

**DEVELOPMENT OF PERFORMANCE  
EVALUATION AND PREDICTION MODELS IN  
LOGISTICS SERVICE AND SUPPLY NETWORKS  
TOWARDS A SUSTAINABLE AND ROBUST  
SUPPLY CHAIN**

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**UNIVERSITI SAINS MALAYSIA**

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SUPPLY CHAIN**

by

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## LIST OF ABBREVIATIONS

ADMU	Anti-ideal Decision Making Unit
AHP	Analytic Hierarchy Process
ANN	Artificial Neural Network
ANP	Analytic Network Process
ARIMAX	Autoregressive Integrated Moving Average with Exogenous Variables
ASEAN	The Association of Southeast Asian Nations
AI	Artificial Intelligence
BSNYH	Bring-service-near-your-home
CAGR	Compounded Annual Growth Rate
CNA	Citation Network Analysis
CoDEA	Coherent Data Envelopment Analysis
COVID-19	The Coronavirus Disease 2019
CRS	Constant Returns to Scale
D	Detection
DDM	Data-driven Modelling
DEA	Data Envelopment Analysis
DMU	Decision-making Unit
DNN	Deep Neural Network
FLQ-OWA	Fuzzy Linguistic Quantifier Order Weighted Aggregation
FMEA	Failure Mode and Effects Analysis
FSP	Functional Service Provider
FTA	Free Trade Agreement
GA	Genetic Algorithm
GDP	Gross Domestic Product
GMV	Gross Merchandise Volume

IDMU	Ideal Decision Making Unit
IoT	Internet of Things
LASSO	Least Absolute Shrinkage and Selection Operator
LPI	Logistics Performance Index
LSP	Logistics Service Provider
LTS	Logistics and Transport Sector
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MCDM	Multiple Criteria Decision-making
MFG	Manufacturing
ML	Machine Learning
MLP	Multi-layer Perceptron
MLR	Multiple Linear Regression
MPAC	Master Plan on ASEAN Connectivity
NTIS	National Technology and Innovation Sandbox
O	Occurrence
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PM	Performance management
PSO	Particle Swarm Optimization
PSSC	Product Service Supply Chain
RF	Random Forest
RFR	Random Forest Regression
RMSE	Root Mean Square Error
RO	Research Objective
RPN	Risk Priority Number
RQ	Research Question

S	Severity
SCM	Supply Chain Management
SCRM	Supply Chain Risk Management
SCV	Supply Chain network Viability
SDGs	Sustainable Development Goals
SNA	Social Network Analysis
SVD	Singular Value Decomposition
SVM	Support Vector Machine
SVR	Support vector Regression
SWARA	Stepwise Weight Assessment Ratio Analysis
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
VBA	Visual Basic for Application
VRS	Variable Returns to Scale

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- Appendix A The summary of reviewed criteria of operational sustainability
- Appendix B Risk analysis metric
- Appendix C Would bank LPI data
- Appendix D S&P global market intelligence data
- Appendix E Microeconomic data of six ASEAN countries

**PEMBANGUNAN MODEL UNTUK PENILAIAN DAN RAMALAN PRESTASI  
DALAM PERKHIDMATAN LOGISTIK DAN RANGKAIAN BEKALAN KE  
ARAH RANTAIAN BEKALAN YANG LESTARI DAN TEGUH**

**ABSTRAK**

Penyelidikan ini menangani masalah kekurangan alat membuat keputusan yang sesuai untuk membentangkan maklumat prestasi semasa dan masa hadapan yang diperoleh daripada kaedah penilaian dan ramalan dalam konteks rantai bekalan. Alat sedemikian mungkin boleh menggalakkan pemikiran sistematik dan membantu pembuat keputusan untuk membangunkan garis panduan pengurusan untuk pengurusan rantai bekalan apabila perlu menyesuaikan model perniagaan kepada cara baharu. Ini akan boleh membolehkan kesalahan dan perangkap dapat dielakkan dalam usaha menangani gangguan dan bencana masa depan dengan menggunakan wabak penyakit koronavirus 2019 sebagai pengajaran yang dipelajari. Objektif utama penyelidikan ini adalah untuk membangunkan model pengoptimuman baharu untuk analisis penyampulan data rangkaian dan algoritma pembelajaran mesin untuk menggunakan model tersebut sebagai alat dan metrik untuk menilai dan meramal prestasi rantai bekalan. Alat dan metrik tersebut kemudiannya digunakan untuk menganalisa perkhidmatan logistik dan rantai bekalan perdagangan global di enam negara Persatuan Negara-Negara Asia Tenggara: Indonesia, Malaysia, Filipina, Thailand, Singapura dan Vietnam. Penyelidikan ini terbahagi kepada dua bahagian. Pada mulanya, model pengoptimuman analisis penyampulan data tradisional dan lanjutan, model pembangunan baru analisis penyampulan data yang koheren, dan analisis penyampulan data digabungkan dengan analisis mod kegagalan dan kesan digunakan dalam bahagian penilaian. Dalam bahagian ini, kecekapan rantai bekalan ditentukan

daripada pelbagai perspektif termasuk pengurusan rantaian bekalan moden seperti kemampuan, kelemahan, risiko dan daya tahan. Dalam bahagian kedua peramalan, data siri masa dan algoritma pembelajaran mesin untuk analitik ramalan mendapat perhatian dalam pengurusan prestasi logistik dan rantaian bekalan, yang memerlukan pendekatan baharu untuk pemantauan prestasi. Data primer dikumpul menggunakan platform dalam talian. Selain itu, sejumlah besar data sekunder digunakan untuk mengimbangi ketiadaan data tinjauan. untuk menambah pengetahuan dalam bidang kajian ini. Mengikut keputusan pembangunan model, model koheren menambah baik kaedah rangkaian sedia ada yang dikekang oleh pembolehubah sambungan pusat. Kaedah gabungan boleh menangani kelemahan model tradisional sambil juga memberikan tahap diskriminasi yang tinggi. Selain itu, pembelajaran mesin bagi algoritma regresi bermanfaat dari segi menyediakan ramalan arah aliran yang tepat. Tambahan pula, hasil penilaian dan ramalan kawasan kajian boleh digunakan untuk membangunkan garis panduan untuk membantu dalam penggubalan dasar di bawah senario pandemik Coronavirus Disease 2019 dan untuk terus meningkatkan prestasi logistik dan rantaian bekalan di setiap negara dan wilayah.

**DEVELOPMENT OF PERFORMANCE EVALUATION AND PREDICTION  
MODELS IN LOGISTICS SERVICE AND SUPPLY NETWORKS TOWARDS  
A SUSTAINABLE AND ROBUST SUPPLY CHAIN**

**ABSTRACT**

This study identified a problem of a lack of appropriate decision tools for providing present and predicted performance information gathered through efficient evaluation and prediction procedures in the supply chain context. Such a tool may promote systems thinking and assist decision-makers in developing managerial guidelines for supply chain management when applying business models in new settings. As a result, faults and pitfalls are avoided in future efforts to handle disruptions and disasters, which use the Coronavirus Disease 2019 pandemic scenario as a lesson learned. The main objective of this research is to develop an optimization model for a novel network data envelopment analysis and machine learning algorithms. And to utilize the models as tools and metrics for evaluating and predicting supply chain performance. The tools and metrics were then performed to examine the logistics service and global trade supply chain in the six countries of the Association of Southeast Asian nations: Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Vietnam. This research is divided into two parts. Initially, an optimization model of traditional and extension of data envelopment analysis, a novel development model of coherent data envelopment analysis, and data envelopment analysis combined with failure mode and effect analysis technique are employed in the evaluation part. In this part, supply chain performance is determined from various perspectives, including state-of-the-art supply chain management toward sustainable and robust supply chains, such as sustainability, vulnerability, risk, and resilience. Consistently, in the second part of the



prediction, time series data and predictive analytics of machine learning algorithms are gaining traction in logistics and supply chain performance management, demanding new ways of performance monitoring. The primary data are gathered using an online platform. In addition, massive and useable secondary data are used to compensate for the unavailability of survey data, and to boost knowledge in this study area. According to model development results, the coherent model improves existing network methods that are constrained by intermediate measures. The combination method can address traditional model weaknesses while also providing a high level of discrimination. Moreover, machine learning of regression algorithms is beneficial in terms of providing accurate trend prediction. Furthermore, the evaluation and prediction results of study areas can be used to develop a guideline to aid in policymaking under the scenario of the Coronavirus Disease 2019 pandemic and to continue to improve the performance of logistics and supply chains in each country and region.

# CHAPTER 1

## INTRODUCTION

### 1.1 Introduction

Global trade is the primary engine of The Association of Southeast Asian Nations (ASEAN) countries' economy. Furthermore, these countries are distinguished by rapid economic growth and active participation in the global economy. The logistics sector and its network are crucial for developing the global trade of ASEAN countries. The robustness of logistics performance is influenced by how effective supply chains connect enterprises to domestic and international trade possibilities. To drive decision-making, it is vital to have specialized, cutting-edge, and trustworthy measuring metrics that accurately reflect the supply chain's actual performance while also predicting future performance.

This research focuses on developing the tool and metric and applying the approach to determine ways to identify performance in a supply chain context. The outcomes of procedures of evaluation and prediction will give insight into the existing and future intensity of performance related. The process of evaluating various operational related data such as sustainability, risk, resilience, and vulnerability will represent supply chain performance, leading to the establishment of improvement methods in the supply chain system's weak areas. The improvement scenarios will be utilized to predict future performance for operation enhancement planning and monitoring. Intentionally, to propel the logistics business, which is regarded as a critical sector for national growth, through a robust and sustainable supply chain. The efficiency evaluation and prediction methods in which the optimization and machine learning (ML) notion is developed are established using a multi-case study of

Malaysian logistics service businesses. It also applies to the global trade supply chain and logistics service supply chain of six ASEAN countries: Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Vietnam, as these are export-oriented economies.

This chapter provides an introduction to the context of this thesis by discussing the research background and defining the research problem and research gaps, followed by the established research purpose and research questions, models development scope and methodology, the significance of the research, scope of the study, definitions of key terms and lastly how the thesis is organized.

## **1.2 Background of the Study**

The background of the study is motivated to study the measurement of performance of the logistics business and its supply network from the perspective of the supply chain management of countries in the ASEAN region. In this section, the study's background is related to insights into the importance of logistics and supply chain for country development, as well as the context of supply chain robustness and sustainability, which is driven by the coronavirus disease 2019 (COVID-19) pandemic scenario. Furthermore, the background is provided for optimization-based methods of evaluation and ML algorithms of prediction, which are critical in logistics and supply chain performance measurement.

### **1.2.1 The importance of logistics and supply chain for country development**

Logistics is defined as a part of the supply chain process of service operations that support physical product movement, cross-border trade, and intra-border business. It also includes warehousing, brokerage, expedited delivery, terminal operations, and

data and information management in addition to the main activity of transportation (World Bank, 2018a). A high-performing logistics system is critical to the economy as a whole (Winkelhaus & Grosse, 2020). Since logistics performance is determined by how efficiently supply chains connect firms to domestic and international as global trade opportunities (World Bank, 2018a). Internationally, many believe that the logistics sector accounts for nearly 12% of the entire globe's Gross Domestic Product (GDP) (Freightwaves, 2020). The logistics sector is crucial for developing countries. The logistics industry development positively relates to the level of whole country development. Low GDP countries typically have a low value in the logistics market (Çakır, 2017).

ASEAN countries are undergoing a rapid mechanical revolution. In 2020, the services sector led ASEAN's economy, accounting for 50.6% of the bloc's GDP, followed by manufacturing (35.8%) and agriculture (10.5%). Travel is the most important contributor to ASEAN's exports and imports in terms of services trade. Other business services and transportation accounted for the majority of ASEAN trade. In the manufacturing domain, electrical and machinery (with equipment and parts) account for 29.7% and 28.1% of total manufacturing goods exports and imports, respectively (HKTDC Research, 2022). The agricultural domains, provide the world with a diverse array of agricultural-based food products (Fan et al., 2021). These are the main engines driving ASEAN's growing trade volume.

Singapore, Vietnam, Malaysia, Thailand, Indonesia, and the Philippines account for six of the ten ASEAN member countries. As illustrated in Figure 1.1, these nations have the greatest levels of exports and imports among ASEAN members (ASEAN Stats, 2021).

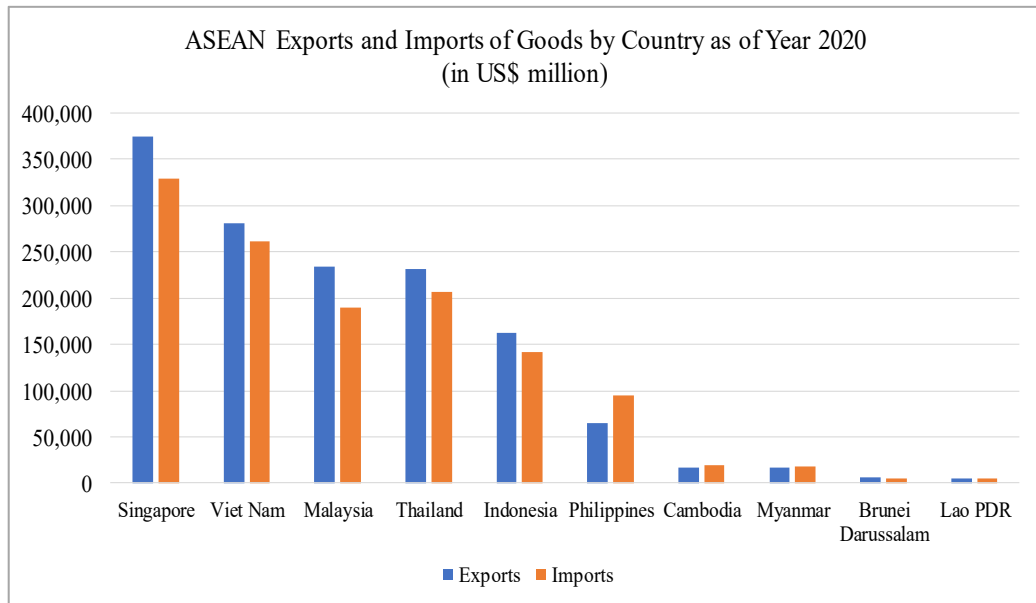


Figure 1.1 Exports and imports of goods of ASEAN countries  
Source: ASEAN Stats (2021)

Yearly, over half of the world's marine trade flows through ASEAN. Improving ASEAN logistics competitiveness is thus critical to sustaining robust industrial growth. To accomplish this, the Master Plan on ASEAN Connectivity (MPAC) 2025 aims to identify particular blockages in important trade routes to reduce the cost of shipping products and services across borders. Through the development of a supply chain framework, the MPAC 2025 offers a novel way to improve the speed and reliability of supply chains in the ASEAN Member States. This includes gathering data and analyzing the time and costs necessary for products to cross the border – whether by land, sea, or air – also identifying and resolving significant trade and investment chokepoints (ASEAN Secretariat, 2018). Global trade, therefore, is the primary engine of the ASEAN nations' economies. Furthermore, these countries are distinguished by rapid economic growth and active participation in the global economy (Nguyen & Almodóvar, 2018).

Furthermore, according to the report of Mordor Intelligence (2021), ASEAN e-commerce logistics are anticipated to increase at a rate of more than 6% throughout the projection year. When cross-border e-commerce changes the dynamics of international trade, Asia gains more than any other region of the globe. The transportation service supplied to the online retail sector is referred to as e-commerce logistics. As indicated in Figure 1.2, e-commerce is expected to expand at a double-digit average rate across ASEAN member countries. Indonesia is the region's largest and fastest-growing e-commerce market, accounting for over half of regional sales. (Statista, 2021).

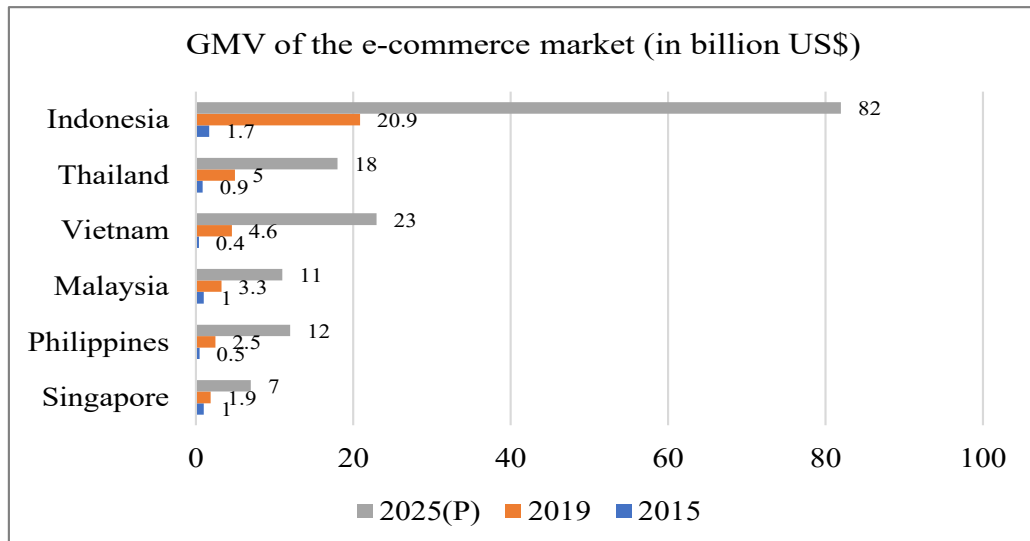


Figure 1.2 Gross merchandise volume (GMV) of the e-commerce market in the six ASEAN countries  
Source: Statista (2021)

For ASEAN, the advantages of e-commerce extend beyond the creation of new trade and commercial possibilities. It also helps the region's social cohesiveness and general economic growth, which are critical components of regional integration (Mordor Intelligence, 2021). It is focused mainly on the direction of logistics infrastructure development in ASEAN's emerging economies during the

previous few years. Since Singapore and Malaysia have the highest overall infrastructure quality, ranking first and 35th in Statista's top 100 list of nations based on their infrastructure quality in 2019. The remaining countries are either at or below the global average; Thailand is ranked 71st, Indonesia is ranked 72nd, Vietnam is ranked 77th, and the Philippines is ranked 96th. Across countries, there are major gaps in logistics infrastructure.

In terms of the region, development is still hampered by poor road conditions, insufficient road and railway networks, inadequate ports, and a lack of service competence. With growing populations and increasing demands to sustain economic growth, the ability of ASEAN's infrastructure to adapt is under increasing strain. As a result, in addition to investing in new projects, ASEAN member states must make better use of existing capacity (Mordor Intelligence, 2021). According to Figure 1.3, the Philippines, Vietnam, and Thailand will increase their infrastructure development investment by more than 10% between 2016 and 2020.

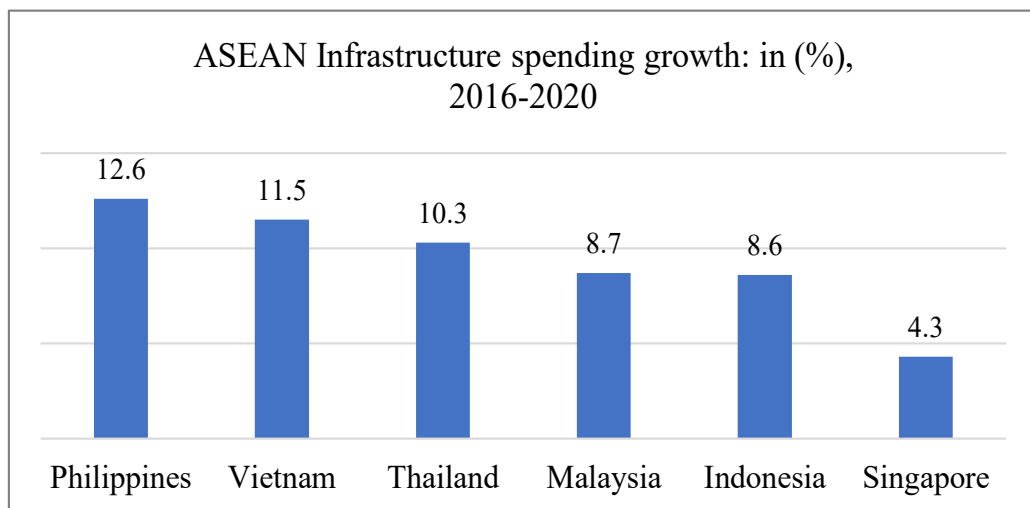


Figure 1.3 Infrastructure spending growth in six ASEAN countries  
Source: Mordor Intelligence (2021)

ASEAN's infrastructure investment needs are estimated to be more than \$110 billion per year until 2025. ASEAN countries continued to expand infrastructure activities, particularly in countries with infrastructure quality below the global average. As part of post-pandemic sustainable recovery measures, these member countries intend to increase infrastructure spending. Thailand, for example, has set aside \$33 billion for infrastructure projects between 2020 and 2027, with 92 projects, 18 of which are high-priority infrastructure plans. The Indonesian government intends to spend \$429 billion on infrastructure between 2020 and 2024, a 20% increase over the \$359 billion spent between 2015 and 2019. The annual infrastructure investment requirement in Vietnam has been estimated at \$24 billion between 2016 and 2040. The majority of the need is expected to be in transportation and electricity. In addition, the Philippine government is promoting a \$180 billion "build, build, build" program to upgrade the country's infrastructure facilities. Many of the projects involve the development or improvement of transportation infrastructures, such as airports, port terminals, rail links, urban light rail transportation, and road and bridge construction (ASEAN Secretariat, 2021a).

However, the logistics sector benefits from more than just infrastructure; the exponential rise of e-commerce and the expansion of intra-regional markets. ASEAN's FTA (Free Trade Agreement) network is anticipated to help international firms by lowering importer costs, improving customs processing, and increasing access to items eligible for preferential treatment (Mordor Intelligence, 2021).

The ASEAN logistics development context is interconnected with the World Bank's guiding pathway. The world's most excellent funding source and developing countries supporter, the World Bank announces a "logistics performance index" (LPI)



two years a time. LPI, this index is calculated based on each country's performance in two main categories, with higher LPI scores generally associated with better logistics performance (Rashidi & Cullinane, 2019; Rezaei et al., 2018). The two main categories of LPI indicators can map as a policy and a performance perspective. Firstly, (i) policy regulation areas, demonstrate the leading supply chain inputs, corresponding to LPI indicators of customs, infrastructure, and services. Secondly, (ii) supply chain performance outcomes, according to LPI indicators of timeliness (time), international shipments (cost), and tracking and tracing (reliability) (World Bank, 2018a). More countries, especially developing economies countries, look at the logistics sector as the economy forcing consistent policymaking (World Bank, 2018a). Policy and trade with logistics procedures must take into matter their influence on trade competitiveness. Thanks to the LPI's introduction, recently made this topic has become effortless to study, which has provided useful information on the actual condition of all countries (Puertas et al., 2014). Tables 1.1 and 1.2 are shown the latest overall LPI score and LPI score of 2018 based-on six indicators of six ASEAN countries, respectively (World Bank, 2018a).

Table 1.1 The overall LPI score

Country	2010	2012	2014	2016	2018	World ranking of 2018
Singapore	4.09	4.13	4.00	4.14	4.00	7
Thailand	3.29	3.18	3.43	3.26	3.41	32
Vietnam	2.96	3.00	3.15	2.98	3.27	39
Malaysia	3.44	3.49	3.59	3.43	3.22	41
Indonesia	2.76	2.94	3.08	2.98	3.15	46
Philippines	3.14	3.02	3.00	2.86	2.90	60

Source: World Bank (2018b)

Table 1.2 LPI score of 2018 based on six indicators

Country	Customs	Infrastructure	Logistics quality and competence	Timeliness	International shipments	Tracking and tracing
Singapore	3.89	4.06	4.10	4.32	3.58	4.08
Thailand	3.14	3.14	3.41	3.81	3.46	3.47
Vietnam	2.95	3.01	3.40	3.67	3.16	3.45
Malaysia	2.90	3.15	3.30	3.46	3.35	3.15
Indonesia	2.67	2.90	3.10	3.67	3.23	3.30
Philippines	2.53	2.73	2.78	2.98	3.29	3.06

Source: World Bank (2018b)

Global logistics has changed in big ways since the first LPI report. New players and new business models have emerged. A recent World Economic Forum report compiled by prominent experts identified eight megatrends that are expected to shape the future of logistics: (i) digital transformation of supply chains, (ii) e-commerce driving demand chains, (iii) restructuring global value chains, (iv) sustainability of supply chains, (v) supply risk and recovery (resilience), (vi) logistics skill shortages, (vii) logistics property and infrastructure, and (viii) collaborative business models (World Bank, 2018a). The majority of these developments are directly relevant to the logistics policy agenda and will reform the LPI metric. The changing trend will aid global logistics operations in improving logistics service providers' (LSPs) performance as it relates to supply chain performance outcomes. According to relates sustainability viewpoint of logistics and supply chain operations (megatrend-iv), and supply chain risk and resilience, which combine to the vulnerability aspect (megatrend-v).

### **1.2.2 COVID-19 pandemic and the context of supply chain robustness and sustainability**

In today's business world, corporations have been affected by natural and man-made disasters such as cyber disasters, trade conflicts, and, most recently, the COVID-19 pandemic. Unfortunately, the COVID-19 epidemic has had a direct influence on the supply chain's logistics operations including the transportation, storage, and flow of products, with a particular emphasis on transport and logistics connections in landlocked areas (United Nations, 2020). COVID-19 has had a major impact on the global economy in three ways: it has directly affected production and order, it has created supply chain and market disruption, and it has had a financial impact on companies and financial markets (360marketupdates, 2020). The worldwide pandemic of COVID-19 is a highly infectious respiratory virus that poses a serious threat to humanity. The COVID-19 epidemic has progressed at a breakneck pace, halting economic activity and supply chains as numerous countries tighten movement restrictions in an attempt to contain the virus' spread.

According to the World Bank (2020), the baseline projection predicts a 5.2% decline in global GDP in 2020. Human capital is eroding as a result of the decreased investment, fragmentation of global trade and supply connections, and employment and education losses. These have an impact on the global supply chain system's international merchandise and trade services. According to the United Nations Conference on Trade and Development's December 2020 projection (UNCTAD, 2020), the value of global goods trade is expected to decline by 5.6% in 2020 compared to 2019. The anticipated reduction in trade services is greater, with a 15.4% drop in 2020 compared to 2019.

The pandemic of COVID-19 exposed the vulnerabilities and risks inherent in global supply systems by interrupting national nodes and internal supply networks (Golan et al., 2020). Vulnerability studies are commonplace to identify weaknesses in the system. The COVID-19 pandemic event was a critical scenario used to assess the supply chain's vulnerability. While risk emphasizes the severity of consequences within the scenario context, resilience refers to the system's ability to continue functioning within an acceptable time after the scenario occurs. As a result, risk and resilience are regarded as components or subsets of a system's ability to respond when determining how vulnerable a system is (Bryce et al., 2020). The effectiveness of risk and resilience management contributes to the supply chain's robustness (less vulnerability). This research then focuses on the development of a tool to reflect the actual level of vulnerability of the supply chain, allowing for more robust new business strategies to be generated.

The disruptions are required to promptly successful adaption. In the business situation, risks and limitations may negatively impact logistics organizations and the supply networks linked to their operations. These risks and limitations cause immense challenges to organizations, and stakeholders must contemplate all the aspects that may affect the logistics and business networks or supply chain performances (Waugh & Badenhorst-Weiss, 2015).

To recognize sustainable operations, several studies (Liu et al., 2020; Rezaghdh & Shokouhyar, 2020; Valinejad & Rahmani, 2018; Xu et al., 2019;) have been conducted to investigate the risk factors that impact supply chain sustainability. Scholars have recently considered supply chain sustainability risk and assessment by considering the three bottom lines collectively: economic, environmental, and social

aspects (Liu et al., 2020). As a result, the perspective of this research has been broadened to include the sustainable operational risk of the logistics service supply chain from economic, environmental, and social viewpoints.

### **1.2.3 Optimization-based methods and the critical in logistics and supply chain performance evaluation**

The suitable method for improving logistics and supply chain performance is judged by current standing. And the ability to represent actual performance is contingent upon the availability of measurement tools and procedures. However, while implementing the models, it is critical to establish the measurement model precisely. It is may unclear how to measure performance which is the output of a whole supply chain directly. Likewise, efficiency refers to how well the transfer corporation converts its available resources into outputs. In other words, efficiency quantifies how well the output is conducted, which may also reflect the supply chain system's performance (Janvier-James, 2012).

Data envelopment analysis (DEA) is a linear optimization problem-solving tool (Krivonozhko et al., 2004). It has become one of the most widely used operational research tools for evaluating the efficiency of many industries in the manufacturing and service sectors, including transportation and logistics (Panayides et al., 2009). Since the standard DEA inception by Charnes et al. (1978), many extended or applied DEA models have been studied to date. Moreover, this model can apply the indicators to measure depending on the critical factor of any field. An appropriate efficiency evaluation system is a fundamental prerequisite for managing a supply chain efficiently, and DEA may also be used to evaluate the supply chain's efficiency (Liang et al., 2006).

Notwithstanding, an efficiency measure in the supply chain concerning a set of decision-making units (DMUs) can be calculated with several DEA models (Pendharkar, 2005). When applied in the supply chain, which intermediate measures necessitate, the DEA of two or multi-stage models is typically used as a theoretical basis. However, drawbacks or errors occur from the doubtful direction or the characteristics of the relationship between the two stages. Also, the difficulty of assigning the intermediate measures has occurred when applied in a network structure like a supply chain. This work offers a coherent DEA (CoDEA) model with an intramural structure for evaluating supply chain efficiency of performance. A unique CoDEA model is being developed to improve existing DEA approaches that suffer from intermediate measure limitations. CoDEA avoids an intermediary system of measurement by focusing on divisional efficiency by utilizing the conventional DEA process.

Nowadays, vulnerability and resilience awareness is at an all-time high, owing to the extraordinary magnitude of the COVID-19 epidemic. Pandemics put systems, including supply chains, to the test of their vulnerability and resilience. These issues have prompted research into the supply chain's vulnerability, risk, and resilience's relatively untapped measurement metrics. Moreover, supply chain efficiency might represent the degree of risk and resilience (Notheisen et al., 2017). Supply chain risk reduction leads to better efficiency levels (Wiengarten et al., 2016). However, risk assessment is distinct from performance evaluation, which is concerned with output. Risk, usually using a specific tool to assess. Failure mode and effects analysis (FMEA) is a well-known risk assessment technique (Mangeli et al., 2019). FMEA is a risk assessment technique comprehensively used across various sectors, i.e., transport and logistics (Dadsena et al., 2016; Huth & Lohre, 2014; Shafiee et al., 2019). However,

the traditional FMEA model retains numerous shortcomings, such as uncertainty and interaction relationships between risk indicators (Wang et al., 2019). Developing a hybrid FMEA framework integrating with other methods to close these gaps is also popular and conducted to improve the risk assessment approach. In this research, the hybrid of FMEA and DEA is used to measure the logistics sector's risk level under sustainable indicators. The information on risk assessment will then evaluate the efficiency, namely, a sustainability operation risk-based efficiency evaluation concept.

#### **1.2.4 Machine learning algorithms and the crucial in logistics and supply chain performance prediction**

The performance management process involves the establishment of metrics, the selection of performance indicators, and the collection of real-time data (Forslund, 2012). The logistics performance evaluation is conducted using publicly accessible quantitative data or by surveying logistics managers about their perceptions of country-level trade facilitation performance factors. One avenue that should be pursued further is the use of information for performance estimation and benchmarking that is already available in the form of big data. This sort of pre-existing data may serve as a robust yet flexible addition to other methods for estimating a country's logistics performance that is accessible in the literature, therefore strengthening global and local decision-making assistance (Kinra et al., 2020). Because big data is constantly updated, rapid data analysis is required (Kamble and Gunasekaran, 2020). The logistics performance related to LPI score and dynamics of big data, if provided in a shorter time frame. It may offer more benefits to policymakers in the case of immediately improving or resharpening their policies.

Big data and predictive analytics are gaining popularity in logistics and supply chain management (SCM). The use of big data can have a primary influence on supply chain performance, necessitating new ways of performance monitoring (Kamble and Gunasekaran, 2020). Researchers have already proposed using artificial intelligence (AI) or ML techniques to evaluate a country's logistics performance (Kinra et al., 2020). The use of ML results in a flexible mathematical structure capable of identifying linear, non-linear, and complicated connections between critical parameters. ML models are among the most explored of the most recent approaches, owing to their ability to recognize complex patterns in numerous applications. Hence, there is a high level of ML applicability in prediction (Henrique et al., 2019).

Predictive analytics is a cutting-edge approach for optimizing any operation. By examining past data and outcomes. It predicts future occurrences based on previous data. In most cases, historical data is used to build a mathematical model that captures key trends. That predictive model is then used to current data to predict what will happen next or to propose which operations to perform for the best results. Predictive analytics provides data for company continuity and longevity. Its "superpower" is the ability to handle massive amounts of data and provide enough knowledge to answer any business issue the organization may have (Garg et al., 2016).

ML arose from the study of pattern recognition and investigation of the idea that algorithms can learn from and predict data. Additionally, as these algorithms get more "intelligent," systems will be able to transcend program instructions in order to make correct, data-driven decisions (Li, Yang et al., 2019). Organizations can generate a wide range of predictions using ML models that evaluate massive quantities of data at apparently unbelievable speeds and scales. As predictions become more accurate –



and more complicated – company executives must understand the reasoning behind each prediction to reduce bias or explain the reason behind a prediction. Explainability is a notion that helps clarify how models generate specific predictions (Thorsen-Meyer et al., 2020).

This study demonstrates how to benefit from up-to-date dynamic economic big time series data, therefore contributing to the selection of economic attributes that reflect logistics performance as indicated by the LPI. The analytical technique employs a high degree of productivity in the field of ML for prediction or regression using an adequate set of economic feature subsets. The accuracy of ML prediction outputs is determined not only by the model structure and training process but also by the feature set. The feature space is generated by the initial feature set and feature selection method (Chandrashekar & Sahin, 2014). Feature selection is frequently used as part of the pre-processing phase in ML applications to obtain a subset of features by removing items with limited predictive information (Hinton & Salakhutdinov, 2006; Vieira et al., 2010).

### **1.3 Problem Statement**

According to the above statistics data, the value of global trade is declining globally as a result of the COVID-19 pandemic, with ASEAN included. In terms of ASEAN, the ASEAN economy contracted by 3.3% in 2020 due to major disruptions in economic activity caused by COVID-19. Border closures and lockdowns, for example, have weakened demand and disrupted supply chains, resulting in a general decline in trade and production. As a result, ASEAN's merchandise trade decreased by 8.0% in 2020 compared to 2019. (HKTDC Research, 2022). This pandemic also disrupts the rapid growth of the logistics service supply chain, which is a critical

component of ASEAN development. Furthermore, because resources were diverted to meet immediate needs and priorities, this outbreak has had an impact on infrastructure development (ASEAN Secretariat, 2021b).

When supply chains are threatened with a disruption such as the COVID-19 pandemic, a sustainable and robust supply chain with an adequate amount of decision information possibly has a lesser impact during the disruption event. It is feasible to significantly reduce loss and rapidly recover capabilities using appropriate strategies. In comparison, several supply chain managers and decision-makers would be unable to make timely judgments due to a lack of decision information throughout an entire network, which is the primary concern of SCM. Afterwards, the research problems for this study may be stated as follow.

The first main problem is a dearth of appropriate decision tools that promote systems thinking and assist decision-makers in anticipating the repercussions of their actions. It also provides managerial guidelines for supply chain managers to implement business models in new settings and avoid faults and pitfalls in the effort to manage disruptions and disasters in the future that may be using the COVID-19 pandemic scenario as a lesson learned.

During the COVID-19 outbreak, the supply chain manager or decision-maker may employ several approaches or short-term strategies to keep the business running. It contains recovery plans for businesses impacted by the COVID-19 outbreak. In general, if there is insufficient information to make a decision, trial and error strategies can be used to find the best option. Such methods, however, can be time-consuming and waste resources. Predictive analysis is another effective decision-making tool. The primary data from the survey method, as well as secondary data from existing big data

sources, may be used in the analysis. By using powerful predictive analytics tools, the results can be used to formulate more appropriate strategies.

Additionally, the second main problem is an absence of predicted information obtained by an effective prediction tool that could aid in policy formulation in responding to disruptive events like the COVID-19 epidemic, and the continuously improving supply chain performance is the other concern.

#### **1.4 Research Gaps**

The research gaps of this study are summarized in three points. First, performance evaluation and prediction models for supply chain measurement are necessary. These models would have to be useful for measuring individual supply chain nodes and the whole supply chain. The current research is restricted in that it presents complexity models that are subject to certain limits when applied to supply chain contexts.

Second, the requirement for measuring metrics that effectively and accurately reflect the performance of the business and supply chain in the modern perspective. For instance, vulnerability, risk, resilience, and sustainability. The implementation of supply chain performance metrics in the context of disruption scenarios such as the COVID-19 pandemic is particularly noteworthy.

Third, the significant gap in the recent year of research is the prediction of supply chain performance using the power of ML algorithms. Prediction information is required for decision-making to implement management policies in supply chain operations in normal and disruptive conditions.

## **1.5 Research Objectives**

This research will build a research framework to evaluate and predict the performance of individual corporations and its network relating to a cutting-edge perspective in SCM. The following are the four research objectives for this study:

- (1) RO1: To develop an optimization model of a novel network DEA used for supply chain efficiency evaluation.
- (2) RO2: To create a measurement metric based on a novel network DEA model for evaluating the vulnerability of a global trade supply chain of ASEAN countries from a risk and resilience perspective that resulted in the introduction of supply chain robustness guidelines under the COVID-19 scenario.
- (3) RO3: To predict risk level utilizing DEA sustainable logistics operation efficiency-based ML used for risk mitigation strategies development of Malaysian logistics service business.
- (4) RO4: To predict logistics performance utilizing DEA economics efficiency-based ML resulting in an improvement in the performance of logistics service supply chains in ASEAN countries.

## **1.6 Research Questions**

To address the research objectives, the following specific research questions are formulated:

- (1) RQ1: Is the CoDEA model suitable for assessing the efficiency of supply chain structure?
- (2) RQ2: How does a metric of risk and resilience-based efficiency of the CoDEA model represent the vulnerability of the global trade supply chain under the COVID-19 pandemic for the ASEAN countries?
- (3) RQ3: Why is the predicted risk efficiency information of ML adequate for representing the operation risk mitigation strategies for Malaysian logistics service businesses to handle the disruption of the COVID-19 pandemic?
- (4) RQ4: Why is the predicted logistics performance information of ML acceptable for portraying the improvement scenarios for the ASEAN logistics service supply chain?

The RQ1, RQ2, RQ3, and RQ4 are consistent with the RO1, RO2, RO3, and RO4, respectively.

## **1.7 Models Development Scope and Methodology**

There are two parts to the model development scope. First, in the evaluation part, a DEA optimization method is used. Second, supervised ML plays an important role during the prediction part.

Begin with the first approach, a novel CoDEA model for the network structure of a supply chain is developed. CoDEA is constantly being used to design risk and resilience-based efficiency assessment metrics. Next to the second approach, from the evaluation part, the sustainable operation risk-based efficiency of the FMEA-DEA cross-efficiency method in the first part is used to anticipate risk mitigation scenarios

using ML of the prediction part. Finally, in the third approach, the logistics performance related to the selected macroeconomic feature will provide performance prediction information using ML regression of the prediction part. This procedure also incorporates financial performance-based efficiency, which is evaluated using microeconomic features.

For the methodology, start with the development of the analytical methods, in the evaluation part, DEA, CoDEA, and FMEA combined with DEA cross-efficiency are employed. In the prediction part, moreover, Correlation, Principal component analysis, Least Absolute Shrinkage and Selection Operator, and Elastic-Net are applied for the feature selection procedure. The Artificial Neural Network, Multilayer Perceptron of Artificial Neural Network, Support Vector Regression, Random Forest Regression, Ridge, Least Absolute Shrinkage and Selection Operator, and Elastic-Net are applied for the ML regression procedure.

For the data source and data analysis tools, the development of a metric that is used to gather primary data on the operation risk of logistics service businesses in Malaysia is collected using the online risk assessment metric. Also, massive and usable secondary data is employed. The secondary data from TRADINGECONOMICS, S&P Global Market Intelligence, and World Bank LPI are gathered for the area of a global trade supply chain and a logistics service supply chain in six ASEAN countries. Finally, the analysis tool for the DEA method is Microsoft Excel Solver with Visual Basic for Applications development, and the analysis tools for ML are MATLAB and RStudio.

## **1.8 The Significance of the Study**

A study of the development of DEA optimization and ML model to supply chain measurement, where the outputs result in the efficiency level, which represents the system's performance is the primary significance of this study in terms of methodological contributions. This study's findings are included in the logistics domain's efficiency enhancement framework. As a result, the primary outcome of this research is the advancement of Malaysia's and other ASEAN countries' logistics industries in the context of logistics business and network development. Development in the way of existing based-information augmentation by prediction based-information may be carried out exactly according to the study's outputs, this is one of the practical contributions.

To support the theoretical contributions, the supply chain is a complicated business system that includes SCM concepts and practices. Supply chain performance evaluation is a critical component of SCM. The performance value may be determined from a variety of aspects, including state-of-the-art of sustainability, vulnerability, risk, and resilience. The one challenge of this research is to create an easy-to-use measurement instrument to quantify contemporary performance compatible with modern SCM concepts. The significance of this research is that it provides dependable findings in assessing the supply chain's complex systems by adopting straightforward ways to deal with a complex system.

Furthermore, measurement findings may be extended to anticipate future results, providing a high level of accuracy and precision for policy-based decision-making. It is another theoretical and practical contribution to applying the data analytics methods that will add to the worth of this research.

## **1.9 Scope of the Study**

The study's scope is determined by the area of research work. There are three parts: a global trade supply chain in six ASEAN countries, a logistics service supply chain in six ASEAN countries, and a logistics service business in Malaysia. Each area's brief information is detailed below.

### **1.9.1 A global trade supply chain of six ASEAN countries**

Six of the ten ASEAN countries were considered in this study. Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Vietnam are all included. The basis for their selection is that they have the highest level of export activity in ASEAN. Global trade, likewise, is the primary engine of their economy. These countries are defined by rapid economic growth and significant participation in the world economy (Nguyen & Almodóvar, 2018). This study was carried out in the ASEAN region using a DEA approach benchmarking tool. Furthermore, the countries have chosen to concentrate on eliminating the significant factor influencing global trade capability, namely continent geography and the enormous disparity in global trade scale.

Global trade, being a complicated supply chain, has several upstream and downstream players. The global trade supply chain structure is classified in this study into three important components, as seen in Figure 1.4. To begin, the producer node serves as the exporter. Second, the logistics and transportation sector's nodes act as intermediaries in the supply chain. It is a facilitator of product flow. Notably, the logistics and transportation industries are critical enablers of global trade (Tang & Abosedra, 2019). Thirdly, the node for international customers serves as an importer.



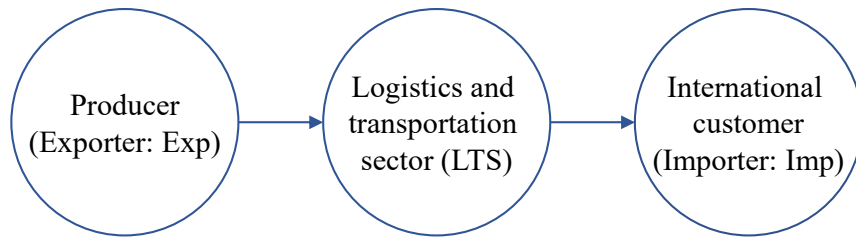


Figure 1.4 A global trade supply chain  
 Note: Developed by Author

**1.9.2 A logistics service supply chain in six ASEAN countries**

Six of ten ASEAN countries as aforementioned are also selected to evaluate the performance of their logistics service supply chain. Based on S&P Global Market Intelligence's industry classification, the logistics service supply chain was created and depicted in Figure 1.5, in which the node of logistics service providers serves as the supplier of focal companies of manufacturing. In addition, the first node of functional service providers serves as the supplier of the logistics service providers node. Figure 1.6 depicts the intended logistics service supply chain.

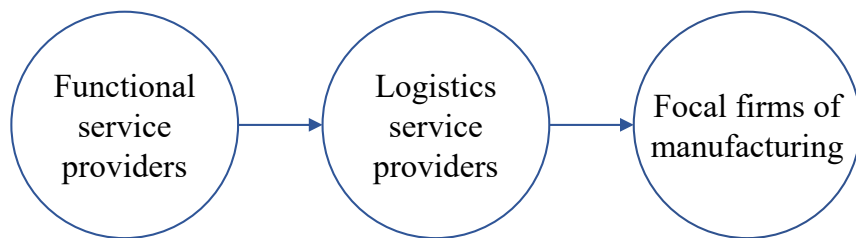


Figure 1.5 A logistics service supply chain  
 Note: Developed by Author