problems, suggestion, development, evaluation, and conclusion. The use of DSR led to the creation of a new AI-based predictive classifier and a new MC-SE framework that aligns criteria with SERVQUAL with new weighting methodologies. MCDM techniques and an Australian case study validated the framework's practicality. Therefore, this study contributes significantly to maritime shipping service providers by introducing an innovative approach to provider selection. Integrating AI models with MCDM techniques, grounded in the SERVQUAL framework, promises streamlined decision making, improved supply chain efficiency, and enhanced customer satisfaction, revolutionising the selection process and boosting overall performance. The next chapter discusses the proposed solutions intricately aligned with the comprehensive research questions.

CHAPTER 4

SOLUTION OVERVIEW

4.1 Introduction

Chapter 3 details the design science research (DSR) methodology to conceptualise an innovative solution: the multi-criteria search engine (MC-SE), an AI-driven multi-criteria selection framework. This chapter provides an in-depth exploration of the proposed solution intricately aligned with the overarching research questions. Figure 4.1 visually depicts the groundbreaking MC-SE. The primary objective of this framework is to unravel the complexities of the maritime shipping market, equipping freight companies with a sophisticated multi-criteria search engine framework. Concurrently, it empowers shippers to conduct a reliable and rational search for shipping providers, ensuring competitive pricing and dependable services. Moreover, this chapter provides an overview of optimising the selection of maritime shipping providers developed using supervised machine learning. The MC-SE operationalises provider-side service quality via SERVQUAL (tangibles, empathy, reliability, responsiveness, and assurance (TERRA)). The framework integrates SERVQUAL dimensions with *cost* as an external, non-SERVQUAL attribute, leveraging analytical hierarchical process (AHP) to handle heterogeneous criteria without altering the SERVQUAL construct.

In this study, the evaluation design is anchored in classical decision science: AHP supports structuring and weighting [28][29], while outranking perspectives (elimination and choice expressing reality (ELECTRE)/preference ranking organisation mETHOD for enrichment evaluations (PROMETHEE)) inform robustness and sensitivity reasoning [99][100]. These families remain widely applied to provider evaluation in logistics and maritime contexts [24][82].

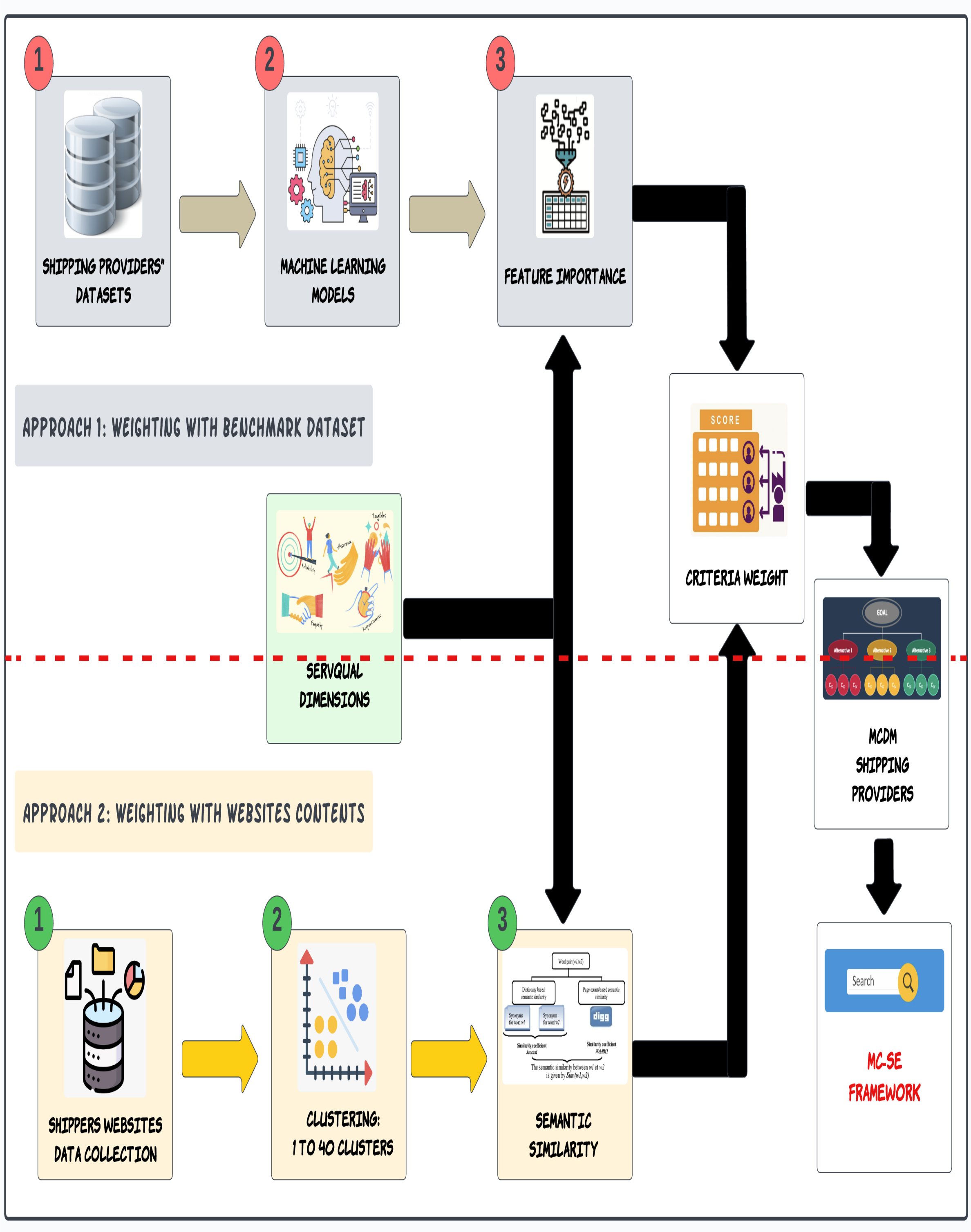


Figure 4.1: Conceptual Components of the Proposed multi-criteria search engine (MC-SE) Framework

4.2 Overview of the Solution for Maritime Shipping Provider Selection using AI (Voting Ensemble)

This study presents a data-driven methodology for selecting maritime shipping providers, which integrates machine learning techniques with the analytical hierarchy process (AHP), addressing the limitations inherent in traditional expert-based multi-criteria decision-making (MCDM). This innovative approach systematically extracts criteria from benchmark datasets and aligns them with the dimensions of service quality (SERVQUAL), covering Tangibles, Empathy, Reliability, Responsiveness, and Assurance (TERRA). The selection process for shipping service providers is automated through machine learning classification models, predicting optimal choices based on a comprehensive set of criteria: category of trade, volume type, load and discharge ports, and item safety conditions.

Figure 4.2 shows the steps involved in using machine learning techniques and integrating them with the MCDM approach by aligning them with the dimensions of SERVQUAL to extract the criteria for selecting shipping service providers. The originality of this solution is in automating the selection of providers without needing expert involvement based on historical data and machine learning predictive models.

Classical estimators are implemented with scikit-learn [88], gradient-boosted trees with eXtreme gradient boost (XGBoost) [89], and ensemble behaviour is interpreted using established bias–variance arguments [90]. Where used, support vector machine (SVM) is motivated by effectiveness in high-dimensional settings [91].

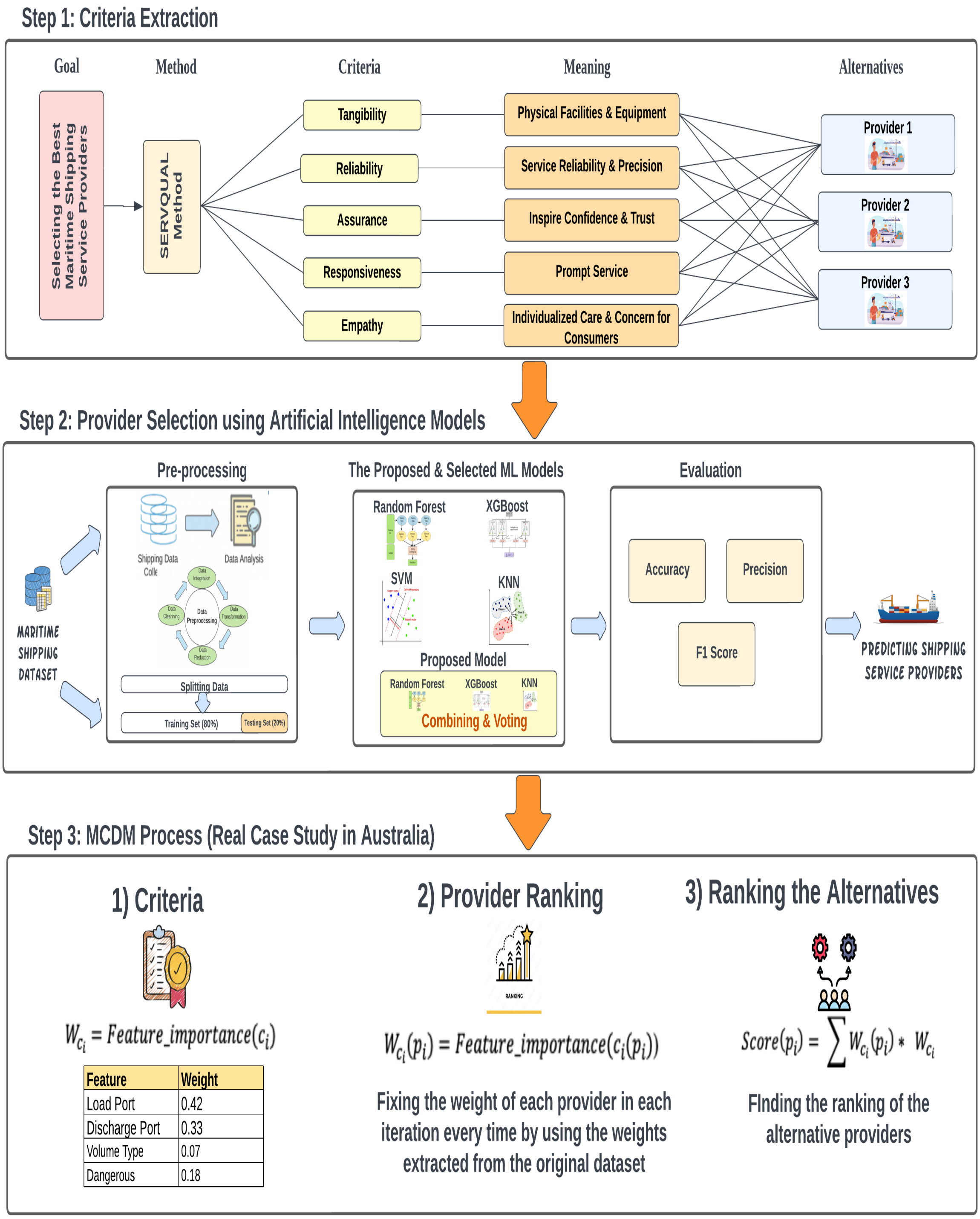


Figure 4.2: Maritime Shipping Provider Selection using AI (Voting Ensemble).

4.2.1 Data Foundation

The proposed solution relies on the robust Voyage Reports dataset from the Australian Bureau of Statistics [44], documenting maritime activities from 1 July 2012 to 6 March 2023. The Voyage Reports dataset used in this analysis encompasses 15 critical features about maritime shippers, including vessel details, trade categories, cargo descriptions, volumes, and port details. Meticulous data preprocessing was undertaken to eliminate irrelevant attributes, handle null values, and address outliers, resulting in a streamlined dataset consisting of six columns (including target) and 22,850 observations.

Beyond describing the dataset, it is important to clarify how it is applied within the proposed framework. The structured Voyage Reports dataset provides quantitative attributes (e.g., vessel type, cargo category, port activity) that are preprocessed and subsequently mapped to service quality dimensions. Although the dataset does not contain service quality (SERVQUAL) indicators directly, its features are aligned with SERVQUAL constructs during the evaluation phase (see Chapter 6), enabling the optimisation of provider selection. In parallel, unstructured data collected from shipping service providers' websites is utilised to complement this process: website content is mined and clustered to extract decision criteria, and semantic similarity techniques are applied to link these criteria to SERVQUAL dimensions. In this way, the framework integrates structured data (Voyage Reports) for predictive modelling with unstructured web content for criteria weighting, ensuring that both quantitative and qualitative perspectives inform the overall provider evaluation and ranking.

In this thesis, two datasets underpin the framework at different phases. The structured Voyage Reports dataset (see Chapter 6, Section 6.2) provides benchmark provider information and is employed in the optimisation and classification stages of the framework. In parallel, the unstructured Ship-SERVQUAL dataset (see Chapter 5, Section 5.4.1) is collected from providers' websites and clustered to extract criteria weights mapped onto SERVQUAL dimensions. By combining the predictive power of the Voyage Reports dataset with the criteria-extraction capability of the web dataset, the framework ensures that both quantitative provider attributes and qualitative service-quality signals are integrated into the evaluation process.

4.2.2 Shipping Service Provider Criteria

Traditionally, the specific criteria for selecting shipping providers have remained proprietary within shipping organisations, shielded from public disclosure. Therefore, this solution leveraged the benchmark dataset to bypass the limited transparency constraints. Here is an example of features and their weights that can be extracted from a benchmark dataset. The mapping is a systematic mapping based on the meaning of each feature from the dataset. The dataset could be limited in covering all aspects of SERVQUAL.

- **Cost (Weight = 0.47):** treated as a complementary decision attribute outside SERVQUAL; weighted alongside SERVQUAL dimensions within the MCDM setup.
- **Safety (Weight = 0.24):** primarily maps to *Assurance* (competence, regulatory compliance, and certifications).
- **Capacity (Weight = 0.22):** proxy for *Reliability* (ability to consistently meet promised service levels).

- **Style (Weight = 0.05):** proxy for *Tangibles* (aesthetics/appearance of physical artefacts, branding, and documentation look).

These examples are dataset-driven proxies; they do not exhaust the guideline indicators. The complete SERVQUAL guidelines are provided in Chapter 5 (Table 5.2) and remain the anchor reference.

4.2.3 Practical Case Study Using AHP

Analytical hierarchy process (AHP) evaluates shipping providers based on selected criteria (feature-importance of the classifiers in the previous step). Therefore, the first step in any AHP process is the weighting of the criteria. Next, the ranking of shipping service providers is generated simply by multiplying the criteria weights by the shipping service provider's respective criteria value and ordering the values. This approach follows prior work on provider selection using AHP [26].

4.3 Overview of the Solution for Identifying Effective Service Provider Selection Criteria Based on the SERVQUAL Framework

This study adopts a systematic approach that integrates established literature review methods, clustering techniques, and semantic similarity analysis to identify effective criteria for selecting service providers based on SERVQUAL (TERRA; cost treated as a complementary non-SERVQUAL attribute). The methodology comprises three key components: (1) a critical review of the literature discussed in Section 2.2 (Table 2.1), (2) clustering of criteria for shipping service providers, and (3) semantic similarity analysis of SERVQUAL clusters. The SERVQUAL framework is widely recognised as a robust and comprehensive tool for evaluating shipping service providers [9][32][45][46].

The criteria were extracted from the literature. The analysis follows the Tranfield *et al.* method [71], which involves three stages: planning, conducting, and reporting. The research question and relevant literature are identified using Google Scholar in the planning stage, which covers the period from 2018 to 2023. The conducting stage involves a systematic data collection, ensuring accuracy and completeness. In contrast, the reporting and dissemination stage synthesises the findings of the critical criteria for effective communication with suppliers and researchers.

In addition to the literature review methods, alternative approaches such as expert consultation, focus groups, and case studies can provide valuable insights into effective service provider selection criteria. Expert consultation offers industry-specific knowledge, while focus groups facilitate stakeholder discussions to uncover nuanced criteria. However, the literature review was chosen for its systematic approach, ensuring comprehensive coverage and credibility of research findings. The originality of following the Tranfield *et al.* method allows for a rigorous process of identifying, extracting, and synthesising criteria from existing literature, enhancing the reliability of the research outcomes.

4.4 Overview of the Solution for an Intelligent AI-based Approach for Weighting Shipping Providers' Selection Criteria

This section introduces the two complementary approaches adopted to weight shipping service provider selection criteria. The first approach utilises feature-importance techniques on the structured Voyage Reports dataset, employing machine-learning models to map quantitative attributes to SERVQUAL dimensions. The second approach utilises clustering and semantic similarity on the unstructured Ship-SERVQUAL dataset, constructed from shipping providers' websites, to extract and group qualitative criteria aligned with SERVQUAL. Together, these approaches ensure that both structured numerical data and unstructured textual content contribute to a balanced and data-driven weighting of provider selection criteria. Figure 8.1 provides an overview of the methodologies applied to quantify the criteria weights within the SERVQUAL framework.

The clustering analysis identifies different groups within the data using term frequency-inverse document frequency (TFIDF) representations and clustering algorithms (hierarchical, k-means, affinity, and Gaussian mixture model (GMM)). Evaluation metrics such as the Silhouette Score, Davies-Bouldin index, and the Calinski-Harabasz index measure clustering performance. These metrics are utilised across varying cluster counts to identify the configuration that maximises cohesion, minimises similarity, and maximises dispersion ratios, ensuring the selection of both the optimal cluster count and the highest clustering quality. The SERVQUAL dimensions are compared with the clusters using the Universal Sentence Encoder (USE), which embeds sentences into high-dimensional vectors to capture semantic relatedness [101], enabling the computational comprehension of meanings and relationships. The USE transforms sentences into high-dimensional vectors, enabling the computational comprehension of meanings and relationships. The resulting similarity matrix indicates associations between clusters and SERVQUAL dimensions, helping evaluate alignment. The matrix is normalised to scores in the range [0, 1], representing criteria weights.

4.5 Overview of the Solution for Conducting SERVQUAL Surveys to Evaluate Shipping Service Providers

This study encompasses an in-depth exploration of conducting surveys in the shipping service provider industry to assess service quality. Although several custom surveys have been used to extract criteria [24][51][52][61], the SERVQUAL survey stands out due to its prominence and comprehensive coverage of service quality dimensions [52][61]. The actual survey is detailed in Appendix A.

4.5.1 Survey Design

There are several steps in building the SERVQUAL survey. First, clear survey objectives are established. These objectives include:

- assessing the relative importance of each SERVQUAL dimension in the shipping service provider selection process.
- measuring respondents' satisfaction levels regarding each SERVQUAL dimension.
- identifying discrepancies between respondents' expectations and perceptions of service quality across the various SERVQUAL dimensions.

The survey instrument presents items grouped by the TERRA sequence (Tangibles, Empathy, Reliability, Responsiveness, and Assurance); cost is collected as a separate decision attribute and not as a SERVQUAL dimension.

Next, the survey is structured to capture additional vital information from respondents, including demographic details such as age, gender, occupation, years of experience, and geographical location. Respondents are asked to rate the importance and level of satisfaction for each SERVQUAL dimension using a 5-point Likert scale [102], ranging from "strongly disagree" to "strongly agree" or "very dissatisfied" to "very satisfied." This structured approach allows participants to express their agreement or satisfaction with specific statements associated with each SERVQUAL dimension.

4.5.2 Sampling and Deployment

The survey deployment strategy was particularly planned, explicitly focusing on selecting participants representing the target demographic, particularly individuals from Australia. Participant selection criteria included demographic information (age, sex, occupation), previous experience with shipping service providers, and geographic location.

To ensure the highest data quality, a group of selected participants with expertise in the field underwent short training sessions to administer the SERVQUAL questionnaire proficiently. This training included a recorded instructional video detailing the form-filling process, conveniently distributed online to the experts. This rigorous approach to participant selection and training strengthens the validity and credibility of the survey results, providing valuable insight into the respondents' perceptions and expectations regarding service quality within the shipping industry.

4.5.3 Survey Pretest

A crucial quality assurance step in our methodology is the pretesting phase of the survey. This pilot test selected a panel of five experts from the Australian shipping service provider industry based on their knowledge and experience. These experts completed the survey and provided detailed feedback based on their expertise. Their feedback was instrumental in evaluating the survey's ability to capture shipping service providers' specific needs and expectations. Although some SERVQUAL questions were predefined, we incorporated modifications into other questions based on the experts' insights. This pretest phase ensures the survey's comprehensibility, relevance, and effectiveness in measuring service quality aspects.

4.5.4 Survey Data Collection

For the primary data collection phase, a panel of 27 experts who met specific selection criteria regarding knowledge, experience, and location was recruited. This panel included professionals from various backgrounds, including industry professionals, researchers, and academics, ensuring a comprehensive and well-rounded perspective.

Each participant was assigned a unique ID to maintain anonymity, and the survey instrument, refined based on the pretest feedback, was administered to the experts through online platforms and personal interviews. Clear instructions ensured that participants understood the purpose of the survey and responded effectively.

4.5.5 Analysis and Interpretation

The collected data served as the basis for the subsequent analysis and interpretation of the survey results. We employed various analysis techniques, including perception scores, expectation scores, gap scores, mean dimension scores, and dimension reliability values for each dimension. These findings bridge the gap between customer expectations and perceptions, providing valuable information to inform strategic decisions and operational improvements within the shipping service provider industry.

4.6 Overview of the Solution for the Intelligent Multi-criteria Search Engine (MC-SE)

The proposed solution aims to develop an intelligent multi-criteria search engine (MC-SE) framework by integrating an AI-based model of criteria weighting, Solution 4.4, with MCDM using AHP, Solution 4.2.3. This framework addresses the challenges decision makers face in selecting maritime shipping service providers by providing a comprehensive and efficient decision support system. This framework, designed to enhance decision-making processes, automates the selection of shipping service providers, offering decision-makers a thorough and objective evaluation.

The MC-SE framework represents a transformative solution for maritime shipping provider selection, seamlessly integrating an AI-based model (a voting ensemble, clustering, and semantic similarity) with MCDM methodologies. Leveraging the approach from Section 4.4, the framework incorporates criteria weighting obtained through extensive analysis. Utilising AHP, maritime providers are ranked to facilitate comprehensive evaluation. Case studies further validate the framework's efficacy, providing practical insights for optimisation. This integration revolutionises provider selection, empowering decision makers with a robust toolset to enhance supply chain performance and customer satisfaction. The framework's effectiveness will be rigorously validated through the real-world testing of machine learning models (Section 4.2) and a comparative analysis with survey data (Section 4.5), ensuring its superiority and offering valuable insights for further refinement and improvement.

4.7 Conclusion

This chapter presents a comprehensive overview of the proposed solutions to address the research questions on maritime shipping service provider selection. The solutions encompass a voting ensemble to optimise provider selection and ensure a more efficient decision-making process. Additionally, a solution based on the service quality (SERVQUAL) framework is introduced to identify effective criteria, enhancing the accuracy of the selection process. In addition, an intelligent AI-based approach for weighting shipping providers' selection criteria is outlined, promoting a balanced and objective decision-making process. The chapter also provides insights into conducting SERVQUAL surveys to evaluate shipping service providers, offering a comprehensive overview for assessing performance and service quality. The proposed multi-criteria search engine (MC-SE) framework, which integrates an AI-based model with the multi-criteria decision-making (MCDM) approach and incorporates the SERVQUAL framework, stands out as a powerful tool for decision-makers.

The findings contribute significantly to maritime logistics and supply chain management, offering valuable insights and practical solutions to enhance the shipping provider selection process. However, it is essential to acknowledge the limitations inherent in the current methodologies, including reliance on existing datasets and potential variations in model effectiveness across different industries. Addressing these limitations through further validation, refinement, and exploration of alternative data sources is essential to enhance the robustness and applicability of the proposed solutions in real-world settings. The following chapter examines the intelligent AI-based approaches used in this study for weighting the shipping service providers' selection criteria. Across this chapter, SERVQUAL is applied in the TERRA order, with dataset-derived features used as proxies where applicable; *cost* remains a complementary, non-SERVQUAL attribute integrated via MCDM.

Chapter 5

Intelligent AI-Based Approach for Weighting Shipping Providers' Selection Criteria

5.1 Introduction

This chapter identifies the criteria used by shipping service providers and details the two proposed approaches for the weighting of criteria, as discussed in Section 4.4. The two criteria weighting approaches are extracting criteria from the benchmark dataset and extracting web content from shipping service providers' websites.

Scope. All numeric weights reported in this chapter come from Section 5.3 (benchmark-derived) and Section 5.4 (web-derived). Throughout, service quality (SERVQUAL) is applied in the TERRA order (Tangibles, Empathy, Reliability, Responsiveness, and Assurance). Consistent with the study scope, cost is treated as a complementary decision attribute outside the SERVQUAL construct and is handled alongside SERVQUAL in downstream decision models.

5.2 Criteria Extracted from the Literature

Section 4.3 provides details on the service provider selection criteria grounded in the SERVQUAL framework following the Tranfield *et al.* method [71]. The extraction goes through several phases: planning, conducting, and reporting. In the planning stage, the SERVQUAL literature review research questions are formulated, and the relevant literature is reviewed based on published articles and indexed in Google Scholar from 2018 to 2023. The conducting step involves systematic data collection and verification, while the reporting stage synthesises findings and discusses implications for supply chain stakeholders. The extracted criteria are listed in and discussed in Table 5.1. However, these criteria could be used for manual decision-making tools and require frequent updates. Furthermore, it is essential to know that there might be a deviation between the criteria used in practice and those reported in the literature [26].

Table 5.1: SERVQUAL dimensions with explanations (Per-study mappings are detailed in Table 2.3, Chapter 2).

SERVQUAL Dimension	**Explanation**
Tangibles	Physical/visible aspects of service delivery (facilities, equipment, documentation appearance) that shape perceptions of professionalism and quality.
Empathy	Individualised care and flexibility in accommodating consignee needs (e.g., schedule changes), fostering trust and longer-term relationships.
Reliability	Dependable and accurate performance (on-time schedules, correct documentation, consistent tracking) that reduces logistics risk.
Responsiveness	Regular and prompt updates to consignors about delivery and proactive issue handling to support planning.
Assurance	The provider's competence, compliance, and credentials (records, certifications, quality of customer service) that inspire confidence.

Per-study factor mappings are consolidated in Table 2.3 (Chapter 2).

Furthermore, the results of the collected shipping provider criteria presented in Table 5.1 align with previous research [24], which identifies service quality in marine transport as a construct with six dimensions: resources, outcomes, processes, management, image, and social responsibility.

This research uses artificial intelligence (AI) methods to automate the weighting of the selection criteria. These methods entail two key strategies: first, using an Australian Bureau of Statistics benchmark dataset [44] to effectively address the issue of proprietary selection criteria, which are often not reported, where the idea is to map the dataset's features to the SERVQUAL dimensions; and second, the clustering of maritime shipping service providers' criteria by extracting essential features from 300 textual documents acquired from their respective websites. The two approaches are depicted in Fig. 5.1 and are discussed in the following. Figure 8.1 also outlines the methods used to quantify criteria weights within the SERVQUAL framework.

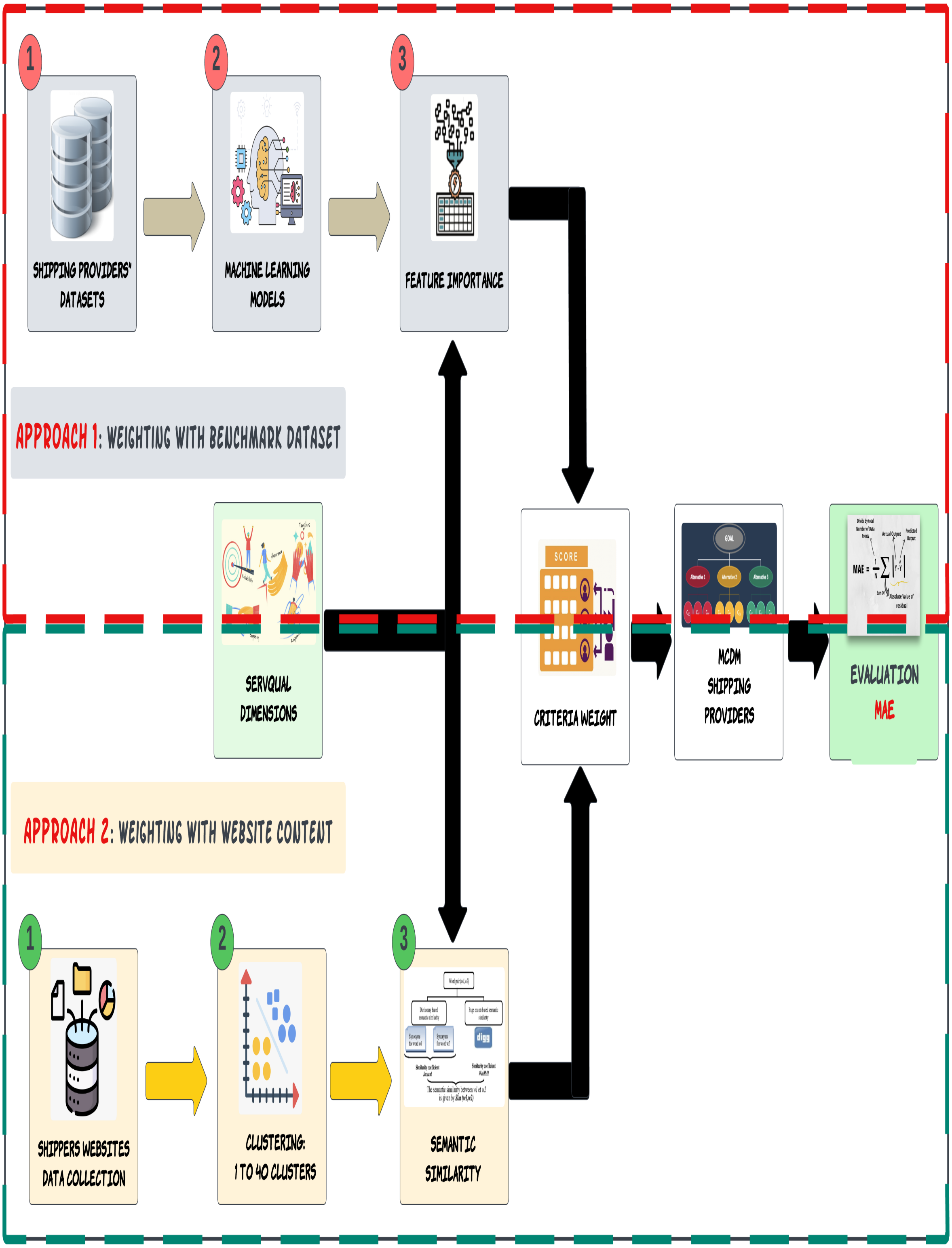


Figure 5.1: Approaches for Criteria Weighting

5.3 Benchmark-derived Criteria Weighting

This study extracts criteria weights based on a benchmark dataset sourced from the Australian Bureau of Statistics [44] to address the challenge of proprietary selection criteria that are often not disclosed. To the best of our knowledge, no publicly available datasets could be used for actual selection criteria for shipping providers, possibly due to proprietary reasons. (Weights reported in Section 5.3 are based solely on the benchmark dataset).

The basic idea is to use machine learning models to train models over the dataset and to find the importance of the features over the features of the datasets. Feature importance is a powerful concept in machine learning that allows us to understand the significance of different aspects of our data. The features (or columns) in this dataset are systematically mapped to SERVQUAL dimensions, and their relevance is determined by calculating the importance of the features. Therefore, this innovative approach allows for a data-driven assessment of the criteria's importance, irrespective of the specific selection criteria.

5.3.1 Criteria Weighting from Voyage Dataset

The importance of the features is available in scikit-learn [88] in most machine learning models and is, by default, normalised. The importance of the feature determines which aspects of service quality have the most significant impact on overall customer satisfaction; therefore, it is used for criteria weighting. However, the features are limited and do not follow a standard rule in comparison; therefore, these features are mapped (manually) to the five dimensions of the SERVQUAL model following the guidelines presented in Table 5.2. Thus, this mapping provides a way to derive criteria for evaluating shipping service providers based on their performance in each SERVQUAL dimension. Consequently, decision makers can prioritise improvements in areas that will have the most substantial impact on service quality.

Table 5.2: Guidelines for mapping shipping provider selection criteria to the SERVQUAL model (TERRA order)

SERVQUAL Dimension	Meaning	Examples
Tangibles	Capability to offer physical facilities, equipment, and an aesthetically pleasing look	Owned vessels Modernised and specialised facilities Documentation appearance
Empathy	Individualised care and concern for consignees	Customised services Ability to cope with schedule changes or new challenges
Reliability	Ability to perform the promised service dependably and accurately	Reliable staff Time of service (schedule adherence) Usage of ICT Brand names
Responsiveness	Prompt service and willingness to help	Timely service providers Proactive status notifications
Assurance	Inspire confidence and trust	Experience in the domain Experienced staff Certifications and licences

Cost is treated as a complementary decision attribute. It is not part of the SERVQUAL construct but is weighted alongside SERVQUAL dimensions for decision-making purposes, consistent with the formal scope in Chapter 3.

5.4 Web-content-derived Criteria Weighting

This section (Section 5.4) reports the web-derived weights, while the benchmark-derived weights are reported separately in Section 5.3.

The operationalisation of provider-side criteria through SERVQUAL dimensions is consistent with sectoral studies that have applied the instrument to retail [38] and maritime transport services [24]. Interpreting SERVQUAL gap scores alongside weighting mechanisms thus situates the present work within a recognised body of logistics and service quality research. Moreover, as emphasised in the SERVPERF debate [37], balancing provider-side expectations with user-side performance data remains essential to avoid bias, an issue that informs the complementary weighting strategies developed here.

5.4.1 Web Content Data Collection

This study collects a dataset for shipping service providers called Ship-SERVQUAL. The dataset consists of 300 textual documents that provide a comprehensive overview of various aspects of these providers. The dataset collection follows a four-step process: (1) defining selection criteria and generating a list of potential providers based on the richness of content on their websites; (2) conducting interviews with crowdsource to ensure compliance with requirements; (3) seeking clarification and validation through ongoing communication with interviewees; and (4) collaboratively verifying, enhancing, and validating the dataset to ensure data accuracy and relevance. The collected data covers various dimensions: service offerings, network coverage, fleet details, operational capabilities, service quality indicators and pricing, and contractual terms.

In particular, the collection process focused on publicly available information provided on the main pages of shipping service providers' websites, especially descriptive sections such as "Services," "About Us," and "Company Profile." Text extracted from these sources commonly highlighted physical assets (e.g., facilities, fleet, and equipment), assurances of reliability and responsiveness (e.g., commitment to timely delivery, safety standards, and customer support), and relational qualities (e.g., empathy and trust-building through company values). These elements naturally align with the SERVQUAL (TERRA) dimensions, ensuring that the dataset reflects provider-side quality attributes as they are portrayed to prospective clients.

Therefore, the dataset is used to evaluate shipping service providers in alignment with the SERVQUAL framework, facilitating a thorough assessment of service quality in the maritime industry. The algorithm for criteria weighting based on clustering is depicted in Algorithm 1 with a various number of clusters (3 to 40) to find the optimal number of clusters. A semantic similarity analysis was also conducted to measure the semantic similarity with SERVQUAL dimensions compared to individual cluster keywords. The resulting similarity matrix was converted into z-scores and binary values for a standardised comparison. Consequently, the criteria weights were measured automatically based on web content.

Algorithm 1: Automated Shipping Service Providers' Criteria Weighting

Data: Data from shipping service providers' websites
Result: Shipping Service Providers' Criteria Weighting (SERVQUAL Weights)

```
Ship-SERVQUAL ← Collect_Data (Shippers Websites) // Collect 300 documents from shippers' websites.
Cleaned_Data ← Clean-Data // remove special characters, stop words, shippers' names, etc.
for num_cluster ← 3 to 40 do
    Clusters ← Apply_clustering (TextVectors, Clustering_methods, clusters_params);
    Clusters_Metrics ← Evaluate (Silhouette Score, Davies-Bouldin Index, Calinski-Harabasz Index);
Best_Clustering_Params ← Maximise: Silhouette Score (Clusters_Metrics), Minimise: Davies-Bouldin Index (Clusters_Metrics), Maximise: Calinski-Harabasz Index (Clusters_Metrics);
Clusters_Keywords ← Extract_keywords (Best_Clustering_Params);
Similarity_Mx ← Semantic_Sim (SERVQUAL definitions, Clusters_Keywords);
z-scores_matrix ← Convert2Z (Similarity_Mx);
Binary_Matrix ← Convert2Bin (z-scores_matrix, one-standard Deviation);
SERVQUAL_Weights ← Average (Binary_Matrix);
return SERVQUAL_Weights;
```

While the present Ship-SERVQUAL dataset is constructed exclusively from provider-facing web content, future extensions should incorporate the consumer voice (e.g., ratings, reviews, direct feedback). Such integration would enable a dual-perspective approach by aligning provider-side service quality (SERVQUAL) with consumer-side service performance

(SERVPERF), and thereby balancing offered and experienced service quality within the weighting process.

5.4.2 Clustering Criteria

Before the clustering phase, data preprocessing was meticulously undertaken. This involves extracting essential features from the providers' websites, encompassing critical elements such as service descriptions, fleet particulars, pricing details, and customer testimonials. Subsequently, four clustering algorithms—hierarchical, k-means, affinity, and gaussian mixture model (GMM) —are applied to this Ship-SERVQUAL dataset, as detailed in Table 5.3. Algorithm 1 shows that data were cleaned (lines 1-2), and then dataset clustering was undertaken, with several algorithms recording each algorithm's performance (lines 3 to 6). The clustering was run for a long range, from cluster 3 to 40, to find the optimal number of clusters.

Table 5.3: Adopted clustering methods (scikit-learn implementation [88])

Method	**Description**
Hierarchical	Organises data into a hierarchy of nested clusters.
K-means	Partitions data into a predetermined number of clusters.
Affinity	Identifies clusters based on similarity measures.
GMM	Represents data points as a combination of Gaussian distributions.

5.4.3 Clustering Metrics

Algorithm 1 selects the best clustering parameters (line 6). The quality and efficacy of the clustering outcomes are assessed using a set of performance metrics: Silhouette Score, the Davies-Bouldin index, and the Calinski-Harabasz index. These metrics guide the systematic exploration of various cluster configurations, ranging from 3 to 40 clusters. Each configuration aims to elucidate the most suitable algorithm and optimal cluster count (Table 5.4 and Table 5.5). Only the best algorithm with the optimal number of clusters was reported using a set of keywords for each cluster (line 7).

Table 5.4: Clustering evaluation metrics

Evaluation Metric	**Description**
Silhouette Score (Higher, better)	The score measures the clustering quality by evaluating the cohesion and separation of cluster data points. This metric considers both intra-cluster similarity and inter-cluster dissimilarity. It helps identify clusters with internally coherent and well-separated data points.
Davies-Bouldin Index (Lower, better)	The index assesses clustering quality by measuring the similarity between clusters considering the cluster size. This metric captures the trade-off between inter-cluster dissimilarity and intra-cluster similarity. It penalises clusters with high similarity to other clusters or overlapping data points, resulting in well-separated and distinct clusters.
Calinski-Harabasz Index (Higher, better)	The index evaluates cluster compactness and separation based on between-cluster and within-cluster dispersion. This metric quantifies the compactness and separation of clusters. Maximising this index leads to clusters with high intra-cluster similarity and low inter-cluster similarity, resulting in distinct and well-defined groups.

Table 5.5: Clustering evaluation metrics for quality assessment

Evaluation Metric	**Description and Formula**
Silhouette Score	The Silhouette Score assesses the quality of clustering by considering the cohesion of data points within clusters (a_i) and the separation between clusters (b_i). It is calculated as: $$\text{Silhouette Score} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{b_i - a_i}{\max(a_i, b_i)}\right)$$ Higher is better. This metric helps identify clusters with internally coherent (high a_i) and well-separated (high b_i) data points, leading to meaningful and distinct clusters.
Davies-Bouldin Index	The Davies-Bouldin Index evaluates clustering quality by measuring the similarity between clusters while considering their size (S_i). It is calculated as: $$\text{Davies-Bouldin Index} = \frac{1}{K}\sum_{i=1}^{K}\max_{j \neq i}\left(\frac{S_i + S_j}{d(c_i, c_j)}\right)$$ Lower is better. This index helps identify clusters with a balanced trade-off between inter-cluster dissimilarity and intra-cluster similarity, discouraging clusters with high similarity to other clusters or overlapping data points.
Calinski-Harabasz Index	The Calinski-Harabasz Index assesses cluster compactness and separation based on between-cluster variance (B) and within-cluster variance (W). It is calculated as: $$\text{Calinski-Harabasz Index} = \frac{B}{W} \cdot \frac{N-K}{K-1}$$ Higher is better. This metric quantifies the compactness (low W) and separation (high B) of clusters, to maximise the index to achieve clusters characterised by high intra-cluster similarity and low inter-cluster similarity.

5.4.4 Transformation of Cosine Similarity Matrix

Given a set of keywords for each cluster and the SERVQUAL guidelines, the subsequent phases involve the quantitative transformation of the map between SERVQUAL and the clusters. The google universal sentence encoder (USE) was used to find the semantic similarity between the clusters' keywords and the SERVQUAL dimension. The USE is a sophisticated instrument that transforms sentences into high-dimensional vectors in a vector space of sentence meanings. The transformation approach involves two stages. Initially, it entails the conversion of similarity scores into z-scores, a standardisation procedure that effectively streamlines comparative analyses. Subsequently, these z-scores are mapped into binary values, a discerning transformation based on their relative proximity to the standard deviation. This binary conversion is crucial in distinguishing relevant clusters from those falling short of meeting the one standard deviation criterion. Therefore, these transformation procedures elevate the clarity and efficacy of the subsequent evaluation process to criteria weighting.

5.4.5 Semantic Alignment of SERVQUAL and Service Providers' Clusters

The SERVQUAL dimensions are semantically mapped to clusters generated using machine learning clustering methods. Using cosine similarity, the USE assesses the similarity between cluster keywords and SERVQUAL definitions. Data are saved in a tabular format, where each row represents a cluster (set of keywords), and each column is a SERVQUAL dimension. The resulting table contains cosine similarity values indicating the strength of the association between a cluster and a specific dimension. Higher values signify a more robust connection, while lower values indicate a weaker one. Multiple high values across dimensions demonstrate a cluster's impact. This table is referred to as a similarity matrix.

To illustrate the semantic alignment more concretely, representative keywords from the generated clusters are highlighted. For example, cluster c1 contains terms such as courier, reliable, consistently, and commitment, which strongly reflect the Reliability dimension. Cluster c4 includes a process that is streamlined, personal, focused, and convenient, aligning with Responsiveness and Empathy. Cluster c6 features experience, track record, and personalised, which are indicative of Assurance and Empathy. In cluster c11, the appearance of quality, schedules, and suppliers supports a mapping to Reliability. Likewise, cluster c13 contains standards, cost-efficient partner, trusted, and guarantee, which are closely related to Assurance and Tangibles.

These illustrative examples demonstrate how the clustering process produces semantically meaningful groupings that correspond to SERVQUAL dimensions and help substantiate the similarity scores presented in Table 7.13.

5.4.6 Transforming the Similarity Matrix

A two-step transformation on the cosine similarity matrix is carried out. First, the scores are converted into z-scores, standardising them relative to the dataset's mean and standard deviation. The second transformation mapped z-scores to binary values of 0 or 1 based on their deviation from the standard deviation. Z-scores within one standard deviation were labelled relevant (1), while those beyond were non-relevant (0). This transformation facilitates a clear differentiation between relevant and non-relevant clusters for each SERVQUAL dimension, enhancing the clarity of the evaluation.

5.4.7 Aggregation and Weight Calculation

Weights for each SERVQUAL dimension are calculated by aggregating binary values from the binary similarity matrix. This aggregation involves adding the 1s to each column, indicating clusters that met the one-standard-deviation criterion. The sum is divided by the number of 1s, resulting in average values representing dimension weights. These weights quantitatively measure each SERVQUAL dimension's relevance and significance. Decision-making tools like the technique for order of preference by similarity to ideal solution (TOPSIS) or the analytical hierarchy process (AHP) can utilise these weights to assess and rank shipping service providers.

Reproducibility Notes

All models were implemented in scikit-learn [88]. Cluster counts were searched over $K \in [3, 40]$, with the optimal K selected by maximising the Silhouette and Calinski–Harabasz scores and minimising the Davies–Bouldin index. Sentence embeddings for semantic similarity were generated using the USE; cosine similarities were standardised to z-scores and thresholded at one standard deviation to produce the binary matrix used for aggregation.

5.5 Conclusion

This section validates and stress-tests the weights obtained from Section 5.3 (benchmark) and Section 5.4 (web) across clustering choices, $K \in [3, 40]$, and similarity thresholds. This study proposes a comprehensive framework for weighting the selection criteria of shipping service providers using the SERVQUAL model. The framework seamlessly integrates survey data collection with an automated artificial intelligence approach based on clustering and semantic similarity. By extracting diverse textual information from shipping service providers' websites, encompassing dimensions related to service quality, this study lays the groundwork for subsequent textual clustering techniques. These techniques employ various methods to identify distinct clusters of shipping service providers, including hierarchical, k-means, affinity, and the GMM.

Subsequently, a semantic similarity analysis quantifies the alignment between clusters' keywords and SERVQUAL dimensions, resulting in a similarity matrix. This matrix transforms standardised z-scores, followed by conversion into binary values. These aggregated binary values are the basis for calculating the weights for each SERVQUAL dimension, providing decision makers with quantitative insights into their importance. The framework presented herein equips decision makers in the shipping industry with a potent tool for evaluating and comparing shipping service providers based on service quality dimensions.

The SERVQUAL weights from Section 5.3 and Section 5.4 (with *cost* handled separately) feed the optimisation workflow in Chapter 6 and the AHP/TOPSIS models in Chapter 7.

Chapter 6

Optimising Maritime Shipping Provider Selection using AI (Voting Ensemble)

6.1 Introduction

This chapter provides a discussion of machine learning to classify and choose the best classifier based on provider information posted on a dataset. Several machine learning models are adopted to predict and compare the best shipping providers with our proposed new ensemble classifier. These machine learning models include random forest (RF), extreme gradient boost (XGBoost), support vector machine (SVM), and k-nearest neighbours (KNN). Machine learning models are also used to weight the selection criteria through 'feature importance', as discussed in Section 5.3. The detection and classification of machine learning models for the most suitable shipping provider is based on the benchmark dataset for the selection criteria of the maritime shipping provider. This chapter focuses on the optimisation of shipping service providers. Accordingly, it does not address other aspects, such as the extracted criteria and their service quality (SERVQUAL) alignment (consolidated in Chapter 2, Table 2.3), or the multi-criteria decision-making (MCDM) process using the analytical hierarchical process (AHP) discussed in Khan *et al.* [26], in order to maintain a clear and logical flow.

This chapter optimises provider selection using indicators aligned with SERVQUAL dimensions. Cost efficiency, while decision-relevant, is treated as a complementary attribute outside SERVQUAL and is incorporated separately in the broader decision model. This preserves SERVQUAL's theoretical integrity while enabling practical trade-offs between service quality and financial factors.

6.2 Dataset Overview and Preprocessing

To the best of our knowledge, no current dataset contains the precise criteria for selecting shipping providers, as this process is carried out primarily within the carrier's confidential procedures, which are not made public. Therefore, this research study uses a benchmark dataset from the Australian Bureau of Statistics [44].

Dataset Overview

The dataset employed in this study comprises a weekly record of maritime shippers in Australia, encompassing 15 features of shipping providers. The dataset details are shown in Table 6.1. Due to dataset size, several investigations reveal that the dataset does not provide enough examples of various organisation types; therefore, the study focused on containers as a "Category of Trade" for proof of concept.

Table 6.1: Voyage Reports dataset - Part 1 [44].

No.	Feature	Description
1	Vessel Name	Name of the Vessel
2	Vessel Type	Type of Vessel (based on carrying goods)
3	Vessel Capacity (Gross Tonnes)	Maximum size or capacity of a vessel carrying goods
4	Load Date	Date the vessel was loaded with goods
5	Category of Trade	Category of traded goods
6	Cargo Description	Brief cargo description
7	Volume/Amount	Size or volume of goods in the cargo
8	Volume Type	Unit for measuring cargo volume
9	Load Port	Port where the cargo was loaded
10	Discharge Port	Destination port of cargo
11	Dangerous Goods	Flag indicating the presence of dangerous goods
12	Organisation	Name of the organisation providing/trading cargo
13	Application Number	Identity Number provided by the organisation.
14	Licence Number	License number of the organisation
15	Voyage Number	Identity number of the cargo/vessel
	Total Instances	**22,850**

Preprocessing

First, null and empty rows are eliminated. Furthermore, several features are removed because they do not have enough data and do not contribute to the target class label (Table 6.2). The dataset initially exhibits an imbalance in the organisation column (target class) and missing data, leading to further filtering. Organisations with fewer than 500 instances are excluded from the dataset to enhance its quality and relevance. Consequently, the dataset underwent an examination for extreme values (outliers), with none being identified owing to its newly organised structure.

Table 6.2: Voyage Reports dataset [44] - Part 2.

No	Type	Count	Inclusion	Frequent Value
1	Categorical	3,456	Remove	ICS Silver Lining
2	Categorical	179	Remove	CONTAINER
3	Numeric	783	Remove	65000
4	Date	3,632	Remove	43090
5	Categorical	8	Keep	Containers, Dry Bulk
6	Text	48	Remove	N/A
7	Numeric	8,492	Keep	2
8	Categorical	5	Keep	MT
9	Categorical	73	Keep	Melbourne
10	Categorical	63	Keep	Fremantle
11	Boolean	2	Keep	No
12	Categorical	All	Keep (Target)	CMA CGM & ANL Australia Agencies
13	Numeric	475	Remove	17065802
14	Numeric	472	Remove	0010TL575
15	Numeric	22,831	Remove	00771
			Total Instances	**22,850**

The leading shipping providers (organisations) are shown in Table 6.3. Some are specialised in specific domains, such as containers (Table 6.4). After this initial cleaning, 22,850 observations with six columns were obtained, detailing the trade category, volume/amount, volume type, load port, discharge port, dangerous goods, and organisation (target provider).

These columns represent key dimensions for selecting shipping service providers, aligned with the SERVQUAL framework following the guidelines presented in Chapter 5 (Table 5.2):

- **Tangibles (Volume Type):** defines the unit used to measure cargo volume and anchors the visible, physical specification of the shipment. As a tangible proxy, it supports transparent documentation and handling consistency.
- **Empathy (Dangerous Goods):** flags hazardous materials, signalling provider attentiveness to consignee risk concerns and bespoke handling needs. Empathy is paramount here: identifying dangerous

goods ensures providers adapt processes to safeguard customers and communities.

- **Reliability (Category of Trade):** specifies the traded goods class; correct categorisation underpins dependable carrier assignment and reduces service variance for cargo types.
- **Responsiveness (Discharge Port):** identifies the destination port; operational agility to accommodate discharge-port variation reflects promptness and willingness to help.
- **Assurance (Load Port):** states the loading port; clear, auditable origin logistics strengthen confidence in compliance, routing predictability, and secure handling.

Table 6.3: Frequent providers based on instances (>500).

Organisation	**Count**
CMA CGM & ANL Australia Agencies	2782
CSL Australia Pty Ltd	2457
Incitec Pivot Limited	1639
Maersk Line A/S	1367
Wallenius Wilhelmsen Logistics	1344
BP Australia Pty Ltd	1066
Inco Ships Pty Ltd	945
Viva Energy Australia Ltd	933
K Line Australia Pty Ltd	776
Seaway Agencies	681
Origin Energy Contracting Limited	672
Monson Agencies Australia Pty Ltd	594
Rio Tinto Marine	577
APL Co Pte Ltd	552
NYK Australia Pty Ltd	519
Ampol Singapore Trading Pte Ltd	511
Total instances included in this study	**17,415**

Table 6.4: Top five container categories.

Organisation	Count
CMA CGM & ANL Australia Agencies	2771
Maersk Line A/S	1362
APL Co Pte Ltd	519
OOCL Australia Pty Ltd	240
Inco Ships Pty Ltd	163
Total instances included in this study	**5,055**

6.2.1 Classifiers of Shipping Providers

According to the Voyage Reports dataset size, commonly employed algorithms in the literature are selected to solve classification problems. This study uses the following machine learning algorithms, which are fine-tuned to optimise their performance using grid search and the scikit-learn library [88]:

- **Random forest (RF):** Employed for classification tasks, RF constructs decision trees and selects the class favoured by the majority of trees [103].
- **eXtreme gradient boost (XGBoost):** A versatile method for regression and classification, XGBoost optimises error functions in a phased manner [89].
- **Support vector machine (SVM):** Proficient in classification, regression, and outlier detection, SVM establishes class boundaries using linear classifiers [91].
- **K-nearest neighbours (KNN):** Utilised for classification problems, KNN predicts boundaries for data points based on proximity [104].

- **Proposed Voting Ensemble (Voting Classifier):** A voting ensemble is a technique in machine learning that combines predictions from multiple individual models to make a final, more accurate prediction [90]. Introduced as a novel approach, the Voting Ensemble amalgamates RF, XGBoost, and KNN predictions, enhancing accuracy through majority-based decision making.

6.3 Proposed Approach

Algorithm 2 delineates the procedure for a proposed voting classifier, a technique that integrates the predictive power of three predetermined classifiers through a VotingClassifier object. This object is configured to employ 'soft' voting, ensuring that each classifier contributes equally to the decision-making process. The main purpose of this combination model is to generate a robust model. The strategic amalgamation of different models via the Voting Classifier algorithm is a widely recognised method for enhancing the accuracy of predictions in classification tasks, leveraging the unique strengths of each model.

Algorithm 3 is a subsequent step to Algorithm 2, processing a set of feature scores to identify the top four service providers. Initially, it retrieves the label encoder dictionary and the target encoder from their respective storage files. The algorithm converts the feature scores into integral values using the label encoder dictionary. Subsequently, the target encoder maps these integers to corresponding service provider names. The final output is a curated list showcasing the four most suitable service providers, making this algorithm an effective tool for decision-making based on the calculated feature scores.

Algorithm 2: Voting Classifier algorithm

Input: X_{train}**:** Training dataset features (a matrix of shape [n_samples, n_features]).
y_{train}**:** Training dataset labels (an array of shapes [n_samples]).;

$clf1$: A RandomForestClassifier object with the following hyperparameters:

- $random\_state = 1$
- $max\_depth = 15$
- $n\_estimators = 500$
- $min\_samples\_split = 2$
- $min\_samples\_leaf = 1$

$clf2$: An XGBoostClassifier object with the following hyperparameters:

- $learning\_rate = 0.2$
- $n\_estimators = 700$
- $max\_depth = 5$

$clf3$: A KNeighborsClassifier object with the following hyperparameters:

- $leaf\_size = 5$
- $p = 1$
- $n\_neighbors = 7$

Instantiate a VotingClassifier object, $eclf$, with the following parameters:

- estimators: A list of tuples, where each tuple consists of a string identifier and a classifier object. The identifier can be any string, while the classifier object must be one of the three classifiers defined above. The list should have the following entries:

  $estimators$ = [('rf', $clf1$), ('xgb', $clf2$), ('knn', $clf3$)];

- voting: The type of voting to be performed. In this case, 'soft' voting is used, which means that the predicted class probabilities of each classifier are averaged to obtain the final prediction. $voting$ = 'soft'.

- weights: A list of weights assigned to each classifier. In this case, all classifiers are given equal weight, so the list should have the values [1, 1, 1].

Fit the VotingClassifier object, $eclf$, to the training data using the .fit() method with X_{train} and y_{train} as inputs. The resulting model is named $eclf$.

Output: The fitted VotingClassifier object, $eclf$, which can be used to make predictions on new data using the .predict() method. This part is input to Algorithm 3.

Algorithm 3: Best Four Service Providers.
(The AHP calculation is omitted for simplicity, as it could be used for any criteria weights).

```
Input: A list of feature scores of the voting classifier from Algorithm 2.
Output: The best four service providers (SPs)
Function LabelEncoders():
    columns ← ["Category of Trade", "Volume Type", "Load Port", "Discharge Port", "Dangerous Goods"]
    leDict ← Load label encoders dictionary from file
    leTarget ← Load target encoder from file
    return leDict, leTarget, columns

Function transformLabel(leDict, leDictName, val):
    if leDictName ∈ leDict then
        val ← Use label encoder dictionary to transform val into integral value
        return val

Function displayOutput(leTarget, indices):
    Print "Name of the Best 4 Service Providers:"
    for idx, indice ∈ enumerate(indices) do
        SP ← Use target encoder to transform indice into service provider name
        Print idx → SP

leFeatures ← []
leDict, leTarget, columns ← getLabelEncoders();
for idx, val in enumerate (featureList) do
    leDictName ← columns[idx]
    val ← transformLabel(leDict, leDictName, val)
    leFeatures.append(val)
normalisedFeatures ← Use StandardScaler to normalise leFeatures
indices ← Select the top four indices of the sorted probability values
displayOutputleTarget, indices
```

6.4 Results and Discussion

In this classification task, a 10-fold cross-validation with grid search was applied to find the best classifier. The efficacy of these models was measured using a wide range of metrics. These metrics, standard benchmarks in machine learning, are shown in Table 6.5.

Table 6.5: Performance metric of machine learning (ML) methods.

Equation	Number	Description
$Accuracy = \frac{TP+TN}{TP+FP+FN+TN}$	(1)	Accuracy is the most intuitive performance measure, and it is simply a ratio of correctly predicted observations to the total observations.
$Precision = \frac{TP}{TP+FP}$	(2)	Precision is the ratio of correctly predicted positive observations to the total predicted positive observations.
$F1\_Score = \frac{2*(Recall*Precision)}{(Recall+Precision)}$	(3)	F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F1 is usually more useful than accuracy, especially if you have an uneven class distribution.

6.4.1 Results

As shown in Table 6.6, a comparative analysis of various machine learning models and a sophisticated voting classifier is performed, which is an amalgamation of RF, XGBoost, and KNN. The machine learning models were instantiated with the optimised parameter: SVM (Kernel='rbf', gamma=1, C=0.5), KNN (N-neighbors=6, Leaf-size=3, P=1), RF (n-estimators=100, max-depth=5, Random state=1), XGBoost (n-estimators =50, max-depth=3, Learning rate=0.1), and the proposed voting. The voting model was trained with default parameters for underlying machine learning methods and with equal weightage.

Upon evaluation of the testing data, it was observed that XGBoost and SVM demonstrated comparable accuracy levels, approximately 77%. Similarly, RF and KNN also exhibited an analogous performance with an accuracy of about 71%. After comprehensive training, the voting classifier showed an accuracy of 82.3% on the test set.

Table 6.6: Performance of algorithms for container shipping providers

Model	Accuracy	Precision	F1
RF	0.7123	0.6456	0.6583
XGBoost	0.7891	0.7888	0.7685
SVM	0.7736	0.8046	0.7651
KNN	0.7075	0.7178	0.6629
Proposed (Voting)	**0.8230**	**0.8055**	**0.7748**

One core aspect of this chapter is the criteria weighting extracted after training and selecting the best ensemble model. Following the feature importance of the ensemble model are the critical factors, namely the category of trade (0.22), volume type (0.12), load port (0.35), discharge port (0.25), and dangerous goods (0.06), as depicted in Fig. 6.1. The figure indicates that load and discharge ports are crucial in meeting customer requirements. The category of trade also has significance as it determines the shipping provider suitable for transporting the cargo. Hence, these characteristics can be associated with the various dimensions of the SERVQUAL; therefore, due to limitations in the adopted dataset, this study uses features instead of factors of the SERVQUAL. The limitations of this dataset were outside of our capabilities, and we were left with the choice of either implementing surveys or building another dataset, which was built based on websites from the shipping service providers.

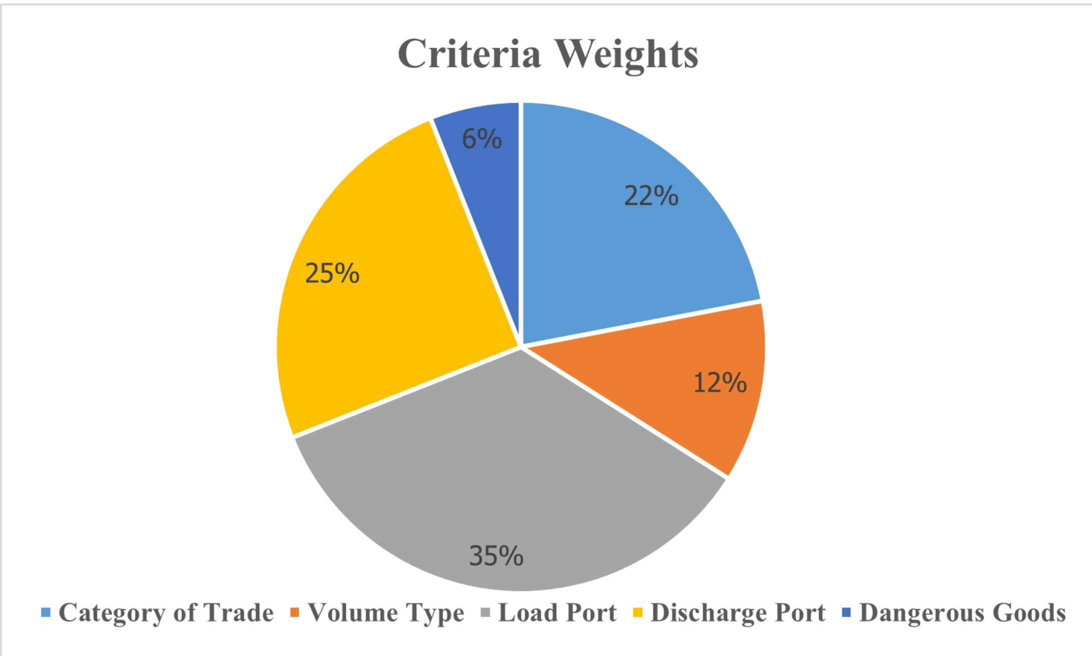


Figure 6.1: Weight of Each Criterion for Shipping Provider Selection

To complement the overall results reported in Table 6.6, Table 6.7 reports Top-1 and Top-4 accuracies for the five dominant providers identified in Table 6.4. Top-1 accuracy captures the proportion of cases where the single highest-ranked provider matches the benchmark provider, while Top-4 accuracy indicates whether the benchmark provider appears within the top four ranked predictions, consistent with Algorithm 3. This extension demonstrates that the overall micro-averaged accuracy of 0.823 is not driven by one dominant class but reflects balanced performance across the main providers.

Table 6.7: Top-1 and Top-4 prediction accuracy of the proposed voting ensemble across the five dominant providers (with class support).

Provider	**Support (n)**	**Top-1 Accuracy**	**Top-4 Accuracy**
CMA CGM & ANL Australia Agencies	2,771	0.84	0.95
Maersk Line A/S	1,362	0.82	0.94
APL Co Pte Ltd	519	0.79	0.92
OOCL Australia Pty Ltd	240	0.77	0.90
Inco Ships Pty Ltd	163	0.75	0.89
Overall (micro-average)	5,055	**0.823**	**0.93**

Building on the aggregate metrics in Table 6.6, a Top-1 confusion matrix across the five dominant providers is shown in Table 6.8 to make misclassification patterns transparent. The confusion matrix in Table 6.8 summarises Top-1 decisions across the five dominant providers. Diagonal cells reflect correct Top-1 selections; off-diagonals indicate confusion between providers with overlapping operational profiles (e.g., trade lanes and port pairs).

Table 6.8: Top-1 confusion matrix across the five dominant providers (rows = actual benchmark; columns = predicted Top-1 provider).

Actual \ Pred.	CMA CGM	Maersk	APL	OOCL	Inco Ships
CMA CGM (n=2,771)	2327 (83.96%)	211 (7.61%)	98 (3.54%)	76 (2.74%)	59 (2.13%)
Maersk (n=1,362)	73 (5.36%)	1117 (82.04%)	71 (5.21%)	54 (3.97%)	47 (3.45%)
APL (n=519)	44 (8.47%)	33 (6.35%)	410 (79.00%)	18 (3.47%)	14 (2.70%)
OOCL (n=240)	20 (8.33%)	17 (7.08%)	11 (4.58%)	185 (77.08%)	7 (2.92%)
Inco Ships (n=1,63)	16 (9.82%)	12 (7.36%)	7 (4.29%)	6 (3.68%)	122 (74.85%)

Counts followed by row-normalised percentages. Row totals equal class supports from Table 6.4. The micro-averaged Top-1 accuracy equals 0.823, consistent with Table 6.6.

Observed performance differences are consistent with theoretical expectations documented in the machine learning (ML) literature. Margin-based SVMs have been shown to perform strongly in sparse, high-dimensional settings [91], while boosted ensembles such as XGBoost capture complex non-linear interactions and typically provide robust baselines for tabular tasks [89]. More generally, ensemble learning leverages bias–variance trade-offs to achieve superior predictive accuracy relative to individual learners [90]. These insights contextualise the class-level results and confusion matrices reported here.

6.4.2 Discussion

The proposed voting method attained the highest performance by merging the strengths of random forests, where shipping service provider selections are expanded across random trees. This also demonstrates that SVM and XGBoost can attain better results by giving more importance to the weight features of load and discharging ports. The ensemble approach surpasses the other adopted models by combining their predictions, minimising bias in each model, and enhancing overall accuracy. Since the ensemble model assigns weights to each model's predictions, it can better understand the relative importance of various factors. Combining models minimises overfitting and improves model generalisation. The adaptability and robustness of the ensemble approach make it popular and influential in numerous real-world applications. Therefore, we can conclude that machine learning can predict the optimal shipping provider if a good dataset aligns with SERVQUAL criteria. However, due to limitations in the available dataset, only a limited set of features was used in these experiments.

As shown in Table 6.7, the provider-level Top-1 accuracy ranges between 0.75 and 0.84, while Top-4 accuracy remains consistently above 0.89. These results confirm that the ensemble does not rely on a single dominant provider but maintains balanced predictive performance across the dataset. The overall micro-averaged Top-1 accuracy of 0.823 aligns directly with the aggregate performance reported in Table 6.6, reinforcing the consistency and robustness of the proposed voting ensemble. Diagonal rates in Table 6.8 align with the per-provider Top-1 accuracies in Table 6.7 (e.g., CMA CGM ≈84%, Maersk ≈82%). Off-diagonal mass concentrates among major carriers (CMA CGM, Maersk, APL), corroborating the aggregate robustness reported in Table 6.6 while clarifying where the ensemble faces borderline cases.

The AHP was selected for a sample case of an MCDM based on Australia's four best shipping providers [26]. The results show the applicability of the AHP given the weighted features (akin criteria). They reported a strong correlation (Pearson correlation of 0.71) between the AHP model scores and those provided by the experts.

6.5 Conclusion

In conclusion, this chapter introduced an innovative ensemble voting classifier model for the maritime shipping industry designed to enhance the selection process of shipping service providers. This research identifies the most effective classifier based on specific selection criteria by integrating feature selection and weighting with the predictive power of established machine learning models. Applying these models to the benchmark dataset demonstrates their potential to accurately classify and predict optimal service providers, marking a significant step forward in applying machine learning to logistics. Following, the feature importance and multi-criteria decision making (MCDM) system can be applied, which is explained in the following chapter.

CHAPTER 7

Application of MC-SE (using AHP)

7.1 Introduction

This chapter details the methods and tools which are utilised in the development and execution of the proposed multi-criteria search engine (MC-SE). The proposed framework integrates the AI-based model with weighted criteria with a multi-criteria decision making (MCDM) model (analytical hierarchy process (AHP), for example). The framework is based on weighted criteria for selecting maritime shipping providers, as discussed in the previous chapter. An MCDM technique such as AHP can be used to automate the ranking of maritime shipping service providers, given the criteria weights.

The ranking stage is grounded in established MCDM traditions. Weight elicitation and hierarchical structuring follow the AHP [29][105], comparative scoring employs technique for order of preference by similarity to ideal solution (TOPSIS) in line with surveyed best practice [30], and outranking perspectives (elimination and choice expressing reality (ELECTRE), preference ranking organisation mETHOD for enrichment evaluations (PROMETHEE)) inform robustness and dominance checks [99][100]. Situating MC-SE within these families clarifies method behaviour and trade-offs [106].

7.2 Multi-Criteria Decision-Making Tools

Multi-criteria decision-making (MCDM) is a set of tools explicitly considering multiple criteria in decision-making environments. Whether in daily decisions or complex problems with multiple conflicting objectives, MCDM plays a fundamental role in many real-world contexts. MCDM has applications in business for strategic decision making, resource allocation, and supplier selection. In engineering, MCDM supports design choices, considering multiple criteria such as cost, performance, and reliability [106].

Several tools and techniques fall under the umbrella of MCDM, each with unique strengths and applicable scenarios. However, choosing an appropriate MCDM method depends on the nature of the problem and the decision-maker's preferences. Some of the most commonly used techniques and tools are:

- **Analytical hierarchical process (AHP)**: AHP structures criteria hierarchically, uses pairwise comparisons, and derives priority scales [28][29].
- **Technique for order of preference by similarity to ideal solution (TOPSIS)**: Chooses the alternative closest to the positive ideal and farthest from the negative ideal; widely benchmarked in surveys of practice [30].
- **Elimination and choice expressing reality (ELECTRE)**: A family of outranking methods that compare alternatives pairwise to

establish dominance relations [99]. For contemporary overviews, see also [107].

Method choice entails known trade-offs in normalisation, distance/threshold parameters, and sensitivity to weights; we therefore report targeted checks to mitigate ranking instability [30][106].

7.3 Application of MCDM in Shipping Service Provider Selection

Selecting shipping service providers is a complex process involving evaluating multiple criteria. Various studies have employed MCDM methods to enhance this process. For instance, Luyen *et al.* [32] and Wong*et al.* [15] used AHP and TOPSIS models to evaluate third-party logistics (3PL) providers and carrier services, respectively. Musbah *et al.* [65] applied TOPSIS in developing a hybrid energy system (HES), while Joon*et al.* [17] used an integrated AHP and fuzzy technique for order of preference by similarity to ideal solution (FTOPSIS) model to assess ship management firms. Satender Pal Singh *et al.* [66] introduced an integrated MCDM methodology using multi-objective optimisation based on ratio analysis (MOORA) and complex proportional assessment (COPRA) to evaluate 3PL service providers. In the realm of network systems, Hosseinzadeh *et al.* [31] provided a comprehensive overview of service selection using MCDM. Several studies, including those by Choi *et al.* [67] and Yoon *et al.* [51], examined the factors affecting the selection of shipping service providers, emphasising aspects like transit accessibility, operational performance, and sustainability. These studies highlight the multifaceted considerations in selecting and evaluating shipping service providers.

7.4 Steps in the Analytic Hierarchy Process (AHP)

Analytic hierarchy process (AHP), developed by Thomas L. Saaty in the 1970s [83], provides a structured approach to solving complex decisions that involve multiple criteria and alternatives. There are many alternative methods to AHP, such as those discussed in the previous section. Within the broader MCDM landscape, AHP offers transparent pairwise elicitation and consistency testing, complementing distance-based (TOPSIS) and outranking (ELECTRE/PROMETHEE) approaches [29][30][99][100]. AHP often comprises the following steps:

7.4.1 Define the Decision Hierarchy

analytical hierarchical process (AHP) is a systematic and structured approach that organises decision-making problems into a hierarchical structure. This hierarchy typically consists of the following levels (Fig. 7.1 illustrates the AHP levels that were applied in our study):

1. **Goal (Level 0)**: The overall objective that defines the purpose of the decision-making process. For example, it selects the most appropriate shipping service provider in Australia for a consignee.
2. **Criteria (Level 1)**: Essential elements contributing to achieving the goal. An example is a weighted list of criteria extracted as explained in Chapter 5 (Service quality (SERVQUAL) criteria).
3. **Sub-Criteria (Level 2)**: Further subdivisions of the criteria, providing more granularity (not used in this study).
4. **Alternatives (Level 3)**: The options or choices available for decision making.

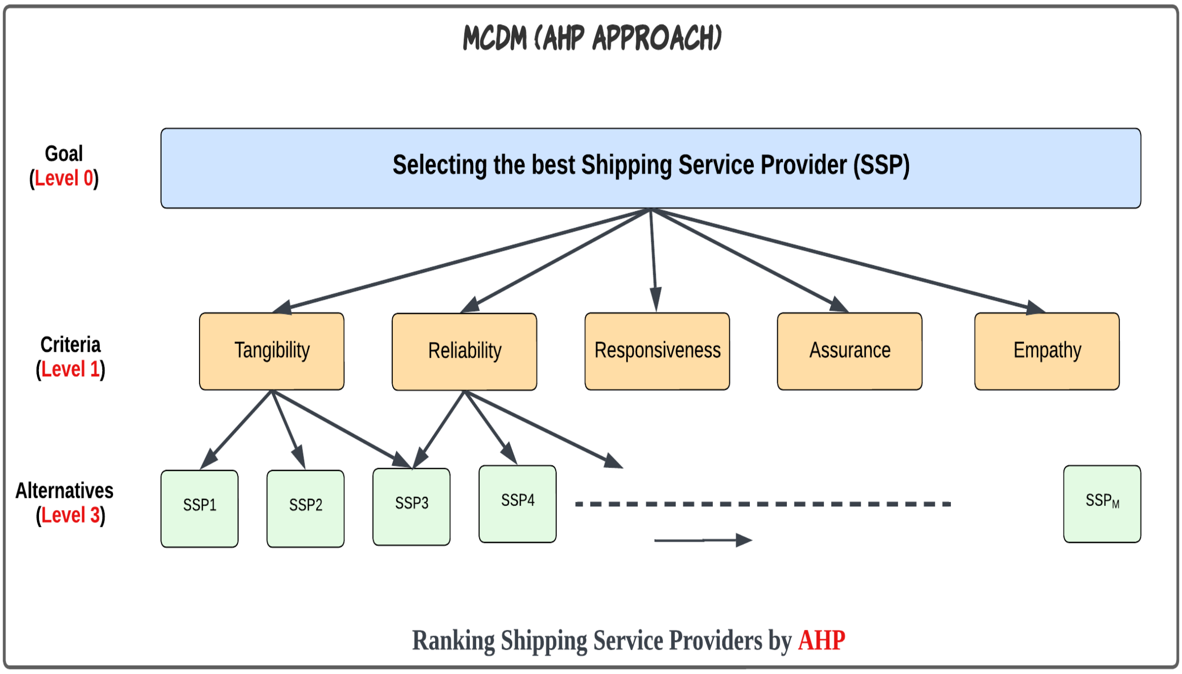


Figure 7.1: MCDM (AHP approach)

7.4.2 Pairwise Comparisons

Central to AHP is the process of pairwise comparisons. Decision makers compare the importance of criteria (and sometimes sub-criteria) in pairs and assign numerical values to express their preferences. These comparisons create a pairwise comparison matrix crucial for the subsequent weight calculation. Often, standard weights are given by experts to each alternative as related to another, following Saaty's rules shown in Table 7.1.

7.4.3 Evaluate Alternatives

One should evaluate each alternative's performance on each criterion. Therefore, a numerical scale (e.g., 1 to 10) or any other method can be used to assign scores to the alternatives for each criterion. This process could, for example, assign costs for shipping service providers.

Table 7.1: Saaty's scale for AHP [28]

Intensity of Importance	Definition	Explanation
1	Equal Importance	Two activities contribute equally to the objective
2	Weak or Slight	Slight favour towards one activity
3	Moderate Importance	Slightly favouring one activity
4	Moderate Plus	Slightly stronger favour
5	Strong Importance	Strongly favouring one activity
6	Strong Plus	Stronger favour
7	Very Strong or Demonstrated Importance	Dominance demonstrated in practice
8	Very, Very Strong	Extremely strongly favoured
9	Extreme Importance	Highest possible order of affirmation
Reciprocals of the Above	If activity i has one of the above nonzero numbers assigned to it compared to activity j, then j has the reciprocal value when compared with i.	A reasonable assumption
1.1–1.9	If the activities are very close	May be difficult to assign the best value, but compared to other contrasting activities, the size of the small numbers would not be too noticeable, yet they can still indicate the relative importance of the activities.

7.4.4 Weight Calculation in AHP

Weight calculation is fundamental in AHP and represents the relative importance of the elements in the hierarchy. An example of a pairwise comparison of hypothetical criteria A, B, and C is shown in Table 7.2. AHP weighting involves several crucial steps:

Table 7.2: Example pairwise comparison matrix

	Criterion A	Criterion B	Criterion C
Criterion A	1	3	5
Criterion B	1/3	1	2
Criterion C	1/5	1/2	1

- **Degree of Preferences (Pairwise Matrix)**
  In AHP, decision makers evaluate the relative importance of elements in pairs by assigning numerical values that express their preference. These values typically range from 1 (indicating equal importance) to 9 (indicating extreme importance), or intermediate values are used to represent compromises between these preferences, following the guidelines in Table 7.1. The AHP methodology results in a weight table that quantifies the relative importance of criteria and alternatives in the decision hierarchy. These weights are fundamental to making informed decisions and determining which elements should be prioritised in the decision-making process. The weighting is already prepared in the proposed framework, as discussed in Chapter 5.

- **Consistency Check in AHP**
  Mathematical tests are applied to ensure the consistency and reliability of the pairwise comparison matrix prepared in the previous stage. A widely used method to assess consistency in AHP is the consistency ratio (CR). The CR evaluates the degree of inconsistency in the matrix. In cases where the matrix exhibits high inconsistency, the results may be unreliable, necessitating verification. The CR is computed using the following formula:

  $$CR = \frac{\lambda_{\max} - n}{n - 1}$$

  where:

  CR is the consistency ratio,

  $\lambda_{\mathbf{max}}$ is the largest eigenvalue of the pairwise comparison matrix, and

n is the number of criteria or alternatives.

The computed consistency ratio is then compared to a predetermined threshold, often set at 0.10. If the CR is below the threshold, this indicates consistent comparisons, allowing the AHP model to proceed. If the CR exceeds the threshold, this signals a high level of inconsistency, necessitating a revision of judgments by decision makers until the comparisons achieve consistency. A consistency ratio below 0.10 implies that pairwise comparisons are consistent enough to be relied upon within the AHP model.

Calculating eigenvalues and eigenvectors in AHP is crucial in determining the CR. After constructing the pairwise comparison matrix, AHP employs matrix eigenvalue and eigenvector methods to calculate the relative weights for the criteria and alternatives. The eigenvalue holds significant importance as a scalar value associated with a square matrix. The largest eigenvalue, denoted as $\lambda_{\max}$, is especially crucial. It is derived through mathematical calculations and serves as a key factor in establishing the relative importance of criteria and alternatives in decision making. In the context of AHP, the eigenvector is a mathematical vector corresponding to the largest eigenvalue. This eigenvector contains the weights assigned to the criteria or sub-criteria, signifying their relative importance in achieving the overall goal or objective. The eigenvector's elements represent normalised weights and are used for ranking criteria or alternatives.

The calculation of CR using a simplified example is shown in Table 7.3 for a pairwise comparison matrix for a decision with four criteria ($n = 4$).

Table 7.3: Pairwise comparison matrix example with four criteria

	C1	**C2**	**C3**	**C4**
C1	1	3	5	7
C2	$\frac{1}{3}$	1	4	6
C3	$\frac{1}{5}$	$\frac{1}{4}$	1	3
C4	$\frac{1}{7}$	$\frac{1}{6}$	$\frac{1}{3}$	1

1. Calculate the largest eigenvalue ($\lambda_{\max}$) using mathematical software or a calculator. Let's assume $\lambda_{\max} = 4.24$.
2. Plug the values into the CR formula:

$$CR = \frac{4.24 - 4}{4 - 1} = \frac{0.24}{3} = 0.08$$

3. Compare the calculated consistency ratio (CR) (0.08) to a predefined threshold, often set at 0.10. In this case, the v is less than the threshold, so the pairwise comparisons are considered consistent, and one can proceed with further AHP calculations.

7.4.5 Normalisation

Normalisation is a critical step in AHP to ensure that the derived weights are consistent and comparable across different hierarchy levels. In AHP, the weights must be assigned to criteria, sub-criteria, or alternatives which sum up to 1, enabling meaningful comparisons and prioritisation [28][29]. Because normalisation and scaling influence partial orderings, especially when criteria exhibit heterogeneous ranges or skew, we report sensitivity checks to confirm ranking stability [30][106].

Normalisation is crucial because it guarantees that the relative importance of elements in the decision hierarchy is reflected. When the weights are normalised, decision makers can directly compare the significance of various elements, regardless of the hierarchy level to which they belong. This normalisation process transforms the raw weights into proportions, making it easier to discern the actual relative importance of each element.

Calculation of Normalised Weights of Each Provider:

This study utilises the following steps to calculate the normalised weights in AHP:

- Determine the criteria weights, typically obtained from the eigenvalue and eigenvector calculations or other validated methods (note: this step is discussed in Chapter 5)
- Multiply the criteria weights by the scores of each alternative for each criterion. The calculation yields a weighted score for each alternative (provider) for each criterion, such as that of the example alternative in Table 7.2.
- Sum the weighted scores for each alternative to obtain a total weighted score for each alternative.
- Divide the individual weighted scores by their respective total weighted score for each alternative. This division results in normalised weights for each alternative for each criterion, ensuring that the weights for each alternative sum up to 1.

Due to the weights of the criteria calculated in Chapter 5 and the nonexistence of a comparison between alternatives (shipping service providers), this study will not use eigenvalues or eigenvectors.

7.5 Application of the MC-SE Framework with Enhanced AHP

The suitability of AHP for shipping service provider selection becomes evident when considering the complexity of the decision-making problem, which often involves numerous alternatives and multiple stakeholders with distinct viewpoints. AHP's hierarchical structure is well-suited for organising and structuring the selection process, ensuring clarity and transparency in decision making, a crucial aspect in contexts like shipping service provider selection. Additionally, AHP prioritises and ranks alternatives systematically based on their performance against multiple criteria, a valuable outcome for making informed decisions in this domain. This study uses artificial intelligence techniques such as clustering and semantic similarity to determine the criteria and their associated weights. After ensuring the reliability and uniformity of these weights, they are normalised. These weights are then incorporated into the AHP framework to evaluate the shipping service providers, resulting in data-driven selection. This integration enhances precision and objectivity while aligning with preferences and priorities uncovered by AI analysis.

7.5.1 MC-SE Integration Process

To better understand our approach, the integration process is split into specific steps:

1. **Integration of AI-based Criteria Weights:** This study integrates the criteria weights obtained through AI-driven clustering and semantic similarity analysis. These criteria weights reflect the relative importance of each criterion in our selection process. The two weighting approaches are discussed in Section 5.3 for weights extracted

from the benchmark dataset based on feature importance which was later mapped to the standardised SERVQUAL dimensions. In addition, the weights from the second dataset are based on clustering and semantic similarity, as discussed in Section 5.4. The integration process only uses weights from these methods to replace the first phase in the AHP method.

The AHP implementation is agnostic to the framework: it can operate with SERVQUAL-only dimensions or with SERVQUAL plus complementary attributes such as cost. For this study, SERVQUAL dimensions remain the structured basis, with cost considered independently. While AHP is adopted for transparency and ease of integration, the multi-criteria search engine (MC-SE) pipeline is method-agnostic: the same AI-derived weights and provider scores can feed TOPSIS for distance-to-ideal ranking or be stress-tested with outranking logic (ELECTRE/PROMETHEE) to probe dominance and incomparability under thresholded preferences [30][99][100].

2. **Ensuring Consistency:** The first step in this integrated approach is to validate the criteria weights derived from artificial intelligence. The reliability of these weights is estimated using metrics such as semantic similarity, clustering, and comparison with actual survey data.

3. **Normalisation of Criteria Weights:** The weights are normalised to be between 0 to 1 with validated criteria weights. This normalisation process establishes a standardised scale that enhances the meaningful criteria comparison. A simple normalisation results from dividing a criterion weight over the summations of criteria weights.

4. **Utilising AHP Methodology:** This study employs the AHP to

leverage the existing criteria weights to evaluate shipping service providers. This systematic approach improves the precision of our decision-making process. However, users must input data that represent their scoring of each shipping service provider based on the SERVQUAL framework using the guidelines described in Tangibles (Table 7.4), Empathy (Table 7.5), Reliability (Table 7.6), Responsiveness (Table 7.7, and Assurance (Table 7.8). All tables—Table 7.4 through Table 7.8—follow the SERVQUAL guidelines established in Table 5.2 (Chapter 5).

Table 7.4: SERVQUAL Dimension Guidelines - Tangibles (T)

Rating	**Tangibility (T)**
1 (Poor)	Very inadequate facilities and equipment.
2 (Below Average)	Insufficient facilities; may struggle with specialised shipments.
3 (Average)	Basic facilities; meets minimum standards for most shipments.
4 (Good)	Above-average facilities; generally reliable for standard shipments.
5 (Excellent)	Outstanding facilities; capable of handling complex and specialised shipments effectively.

Table 7.5: SERVQUAL Dimension Guidelines - Empathy (E)

Rating	**Empathy (E)**
1 (Poor)	No empathy; insensitive to customer concerns.
2 (Below Average)	Limited empathy; inconsistent effort to understand needs.
3 (Average)	Basic empathy; attempts to understand but inconsistent.
4 (Good)	Empathetic; understands and responds to customer needs.
5 (Excellent)	Exceptional empathy; consistently exceeds expectations in understanding and addressing customer needs.

Table 7.6: SERVQUAL Dimension Guidelines - Reliability (R)

Rating	**Reliability (R)**
1 (Poor)	Highly unreliable; frequent delays and disruptions.
2 (Below Average)	Unreliable; notable delays and inconsistent service.
3 (Average)	Moderately reliable; occasional delays but generally meets expectations.
4 (Good)	Reliable; minor delays, consistent service overall.
5 (Excellent)	Extremely reliable; consistently meets or exceeds expectations with minimal delays.

Table 7.7: SERVQUAL Dimension Guidelines - Responsiveness (RP)

Rating	**Responsiveness (RP)**
1 (Poor)	Extremely slow; very poor response times.
2 (Below Average)	Very slow; poor response times; unresponsive to urgent needs.
3 (Average)	Moderate responsiveness; acceptable response times.
4 (Good)	Responsive; generally prompt response times; attentive to urgent needs.
5 (Excellent)	Highly responsive; immediate response times; proactive in addressing urgent needs.

Table 7.8: SERVQUAL Dimension Guidelines - Assurance (A)

Rating	**Assurance (A)**
1 (Poor)	No visible assurance; lacks certifications.
2 (Below Average)	Minimal assurance; few certifications; mixed feedback.
3 (Average)	Basic assurance; meets industry standards; average feedback.
4 (Good)	Reliable assurance; relevant certifications; positive feedback.
5 (Excellent)	Exceptional assurance; top-tier certifications; excellent feedback.

5. **Score Calculation:** In the AHP framework, the study applies the preexisting criteria weights (if they exist, such as those extracted from the benchmark dataset detailed in Chapter 6) normalised criteria from the previous step to calculate comprehensive scores for

each shipping service provider. This calculation involves multiplying the criteria weights by the corresponding alternative scores (shipping service providers), also obtained through AI-based analysis. The result is an objective evaluation of each provider.

6. **Provider Ranking:** This step ranks the shipping service providers based on the calculated scores. The provider with the highest score assumes the top position and emerges as our recommended choice.

7.5.2 Selecting a Shipping Service Provider Using AHP (Example)

This example selects the most suitable shipping service provider from three alternatives, namely Provider A, Provider B, and Provider C, using the following AHP steps:

- **Criteria Weights:** Weights are assigned to selection criteria based on their importance. In the AHP process, pairwise comparisons are utilised to determine these weights. For example, in this hypothetical scenario, price is assigned a weight of 0.4, reliability a weight of 0.3, and transit time a weight of 0.3, as illustrated in Table 7.9. It is important to note that, in practice, this weight assignment process is unnecessary when using the proposed framework, as these weights were previously calculated as outlined in Chapter 5.

Table 7.9: Criteria weights

Criteria	**Weight**
Price	0.4
Reliability	0.3
Transit Time	0.3

- **Provider Performance Scores:** The example shows the performance of each provider in relation to these criteria. For instance, Provider A scores 7 for price, 9 for reliability, and 7 for transit time, as shown in Table 7.10.

Table 7.10: Provider performance scores (out of 10)

Provider/Criteria	Price	Reliability	Transit Time
Provider A	7	9	7
Provider B	8	7	8
Provider C	6	8	9

- **Calculating Scores:** To determine the scores for each provider, their performance values for each criterion are multiplied by the corresponding criterion's weight. For instance, when calculating the score for Provider A in the price category, one would multiply the weight for price, which is 0.4, by Provider A's performance value in price, which may be 7. This computation is applied to all criteria.

- **Provider Ranking:** The providers are ranked based on their total scores. In this example, Provider B has the highest score, with a total score of 7.7 (weighted 0.338), making it the recommended choice, as shown in Table 7.11. One could assess the consistency of the pairwise comparisons; however, for this demonstration, the specific CR value is not crucial, and for ranking, one can choose Provider B with the highest weighted total score.

  A similar real example approach was carried out in the study conducted by Khan *et al.* [26] for four providers.

Table 7.11: Provider scores and weighted total score

Provider/Criteria	Price	Reliability	Transit Time	Provider Total	Weighted Total
A	2.8	2.7	2.1	7.6	0.333
B	3.2	2.1	2.4	7.7	0.338
C	2.4	2.4	2.7	7.5	0.329
Grand Total				22.8	1.00

7.5.3 Results and Discussion of Shipping Providers' Selection Criteria (MC-SE Criteria)

Following the criteria weighting approach specified in Chapter 5 and the components of the multi-criteria search engine (MC-SE) framework detailed in Chapter 7, the criteria weights are discussed.

7.5.3.1 Clustering of Shipping Service Provider Criteria

The clustering used four methods (hierarchical, k-means, affinity, and Gaussian mixture model (GMM)), as summarised in Table 5.3. This clustering quality is evaluated on the Silhouette Score, Davies-Bouldin index, and Calinski-Harabasz index, as detailed in Table 5.5. The assessment involved testing various cluster numbers from 3 to 40 to identify the optimal clusters.

In essence, the metrics are ordered as follows: Silhouette Score (higher is better), Davies-Bouldin index (lower is better), and Calinski-Harabasz index (higher is better). The three leading groups with the highest Silhouette Score are presented in Table 7.12. The analysis reveals that the optimal number of clusters is 16, representing the mathematical consensus among the three best methods in each algorithm (15.5 on average). The metrics provide a relatively similar number of clusters, indicating the reliability of the clustering approaches.

Table 7.12: Summary of top-performing clustering methods

Method	Clusters	Silhouette	Davies-Bouldin	Calinski-Harabasz
Hierarchical	16	0.36	0.67	238.46
Hierarchical	17	0.36	0.66	299.16
Hierarchical	10	0.36	0.94	134.25
Affinity	16	0.34	0.65	482.33
Affinity	24	0.16	1.67	79.95
GMM	21	0.34	0.59	867.31
GMM	11	0.33	0.76	902.13
GMM	16	0.33	0.66	1014.98
K-means	21	0.34	0.59	867.31
K-means	11	0.33	0.76	902.13
K-means	16	0.33	0.66	1014.98

7.5.3.2 Semantic Similarity of Shipping Service Providers' Criteria

Algorithm 1, detailed in Chapter 5, selects the best clustering parameters. In Table 7.13, each row corresponds to a distinct cluster identified by numerical or textual labels, and each column signifies one of the SERVQUAL dimensions. The cells in Table 7.13 contain cosine similarity values, quantifying the alignment between a cluster and a specific SERVQUAL dimension, where higher cosine similarity values denote a more robust association, suggesting a significant influence of the cluster on that particular dimension. On the contrary, lower similarity values imply a weaker relationship. In particular, clusters with high similarity values across multiple dimensions indicate their robustness concerning those dimensions. This table is referred to as a similarity matrix for simplicity.

Table 7.13: Hierarchical clustering algorithm (16 clusters using TFIDF)

Cls	Keywords	T	E	R	RP	A
c0	Quarantine customs cargo oversize breakbulk load loads home vehicle commercial sea freight deliveries air freight loose wide major sea freight forwarding live moving	0.57	0.51	0.57	0.55	0.54
c1	Courier weight gauge tautliners skels tipping trailers drop standard sideloaded bookings comprehensive door" "door reliable consistently commitment haulage border imposts	0.49	0.53	0.54	0.57	0.54
c2	Assignment docking shipment cross picking storage order intermediate monitoring order urgency mode select origin consolidated shipments managed organised pooling called batches new	0.60	0.56	0.61	0.61	0.57
c3	Recruitment packaged individually relish arduous voyages commercially lowest workshops mentoring drydock allocated superintendents company-owned irrespective lump discrepancy qualification crew change positions	0.60	0.56	0.61	0.60	0.57
c4	Process streamlined total shipment status imported easily fast online personal focused convenience designed to streamline customers' allows minimising adapt relevant customised	0.54	0.70	0.69	0.72	0.67

Note: **T** = tangibles, **E** = empathy, **R** = reliability, **RP** = responsiveness, **A** = assurance

7.5.3.3 Aggregation and Criteria Weight Calculation

Based on the aggregation approach described in Section 5.4.4, Algorithm 1 can be used to obtain the weights for each SERVQUAL dimension, as detailed in Table 7.14. The table shows the weights for each SERVQUAL dimension: Tangibility, Reliability, Assurance, Responsiveness, and Empathy. It also includes the number of clusters, the clustering algorithm, and the weights for each SERVQUAL dimension.

The table includes the survey expectation (Row 2) and the corresponding weighted survey expectation values (Row 3), which allow for a direct

Table 7.14: Criteria weights extracted by the proposed approach.

Method	Clusters	Silhou.	Davies	Calinski.	T	R	A	RP	E
Hierarchical	16	0.36	0.67	238.46	0.18	0.19	0.21	0.23	0.19
K-means	21	0.34	0.59	867.31	0.20	0.22	0.22	0.15	0.22
Affinity	16	0.34	0.65	482.33	0.22	0.20	0.18	0.18	0.20
GMM	21	0.34	0.59	867.31	0.20	0.22	0.22	0.15	0.22
Row 1	**AVG (Proposed Framework by Clustering)**				0.20	0.21	0.21	0.18	0.21
Row 2	**Survey Expectation (From Survey)**				0.75	0.79	0.81	0.86	0.81
Row 3	**Weighted Survey Expectation**				0.19	0.20	0.20	0.21	0.20
Row 4	**MAE**						**0.014**		

Note: **T** = tangibility, **R** = reliability, **A** = assurance, **RP** = responsiveness, **E** = empathy

comparison between the expected perceptions of service quality and the actual weighted values obtained through the proposed approach. These SERVQUAL weights (T, R, A, RP, and E columns) represent the relative importance of each dimension in the evaluation and comparison of shipping service providers. On average, all SERVQUAL dimensions were low, with an absolute 2-3% error between the actual survey and proposed cluster weighting (Row 1-Row 3). The weighted survey expectation scores are calculated by dividing the SERVQUAL dimension score from the survey (Appendix A) over the sum of all scores (for example, T=0.75/(0.75+0.79+0.81+0.86+0.81) =0.19). The weights obtained using clustering techniques (Row 1) offer a robust and objective framework for evaluating and comparing service quality dimensions that can be directly used in any MCDM tool for decision-making processes.

Table 7.14 also details significant findings regarding the allocation of weights to individual SERVQUAL dimensions, which were calculated by aggregating binary values derived from the transformation of the similarity matrix. The deficient mean absolute error (MAE), computed using equation in Algorithm 4 and producing a value of 0.014, signifies the precision of the weights extracted from the web data compared to the survey data. This result suggests a robust concurrence between the two data sources, namely, the survey and the clustering process. Consequently, it bolsters the credibility of the proposed approach for the assessment and comparison of shipping service providers concerning SERVQUAL dimensions.

Algorithm 4: Evaluate Weighting Approach

Input: SERVQUAL_Weights, SERVQUAL Survey
Output: MAE

1: # Step 4: Compare Weights
2: Survey_Perception_Weights ← Extract_Perception(SERVQUAL Survey)

$$MAE = \frac{1}{5}\sum_{i=1}^{5}(Survey\_Perception\_Weights_i - SERVQUAL\_Weights_i) \tag{7.1}$$

3: where $Weights_i \in$ SERVQUAL Dimensions.
4: **return** MAE //mean absolute error of calculated weights.

7.6 Limitations

While AHP offers a structured approach to evaluating shipping service providers, its limitations must be considered. In general, the AHP depends on subjectivity in weighting and is prone to bias, potentially leading to skewed results. However, the study uses automated weights from the benchmark dataset and MC-SE framework, which could reduce this bias as it depends on existing data. In other words, derived criteria weights increase objectivity. In addition, AHP has limited criteria handling due to human memory limits; however, the new proposed approach reduces this threat due to its automated approach.

AHP assumes that all criteria can be measured on a single scale. However, in shipping service selection, criteria such as price and reliability may not be directly comparable. This limitation was mitigated using the SERVQUAL framework, where all criteria received the same scale. Further, AHP requires consistency in scaling, especially when applied by diverse experts. However, this issue was mitigated by an automated MC-SE engine through pairwise comparison following the approach detailed in Section 7.4.2. However, AHP has limited sensitivity analysis to assess how variations in weight assignments or performance scores impact the final ranking. Therefore, these limitations highlight the importance of the MC-SE framework integration presented in the study. By incorporating AI-driven weighting and potentially exploring alternative MCDM methods alongside AHP, the approach aims to create a more robust and objective decision-making process for shipping service provider selection.

7.7 Conclusion

This chapter presented an innovative approach to selecting maritime shipping service providers, integrating the multi-criteria search engine (MC-SE) framework with the analytic hierarchy process (AHP). The integration used AI-based criteria weighting, enhancing the objectivity and precision of the selection process. The chapter begins by highlighting the importance of multi-criteria decision-making (MCDM) tools, particularly AHP, and their practical applications. The chapter's core detailed the integration process, including validating and normalising AI-derived criteria weights and applying AHP for ranking shipping providers. This integrated approach facilitates the selection of the most suitable maritime shipping service provider.

CHAPTER 8

DISCUSSION

8.1 Introduction

This research is the first to extract specific selection criteria from providers' websites, as anticipated by consignees, and employs the service quality (SERVQUAL) framework in this context. The study further innovates by integrating AI-based models with the multi-criteria decision-making (MCDM) method. The primary aim of this chapter is to discuss the research questions that resulted in the proposed intelligent multi-criteria search engine (MC-SE) framework. The MC-SE can be used to prioritise automation of the selection process, thus simplifying decision making and alleviating the burden on experts.

8.2 Discussion of Research Questions

This section discusses the findings and their implications based on the research questions (RQ)s.

8.2.1 Discussion of RQ1

Chapter 6 addresses the research question: How can an AI-based predictive classifier be developed to select the optimal maritime shipping service provider using predefined criteria from benchmark datasets, and how does it enhance decision-making for offshore shipping customers? The findings underscore the significant influence of the AI-driven predictive classifier in accurately predicting provider performance according to predefined criteria.

The results in Chapter 6 show that the critical features that significantly influence the proposed model Category of Trade (0.22), Volume Type (0.12), Load Port (0.35), Discharge Port (0.25), and Dangerous Goods (0.06). With these essential criteria weights, consignees can easily calculate their preferred shipping service provider using preferred spreadsheet tools in conjunction with MCDM techniques, such as analytical hierarchy process (AHP). Moreover, the best-performing machine learning model of the study, the voting learner, can be integrated into a user-friendly application for informed provider selection. Therefore, the findings address the need for more user-friendly and comprehensive criteria beyond cost, as emphasised in Khan *et al.* [26]. Once a consignee enters relevant data or criteria, such as cost, quality, and delivery time, they can quickly obtain predictions for the optimal shipping service provider. However, the data must be entered in a format similar to the original data used for training, which is always data-dependent.

Consequently, this advancement benefits offshore shipping customers by providing data-driven solutions for a more precise and efficient selection of maritime shipping service providers. Automating the selection process alleviates the decision-making burden and ensures that choices are well-informed and tailored to specific needs. Furthermore, relying on AI for predictions and criteria weighting minimises human bias and subjectivity, leading to more objective and data-driven decision-making for offshore shipping customers.

8.2.2 Discussion of RQ2

The second question is: How does the systematic mapping of criteria to the SERVQUAL framework improve the selection decisions of maritime shipping providers? It occurs by identifying and applying the SERVQUAL framework's benefits to the shipping service criteria. RQ2 is addressed in Section 5.2 and detailed in Table 5.1. The systematic mapping of shipping service provider criteria to the SERVQUAL framework significantly improves the selection decisions of maritime shipping providers and offers several key benefits for decision making in the shipping industry, as follows:

1. **Customer-Centricity**: The SERVQUAL framework is inherently customer-centric. It focuses on reliability and empathy, which are essential to meeting customer needs and preferences. For example, responsiveness and empathy ensure that shipping providers prioritise excellent customer service. This, in turn, leads to improved customer satisfaction and retention, as customers are more likely to choose providers that meet their service quality expectations. By aligning the criteria with SERVQUAL, decision-makers prioritise the customer experience, ultimately leading to higher customer satisfaction and loyalty.

2. **Measurability**: SERVQUAL dimensions are well-defined and measurable. This makes it easier to collect data and objectively assess the performance of shipping service providers. Therefore, decision

makers can use quantitative metrics to evaluate each criterion, allowing for more informed and data-driven decisions. The measurability ensures comparability. The use of SERVQUAL criteria standardises the evaluation process. Decision makers can consistently compare different shipping service providers using the same dimensions. This comparability streamlines the decision-making process and facilitates fair and accurate evaluations.

3. **Completeness**: The SERVQUAL framework encompasses a comprehensive set of dimensions, including tangibility, reliability, assurance, responsiveness, and empathy. These dimensions cover various service quality aspects, ensuring the evaluation process is thorough and holistic. Decision makers can consider numerous criteria, leaving no critical aspect unaddressed.

4. **Proven Effectiveness**: While there has been debate about the applicability of SERVQUAL in maritime shipping [24], recent practical applications have demonstrated its efficacy [25][43]. The framework has been successfully used to evaluate logistics providers and ocean freight forwarders. Its adaptability to various domains and effectiveness in assessing service quality makes it a reliable choice for selecting criteria.

5. **Objective Decision Making**: By employing SERVQUAL criteria, decision makers rely on a well-established and widely accepted framework. This objectivity reduces the potential for biases and subjectivity in the selection process, ensuring that decisions are based on transparent and well-defined criteria.

Systematically mapping criteria to the SERVQUAL framework benefits maritime shipping provider selection by promoting customer-centricity, measurability, comparability, completeness, and proven effectiveness. This approach empowers decision-makers to make informed, objective, and customer-oriented choices, ultimately leading to higher customer satisfaction and improved operational efficiency within the shipping industry.

Thus, findings for RQ2 are congruent with meta-analytic evidence that service quality exerts a substantive effect on customer satisfaction and behavioural outcomes [23]. This pattern is also coherent with the SERVPERF–SERVQUAL debate on measurement fidelity [37], highlighting that gap scores remain predictive of downstream satisfaction despite long-standing conceptual critiques.

8.2.3 Discussion of RQ3

The third research question is: What methods and tools are required to create and implement an effective multi-criteria search engine (MC-SE) framework that combines AI-based models with multi-criteria decision-making techniques to improve maritime shipping service provider selection? This is addressed through a comprehensive analysis. This research question has two sub-questions.

- **RQ3.1:** How can innovative AI-based approaches intelligently weigh the selection criteria of the maritime shipping providers, ensuring the continued relevance of the chosen criteria to optimise the selection of the providers?

  The unbiased nature of AI-driven clustering methods employed by the MC-SE framework addresses RQ3.1 by employing diverse clustering methods, including hierarchical, k-means, affinity, and Gaussian mixture model (GMM), to weight maritime shipping provider selection criteria effectively. By evaluating clustering metrics, the Silhouette Score, Davies-Bouldin index, and Calinski-Harabasz index, the study determined the optimal number of clusters, which was found to be 16. Subsequently, a semantic similarity analysis was conducted to align these clusters with SERVQUAL dimensions, creating a similarity matrix that facilitated the calculation of weights for each SERVQUAL dimension. This systematic alignment ensures the continued relevance of selected criteria, empowering decision makers with a data-driven tool for the precise evaluation and comparison of shipping service providers. Therefore, the weights could improve customer satisfaction, operational efficiency, and well-informed decision making in the maritime shipping industry. Ultimately, this method signifies a significant advancement in selecting maritime shipping providers, promising substantial benefits for customers and the industry.

- **RQ3.2:** How can multi-criteria decision-making techniques efficiently automate the ranking of maritime shipping service providers based on AI-identified weighted criteria, specifically within the context of maritime shipping service selection in Australia?

  The MC-SE framework, comprising criteria weighting and the MCDM tool (AHP as an example), aims to automate the ranking of maritime shipping service providers in Australia's maritime shipping service selection process. Artificial intelligence (AI) techniques, including clustering and semantic similarity, improve the precision and objectivity of the selection process. The weights of the AI-derived criteria are integrated into the process based on the semantic similarity analysis of the clustered criteria of the shipping service providers with SERVQUAL metrics. A set of metrics, including semantic similarity, clustering, and comparison with actual survey data, ensure the consistency and reliability of these AI-derived weights. The AHP methodology is applied, using AI-derived criteria weights to evaluate shipping service providers. Scores are calculated in the AHP framework by multiplying criteria weights by the corresponding alternative scores, also obtained through AI-based analysis.

Consequently, the MC-SE approach embeds AI-identified weighted criteria and the AHP methodology to streamline the ranking of maritime shipping service providers while carefully considering the relative importance of criteria and the specific performance of providers. This integrated method blends AI-driven insights with systematic AHP analysis, resulting in a robust, data-driven solution to select optimal shipping service providers in the unique context of Australian maritime shipping. By leveraging AI for criteria weighting and automation, the MC-SE framework minimises human error and streamlines the ranking process, leading to more consistent and reliable results.

One of the significant findings of this AI-based weighting technique is its automation, where new data can generate new weightings. Therefore, with instant and updated shipping service criteria weighting, shipping service providers can be ranked based on any MCDM tool, such as a technique for order of preference by similarity to ideal solution (TOPSIS) or analytical hierarchical process (AHP).

Regarding RQ3, the determinants identified in this study resonate with contemporary logistics and provider selection research [45][46]. At the same time, they align with sustainability-oriented frameworks in city logistics [36] and crowd-based or platform-mediated logistics [35]. These findings extend MC-SE beyond static service quality, showing how dynamic considerations such as environmental performance and innovative delivery models are increasingly salient.

8.2.4 Discussion of RQ4

How can a SERVQUAL survey assess service quality in the shipping service provider industry and utilise them for decision-making or AI-based data-driven models?

RQ4 investigates the use of SERVQUAL surveys to evaluate service quality in the shipping service provider industry and their role in facilitating decision making and AI-driven data models. This discussion underscores the value of employing SERVQUAL surveys to validate the existing MC-SE framework for service provider selection. These surveys offer a robust mechanism to assess service quality by considering five critical dimensions. Moreover, the resultant data from the SERVQUAL surveys corroborates the MC-SE framework, enhancing its authenticity in reflecting real customer priorities. Furthermore, the data generated from these surveys serves as a valuable resource for informed decision-making by guiding the allocation of resources for improvements based on the insights from the survey. Additionally, the data lend themselves to AI-driven models for in-depth pattern analysis, ultimately elevating the quality of decision making. In conclusion, integrating SERVQUAL surveys and AI-driven techniques for criteria weighting inside the MC-SE framework improves service quality and customer satisfaction in the shipping service provider industry. Figure 8.1 summarises the methodologies employed in the discussion of research questions 3 and 4 to quantify the criteria weights using the SERVQUAL dimensions.

The decision-analytic implications of our ranking approach map directly onto well-established MCDM families [29][30][99]. Furthermore, they echo recent developments in Group Decision Making under Shipping Industry 4.0, where collaborative and AI-assisted protocols are emphasised [75].

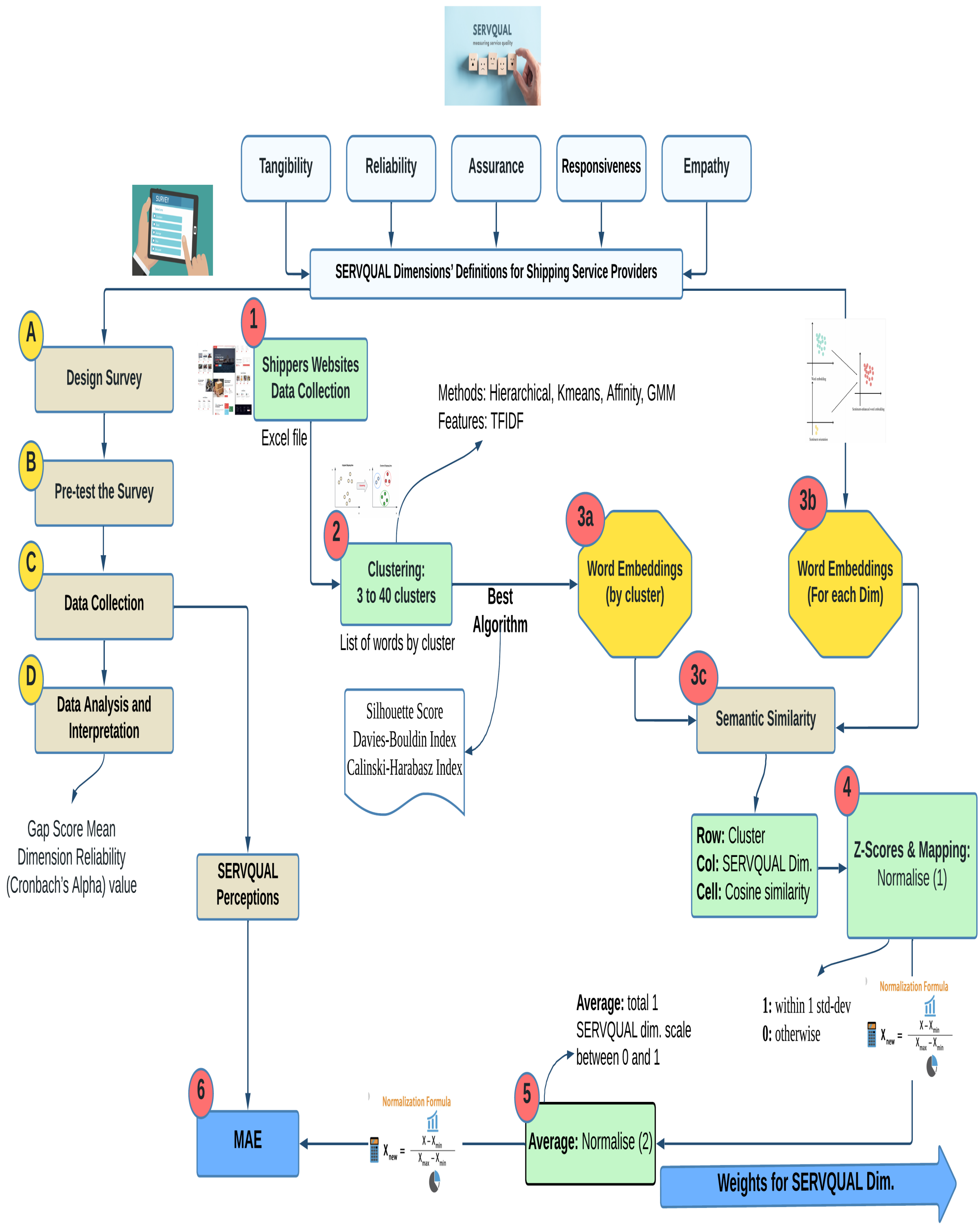


Figure 8.1: Methodologies Employed in the Discussion of Research Questions 3 and 4 to Quantify the Criteria Weights Using the SERVQUAL Dimensions

8.2.5 Discussion of RQ5

The fifth research question is: How to validate the effectiveness and reliability of the MC-SE framework and AI models developed for selecting maritime shipping service providers, and which validation methodologies and criteria are suitable for this purpose? The answer to this question centres on validating the MC-SE framework developed for maritime shipping service provider selection.

The MC-SE framework is used to classify maritime shipping service providers by integrating AI-driven insights with the AHP methodology. It is essential to validate the proposed approach; therefore, this study utilises SERVQUAL surveys to validate the MC-SE framework. Despite their lag, surveys are considered valid estimations of shipping service providers. SERVQUAL surveys comprehensively evaluate service quality, capturing customer perceptions across five key dimensions: tangibility, reliability, responsiveness, assurance, and empathy. The Gap analysis, a core component of SERVQUAL, identifies discrepancies between customer expectations and perceptions, guiding targeted improvement initiatives. As shown in Table 7.14, the assignment of weights to individual SERVQUAL dimensions by the proposed MC-SE framework was relatively similar to those induced by the SERVQUAL survey, with a relatively low mean absolute error (MAE) of 0.014. This result underscores a strong agreement between the two data sources – the survey and the clustering process. As a result, it improves the reliability of the proposed method for evaluating and comparing shipping service providers. Consequently, the study contributes to the academic discourse on service quality assessment and provider selection in the maritime shipping service provider industry.

8.3 Implications of MC-SE

Table 8.1 summarises the key findings for each research question and highlights the specific contributions of AI in each stage of the proposed approach. Table 8.2 and Table 8.3 summarise the benefits of using or not using AI and its benefits in this study.

Table 8.1: Summary of key findings and AI's role

Research Question (RQ)	Key Findings	Emphasis on AI
RQ1: AI-based Classifier	Develops a classifier to select optimal providers using predefined criteria.	Improves decision-making by automating predictions and reducing bias.
RQ2: SERVQUAL Mapping	Systematic mapping improve selection decisions.	Leverages AI for objective and measurable criteria selection.
RQ3.1: AI-based Weighting	Employs AI clustering for unbiased criteria weighting.	Ensures continued relevance and objectivity in criteria selection.
RQ3.2: Multi-criteria Ranking	Automates ranking using AI-derived weights and AHP.	Minimises human error and streamlines ranking for consistent results.
RQ4: SERVQUAL Surveys	Integrates SERVQUAL surveys for decision making and AI models.	AI goes beyond data analysis to extract deeper customer insights for service quality improvement.
RQ5: Framework Validation	Validates MC-SE framework through SERVQUAL survey comparison.	AI-powered analysis strengthens validation by identifying potential data issues.

The research findings on AI-driven criteria selection, multi-criteria decision-making, and service quality assessment using SERVQUAL can be applied to various industries beyond maritime shipping. These applications include logistics, supply chain management, travel and tourism, and financial services, where selecting optimal service providers is crucial.

While the SERVQUAL surveys offer valuable insights, alternative approaches can further validate the MC-SE framework:

- Case Studies: Applying the framework to real-world scenarios with documented outcomes can demonstrate its effectiveness.

- Expert Evaluation: Involving domain experts in maritime shipping to assess the framework's accuracy and practicality can be beneficial.
- Comparison with Existing Selection Methods: Benchmarking the MC-SE framework against traditional selection methods can highlight its advantages.

Table 8.2: Not Employing AI

Outcome	**Not Employing AI**
Decision Accuracy	Relies on human expertise and interpretation, leading to potential inaccuracies and suboptimal selections. Manual analysis is time-consuming and less efficient, especially with increasing data volume and complexity.
Consistency and Objectivity	Decisions can vary significantly based on personal biases and experiences, leading to inconsistency.
Automated Criteria Weighting	Subjective and inconsistent manual weighting of criteria, potentially leading to imbalanced decisions.
Continuous Improvement	Decision making remains static, with limited improvement based on individual learning and experience.
Example Process	Manual review of data, subjective mapping to SERVQUAL, estimated weights based on experience, and manual ranking.

Table 8.3: Employing AI

Outcome	**Employing AI**
Decision Accuracy	High accuracy with systematic analysis of complex datasets and multiple criteria (82.3% classifier performance in approach (1), and a criteria weighting MAE of 0.014 compared to the survey results in the second approach). Can handle large datasets and complex decision processes quickly and accurately.
Consistency and Objectivity	Provides consistent and objective decisions, reducing variability and subjectivity.
Automated Criteria Weighting	Objectively determine criteria importance using clustering and semantic similarity techniques, followed by normalisation of weights.
Continuous Improvement	Machine learning models learn from new data, continuously improving decision-making. Research could learn from human and AI models with some weight preference.
Example Process	AI-driven multi-criteria search engine (MC-SE) analyses data, maps criteria to SERVQUAL, clusters, weights, and ranks providers.

An important implication of the present study is that its evaluation design privileges provider-side service quality, operationalised through SERVQUAL, while treating cost as a complementary attribute rather than a dimension. This preserves construct validity and analytic tractability, but also means that consumer-side performance measures (SERVPERF) and customer-voice signals (e.g., CSAT, NPS, sentiment) remain outside the present scope. Accordingly, the current framework advances provider-focused optimisation with integrated cost efficiency, while the incorporation of consumer-side outcomes is identified for subsequent research and is addressed further in Chapter 9.

8.4 Conclusion

This chapter addressed several critical research questions about selecting maritime shipping service providers. This chapter discussed the procedures for developing an AI-based predictive classifier and how it improves decision making for offshore shipping customers. It also explored the benefits of mapping selection criteria to the service quality (SERVQUAL) framework, focusing on customer-centricity, measurability, completeness, proven effectiveness, and objective decision making. Furthermore, it elaborated on creating and implementing the multi-criteria search engine (MC-SE) framework, detailing how AI-based methods weigh criteria intelligently and how multi-criteria decision-making (MCDM) techniques automate the ranking of maritime shipping service providers. The study also addressed the use of SERVQUAL surveys to assess service quality and support AI models driven by data. Finally, it validated the effectiveness and reliability of the MC-SE framework through a comparison with SERVQUAL survey data, highlighting the robustness of the proposed approach. The final chapter concludes this research study, discusses its limitations, and provides directions for future work.

CHAPTER 9

Conclusion, limitations, and Future Work

9.1 Conclusion

This research addresses the complex task of selecting maritime shipping service providers using multi-criteria decision-making (MCDM) and artificial intelligence (AI) tools. This study pinpoints and utilises the methods and tools necessary for the development and execution of the proposed intelligent multi-criteria search engine (MC-SE). It focuses on defining decision parameters, integrating the decision-maker's expertise with AI models, and ensuring the applicability of findings beyond the Australian shipping industry. The study uses the service quality (SERVQUAL) framework and machine learning techniques to extract criteria from provider websites. It aims to improve decision-making processes, improve the efficiency of the ocean freight market, and allow stakeholders to make informed decisions.

9.1.1 Study Contribution

This study makes several contributions.

9.1.1.1 Contributions and Novelty

This research contributes to maritime shipping service selection by selecting providers and being the first to extract specific selection criteria from providers' websites, as expected by consignees. It uniquely employs the SERVQUAL framework to extract these criteria and introduces an innovative method that combines AI-based models with the MCDM method, called the intelligent MC-SE framework. The study prioritises the automation of the selection process, simplifying decision making, and significantly reducing the burden on experts. This pioneering approach addresses the challenges experts face in selecting shipping service providers.

9.1.1.2 Enhancing Efficiency and Sustainability

This research improves efficiency and sustainability in maritime shipping by integrating AI technologies into advanced decision-making models, thus reducing costs and promoting environmental responsibility. It facilitates informed choices by providing a transparent evaluation framework for selecting service providers, fostering fair competition and inclusivity. In addition, the study prioritises social responsibility, incorporating ethical practices, labour rights, and community involvement into the decision-making framework, thus promoting responsible shipping practices and contributing to a socially conscious maritime industry.

9.1.2 Transforming Decision-Making Processes

This research is at the forefront of transforming decision-making processes in the maritime shipping industry. It introduces an AI-driven multi-criteria selection framework, aligns with the SERVQUAL framework, innovates criteria weighting, and applies MCDM techniques, offering a comprehensive toolkit for efficient provider selection. The practicality and effectiveness of this framework are further validated through a real-world case study in Australia. The proposed framework can improve maritime shipping service providers' evaluation, thus improving supply chain performance and customer satisfaction.

9.2 Research Implications

Following the rigorous design science research (DSR) methodology, this research navigates through problem awareness, suggestion, development, and evaluation stages, culminating in the potential for the broader adoption in academia and practice. This comprehensive approach marks a significant stride in reshaping the logistics and supply chain management landscape to meet the demands of the 21st century.

The research findings on AI-driven criteria selection, multi-criteria decision-making, and service quality assessment using SERVQUAL can be applied to various industries beyond maritime shipping. These applications include logistics, supply chain management, travel and tourism, and financial services, where selecting optimal service providers is crucial.

The potential impact of this research extends beyond improved efficiency and cost reduction. By incorporating social responsibility considerations (future work) into the MC-SE framework, the research can promote ethical practices, fair labour conditions, and responsible environmental practices in the maritime industry and potentially other sectors that adopt the framework.

In conclusion, our contributions intersect two active trajectories: artificial intelligence (AI)/machine learning (ML) for logistics decision support [92] and structured multi-criteria selection in maritime and supply-chain contexts [75]. Future research should also extend SERVQUAL with consumer-side performance measures (SERVPERF) to ensure a balanced framework for evaluating cost, service quality, and sustainability outcomes.

9.3 Study Limitations

Data Source Limitations

The study relies heavily on benchmark datasets to select maritime shipping service providers. These datasets may have inherent limitations and biases that can affect the generalisability of the findings. However, the study collected a new dataset from various maritime shipping service providers.

Criteria Selection and Completeness

While the study highlights the alignment of criteria with the SERVQUAL framework, it does not extensively explore the potential unsuitability of some other critical criteria that decision makers can consider in their decision making, potentially limiting the comprehensiveness of the analysis.

Model Generalisability and Applicability

The MC-SE framework developed in this study may have limitations when applied to different regions or contexts. Its performance in other scenarios or industries has not been thoroughly evaluated, limiting its broader applicability.

Limitations and the Role of Cost

While this study advances the automation of maritime shipping provider selection, an important limitation lies in its reliance on provider-side service quality through SERVQUAL, with cost modelled only as a complementary attribute rather than a theoretical dimension. This choice ensures construct validity and analytic simplicity, yet it excludes consumer-side performance measures such as SERVPERF and broader customer-voice indicators like CSAT, NPS, and sentiment analysis, which may significantly influence trade-offs in real-world decision making. Clarifying this boundary, cost is not treated as a SERVQUAL dimension but is explicitly represented as a distinct decision attribute within the MC-SE framework. As such, the present findings should be understood as advancing provider-focused optimisation with integrated cost efficiency, while future work is encouraged to unify provider-side quality, cost efficiency, and consumer-side outcomes into a more balanced and holistic evaluation framework.

9.4 Future Directions

This research has substantially contributed to the maritime shipping industry, bridging gaps in the provider selection process and promoting efficiency, sustainability, and social responsibility. However, the study suggests how can the MC-SE framework be adapted for other industries, including refining and extending the intelligent MC-SE, validation in diverse geographic contexts, and ongoing efforts to enhance the decision-making process.

9.4.1 Future Research

This research has significantly contributed to the maritime shipping industry. Potential future research directions to further develop the MC-SE framework are as follows:

- **Adapting the MC-SE Framework for Other Industries:** Future work could investigate how the MC-SE framework can be adapted and applied to other industries with multi-criteria service provider selection needs. This could involve identifying relevant criteria specific to different industries and tailoring the framework's functionalities accordingly.

- **Refining and Extending the Intelligent MC-SE:** Future work could focus on refining the existing framework based on real-world application and user feedback. It could also explore potential extensions for enhanced functionality, such as incorporating real-time data on factors like fuel prices or environmental regulations.

- **Validation in Diverse Geographic Contexts:** Future work could evaluate the performance and generalisability of the MC-SE framework in different geographical contexts. This could involve testing the framework with maritime shipping service providers in other regions and assessing its effectiveness in diverse market conditions.

- **Model Expansion:** Future work should extend the provider-side SERVQUAL core by incorporating a consumer-side SERVPERF module together with an explicit cost layer. Specifically: (i) derive SERVPERF scores from outcome-based data such as on-time delivery records, customer ratings, and qualitative reviews to capture perceived performance and value-for-money; and (ii) operationalise cost through total-landed-cost metrics and time–cost trade-offs to generate a quality-per-dollar index. Embedding these dimensions as additional objectives within the existing MC-SE pipeline would enable dual-perspective, multi-objective optimisation across quality and cost, producing Pareto-efficient recommendations while preserving the current architectural integrity of the framework.

APPENDIX A

APPENDIX

A.1 Survey Objectives and Design

Crowdsourcing plays a crucial role in gaining a comprehensive understanding of service quality in the realm of service providers. The survey achieved three key objectives: (1) assessing the importance of service quality (SERVQUAL) dimensions when selecting a shipping service provider, (2) measuring respondent satisfaction with these dimensions, and (3) revealing disparities between service quality expectations and perceptions. The survey was structured thoughtfully into sections. It started by collecting demographic data to capture various viewpoints and progressed to evaluating individual SERVQUAL dimensions. Participants provided significance and satisfaction ratings on a 5-point Likert scale and had the opportunity to give open-ended feedback. The participant selection process included considerations of demographics, prior experience with shipping services, and geographic location, and the experts chosen underwent training to ensure survey proficiency. The details of the participants are provided in Table A.1.

Table A.1: Descriptive analysis of participants.

Group ID	Gender Distribution	Age Range (Years)	Experience Range (Years)	Expertise
Group 1	Male: 4, Female: 2; Not Disclosed 2	30-45	3-10	Operations
Group 2	Male: 3, Female: 1	35-55	8-15	Logistics
Group 3	Male: 2, Female: 3	40-50	10-20	Supply Chain
Group 4	Male: 1, Female: 4	28-40	5-12	Customer Service
Group 5	Male: 3, Female: 2	35-50	12-18	Quality Management

A.2 Survey Platform

The Qualtrics XM platform was used to design the survey for this study, the Shipping Service Providers Selection survey. Qualtrics XM is a holistic platform that enables researchers to listen to and understand the insights and voices of customers, employees, experts, and other stakeholders to improve researchers' experiences. The Shipping Service Providers Selection Survey comprises several sections that handle various aspects of applying SERVQUAL dimensions to the services introduced by the shipping service providers. The survey started with a polite request to the participants (experts) to complete the survey, which presented the primary aim of this survey, namely to gather information to improve the process of selecting shipping service providers in Australia. The following section identified participants using a unique ID and the organisation to which the participant belongs to maintain anonymity. The next section requested information on the participants' professional characteristics and demographics. The remainder of the survey addressed the five dimension questions about the SERVQUAL framework. The survey ended with open questions to give participants the opportunity to add additional comments, suggestions, or concerns related to service quality (shown in Table A.2).

Table A.2: SERVQUAL survey instrument with expectation vs perception items.

Section/Dimension	Survey Questions (Q# and items)
Start (Identity)	Q1. Are you a decision-maker in selecting maritime shipping providers? (Yes/No) Q2. Kindly mention your organisation name.
Demographics	Q3. Gender (Male, Female, Non-binary / third gender, Prefer not to say) Q4. Years of experience (<3, 3–5, 6–10, >10) Q5. Company role (Freight Forwarder, Shippers, 3PL providers, Import/Export, Other) Q6. Experience with SERVQUAL (high, medium, low, no experience)
Tangibles (T)	**Expectations (Q7):** excellent provider will have modern-looking facilities visually appealing physical facilities neat employees visually appealing service materials **Perceptions (Q8):** "XYZ company" has modern-looking facilities visually appealing facilities neat employees visually appealing service materials
Empathy (E)	**Expectations (Q15):** gives customers individual attention has operating hours convenient to all customers employees give personal attention has customers' best interests at heart understands specific needs **Perceptions (Q16):** "XYZ company" gives individual attention has convenient operating hours employees give personal attention has customers' best interests at heart understands specific needs

Continued on next page

Table A.2 (continued)

Section/Dimension	Survey Questions (Q# and items)
Reliability (R)	**Expectations (Q9):** does what is promised at the time promised shows sincere interest in solving problems performs the service right the first time provides service at the time promised insists on error-free records **Perceptions (Q10):** "XYZ company" does what is promised at the time promised shows sincere interest in solving problems performs the service right the first time provides service at the time promised insists on error-free records
Responsiveness (R)	**Expectations (Q11):** tells customers exactly when services will be performed gives prompt service always willing to help never too busy to respond **Perceptions (Q12):** "XYZ company" tells when services will be performed gives prompt service always willing to help never too busy to respond
Assurance (A)	**Expectations (Q13):** behaviour of employees instils confidence customers feel safe in transactions employees are consistently courteous employees have the knowledge to answer questions **Perceptions (Q14):** employees in "XYZ company" instil confidence make customers feel safe are consistently courteous have the knowledge to answer questions
SERVQUAL Importance Weights	Q17. Allocate 100 points across the five SERVQUAL dimensions (Tangibles, Empathy, Reliability, Responsiveness, Assurance).
Suggestions / Validation	Q18. Do you think SERVQUAL is a valid model for shipping provider selection? Q19. Kindly provide any feedback that might enhance our study.

Figures A.1, A.2, A.3, A.4, A.5, A.6, A.7, A.8, A.9, and A.10 present examples of the sections of this survey. Figure A.1 depicts the sequence of the survey flow.

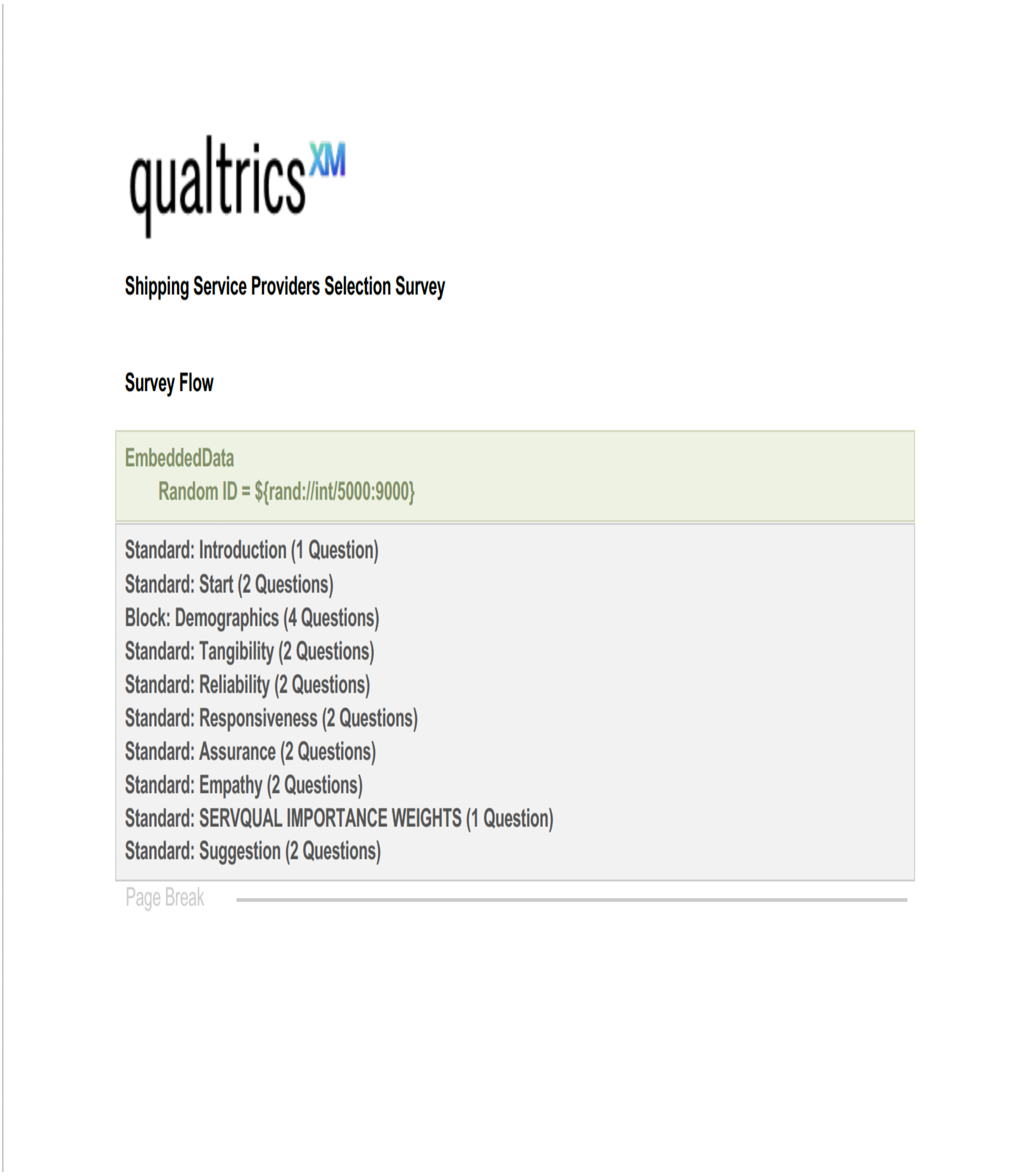


Figure A.1: Survey Flow

Figure A.2 shows the introductory message and request for the participants to complete the survey.

qualtrics XM

Start of Block: Introduction

Hi there

I hope this email finds you well and safe. Foremost, I would like to introduce myself: Ibraheem Khan, a PhD candidate at the University of Technology Sydney (UTS).

I am conducting an academic survey to collect authentic information regarding maritime shipment criteria followed in Australia. The selection follows the SERVQUAL framework defined below. However, the findings of this study could extract criteria for selecting shipping service providers to overcome the heterogeneity in shipping service provider selection.

I need to understand your opinion about selecting shipping service providers from the service quality introduced perspective by completing the survey below. **The survey is likely to take less than 10 minutes to complete**. You can complete the survey by **30 Sep 2022**.

Upon completion of this survey, I will provide you with the results of this survey.

I am looking forward to your participation in adding value to my research.

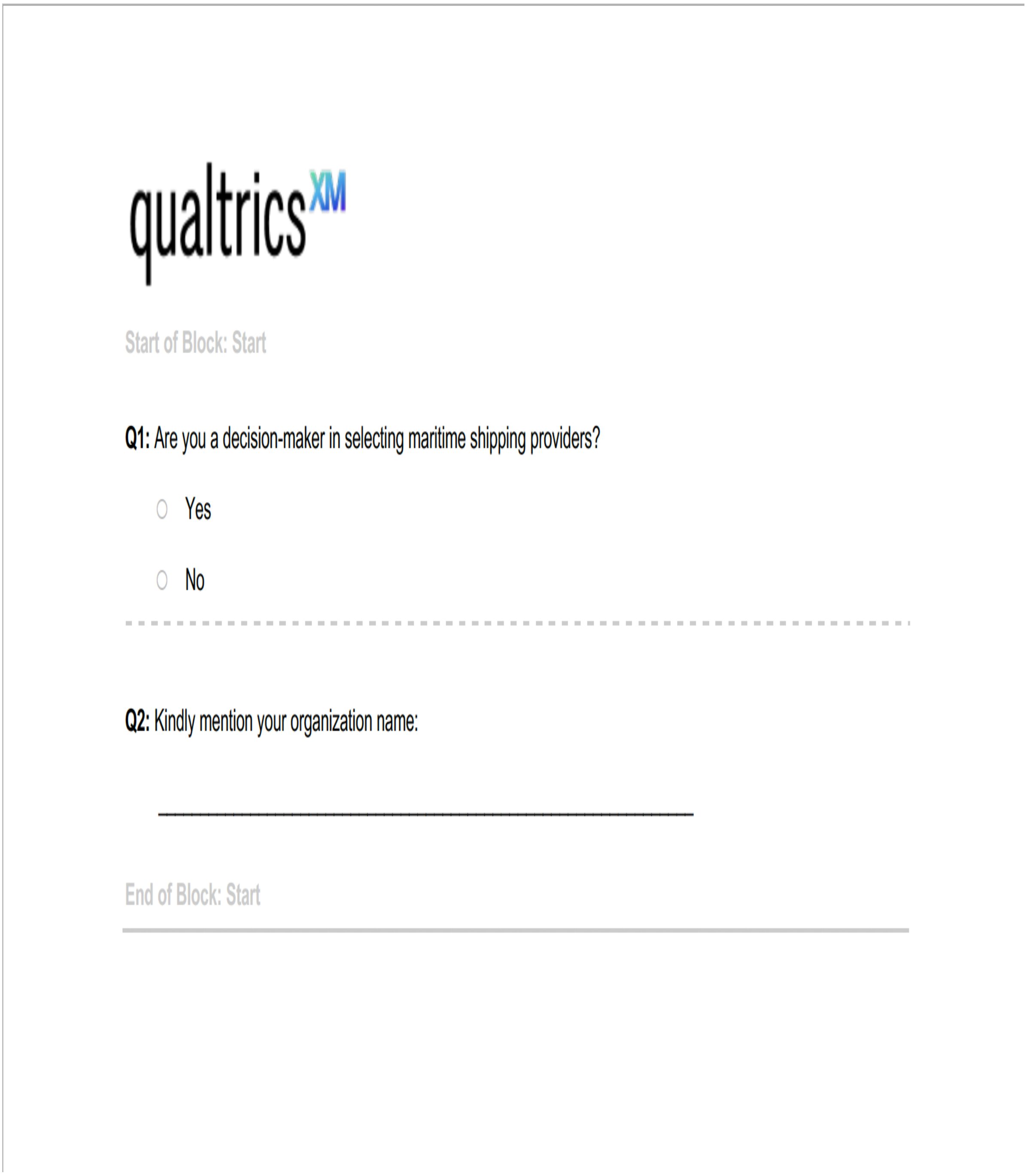
Thank you very much in advance.
Best Regards,

Ibraheem Abdulhafiz Q. Khan

End of Block: Introduction

Figure A.2: Introductory Request to Complete the Survey

Figure A.3 displays the questions regarding identifying the respondents.



qualtrics XM

Start of Block: Start

Q1: Are you a decision-maker in selecting maritime shipping providers?

- ○ Yes
- ○ No

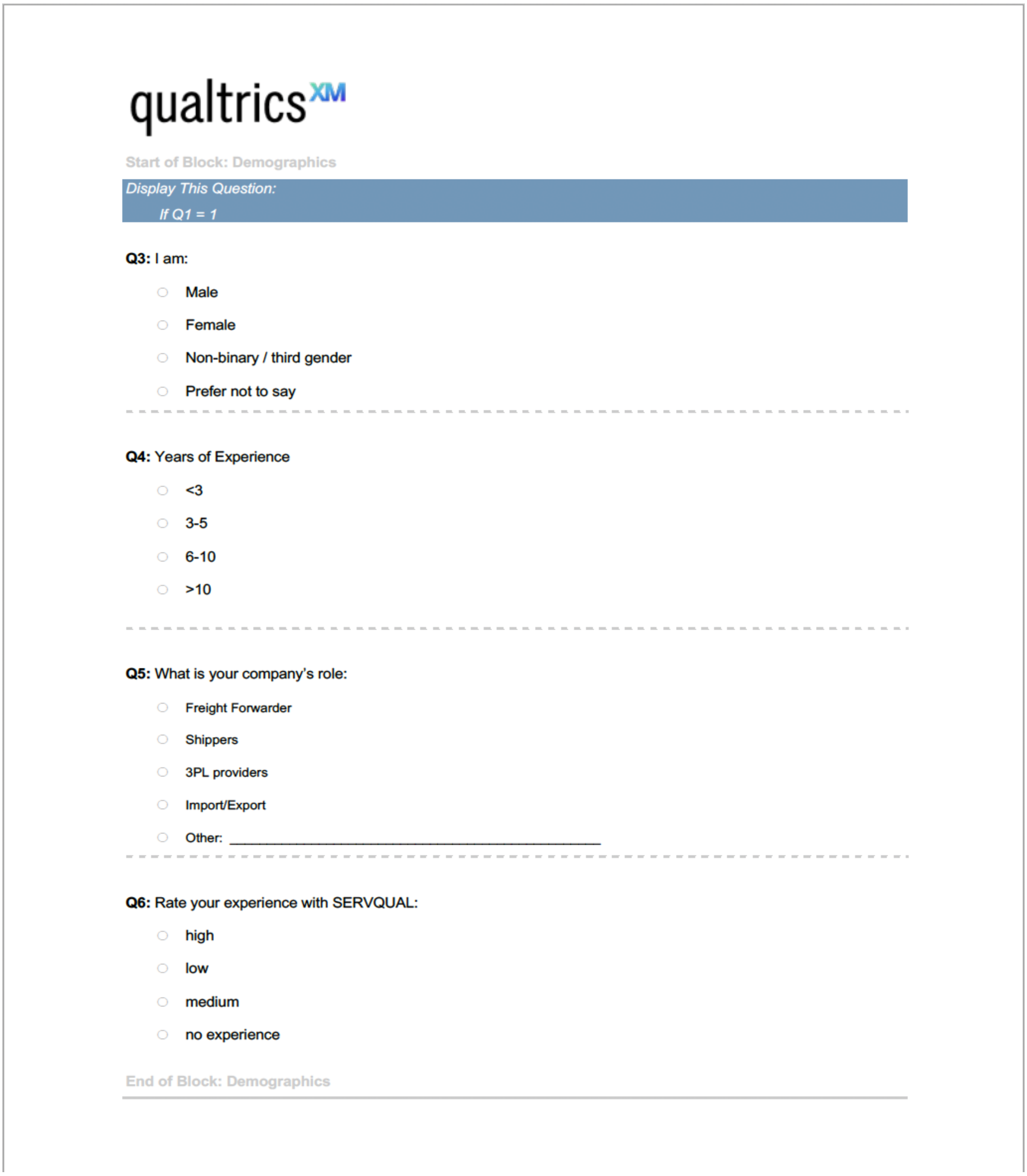
Q2: Kindly mention your organization name:

____

End of Block: Start

Figure A.3: Identifying the Respondents.

Figure A.4 shows the participants' demographics.



qualtrics XM

Start of Block: Demographics

Display This Question:

If Q1 = 1

Q3: I am:

- Male
- Female
- Non-binary / third gender
- Prefer not to say

Q4: Years of Experience

- <3
- 3-5
- 6-10
- >10

Q5: What is your company's role:

- Freight Forwarder
- Shippers
- 3PL providers
- Import/Export
- Other: ____

Q6: Rate your experience with SERVQUAL:

- high
- low
- medium
- no experience

End of Block: Demographics

Figure A.4: Demographics of the Participants.

Figure A.5 shows the questions regarding the tangibility dimension of the SERVQUAL framework.

qualtrics XM

Start of Block: Tangibility

Q7: Please show the **extent to which you think shipping providers'** selection **should** possess the following features. What we are interested in here is a number that best shows your expectations about shipping providers services.

	Strongly Disagree (1)	Disagree (2)	Somewhat Disagree (3)	Neither Agree Nor Disagree (4)	Somewhat Agree (5)	Agree (6)	Strongly Agree (7)
Excellent shipping provider will have modern looking (1)	o	o	o	o	o	o	o
The physical facilities at excellent shipping providers will be visually appealing (2)	o	o	o	o	o	o	o
Employees at excellent shipping providers will be neat (3)	o	o	o	o	o	o	o
Materials associated with the service (such as pamphlets or statements) will be visually appealing at an excellent shipping providers. (4)	o	o	o	o	o	o	o

Q8: The following statements relate to your feelings about the particular shipping provider XYZ you chose. Please show the extent to which you believe XYZ has the feature described in the statement. Here, we are interested in a number that shows your perceptions about XYZ shipping provider.

	Strongly Disagree (1)	Disagree (2)	Somewhat Disagree (3)	Neither Agree Nor Disagree (4)	Somewhat Agree (5)	Agree (6)	Strongly Agree (7)
When "XYZ company" promises to do something by a certain time, it does so (1)	o	o	o	o	o	o	o
The physical facilities at XYZ shipping providers will be visually appealing (2)	o	o	o	o	o	o	o
When you have a problem, "XYZ company" shows a sincere interest in solving it (3)	o	o	o	o	o	o	o
"XYZ company" performs the service right the first time (4)	o	o	o	o	o	o	o

End of Block: Tangibility

Figure A.5: Survey Tangibility Questions

Figure A.6 shows the questions regarding the reliability dimension of the SERVQUAL framework.

Start of Block: Reliability

Q9: Please show the **extent to which you think shipping providers'** selection **should** posses the following features. What we are interested in here is a number that best shows your expectations about shipping providers' services.

	Strongly Disagree (1)	Disagree (2)	Somewhat Disagree (3)	Neither Agree Nor Disagree (4)	Somewhat Agree (5)	Agree (6)	Strongly Agree (7)
When excellent shipping provider promise to do something by a certain time, they do (1)	○	○	○	○	○	○	○
When a customer has a problem, excellent shipping provider will show a sincere interest in solving it (2)	○	○	○	○	○	○	○
Excellent shipping provider will perform the service right the first time (3)	○	○	○	○	○	○	○
Excellent shipping provider will provide the service at the time they promise to do so (4)	○	○	○	○	○	○	○
Excellent shipping provider will insist on error free records (5)	○	○	○	○	○	○	○

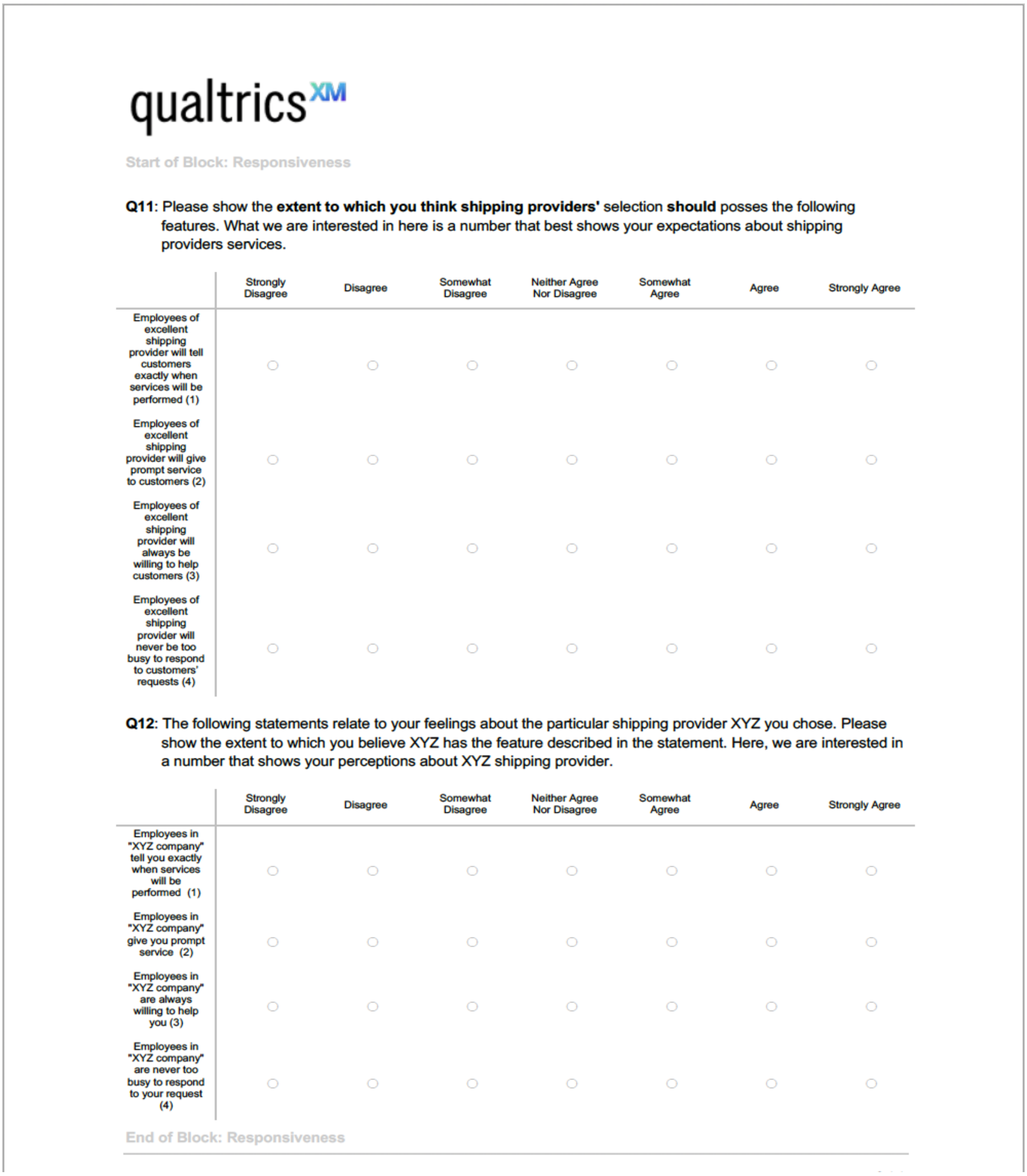
Q10: The following statements relate to your feelings about the particular shipping provider XYZ you chose. Please show the extent to which you believe XYZ has the feature described in the statement. Here, we are interested in a number that shows your perceptions about XYZ shipping provider.

	Strongly Disagree (1)	Disagree (2)	Somewhat Disagree (3)	Neither Agree Nor Disagree (4)	Somewhat Agree (5)	Agree (6)	Strongly Agree (7)
When "XYZ company" promises to do something by a certain time, it does so (1)	○	○	○	○	○	○	○
When you have a problem, "XYZ company" shows a sincere interest in solving it (2)	○	○	○	○	○	○	○
"XYZ company" performs the service right the first time (3)	○	○	○	○	○	○	○
"XYZ company" provides its service at the time it promises to do so (4)	○	○	○	○	○	○	○
"XYZ company" insists on error free records (5)	○	○	○	○	○	○	○

End of Block: Reliability

Figure A.6: Survey Reliability Questions

Figure A.7 shows the questions regarding the responsiveness dimension of the SERVQUAL framework.



qualtrics XM

Start of Block: Responsiveness

Q11: Please show the **extent to which you think shipping providers'** selection **should** posses the following features. What we are interested in here is a number that best shows your expectations about shipping providers services.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree Nor Disagree	Somewhat Agree	Agree	Strongly Agree
Employees of excellent shipping provider will tell customers exactly when services will be performed (1)	○	○	○	○	○	○	○
Employees of excellent shipping provider will give prompt service to customers (2)	○	○	○	○	○	○	○
Employees of excellent shipping provider will always be willing to help customers (3)	○	○	○	○	○	○	○
Employees of excellent shipping provider will never be too busy to respond to customers' requests (4)	○	○	○	○	○	○	○

Q12: The following statements relate to your feelings about the particular shipping provider XYZ you chose. Please show the extent to which you believe XYZ has the feature described in the statement. Here, we are interested in a number that shows your perceptions about XYZ shipping provider.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree Nor Disagree	Somewhat Agree	Agree	Strongly Agree
Employees in "XYZ company" tell you exactly when services will be performed (1)	○	○	○	○	○	○	○
Employees in "XYZ company" give you prompt service (2)	○	○	○	○	○	○	○
Employees in "XYZ company" are always willing to help you (3)	○	○	○	○	○	○	○
Employees in "XYZ company" are never too busy to respond to your request (4)	○	○	○	○	○	○	○

End of Block: Responsiveness

Figure A.7: Survey Responsiveness Questions

Figure A.8 shows the questions regarding the assurance dimension of the SERVQUAL framework.

qualtrics XM

Start of Block: Assurance

Q13: Please show the **extent to which you think shipping providers'** selection **should** posses the following features. What we are interested in here is a number that best shows your expectations about shipping providers services.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree Nor Disagree	Somewhat Agree	Agree	Strongly Agree
The behavior of employees in excellent shipping provider will instill confidence in customers (1)	○	○	○	○	○	○	○
Customers of excellent shipping provider will feel safe in transactions (2)	○	○	○	○	○	○	○
Employees of excellent shipping provider will be consistently courteous with customers (3)	○	○	○	○	○	○	○
Employees of excellent shipping provider will have the knowledge to answer customers' questions (4)	○	○	○	○	○	○	○

Q14: The following statements relate to your feelings about the particular shipping provider XYZ you chose. Please show the extent to which you believe XYZ has the feature described in the statement. Here, we are interested in a number that shows your perceptions about XYZ shipping provider.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree Nor Disagree	Somewhat Agree	Agree	Strongly Agree
The behavior of employees in "XYZ company" instills confidence in you (1)	○	○	○	○	○	○	○
You feel safe in your transactions with "XYZ company" (2)	○	○	○	○	○	○	○
Employees in "XYZ company" area consistently courteous with you (3)	○	○	○	○	○	○	○
Employees in "XYZ company" have the knowledge to answer your questions (4)	○	○	○	○	○	○	○

End of Block: Assurance

Figure A.8: Survey Assurance Questions

Figure A.9 shows the questions regarding the empathy dimension of the SERVQUAL framework.

qualtrics XM

Start of Block: Empathy

Q15: Please show the **extent to which you think shipping providers'** selection **should possess** the following features. What we are interested in here is a number that best shows your expectations about shipping providers services.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree Nor Disagree	Somewhat Agree	Agree	Strongly Agree
Excellent shipping provider will give customers individual attention (1)	○	○	○	○	○	○	○
Excellent shipping provider will have operating hours convenient to all their customers (2)	○	○	○	○	○	○	○
Excellent shipping provider have employees who give customers personal attention (3)	○	○	○	○	○	○	○
Excellent shipping provider will have their customer's best interests at heart (4)	○	○	○	○	○	○	○
The employees of excellent shipping provider will understand the specific needs of their customers (5)	○	○	○	○	○	○	○

Q16: The following statements relate to your feelings about the particular shipping provider XYZ you chose. Please show the extent to which you believe XYZ has the feature described in the statement. Here, we are interested in a number that shows your perceptions about XYZ shipping provider.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree Nor Disagree	Somewhat Agree	Agree	Strongly Agree
"XYZ company" gives you individual attention (1)	○	○	○	○	○	○	○
"XYZ company" has operating hours convenient to all its customers (2)	○	○	○	○	○	○	○
"XYZ company" has employees who give you personal attention (3)	○	○	○	○	○	○	○
"XYZ company" has your best interest at heart (4)	○	○	○	○	○	○	○
The employees of "XYZ company" understand your specific needs (5)	○	○	○	○	○	○	○

End of Block: Empathy

Figure A.9: Survey Empathy Questions

Figure A.10 shows the open questions in the survey.

qualtrics XM

Start of Block: SERVQUAL IMPORTANCE WEIGHTS

*

Q17: Listed below are five features pertaining to banks and the services they offer. We would like to know how much each of these features is important to the customer. Please allocate 100 points among the five features according to how important it is to you. **Make sure the points add up to 100**.

_______ The appearance of the shipping providers' physical facilities, equipment, personnel, and communication materials.
_______ The shipping providers' ability to perform the promised service dependably and accurately.
_______ The shipping providers' willingness to help customers and provide prompt service.
_______ The knowledge and courtesy of the shipping providers' employees and their ability to convey trust and confidence.
_______ The caring, individual attention the shipping providers provide their customers.

End of Block: SERVQUAL IMPORTANCE WEIGHTS

Start of Block: Suggestion

Q18: Do you think that SERVQUAL is valid model for shipping provider selection?

____

Q19: Kindly provide any feedback that you think might enhance our study.

____

End of Block: Suggestion

Figure A.10: Survey Open Questions

A.3 Survey Results

The complete survey instrument used in this study is documented in this appendix (Table A.2), which provides full transparency regarding each service quality (SERVQUAL) question, organised by dimension. The main results are presented through a complementary table (Table A.3), which summarises the perception and reports satisfaction ratios (Perception ÷ Expectation) by dimension. Results indicate that the gap scores reveal the disparity between customers' perceptions and expectations, while the satisfaction ratios (Table A.3) offer a percentage-based interpretation of how far perceptions met or exceeded expectations. Both tables also report mean dimension scores and Cronbach's alpha values to assess the internal consistency of each SERVQUAL construct.

The perception and expectation scores are measured on a seven-point Likert scale, with gap values calculated as the difference (Perception - Expectation). Satisfaction ratios are then expressed as percentages, with values above 100% indicating that perceptions exceeded expectations.

Across all dimensions, a common trend emerges, marked by negative gap scores, signifying that customers perceive service quality to fall short of their expectations with the exception of the Tangibles dimension, where perceptions surpassed expectations (satisfaction ratio of 107.2%). The internal consistency of the measurement scale was assessed using Cronbach's alpha, with values above 0.7 typically considered acceptable [108].

Table A.3: SERVQUAL survey gap analysis with reliability and satisfaction ratios

Dimension (Q#)	Perception	Expectation	Gap	Reliability α / Satisfaction (%)
Tangibles (Q7/Q8)	5.67	5.04	+0.63	0.798 / 107.2%
	5.41	5.19	+0.22	
	5.81	5.41	+0.41	
	5.70	5.44	+0.26	
Empathy (Q15/Q16)	5.41	5.67	-0.26	0.824 / 92.6%
	5.22	5.52	-0.30	
	4.96	5.37	-0.41	
	5.07	5.70	-0.63	
	5.59	6.07	-0.48	
Reliability (Q9/Q10)	5.48	5.56	-0.07	0.501 / 95.4%
	5.44	5.48	-0.04	
	5.30	5.74	-0.44	
	5.37	5.70	-0.33	
	4.74	5.15	-0.41	
Responsiveness (Q11/Q12)	5.41	5.74	-0.33	0.767 / 94.0%
	5.48	5.85	-0.37	
	5.59	5.96	-0.37	
	4.93	5.19	-0.26	
Assurance (Q13/Q14)	5.70	5.81	-0.11	0.536 / 96.1%
	5.93	6.11	-0.19	
	5.70	5.85	-0.15	
	5.74	6.22	-0.48	
Unweighted Average SERVQUAL Score			**-0.85**	**95.6%**

The results reveal varying levels of internal consistency across different dimensions. The tangibility dimension has a high-reliability value of 0.798, signifying internal solid consistency. In contrast, the reliability and assurance dimensions exhibit moderate reliability values of 0.501 and 0.536, respectively. The responsiveness and empathy dimensions have high-reliability values of 0.767 and 0.824, respectively.

Bibliography

[1] United Nations Conference on Trade and Development, Trade and environment review 2023, Report, 2023.

[2] Q. Xia and F. Chen, "Shipping economics development: A review from the perspective of the shipping industry chain for the past four decades," Journal of Shanghai Jiaotong University (Science), vol. 27, no. 3, pp. 424–436, 2022. DOI: 10.1007/s12204-022-2449-y.

[3] P. D. Fanam and L. Ackerly, "Evaluating ocean carrier selection criteria: Perspectives of tasmanian shippers," Journal of Shipping and Trade, vol. 4, no. 1, pp. 1–16, 2019. DOI: 10.1186/s41072-019-0055-5.

[4] I. A. Khan and F. K. Hussain, "Regression analysis using machine learning approaches for predicting container shipping rates," In Advanced Information Networking and Applications, L. Barolli, F. Hussain, and T. Enokido, Eds., Cham: Springer International Publishing, 2022, Pp. 269–280, ISBN: 978-3-030-99587-4. DOI: 10.1007/978-3-030-99587-4_23.

[5] A. Ergin, M. J. Feizollahi, and C. Kutlu, "Ocean container carrier selection using fuzzy topsis method: Customers' perspective," Marine Technology Society Journal, vol. 56, no. 1, pp. 59–71, 2022. DOI: 10.4031/mtsj.56.1.2.

[6] G. Balci, I. B. Cetin, and M. Tanyeri, "Differentiation of container shipping services in turkey," Transport Policy, vol. 61, pp. 26–35, 2018. DOI: 10.1016/j.tranpol.2017.10.004.

[7] C.-A. Tsai, T.-H. Ho, J.-S. Lin, C.-C. Tu, and C.-W. Chang, "Model for evaluating outsourcing logistics companies in the covid-19 pandemic," Logistics, vol. 5, no. 3, p. 64, 2021. DOI: 10.3390/logistics5030064.

[8] E. D'agostini, S. Jo, H.-S. Nam, and Y. S. Kim, "Q-method and its application in clustering hong kong shippers' selection criteria of ocean carriers," Research in Transportation Business & Management, p. 100 785, 2022. DOI: 10.1016/j.rtbm.2022.100785.

[9] S. Subhashini and S. Preetha, "An empirical analysis of service quality factors pertaining to ocean freight forwarding services," Maritime Business Review, 2018. DOI: 10.1108/mabr-01-2018-0004.

[10] A. Paul, M. A. Moktadir, and S. K. Paul, "An innovative decision-making framework for evaluating transportation service providers based on sustainable criteria," International Journal of Production Research, vol. 58, no. 24, pp. 7334–7352, 2020. DOI: 10.1080/00207543.2019.1652779.

[11] R. Rostamzadeh, A. Esmaeili, H. Sivilevičius, and H. B. K. Nobard, "A fuzzy decision-making approach for evaluation and selection of third party reverse logistics provider using fuzzy aras," Transport, vol. 35, no. 6, pp. 635–657, 2020. DOI: 10.3846/transport.2020.14226.

[12] A. K. Yazdi, A. Mehdiabadi, P. F. Wanke, N. Monajemzadeh, H. L. Correa, and Y. Tan, "Developing supply chain resilience: A robust multi-criteria decision analysis method for transportation service provider selection under uncertainty," International Journal of Management Science and Engineering Management, vol. 18, no. 1, pp. 51–64, 2023. DOI: 10.1080/17509653.2022.2098543.

[13] F. Farchi, C. Farchi, B. Touzi, and C. Mabrouki, "A comparative study on ai-based algorithms for cost prediction in pharmaceutical transport logistics," Acadlore Transactions on AI and Machine Learning, vol. 2, no. 3, pp. 129–141, 2023.
DOI: 10.56578/ataiml020302.

[14] H.-S. Jang, T.-W. Chang, and S.-H. Kim, "Prediction of shipping cost on freight brokerage platform using machine learning," Sustainability, vol. 15, no. 2, p. 1122, 2023.
DOI: 10.3390/su15021122.

[15] P. C. Wong, H. Yan, and C. Bamford, "Evaluation of factors for carrier selection in the china pearl river delta," Maritime Policy & Management, vol. 35, no. 1, pp. 27–52, 2008.
DOI: 10.1080/03088830701848854.

[16] A. Lopatin, N. Ishchenko, O. Filimonova, and N. Rudenko, "Criteria for evaluating and selecting suppliers for maritime enterprises," Vol. 339, 2021.
DOI: 10.1051/matecconf/202133901009.

[17] Y. J. Seo, M. H. Ha, Z. Yang, and S. Bhattacharya, "The ship management firm selection: The case of south korea," The Asian Journal of Shipping and Logistics, vol. 34, no. 3, pp. 256–265, 2018.
DOI: 10.1016/j.ajsl.2018.09.008.

[18] A. R. Krishnan, M. M. Kasim, R. Hamid, and M. F. Ghazali, "A modified critic method to estimate the objective weights of decision criteria," Symmetry, vol. 13, no. 6, p. 973, 2021.
DOI: 10.3390/sym13060973.

[19] C.-L. Hsu and T.-C. Ho, "Evaluating key factors of container shipping lines from the perspective of high-tech industry shippers," Journal of Marine Science and Technology, vol. 29, no. 1, p. 3, 2021.
DOI: 10.51400/2709-6998.1002.

[20] A. Parasuraman, V. A. Zeithaml, and L. L. Berry, "Servqual: A multiple-item scale for measuring consumer perceptions of service quality," Journal of Retailing, vol. 64, no. 1, pp. 12–40, 1988.

[21] A. Parasuraman, V. A. Zeithaml, and L. L. Berry, "Refinement and reassessment of the servqual scale," Journal of Retailing, vol. 67, no. 4, pp. 420–450, 1991.

[22] R. Ladhari, "A review of twenty years of servqual research," International Journal of Quality and Service Sciences, 2009. DOI: 10.1108/17566690910971445.

[23] F. A. Carrillat, F. Jaramillo, and J. P. Mulki, "Examining the impact of service quality: A meta-analysis of empirical evidence," Journal of Marketing Theory and Practice, vol. 17, no. 2, pp. 95–110, 2009. DOI: 10.2753/mtp1069-6679170201.

[24] V. V. Thai, "Service quality in maritime transport: Conceptual model and empirical evidence," Asia Pacific Journal of Marketing and Logistics, 2008. DOI: 10.1108/13555850810909777.

[25] A. Jonkisz, P. Karniej, and D. Krasowska, "The servqual method as an assessment tool of the quality of medical services in selected asian countries," International journal of environmental research and public health, vol. 19, no. 13, p. 7831, 2022. DOI: 10.3390/ijerph19137831.

[26] I. A. Khan, F. K. Hussain, and O. K. Hussain, "Selection of maritime shipping providers based on machine learning and ahp," Dec. 2022, Preprint paper. DOI: 10.2139/ssrn.4310991.

[27] L. Chen, Y. Zhang, and Z. Wang, "Logistics Service Supply Chain Model Applying Artificial Intelligence and Big Data Analysis," Security and Communication Networks, vol. 2022, M. A. Khan, Ed., p. 1 575 813, 2022, ISSN: 1939-0114. DOI: 10.1155/2022/1575813.

[28] T. L. Saaty, "Decision making with the analytic hierarchy process," International Journal of Services Sciences, vol. 1, no. 1, pp. 83–98, 2008. DOI: 10.1504/IJSSci.2008.017590.

[29] T. L. Saaty and L. G. Vargas,

Models, Methods, Concepts and Applications of the Analytic Hierarchy Process (International Series in Operations Research & Management Science),
2nd ed.
New York, NY: Springer, 2012,
Pp. XIV, 346,
Hardcover ISBN: 978-1-4614-3596-9; Softcover ISBN: 978-1-4899-9009-9,
ISBN: 978-1-4614-3597-6.
DOI: 10.1007/978-1-4614-3597-6.

[30] M. Behzadian, S. K. Otaghsara, M. Yazdani, and J. Ignatius, "A state-of the-art survey of topsis applications,"
Expert Systems with applications, vol. 39, no. 17, pp. 13 051–13 069, 2012.
DOI: 10.1016/j.eswa.2012.05.056.

[31] M. Hosseinzadeh, H. K. Hama, M. Y. Ghafour, M. Masdari, O. H. Ahmed, and H. Khezri, "Service selection using multi-criteria decision making: A comprehensive overview,"
Journal of Network and Systems Management, vol. 28, no. 4, pp. 1639–1693, 2020.
DOI: 10.1007/s10922-020-09553-w.

[32] L. A. Luyen and N. V. Thanh, "Logistics service provider evaluation and selection: Hybrid servqual-fahp-topsis model,"
Processes, vol. 10, no. 5, p. 1024, 2022.
DOI: 10.3390/pr10051024.

[33] S. Jovčić and P. Průša, "A hybrid mcdm approach in third-party logistics (3pl) provider selection,"
Mathematics, vol. 9, no. 21, 2021,
ISSN: 2227-7390.
DOI: 10.3390/math9212729.

[34] N. Pourmohammadreza and M. R. Akbari Jokar, "Efficient last-mile logistics with service options: A multi-criteria decision-making and optimization methodology,"
International Journal of Industrial Engineering Computations, vol. 15, no. 2, 2024.
DOI: 10.5267/j.ijiec.2024.2.003.

[35] J. Kozoderović, M. Andrejić, and V. Pajić, "Strategic selection of crowd logistics platforms: A multi-criteria decision-making approach,"
Mechatronics and Intelligent Transportation Systems, vol. 3, no. 4, pp. 235–253, 2024.

DOI: 10.56578/mits030404.

[36] M. Veličković, Đ. Stojanović, V. Ilin, and D. Mirčetić, "A combined multi-criteria decision-making and social cost–benefit analysis approach for evaluating sustainable city logistics initiatives," Sustainability, vol. 17, no. 3, p. 884, 2025. DOI: 10.3390/su17030884.

[37] J. J. Cronin Jr and S. A. Taylor, "Measuring service quality: A reexamination and extension," Journal of marketing, vol. 56, no. 3, pp. 55–68, 1992. DOI: 10.1177/002224299205600304.

[38] C. K. Naik, S. B. Gantasala, and G. V. Prabhakar, "Service quality (servqual) and its effect on customer satisfaction in retailing," European Journal of Social Sciences, vol. 16, no. 2, pp. 231–243, 2010.

[39] E. W. Anderson, C. Fornell, and D. R. Lehmann, "Customer satisfaction, market share, and profitability: Findings from sweden," Journal of Marketing, vol. 58, no. 3, pp. 53–66, 1994. DOI: 10.1177/002224299405800304.

[40] F. F. Reichheld, "The one number you need to grow," Harvard business review, vol. 81, no. 12, pp. 46–55, 2003.

[41] I. Lee and Y. J. Shin, "Machine learning for enterprises: Applications, algorithm selection, and challenges," Business Horizons, vol. 63, no. 2, pp. 157–170, 2020. DOI: 10.1016/j.bushor.2019.10.005.

[42] Y. Zhou, X. Li, X. Wang, and K. F. Yuen, "Intelligent container shipping sustainability disclosure via stakeholder sentiment views on social media," Marine Policy, vol. 135, p. 104 853, 2022. DOI: 10.1016/j.marpol.2021.104853.

[43] A. Jonkisz, P. Karniej, and D. Krasowska, "Servqual method as an "old new" tool for improving the quality of medical services: A literature review," International Journal of Environmental Research and Public Health, vol. 18, no. 20, p. 10 758, 2021. DOI: 10.3390/ijerph182010758.

[44] Australian Government. "Voyage reports." Accessed: June 15, 2022,

Australian Government Department of Infrastructure, Transport, Regional Development and Communications.

[45] R. Banomyong and N. Supatn, "Selecting logistics providers in thailand: A shippers' perspective,"
European journal of marketing, 2011.
DOI: 10.1108/03090561111107258.

[46] A. Gupta, R. K. Singh, and S. K. Mangla, "Evaluation of logistics providers for sustainable service quality: Analytics based decision making framework,"
Annals of Operations Research, vol. 315, no. 2, pp. 1617–1664, 2022.
DOI: 10.1007/s10479-020-03913-0.

[47] K. Storms, C. Sys, T. Vanelslander, and R. Van Deuren, "Demurrage and detention: From operational challenges towards solutions,"
Journal of Shipping and Trade, vol. 8, no. 1, pp. 1–31, 2023.
DOI: 10.1186/s41072-023-00132-1.

[48] W.-P. Wong and K.-L. Soh,
"Review of pharmaceutical sea freight and malaysian third-party logistics service providers — a supply chain perspective,"
In Pharmaceutical Supply Chains - Medicines Shortages,
A. P. Barbosa-Povoa, H. Jenzer, and J. L. de Miranda, Eds.,
Cham: Springer International Publishing, 2019,
Pp. 125–146,
ISBN: 978-3-030-15398-4.
DOI: 10.1007/978-3-030-15398-4_8.

[49] D. F. Peter, N. Hong-Oanh, and C. Stephen, "Selection of ocean container carriers: One country's perspective,"
African Journal of Business Management, vol. 10, no. 23, pp. 576–584, 2016.
DOI: 10.5897/AJBM2016.8173.

[50] B. Iqbal and D. A. Siddiqui, "Factors influencing selection of container shipping lines in pakistan-a logistics perspective,"
A Logistics Perspective. Asian Business Review, vol. 7, no. 1, pp. 35–44, 2017.
DOI: 10.18034/abr.v7i1.8.

[51] D.-G. Yoon, P. T. Ngo, and J.-S. Keum, "Fuzzy ahp evaluation for performance of container shipping companies in vietnam (developing on the model of previous study for the domestic lines),"

Journal of Navigation and Port Research, vol. 42, no. 5, pp. 365–370, 2018.
DOI: 10.5394/KINPR.2018.42.5.365.

[52] V. Kannan, S. Bose, and N. Kannan, "An evaluation of ocean container carrier selection criteria: An indian shipper's perspective," Management Research Review, 2011.
DOI: 10.1108/01409171111146661.

[53] J.-F. Ding, C.-T. Hsu, M.-T. Chou, and Y. L. Ong, "A qualitative-quantitative fuzzy evaluation model for selecting an international ocean freight logistics provider," International Journal of Maritime Engineering, vol. 163, no. A4, 2021.
DOI: 10.5750/ijme.v163ia4.745.

[54] J. Witkowski, J. Marcinkowski, and M. Kiba-Janiak, "A comparative analysis of electronic freight exchanges in the united states and europe with the use of the multiple criteria decision-making method "promethee"," European Research Studies Journal, vol. 23, no. Special Issue 1, 2020.
DOI: 10.35808/ersj/1916.

[55] B. Davis-Sramek, J. L. Robinson, J. L. Darby, and R. W. Thomas, "Exploring the differential roles of environmental and social sustainability in carrier selection decisions," International Journal of Production Economics, vol. 227, p. 107 660, 2020.
DOI: 10.1016/j.ijpe.2020.107660.

[56] R. Tepe and G. Arabelen, "Relationship marketing strategies in the container shipping industry: A qualitative approach," Scientific Journals of the Maritime University of Szczecin, vol. 141, no. 69, pp. 76–88, 2022.
DOI: 10.17402/501.

[57] E. Ejem, C. Uka, D. Dike, C. Ikeogu, C. Igboanusi, and O. Chukwu, "Evaluation and selection of nigerian third-party logistics service providers using multi-criteria decision models," LOGI-Scientific Journal on Transport and Logistics, vol. 12, no. 1, pp. 135–146, 2021.
DOI: 10.2478/logi-2021-0013.

[58] Y.-T. Chang, S.-Y. Lee, and J. L. Tongzon, "Port selection factors by shipping lines: Different perspectives between trunk liners and feeder service providers," Marine Policy, vol. 32, no. 6, pp. 877–885, 2008.

DOI: 10.1016/j.marpol.2008.01.003.

[59] T.-C. Ho, R.-H. Chiu, C.-C. Chung, and H.-S. Lee, "Key influence factors for ocean freight forwarders selecting container shipping lines using the revised dematel approach," Journal of Marine Science and Technology, vol. 25, no. 3, p. 6, 2017. DOI: 10.6119/JMST-016-1227-1.

[60] ARC MARINE CARRIER SELECTION CRITERIA.

[61] B.-S. KIM and B.-Y. Kim, "The effect of selection factors of marine transportation service on transaction continuity," The Journal of Asian Finance, Economics and Business, vol. 7, no. 1, pp. 217–228, 2020. DOI: 10.13106/jafeb.2020.vol7.no1.217.

[62] A. Kaliszewski, A. Kozłowski, J. Dąbrowski, and H. Klimek, "Key factors of container port competitiveness: A global shipping lines perspective," Marine Policy, vol. 117, p. 103 896, 2020, ISSN: 0308-597X. DOI: 10.1016/j.marpol.2020.103896.

[63] I. M. Cavalcante, E. M. Frazzon, F. A. Forcellini, and D. Ivanov, "A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing," International Journal of Information Management, vol. 49, pp. 86–97, February 2019, ISSN: 02684012. DOI: 10.1016/j.ijinfomgt.2019.03.004.

[64] J. D. German, A. K. S. Ong, A. A. N. Perwira Redi, and K. P. E. Robas, "Predicting factors affecting the intention to use a 3pl during the covid-19 pandemic: A machine learning ensemble approach," Heliyon, vol. 8, no. 11, e11382, 2022, ISSN: 2405-8440. DOI: 10.1016/j.heliyon.2022.e11382.

[65] H. Musbah, G. Ali, H. H. Aly, and T. A. Little, "Energy management using multi-criteria decision making and machine learning classification algorithms for intelligent system," Electric Power Systems Research, vol. 203, p. 107 645, 2022.

DOI: 10.1016/j.epsr.2021.107645.

[66] S. P. Singh, A. Adhikari, A. Majumdar, and A. Bisi, "Does service quality influence operational and financial performance of third party logistics service providers? a mixed multi criteria decision making -text mining-based investigation," Transportation Research Part E: Logistics and Transportation Review, vol. 157, p. 102 558, 2022.
DOI: 10.1016/j.tre.2021.102558.

[67] T.-S. X. Kyoung-Suk Choi and P. T.-W. Lee, "Structural relationships among shipper's perception, value, and choice intention of korea–china train ferry service," Maritime Policy & Management, vol. 47, no. 6, pp. 703–717, 2020.
DOI: 10.1080/03088839.2020.1729431. eprint: https://doi.org/10.1080/03088839.2020.1729431.

[68] K. M. Kumar, "The influence of sustainable logistic practices and supplier support on logistics transport performance: An empirical review on malaysian logistics service providers," Journal of Entrepreneurship, Business and Economics, vol. 10, no. 1, pp. 141–177, 2022.

[69] R. K. Singh, A. Gunasekaran, and P. Kumar, "Third party logistics (3PL) selection for cold chain management: a fuzzy AHP and fuzzy TOPSIS approach," Annals of Operations Research, vol. 267, no. 1, pp. 531–553, 2018,
ISSN: 1572-9338.
DOI: 10.1007/s10479-017-2591-3.

[70] L. Tu, Y. Lv, Y. Zhang, and X. Cao, "Logistics service provider selection decision making for healthcare industry based on a novel weighted density-based hierarchical clustering," Advanced Engineering Informatics, vol. 48, p. 101 301, 2021,
ISSN: 1474-0346.
DOI: 10.1016/j.aei.2021.101301.

[71] D. Tranfield, D. Denyer, and P. Smart, "Towards a methodology for developing evidence-informed management knowledge by means of systematic review," British Journal of Management, vol. 14, no. 3, pp. 207–222, 2003.
DOI: 10.1111/1467-8551.00375.

[72] K. Kozioł-Nadolna and K. Beyer, "Determinants of the decision-making process in organizations,"

Procedia Computer Science, vol. 192, pp. 2375–2384, 2021.
DOI: 10.1016/j.procs.2021.09.006.

[73] G. Yannis, A. Kopsacheili, A. Dragomanovits, and V. Petraki, "State-of-the-art review on multi-criteria decision-making in the transport sector," Journal of traffic and transportation engineering (English edition), vol. 7, no. 4, pp. 413–431, 2020.
DOI: 10.1016/j.jtte.2020.05.005.

[74] E. Dimara, H. Zhang, M. Tory, and S. Franconeri, "The unmet data visualization needs of decision makers within organizations," IEEE Transactions on Visualization and Computer Graphics, vol. 28, no. 12, pp. 4101–4112, 2021.
DOI: 10.1109/TVCG.2021.3074023.

[75] Y. Yang, T. Gai, M. Cao, Z. Zhang, H. Zhang, and J. Wu, "Application of group decision making in shipping industry 4.0: Bibliometric analysis, trends, and future directions," Systems, vol. 11, no. 2, p. 69, 2023.
DOI: 10.3390/systems11020069.

[76] G. Theotokatos, J. L. D. Dantas, G. Polychronidi, G. Rentifi, and M. M. Colella, "Autonomous shipping — an analysis of the maritime stakeholder perspectives," WMU Journal of Maritime Affairs, vol. 22, no. 1, pp. 5–35, 2023.
DOI: 10.1007/s13437-022-00290-2.

[77] L. F. Pratson, "Assessing impacts to maritime shipping from marine chokepoint closures," Communications in Transportation Research, vol. 3, p. 100 083, 2023.
DOI: 10.1016/j.commtr.2022.100083.

[78] A. C. Trapp, I. Harris, V. S. Rodrigues, and J. Sarkis, "Maritime container shipping: Does coopetition improve cost and environmental efficiencies?" Transportation Research Part D: Transport and Environment, vol. 87, p. 102 507, 2020.
DOI: 10.1016/j.trd.2020.102507.

[79] A. R. E. Najaf, A. S. Fitri, S. F. A. Wati, A. Wulansari, D. S. Y. Kartika, and E. M. Safitri, "Implementation of weighted product method as fuzzy multi-criteria decision analysis (fmadm) in vendor selection,"

In 2022 IEEE 8th Information Technology International Seminar (ITIS),
2022,
Pp. 359–362.
DOI: 10.1109/ITIS57155.2022.10010305.

[80] B. Ayan, S. Abacıoğlu, and M. P. Basilio, "A comprehensive review of the novel weighting methods for multi-criteria decision-making,"
Information, vol. 14, no. 5, p. 285, 2023.
DOI: 10.3390/info14050285.

[81] H. Taherdoost and M. Madanchian, "Multi-criteria decision making (mcdm) methods and concepts,"
Encyclopedia, vol. 3, no. 1, pp. 77–87, 2023.
DOI: 10.3390/encyclopedia3010006.

[82] B. Ceballos, M. T. Lamata, and D. A. Pelta, "A comparative analysis of multi-criteria decision-making methods,"
Progress in Artificial Intelligence, vol. 5, no. 4, pp. 315–322, 2016.
DOI: 10.1007/s13748-016-0093-1.

[83] T. Saaty,
"Modeling unstructured decision-making-ahp,"
In International Conference on Mathematical Modeling,
1977.
DOI: 10.1007/978-3-642-50244-6_4.

[84] T. L. Saaty,
"Group decision making and the ahp,"
In The Analytic Hierarchy Process: Applications and Studies,
B. L. Golden, E. A. Wasil, and P. T. Harker, Eds.,
Berlin, Heidelberg: Springer, 1989,
Pp. 59–67,
ISBN: 978-3-642-50244-6.
DOI: 10.1007/978-3-642-50244-6_4.

[85] J. E. Leal, "Ahp-express: A simplified version of the analytical hierarchy process method,"
MethodsX, vol. 7, p. 100 748, 2020.
DOI: 10.1016/j.mex.2019.11.021.

[86] A. M. Saghiri, S. M. Vahidipour, M. R. Jabbarpour, M. Sookhak, and A. Forestiero, "A survey of artificial intelligence challenges: Analyzing the definitions, relationships, and evolutions," Applied Sciences, vol. 12, no. 8, p. 4054, 2022. DOI: 10.3390/app12084054.

[87] I. H. Sarker, "Ai-based modeling: Techniques, applications and research issues towards automation, intelligent and smart systems," SN Computer Science, vol. 3, no. 2, p. 158, 2022. DOI: 10.1007/s42979-022-01043-x.

[88] F. Pedregosa et al., "Scikit-learn: Machine learning in python," Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.

[89] T. Chen and C. Guestrin, "Xgboost: A scalable tree boosting system," In Proc. 22nd ACM SIGKDD Int. Conf. on Knowledge Discovery and Data Mining, Ser. KDD '16, San Francisco, California, USA: Association for Computing Machinery, 2016, Pp. 785–794, ISBN: 9781450342322. DOI: 10.1145/2939672.2939785.

[90] T. G. Dietterich, "Ensemble methods in machine learning," In Multiple Classifier Systems, Berlin, Heidelberg: Springer, 2000, Pp. 1–15, ISBN: 978-3-540-45014-6. DOI: 10.1007/3-540-45014-9_1.

[91] W. S. Noble, "What is a support vector machine?" Nature biotechnology, vol. 24, no. 12, pp. 1565–1567, 2006. DOI: 10.1038/nbt1206-1565.

[92] A. E. Ezugwu et al., "A comprehensive survey of clustering algorithms: State-of-the-art machine learning applications, taxonomy, challenges, and future research prospects," Engineering Applications of Artificial Intelligence, vol. 110, p. 104 743, 2022. DOI: 10.1016/j.engappai.2022.104743.

[93] R. I. Mukhamediev et al., "Review of artificial intelligence and machine learning technologies: Classification, restrictions, opportunities and challenges," Mathematics, vol. 10, no. 15, p. 2552, 2022. DOI: 10.3390/math10152552.

[94] S. Harispe, S. Ranwez, S. Janaqi, and J. Montmain, Semantic Similarity from Natural Language and Ontology Analysis (Synthesis Lectures on Human Language Technologies). Cham: Springer, 2022, Vol. 27, Reprint of original edition © Morgan & Claypool 2015, ISBN: 978-3-031-01028-6. DOI: 10.1007/978-3-031-02156-5.

[95] D. Chandrasekaran and V. Mago, "Evolution of semantic similarity—a survey," ACM Computing Surveys, vol. 54, no. 2, pp. 1–37, 2021. DOI: 10.1145/3440755.

[96] R. Singh, Z. Ahmad, H. Suhaimi, S. A. Salman, et al., "Service quality and perceived service quality in the maritime business post-covid-19," Journal of Survey in Fisheries Sciences, pp. 3045–3052, 2023.

[97] P. Järvinen, "Action research is similar to design science," Quality & Quantity, vol. 41, no. 1, pp. 37–54, 2007. DOI: 10.1007/s11135-005-5427-1.

[98] L. Butgereit, M. Niland, J. Schmidt, and W. Rheeder, "A design science model for the application of data mining and machine learning models on constrained devices in low bandwidth areas," In Proc. 2018 Int. Conf. on Adv. in Big Data, Comput. and Data Commun. Syst. (icABCD), Springer, 2018, Pp. 1–7. DOI: 10.1109/icabcd.2018.8465407.

[99] B. Roy, "The outranking approach and the foundations of electre methods," Theory and Decision, vol. 31, no. 1, pp. 49–73, 1991, ISSN: 1573-7187. DOI: 10.1007/BF00134132.

[100] B. Mareschal, J. P. Brans, and P. Vincke,

"Prométhée: A new family of outranking methods in multicriteria analysis," English,
In Proc. 10th IFORS Int. Conf. on Operational Research (Operational Research '84),
J. P. Brans, Ed.,
RePEc:ulb:ulbeco:2013/9305,
Amsterdam: North-Holland, 1984,
Pp. 477–490.

[101] D. Cer et al.,
"Universal sentence encoder for english,"
In Proc. 2018 Conf. on Empirical Methods in NLP: Syst. Demonstrations,
Brussels, Belgium: Association for Computational Linguistics, 2018,
Pp. 169–174.
DOI: 10.18653/v1/D18-2029.

[102] R. Likert, "A technique for the measurement of attitudes,"
Archives of Psychology, no. 140, pp. 1–55, 1932.

[103] A. Parmar, R. Katariya, and V. Patel,
"A review on random forest: An ensemble classifier,"
In Intelligent Data Communication Technologies and Internet of Things (ICICI) 2018,
J. Hemanth, X. Fernando, P. Lafata, and Z. Baig, Eds.,
Cham: Springer International Publishing, 2019,
Pp. 758–763,
ISBN: 978-3-030-03146-6.
DOI: 10.1007/978-3-030-03146-6_86.

[104] O. Kramer,
"K-nearest neighbors,"
In Dimensionality Reduction with Unsupervised Nearest Neighbors,
Ser. Intelligent Systems Reference Library,
Berlin, Heidelberg: Springer, 2013,
Pp. 13–23.
DOI: 10.1007/978-3-642-38652-7_2.

[105] T. L. Saaty,
"What is the analytic hierarchy process?"
In Mathematical Models for Decision Support,
G. Mittra et al., Eds.,

Berlin, Heidelberg: Springer, 1988,
Pp. 109–121.
DOI: 10.1007/978-3-642-83555-1_5.

[106] E. Triantaphyllou and E. Triantaphyllou, Multi-criteria Decision Making Methods: A Comparative Study. Springer, 2000.
DOI: 10.1007/978-1-4757-3157-6.

[107] N. Rane, A. Achari, and S. P. Choudhary, "Multi-criteria decision-making (mcdm) as a powerful tool for sustainable development: Effective applications of ahp, fahp, topsis, electre, and vikor in sustainability," International Research Journal of Modernization in Engineering Technology and Science, vol. 5, no. 4, pp. 2654–2670, 2023.
DOI: 10.56726/irjmets36215.

[108] M. A. Bujang, E. D. Omar, and N. A. Baharum, "A review on sample size determination for cronbach's alpha test: A simple guide for researchers," Malaysian Journal of Medical Sciences, vol. 25, no. 6, pp. 85–99, 2018.
DOI: 10.21315/mjms2018.25.6.9.