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Exploring the impact of Big Data analytics capability on port performance: The mediating role of sustainability

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Exploring the impact of Big Data analytics capability on port performance: The mediating role of sustainability

by

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Copyright statement

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At no time during the registration for the degree of Doctor of Philosophy has the author been registered for any other University award without prior agreement of the Doctoral College Quality Sub-Committee.

Work submitted for this research degree at the University of Plymouth has not formed part of any other degree either at the University of Plymouth or at another establishment.

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Exploring the impact of Big Data analytics capability on port performance: The mediating role of sustainability

Xiaotian Xie

Abstract

Many ports are redefining business processes and operations by adopting digital technologies. These can help them to provide efficient and competitive port operations and meet the growing demand for comprehensive port logistics services. Digital technologies provide a harvest of immense amounts of data, known as Big Data. Port management needs the capability to store, process and analyse Big Data to provide meaningful information and thus to maximise organisational performance. Furthermore, one of the most important trends in port development is increased sustainability awareness by regulators and customers. Port managers can employ Big Data technology to reduce environmental pollution and use resources more efficiently, improving the sustainability of ports. Resource-based theory provides a useful theoretical framework to investigate these issues, including the impact on port performance. There is some evidence that port sustainability has a mediating role in the association between BDAC and port performance. However, more research is needed to investigate the association between BDAC and port performance and to explore the mediation role of port sustainability.

To address this research gap, this thesis employs a multi-phase approach to investigate the impact of BDAC on port performance and the role of port sustainability in this context. In phase one of the empirical study, a conceptual model for the structural relationship between BDAC, port sustainability and port performance was developed by examining the existing research literature. After a pilot survey to examine the validity and reliability of the survey instrument, a survey was conducted in the world’s top 50 ports, which provided 175 valid responses for assessing the model. The results from these questionnaires were analysed by Partial Least Squares Structural Equation Modelling (PLS-SEM).

Analysis of the collected data revealed four main findings. Firstly, this study provides evidence that managerial skills and data-driven culture play a significant role in developing the BDAC of ports. The second major finding provides empirical evidence that BDAC positively enhances port performance. Thirdly, the finding shows that ports can improve sustainability by developing BDAC. Finally, the findings highlighted that port sustainability mediated the relationship between BDAC and port performance. Ports that aim to improve performance should leverage BDAC to implement sustainable port strategies. The study makes several theoretical and practical contributions. The main contribution of this study is developing a hierarchical model based on resource-based theory to evaluate the impact of BDAC on port performance, providing a better understating of how the port builds BDAC and their significant role in port performance. Moreover, this study reveals the mechanism driving the impact of BDAC on port performance, providing a deeper understanding of the significance of sustainability. Furthermore, this study provides practical guidance for port managers to assist them in making clear strategies to build and utilise BDAC. Port managers should leverage port sustainability to catalyse the impact of BDAC on port performance.

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List of Abbreviations

AI	Artificial Intelligence
AMOS	Analysis of Moment Structures
AVE	Average Variance Extracted
BDA	Big Data analytics
BDAC	Big Data analytics capability
CB-SEM	Covariance-based Structural Equation Modelling
CITC	Corrected Item-total Correlation
DMP	Data Management Plan
GHG	Greenhouse Gases
HOC	Higher-order component
HOM	Higher-order model
HTMT	Heterotrait-monotrait Ratio
IBM	International Business Machines Corporation
ICS	Information and communication systems
IMTS	Inter-modal transport services
IOT	Internet of Things
IT	Information Technology
KBV	Knowledge-based view
LISREL	Liner Structural Relations Statistical Software
LOC	Lower-order component
LRT	Long-term relationships
MSO	Multimodal systems and operations
OPIT	Organisational information processing theory
PLS-SEM	Partial Least Squares Structural Equation Modelling
POC	Port Operation Companies
PSC	Port Supply Chain
PSCI	Port Supply Chain Integration
RBT	Resource-based Theory
SCIP	Supply Chain Integration Practices
SCM	Supply Chain Management
SEM	Structural Equation Modelling
SPSS	Statistics Package for the Social Science
TBL	Triple Bottom Line
TESCI	Seaport Terminal Supply Chain Integration
TOC	Terminal Operating Companies
VAF	Variance Accounted For
VALS	Value-added Logistics Service
VAS	Value-added Services

Chapter 1. Introduction

1.1 Introduction

New technology, such as the Internet of Things (IoT), artificial intelligence (AI), sensing solutions, Big Data analytics (BDA) and automation technologies, are significantly affecting world supply chains. As core nodes of the global supply chain network and logistics, ports need to introduce new technologies, management concepts and business models to adapt to the highly connected and dynamic global environment (Jardas et al., 2018). One shift in the new business model is the adoption of digital technology to reshape existing processes and business operations at the port (Tijan et al., 2021, Zarzuelo, 2021). To achieve the digital transformation and gain competitiveness from this transformation, port authorities need to develop a capability to utilise the rich data resources of the port area (Philipp, 2020, Munim et al., 2020).

This Chapter presents an overview of the research and is divided into five sections. The first section explains the background and motivation of this study. Secondly, the research aim and objectives are outlined. The third section highlights the research gap and the significance of this research, while the next section briefly explains the research method. Lastly, a summary of the research structure is provided.

1.2 Research Background and motivation

Since the onset of the COVID-19 pandemic in 2019-2020, countries and authorities have implemented lockdowns, social separation, and border closures. These safety measures interrupted and disrupted sustainable development of supply chains, functioning of the global supply chain and international trade flows (Chowdhury et al., 2021). Ports are significant nodes of the supply chain network and have been impacted (Mańkowska et al., 2021, Narasimha et al., 2021). For example, such as the port of Genoa recorded a reduction of 14% in overall traffic in 2020 (Caballini et al., 2022). In addition, due to COVID-19, the effective workforce at many ports has decreased, schedule reliability has fallen from 80% to 30%, and waiting times and turnaround times have increased, consequently leading to supply chain disruption (Merk et al., 2022). Although the COVID-19 pandemic significantly impacted port operations, it can be viewed as the catalyst for the restructuring of port operations, especially through the use of smart and digital technologies such as IoT, Big Data, cloud analytics, Blockchain and digital supply chains, and the improvement of sustainability (Alamoush et al., 2022, Cuong et al., 2022, Merk et al., 2022).

It has been stated that the use of Big Data is one of the most significant enabling factors of digitalisation (Talwar et al., 2021, Vaggelas and Leotta, 2019). Ports can create and gather rich data from their operations and supply chain participants (Mirović et al., 2018). To digitise the port and derive value from this transformation, port authorities need to develop a capability to utilise rich data resources of the port area (Philipp, 2020, Munim et al., 2020). Much previous work (Shamim et al., 2020, Jha et al., 2020, Ciampi et al., 2020a, Mikalef et al., 2019a, Gopal et al., 2022) on Big Data technology has indicated that Big Data analytics capability (BDAC) is a crucial capability that drives firm performance to realise firms' differential value. Organisations that developed BDAC can better manage and analyse massive data to gain insight, thereby achieving effective and efficient decision-making and improving organisational performance (Su et al., 2021). Although the importance of BDAC has been investigated by different scholars adopting different perspectives, the research on BDAC and organisational performance remains in its infancy (Lozada et al., 2019, Dubey et al., 2019b, Mikalef et al., 2019a, Olabode et al., 2022, Wei et al., 2022). Thus, it is necessary to investigate further the correlation between BDAC and organisational performance to help organisations better utilise BDAC and gain competitive advantages from digital transformation.

Furthermore, while advanced technologies are available to ports, such as smart cargo handling equipment and machine learning (Yeo et al., 2019, Jović et al., 2019a), digital transformation does not depend solely on a technology strategy. The state-of-the-art technologies should be firmly anchored to a larger strategy and must be supported by top managers and organisational culture (Davenport and Bean, 2018). BDAC is about more than technology, since it includes human resources and intangible resources that are required to build an inimitable BDAC resource (Mikalef et al., 2020). Based on resource-based theory (RBT), building BDAC requires seven resources: data resources, technology resources, basic resources (time and investment), technical skills resources, managerial skills resources, data-driven culture resources and organisational learning resources (Gupta and George, 2016). Although there is a growing body of literature focused on BDAC, most recent research work on BDAC has related to financial firms, information firms, manufacturing firms and hospitals (Upadhyay and Kumar, 2020, Shamim et al., 2020, Yu et al., 2021b, Gu et al., 2021, Dubey et al., 2021, Ciasullo et al., 2022). The concept of BDAC extends the view of Big Data technologies and could help port authorities to better deploy and manage Big Data initiatives and gain insights into the process. Thus, ports need to learn more about how to build BDAC and get ready to use it.

Ports are a driving force of economic development and high-quality employment. However, with the ever-increasing commercial activities of ships and the operation of containers continuing to pressure terminals, ports are carbon-intensive and experience substantial pollution levels (Alzahrani et al., 2021). Meanwhile, due to the increased pressure from international (e.g. 2015 COP21 Paris agreement) and regional regulations (e.g. EU European green deal), ports have received significant attention to reduce their carbon footprint and optimise energy consumption (Sadiq et al., 2021). Thus, ports need to keep innovating to address port sustainability concerns (Stanković et al., 2021). A growing body of literature (Del Giudice et al., 2022, Philipp et al., 2021, Tsolakis et al., 2021, Yau et al., 2020, Jović et al., 2020) argues that digital technologies are a reliable approach to addressing port environmental and social issues while attaining economic benefits. Hence, it can be posited that sustainability has a mediation role between BDAC and port economic performance. For example, Big Data technology could help port managers evaluate water and air pollution monitoring data to make informed decisions to improve sustainability (Heilig and Voß, 2017). Although sustainability has been highlighted by various scholars (Kronfeld-Goharani, 2018, Parola et al., 2017, Ashrafi et al., 2020, Styliadis et al., 2022, Campisi et al., 2022) as a central point for improving port competitiveness, the mediation role of sustainability still seems to be neglected. This was supported by existing literature review studies (Lim et al., 2019, Davarzani et al., 2016, Shin et al., 2018, Del Giudice et al., 2022, Lee and Mangalaraj, 2022). Their research result shows that there was a lack of empirical evidence for investigating the mediating effect of port sustainability on the relationship between BDAC and port performance. In addition, understanding the methods by which a BDAC can affect organisational performance is restricted (Awan et al., 2021, Bahrami et al., 2022, Wamba and Akter, 2019). Therefore, considering the aforementioned arguments, the motivation of this study is to investigate the impact of BDAC on port performance and the mediating effect of port sustainability on this relationship.

1.3 Research aim and objectives

As discussed above, the relationships between BDAC, port sustainability and port performance need to be investigated in greater depth. Thus, the researcher formulated the following research aims and research objectives:

The aim of this research:

- To investigate the association between BDAC and port performance and explore the mediation role of port sustainability.

The following objectives were used to achieve this aim:

- To develop a structural model for BDAC, port sustainability and port performance and create a relevant measurement.
- To identify the key components of BDAC in the port area.
- To assess the direct relationships within the proposed structural model.
- To investigate the mediation role of port sustainability on the relationship between BDAC and port performance.
- To provide recommendations for port managers to develop BDAC and improve performance.

1.4 Significance of the Research

This research contributes to understanding the relationship between BDAC, port sustainability and port performance in several ways. According to a study of the pertinent literature, prior research has focused on examining the potential and problems that BDAC presents to financial organisations, information firms, manufacturing firms, and hospitals (Awan et al., 2021, Mikalef et al., 2020, Gunasekaran et al., 2017, Wang et al., 2018b, Galetsi et al., 2020, Upadhyay and

Kumar, 2020). However, based on recent publication (Inkinen et al., 2021, González-Cancelas et al., 2020, Zarzuelo et al., 2020, Yau et al., 2020, Heikkilä et al., 2022), it indicates that research on Big Data and sustainability remains relatively scarce within the domain of port studies. Consequently, by investigating the effect of BDAC on port performance, this study will help to fill a gap in the research literature and help port managers in acquiring a more thorough understanding of the potential value of BDAC.

Moreover, the research has identified seven resources, including data, technology, basic resources, technical skills, managerial skills, data-driven culture and organisational learning, that can help the port authority to build BDAC. In order to structure and leverage BDAC, ports need to combine technology and data resources with several complementary resources. Some scholars (Dubey et al., 2018a, Gupta and George, 2016, Yasmin et al., 2020, Awan et al., 2021) have explored what organisational resources are necessary for implementing Big Data initiatives in the manufacturing, financial services and consumer goods sector. However, BDAC is a construct which has not been widely studied in port areas (Philipp, 2020, Yap and Ho, 2021). Different organisations have different management initiatives, technology requirements, internal organisational processes and organisational cultures. Hence, it is significant to understand the organisational resources and development process that ports require to build their BDAC (Vrakas et al., 2021). This research adopts the RBT perspective to investigate the key resources that can drive the BDAC of ports. By exploring the significance of human and intangible resources, this study contributes to the current literature and practice of BDAC construction.

Furthermore, this research is effectively a response to the call by various international scholars for more research on BDAC and its impact on firms (Mikalef et al., 2019b, Arunachalam et al., 2018, Rialti et al., 2019, Wamba and Akter, 2019, Ferraris et al., 2019, Awan et al., 2021). Although these studies reveal the benefits that BDAC bring to organisations, there is a limited body of understanding on how BDAC can be utilised at the firm level and the mechanisms through which BDAC can improve firm performance (Mikalef et al., 2020, Bahrami et al., 2022). This study develops a structural model to investigate the relationship between BDAC, port sustainability and port performance. It provides a more holistic understanding of leveraging BDAC to create value. Meanwhile, this study embeds port sustainability into the strategy that ports gain competitive advantages from Big Data initiatives. Although a number of studies have explored the relationship between digitalisation and port sustainability, most of them have focused on utilising new technologies to improve energy efficiency, operation efficiency and environmental performance (Alamoush et al., 2020, Tsolakis et al., 2021, Garrido Salsas et al., 2022, Gerlitz and Meyer, 2021, D'Amico et al., 2021). Little attention is paid to the impact of digitalisation on the business model of ports, especially integrating sustainability into the digitalisation of processes to create value (Del Giudice et al., 2022, Wang and Sarkis, 2021). Thus, this study fills this research gap by adopting port sustainability as a mediator to explain how BDAC affects port performance. It also can help port managers better leverage BDAC and guide port managers to develop Big Data related strategies.

Last, there is a gap in the literature regarding developing a measurement model for the construction of ports' BDAC and port performance. This aspect has recently been identified as requiring additional work. Most previous work on BDAC's influence has focused on financial management, healthcare management, industry 4.0, and supply chain management (Khanra et al., 2020, Kushwaha et al., 2021, Maheshwari et al., 2021, Sabharwal and Miah, 2021, Yu et al., 2021b, Ramadan et al., 2020). In the professional and scholarly domains of ports, there is a lack of a universal model to evaluate the development of BDAC (Philipp, 2020, Brunila et al., 2021, Boullauazan et al., 2022). As an increasing number of ports have implemented Big Data initiatives, port managers need a model to guide them in developing digital strategies for ports (Molavi et al., 2020, Heilig et al., 2017). Thus, this research presents a measurement model for the BDAC of ports, covering three dimensions: tangibles, intangibles and human resources. This is a benefit for future researchers to investigate the role of ports' BDAC. It also can help port managers and stakeholders to evaluate their efforts and develop more effective strategies.

1.5 Method

The study uses a survey to collect quantitative data to examine the relationship between BDAC, port sustainability and port performance. The five-point Likert scale questionnaires were distributed to ports' managers and employees at the world's top 50 ports. The questionnaire was translated into Chinese as many of the world's top 50 ports are located in China. PLS-SEM was then used to analyse collected data and assess the research hypotheses. PLS-SEM can provide analysis efficiently with small sample sizes and achieve more validity and reliable results when the research model is extremely complicated.

1.6 Structure of the thesis

This thesis is organised into eight chapters. In Chapter One, the research background and motivation of the study have been presented. Then research aim, objective, gaps, research method was briefly outlined and key contribution were explained. Finally, the thesis structure is outlined. The diagrammatic framework of this thesis is shown in Figure 1.1 as an overview.

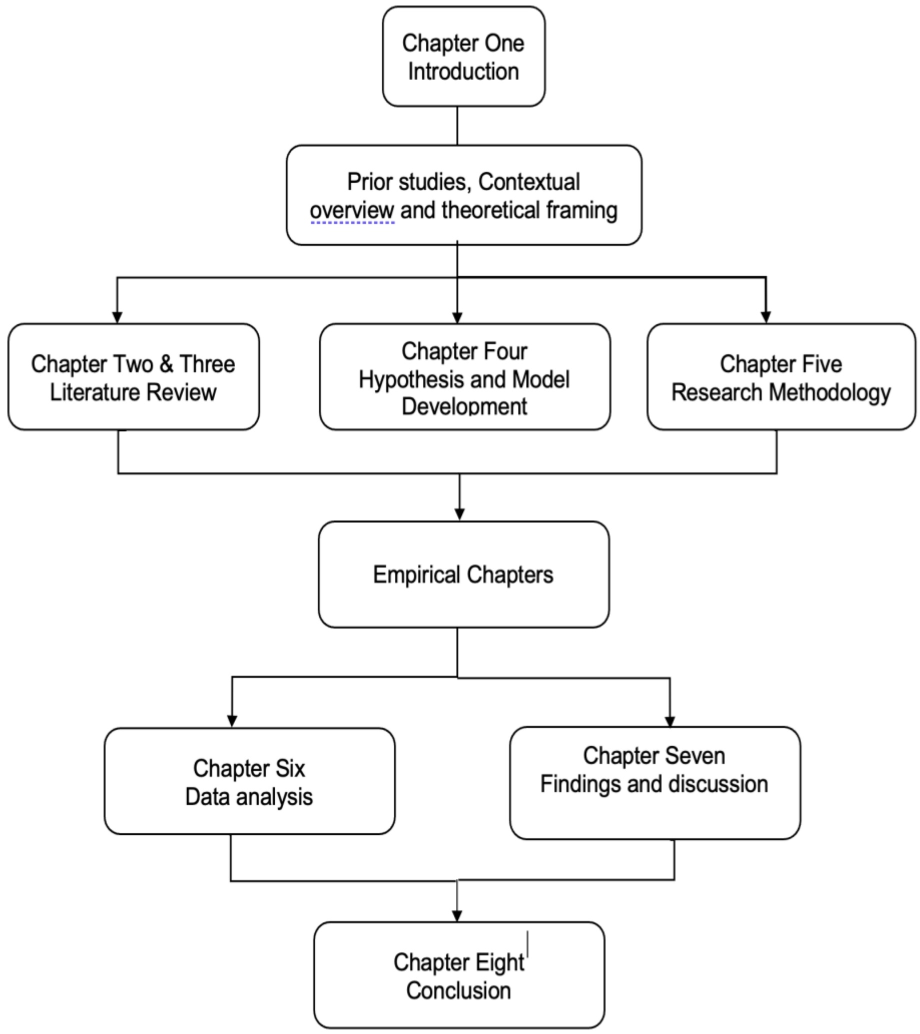

Figure 1.1 Thesis structure

The second chapter examines port sustainability and port performance. It describes the evolution of ports and explains their shifting function. The chapter then investigates port sustainability in-depth and discusses its three dimensions. Finally, the chapter evaluates the available research on port performance and identifies the most significant research gaps.

Chapter three focuses on reviewing Big Data and BDAC. It starts with the definition of Big Data, followed by a discussion of the characteristics of Big Data. Then the chapter gives an overview of Big Data technology in the ports, supply chain, and maritime areas and identifies the challenges of applying Big Data technology in ports. Finally, this chapter discusses the definition and determinants of BDAC.

After reviewing the literature and identifying research gaps, Chapter four develops the theoretical mode of the relationship among BDAC, port sustainability and port performance. This chapter starts by outlining and explaining the hypotheses that will be tested. Following a discussion of the relationships of the selected constructs, this chapter presents the structural and measurement models used for analysis.

The fifth chapter describes the research methods utilised for the study. It begins with discussing and justifying the research philosophy and research paradigm. Then, the research approach and strategy are selected based on the discussion. This chapter discusses the data collection and analysis methods used to test the proposed model. Meanwhile, this chapter details the sampling design, questionnaire development and improvement. Finally, the result of the pilot survey is presented, and the issues of reliability and validity are discussed.

The data analysis and survey findings are presented in the sixth chapter. The chapter starts with descriptive statistics to describe the sample statistics and characterises. Then, the chapter details how the analysis was carried out using partial least squares structural equation modelling (PLS-SEM). The chapter assesses the measurement model to test the validity and reliability of the model used in the survey. Finally, the chapter concludes by testing hypotheses.

Chapter seven provides a discussion of the main finding and study results. It begins by discussing each research hypothesis and linking them to the literature. The research objectives proposed in the thesis are addressed systematically. This chapter also examines whether the findings confirm or contradict the literature and provides reasons why these contradictions exist.

The eighth chapter summarises the results of the research in accordance with the aim and objective of the investigation. Then the theoretical contributions and managerial implications are discussed. Finally, the chapter also outlines the limitations of this research and provides recommendations for future research.

Chapter 2 Port performance and port sustainability

2.1 Introduction

During the last decades, the significance of ports has transformed from traditional transhipment points into vital nodes in the supply chain and logistics activities. Digitalisation is currently regarded as one of the primary port development strategies (Paulauskas et al., 2021). Digital technologies are reshaping the supply chain and transforming how ports operate in the global supply chain network. This transition may result in significant improvement in port performance. Moreover, sustainability development is challenging ports around the world. Port managers need to recognise the significant role of the triple bottom line principle in port management and find ways to improve environmental, social, and economic performance (Stanković et al., 2021).

This chapter includes three sections. This chapter begins by examining the evolving function of ports in the supply chain and port development, focusing on relevant definitions, concepts, and features. Second, it reviews existing literature on port performance and explores the factors that can be used for evaluating the port performance after the port integration into the supply chain. Finally, it reviews existing literature on port sustainability, including environmental, social, and economic sustainability.

2.2 New Role of Ports

The management concepts and business models of ports have shifted over the last few decades to adapt to the highly connected and dynamic global environment (Jardas et al., 2018). Ports are important in terms of transportation and trade. There are many different definitions that exist for ports. For example, Hlali and Hammami (2017) defined a port as a geographical area where ships and other kinds of transport can load and unload cargo from ship to shore and vice-versa. Moon et al. (2018) indicated that ports are locations for cargo handling and passenger traffic exchange between vessels, between vessels and overland transports, and alongshore sites. From both definitions, the important role of ports can be identified. Traditionally, the port played a significant role in transhipment which is an interface between water and land transportation and provides infrastructure and basic service for loading/unloading, ship operation, storage and transportation. Fahim et al. (2021b) indicated that ports have historically been less involved in hinterland integration and cooperation with the port community. With the supply chain becoming the basis of competitiveness, the role and strategy of ports are reshaped in the global supply chain area. In the new role, the port has become a significant part of the global supply chain, creating more value by collaborating with stakeholders involved in PSC (Tongzon et al., 2009, Botti et al., 2017, Wang and Du, 2019).

2.2.1 Port supply chain

The growing importance of ports in the supply chain necessitates a closer look at the port supply chain (PSC). Many academic studies evaluated the concept of PSC and analysed PSC from different perspectives. Lee et al. (2003) decomposed the supply chain into port levels and developed the concept of the PSC, which focuses on the supply chain of import and export services, materials and products within port operation. They demonstrate that the entities comprising the PSC include suppliers, ships, ports, and distributors, and they concentrate on the port operation of the products and services supply chain. Although analysing PSC from the port level has some limitations, it provides a basic understanding of PSC. Robinson (2006) investigated the concept of PSC from the dimension of a landside supply chain and developed the concept port-oriented supply chain. The study of Robinson integrated ports with functions and activities of landside logistics, which extend the boundary of the concept of PSC, meet the requirement of customers and create more value. PSC entities include port authority, terminal, rail operator, trucking operator and depot. (Alamoush et al., 2021a). From the ports' point of view, a port-oriented supply chain not only could improve cargo throughput but also could transfer some non-essential activities inland to face the increasingly complex business environment (Monios and Wilmsmeier, 2012). Port-oriented supply chain integrates port and landside supply chains and develops a comprehensive concept of PSC.

However, with the development of ports' value proposition, Mangan et al. (2008) recognised the impact of ports on the port perimeter and supply chain. They suggested ports provided more value-adding services and activities to support a wider supply chain, undertaking a critical role in the supply chain. The value proposition of ports should evolve beyond providing basic service to becoming a strategic logistics server in the whole supply chain (Stevens and Vis, 2016). Shi and Li (2016) indicated that logistics service providers and terminal operators are reconsidering their strategies to develop the logistics network between port and inland terminals to gain more profit and create more value for customers. Several scholars (Amonkar et al., 2021, Veenstra et al., 2012, Protic et al., 2020, Han, 2018) have argued that intermodal transport services can help ports collaborate with inland logistics providers, offering value-added service for shippers. These studies investigated the PSC from a value perspective and indicated that the port as the value canter could integrate multiple service chains to improve the flow and value of the whole supply chain.

Although the studies of Lee et al. (2003), Robinson (2006), Alamoush et al. (2021a), Shi and Li (2016) and Protic et al. (2020) demonstrate that the concept of PSC is constantly evolving from port-level to a network involved in the co-creation of value, most of them consider the PSC as a network of participants sharing resources. Few studies have investigated the PSC as a complex system (Botti et al., 2017). Therefore, this research considers that PSC could be referred to as combining various services providers (multimodal transportation, storage, handling, processing, distribution, customs, and even financial and business services companies) and customers (shippers and shipping companies, etc.) into one system by IT to achieve the smooth flow of information, logistics, and capital across the entire supply chain. Numerous scholars (Alavi et al., 2018, Di Vaio and Varriale, 2020, Botti et al., 2017, Seo et al., 2016, Amonkar et al., 2021) pointed out that building PSC requires the support of advanced IT, which can help ports managing data and enhance communication between ports and supply chain participant. Therefore, ports need to build advanced data technology to achieve a new role in the global supply chain. The following section will investigate the function of ports in logistics and supply chains further.

2.2.3 Port Supply Chain Integration

In the supply chain framework, ports need to attain a higher level of integration with the supply chain, which is relevant to their business. Some scholars recognise that manufacturers and traders require PSC to integrate information and goods flows to construct a global supply chain (Han, 2018, Tseng and Liao, 2015, Osobajo et al., 2021). Supply chain integration can be defined as a set of practices or a process of identifying and connecting supply chain participants through coordinating or sharing information and resources (Tiwari, 2020). Thus, port supply chain integration (PSCI) is the process in which ports can coordinate and interconnect inter-organisational and stakeholders (Bo and Meifang, 2021). An increasing number of studies (Woo et al., 2013, Stevens and Vis, 2016, Yuen et al., 2019, Han, 2018, Host et al., 2018, Panayides and Song, 2009, Venkatesh et al., 2020, Li et al., 2021) have investigated the concept, patterns and implications of PSCI. The concept and influence of PSCI will be discussed thoroughly below.

Panayides and Song (2009) have investigated the new role of the port in the supply chain and found the phenomenon of integration of ports in supply chains. They termed the integration of seaport/terminals in supply chains as 'Seaport Terminal Supply Chain Integration (TESCI)’ and defined the term as "the extent to which the terminal establishes systems and processes and undertakes functions relevant to becoming an integral part of the supply chain as opposed to being an isolated node that provides basic ship-shore operation" (Panayides and Song, 2019, p. 134). The study of Woo et al. (2013) uses the term 'Port Supply Chain Integration (PSCI)' for the phenomenon. Adapting the definition of Song and Panayides (2008), Woo et al. (2013) considered that PSCI is a strategy undertaken by a seaport terminal to integrate various functions and organisations in a supply chain to become an integral part of the supply chain. They indicated that the entity to execute the strategy is a company operating a seaport terminal termed Terminal Operating Company (TOC) or Port Operating Company (POC).

Panayides and Song (2009) discussed the components or constructs that can be utilised to conceptualise PSCI, and they conceptualised TESCI with four components: information and communication systems (ICS), value-added service (VAS); multimodal systems and operations (MSO); and supply chain integration practices (SCIP). Tongzon et al. (2009) tested the components and measured variables used from TESCI and assessed the extent of supply chain integration of terminals at the Korean port of Inchon using the measurement instruments. Woo et al. (2013)

developed the TESCI model and presented five constructs to constitute PSCI: ICS, long-term relationships (LTR), value-added logistics services (VALS), inter-modal transport services (IMTS), and SCIP. PSCI refers to the actions made by terminals to expand their service range from fragmented transportation to integrated logistics, which encompasses multimodal transport and value-added operations. Thus, value-adding services and intermodal transportation are the core components of PSCI.

With the PSC extending to the hinterland, PSCI should be discussed at the border level rather than the level of port operating companies. Stevens and Vis (2016) described the concept of PSCI through a changing value proposition. They defined PSCI as the amount to which a port authority plans, organises, and coordinates activities, processes, and procedures linked to physical, informational, and financial flows throughout the supply chain beyond its gates and monitor the performance of such activities. This perspective is supported by port regionalisation. Much research (Nebot et al., 2017, Wang et al., 2018a, Santos and Soares, 2017) on port regionalisation suggest that it involves the simultaneous functional-economic and spatial integration of ports, inland logistics zones, suburban and urban economies and hinterlands. PSCI could be considered as part of port regionalisation.

Wang et al. (2018a) indicated that port regionalisation needs some strategies to build an efficient and seamless supply chain and transportation system to link ports more closely to hinterland freight distribution centres. Nebot et al. (2017) and Santos and Soares (2017) emphasised the relationship between port regionalisation and intermodal transportation, explaining that port regionalisation needs to develop a corridor within ports and hinterland rather than a low connectivity transportation system. Thus, the development of intermodal transport services which link the ports and hinterland should be an important component for PSCI and port regionalisation.

Therefore, the perspective of PSCI should develop to a higher scale beyond the port perimeter. The following Figure 2.1 shows the diagram of PSCI.

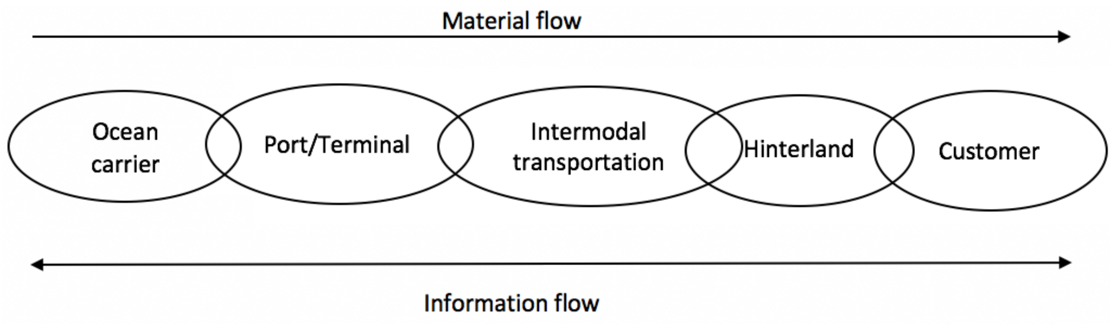

Figure 2.1 Port supply chain integration
Source: Adapted from Jiang et al. (2018)

Figure 2.1 emphasises two key factors for improving PSCI: inter-modal transport and information integration. PSCI should involve extended port activities into the hinterland through intermodal transportation services to achieve integration in a broader sense. Moreover, ports need to cooperate with all supply chain members to share operational and strategic information, meeting the customers' requirements. It is clear that the PSCI depend on information and communication integration. IT and communication systems are significant ingredients for developing PSCI (Ascencio et al., 2014, Yang et al., 2015). IT enables ports to share information such as cargo handling, transport operation and distributor inventory levels with upstream and downstream partners. Port supply chain participants can make the right decision quickly by sharing information, improving the timeliness and reliability of ports (Kia et al., 2000, Yuen and Thai, 2017). Furthermore, IT can assist ports in integrating information systems and goal alignment with all network members to respond to customers' needs, offering more VAS to provide maximum customer value (Thai and Jie, 2018). There are numerous scholars have contended that IT can help port developing PSCI and reveals the significance of IT capabilities for port developments. Thus, the researcher needs to assess the extent to which BDAC contribute to improving the status of the ports as an impotent node in the global supply chain.

2.2.4 Digitalisation of Ports

In the background of global digital transformation, ports are particularly affected by technological change. Digitisation is a dynamic process of changing production factors, productivity, and production relations through the rapid development of new-generation IT such as Big Data, cloud computing, and AI (Ritter and Pedersen, 2020). The ports have evolved over five generations. The following figure shows the characteristics of the ports' five generations. The ports of the first generation acted as a hub for land and marine transports and provided straightforward operating activities. The second-generation ports integrate with their surroundings via transport, industrial, and commercial functions. The third-generation ports exceeded the requirements of a simple port and served as a logistic centre to provide intermodal transportation and VAS. Based on the port development strategy, the range of providing port services and the level of IT integration, the fourth-generation ports use communication networks to connect different port areas and allow collaboration with other ports (Yau et al., 2020). Meanwhile, their ports can integrate into an intermodal transportation network to achieve internationalisation and diversify their activity. Due to digitalisation and smart technologies, ports are ready to face the fifth-generation challenge. Compared with 4th generation ports, the 5th generation ports are more customer-centric and community-focused smart ports (Yau et al., 2020).

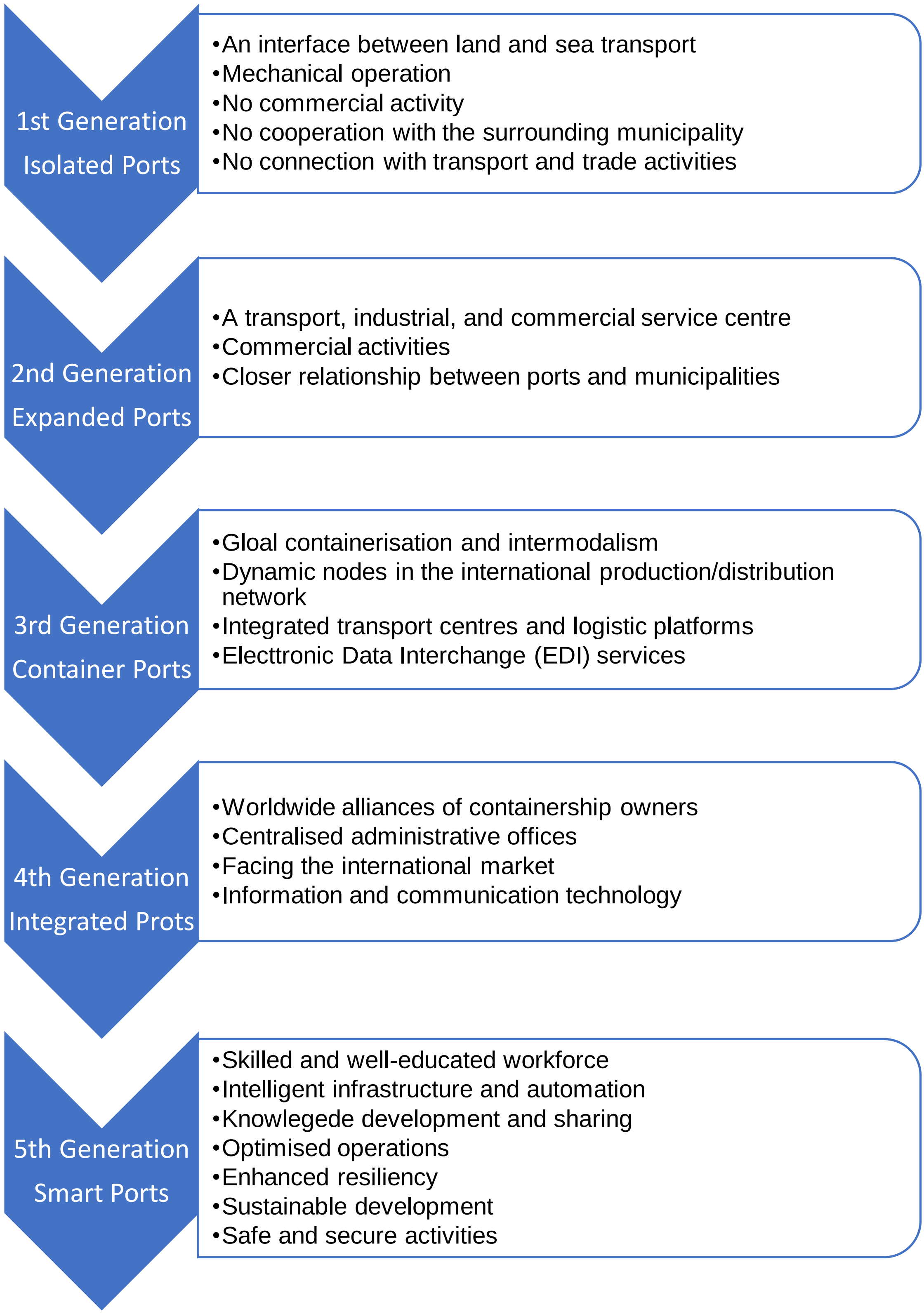

Figure 2.2 Five generation of ports

Source: Adapted from UNCTAD (1999), Molavi et al. (2020) and Rajabi et al. (2018)

To become a 5th generation port, ports need to provide high-level customer-centric by implementing high-end IT solutions (Lee et al., 2018b). Smart port technology can be explained as integrating new technologies, including Big Data, IoT, autonomous vehicles, AI, augmented reality and 3D printing (Jun et al., 2018, Inkinen et al., 2021). These digital technologies are regarded as enablers for digital transformation; hence, smart ports present that the digitalisation of port activities is at the forefront (Jović et al., 2019a). Through digitalisation, ports can change the business environment and operation mode to optimise the operation and function, bringing new business opportunities and progress (Ilin et al., 2019). In addition, the existing literature (Jun et al., 2018, Di Vaio and Varriale, 2020, Rodrigo González et al., 2020, Kaliszewski, 2018) emphasises that digitisation can help ports build an intelligent and collaborative platform which could allow community members to share and manage data, improving participation and collaboration among related stakeholders. As digitisation deepens, port managers can better monitor the operational process and gather data to make decisions, enhancing the efficiency of port operations and competitiveness (Yau et al., 2020). Much previous work on the potential of port digitisation has focused on adopting new digital technologies to optimise the network, improve cargo handling, and improve port operation (Inkinen et al., 2019). Although ports have various digital technologies to choose from, the key issue to the success of the digital transformation is the adaptation of organisational aspects (González-Cancelas et al., 2020). Therefore, it is necessary to investigate the impact of BDAC on port development.

2.3 Port performance

Ports need to monitor their performance from broader aspects rather than purely operational features since digitalisation reshapes existing processes and business operations after the port (Vaggelas, 2019, Tijan et al., 2021). Much previous work on port performance focus on port productivity and internal operation efficiency (Bichou and Gray, 2004, Brooks and Pallis, 2008, de Langen et al., 2007, Feng et al., 2012). Thus, numerous research on port performance in the literature either utilised operation performance in place of port performance or incorporated an operational indicator into port performance (Bucak et al., 2020). The Operation efficiency of ports is mainly determined by container cargo handling, cargo handling capacity, and duration time of ship’s stay in the port (Song and Liu, 2020). As rivalry among ports has intensified, ports must operate with little delay, maximum efficiency, and fair costs to capture customers' interest (Olalere et al., 2015). Chandrakumar et al. (2016) argued that in the context of lean ports, ports focus on reducing resource consumptions, non-value operations and idle times to enhance the transhipment productivity. With port integration into the supply chain and providing a wider range of services, efficiency becomes a significant factor in reflecting the performance of ports. (Brooks, 2006). There is a growing body of research attempting to broaden the port performance debate beyond operating efficiency (Woo et al., 2011, Rezaei et al., 2018, Talley et al., 2014, Fahim et al., 2021a, Dong et al., 2019). They claimed that port authorities must better understand the cost-effectiveness and quality of their operations. Ports add more value to the cargo through various providers of port services, thereby further integrating into the value chain and service network. The flowability of PSC can be greatly influenced by the quality of port services, and unreliable services can cause customer dissatisfaction (Thai, 2016, Talley et al., 2014). Ports must strive to provide high-quality services at a low cost to improve customer satisfaction and competitiveness (Fahim et al., 2021a). The level of port services is determined by operational efficiency, quality and cost-effectiveness of services. Thus, these elements are the decisive factors for ports to attract customer competition (Hlali and Hammami, 2017).

In addition, based on the discussion of port development (sections 2.2 & 2.3), many scholars have noted that ports will compete not simply based on operational efficiency and service quality but focus on providing VAS and becoming customer-centric (Menegaki and Alexopoulos, 2017, Protic et al., 2020, Zhang et al., 2019c, Woo et al., 2011, Stevens and Vis, 2016). Among all stakeholders, customers are the most significant stakeholder group. Ports should provide VAS that is connected with cargo, information, financial, and business flows in response to customers' demands for additional services beyond the typical port services (Shi and Li, 2016). Menegaki and Alexopoulos (2017) also emphasised that VAS given by ports have become a critical aspect in attracting and maintaining the number of customers, which could help ports to face the competition among the ports. Furthermore, due to ports being regarded as a significant node of the global supply chain, the value proposition of ports should orient towards serving the customers' needs (Stevens and Vis, 2016). There are many scholars (Giannikas et al., 2019, Göçer et al., 2019, Jeng, 2018, Karatas-Cetin, 2021) have indicated that customer orientation is a key success element, and ports and supply chain participants target to offer more customer-oriented services by providing customisation and flexibility to their customers. Göçer et al. (2019) highlighted that the resources of the port are limited. Ports need to analyse the markets and discover the requirement of customers to distribute resources efficiently, achieving sustainable success. Given the preceding debate, new port performance indicators should be formed due to the shifting functions of ports. Therefore, following the prior studies, this employs service quality, cost, operational efficiency, VAS, and customer orientation to assess port performance comprehensively.

2.4 Port Sustainability

Ports are under increased pressure to meet regulatory and social requirements for operational sustainability. This section focused on port sustainable development and investigated the three dimensions of port sustainability. Sustainable development was defined as "meeting the need of the present generation without compromising the ability of future generations to meet their own needs" by the report "Our Common Future" by the World Commission on Environment and Development produced in 1987 (Brundtland and Khalid, 1987, p. 43). In 1997, John Elkington disseminated the concept of the Triple Bottom Line (TBL), which demonstrated three dimensions of sustainable development (Elkington and Rowlands, 1999). Figure 2.3 will show the TBL.

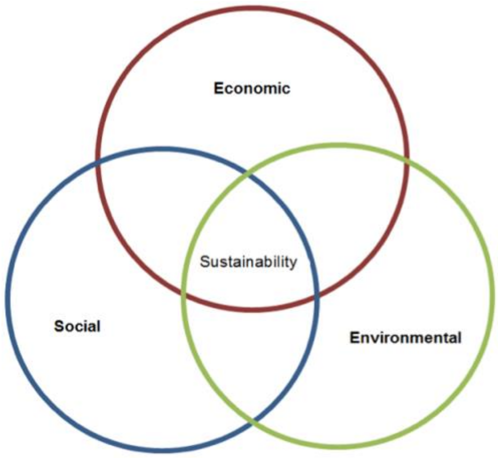

Figure 2.3 Triple Bottom Line

Source: Elkington and Rowlands (1999)

In Figure 2.3, true sustainability is shown as the intersection of the economic, environmental and social dimensions. Therefore, achieving the sustainable development of ports must find an appropriate balance of economic, social and environmental impacts. Although the development of ports benefits the economy and society, it generates environmental and social challenges (Lam and Li, 2019). Due to the management and operation of ports involving many stakeholders, ports need to balance the three-legged stool of environmental sustainability, commercial sustainability and engagement with the widest possible community of interests. Moreover, stakeholders of ports pay more attention to ports' environmental, social and ethical performance and bring greater pressure on the port development strategy (Sislian et al., 2016). The bias among stakeholders will restrict the integrated consideration of economic, social and environmental factors (Amankwah-Amoah et al., 2019). As ports become increasingly accountable to a broader range of stakeholders (Ashrafi et al., 2020), the influence of each stakeholder's perspective on all aspects of strategic port management is crucial and should be acknowledged. Several studies (Dooms, 2019, Cheon, 2017, Ashrafi et al., 2020, Ignaccolo et al., 2018) have determined that port sustainability should involve collaboration both within the organisation and with port partners, including terminal operators, stevedoring companies, ocean carriers, and trucking companies. Roh et al. (2023) have carried out an extensive study on external management practices of sustainable port development and note that port managers have recognised the importance of working with business partners to implement sustainable port development. Specifically, Roh et al. (2023) point out that a high level of buy-in is required from port managers to work with business partners to set environmental goals, agree on environmental responsibility, cooperate to address environmental risks and build green supply chains. Moreover, Lu et al. (2016b) proposed the impact of sustainable PSC on port sustainability performance. They found that port managers should establish collaborations with various stakeholder groups to accelerate the adoption of sustainable supply chain management (SCM) and enhance sustainability performance. Thus, ports need to incorporate stakeholders into the decision-making process to facilitate sustainable port development.

Furthermore, ports are considered an essential infrastructure for developing the environmental, economic, and social sustainability of port cities. Smart ports utilise technological innovation and sustainable initiatives to achieve sustainable management of port operations and services, thus assisting ports to become competitive and sustainable communities (Othman et al., 2022, D'Amico et al., 2021). With ports being closely connected with cities, the sustainability of ports is facing increasing pressure from port authorities, local government, customers and residents (Zheng et al., 2020). This study defines port sustainability as pursuing economic prosperity, environmental excellence, and social responsibility simultaneously. The achievement of port sustainable development requires considering the relevant policies and strategic planning and collaborations with all stakeholders, including market participators, policymakers, internal shareholders and residents (Kang and Kim, 2017). Thus, the examination of the whole system of PSC and port community is needed to analyse related factors to find the balance point of economy, society and environment.

2.4.1 Environmental Dimension

Most of the literature related to sustainable port development focused on social and environmental aspects (Lu et al., 2016a). Air, water, and soil quality deterioration in the proximity of port regions, as well as noise pollution, are the most prevalent problems (Sislian et al., 2016). Air pollution, including NOx, SOx, VOC, CO, PM, and greenhouse gases (GHG), is one of the significant environmental repercussions of ports (Bermúdez et al., 2019). Badurina et al. (2017) indicated that ships that call at ports, landside transportation activities and cargo operations at the terminal are the major sources of air pollution. This finding is congruent with the work of Botana et al.

(2023); the main sources of the carbon footprint come from the fuel consumed during the berthing time, which contributes to almost half of the total impact. Ports could reduce unloading time by employing digital and automated technologies such as automated guided vehicles, robotics, and AI (Tsolakis et al., 2021). Moreover, ports can provide on-shore power supply or cold-ironing to allow ships to switch off their fossil-fuel engines (Sifakis and Tsoutsos, 2021). Meanwhile, to reduce environmental pollution, port authorities must collaborate with shipping companies continuously. Governments and relevant organizations need to introduce policies to regulate ports and relevant companies at national and international levels. Chiu et al. (2014) explored the collaboration of port and ship companies by reducing the port dues for ships which use clean-burning low-sulphur fuels and low steaming to protect the environment.

Moreover, port-handled freight should be linked to the hinterland, which increases greenhouse gas emissions of inland transportation. Thus, intermodal transportation service as a significant activity connecting the port and hinterland plays a more important role in port sustainability. Liao et al. (2010) evaluated the greenhouse gas emissions of inland container transhipment resulting from the established port to Taipei in Taiwan, and they found there are greater reductions in CO2 when using coastal shipping to transport containers rather than traditional road transport routes. Kurtulus and Cetin (2019) have conducted more in-depth and extensive research. They indicated that ports and logistics services providers use intermodal transportation systems to decrease the environmental impact. Thus, the collaboration between ports and inland stakeholders is required to improve emissions (Aregall et al., 2018).

Water pollution and its impact on marine ecosystems is a further major environmental concern. Alamoush et al. (2021b) revealed that some port activities can lead to water pollution, including oil discharges, leakages, dredging and bilge wastes, resulting in a potentially catastrophic impact on beaches, groundwater, food chains and fishing communities. The environment can be further damaged by anchoring, oil spills and garbage, which endanger marine habitats and wildlife (Di Vaio et al., 2019). The introduction of invasive organisms during ballast water transfers may disrupt delicate ecosystems (Dinwoodie et al., 2012). Furthermore, ship, port activities and logistics services can cause noise pollution, which affects a wide range of receivers' health, including crew, port employees, marine fauna and residents of coastal areas (Sislian et al., 2016, Bermúdez et al., 2020). Fredianelli et al. (2021) indicated that exposure to noise can cause hypertension, cardiovascular disease and sleep disturbance, even causing permanent hearing loss when prolonged exposure to noise. Therefore, ports should direct efforts to tackle these environmental issues.

2.4.2 Social Dimension

Out of the three dimensions of sustainability, the social dimension is a major research focus point. Air pollution from shipping not only impacts the environment but also becomes a social issue. The impact of hazardous pollutants released into the air negatively affects the human health of people who live near the coastlines and port-city areas. Alzahrani et al. (2021) state that the pollution of ports has obviously affected the health of the local population. People who live near the port have a higher rate of asthma, lung cancer and other mortal diseases than those living in other areas. As the interaction between ports and cities becomes increasingly important, ports need to implement policies to reduce emissions, both due to increased social demand and to comply with international and European targets (Botana et al., 2023). Moreover, residents near the port are worried about their health and traffic. Shiau and Chuang (2015) stated that local Keelung residents living in the area surrounding Keelung Port are concerned about the traffic fatalities in the area surrounding the port and the annual accident rate in the port area. Residents who live near the Rotterdam port are worried that their health and traffic will be affected by port development since the trucks of port transportation companies cause road congestion, noise and air pollution (Tobollik et al., 2016). Therefore, sustainable port development could not ignore the social impact and public participation. Argyriou et al. (2022) also indicate that making citizens aware of environmental issues and ensuring that their input is taken into account in the design of future ports is a key measure to increase environmental performance. Furthermore, port developers need to consider the impact on the employment of residents and quality of life to achieve sustainable development to gain support from city managers and residents (Witte et al., 2018). Ports should support local communities and utilise various activities of communities such as consolation, complaint resolution and noise reduction to improve social performance (Hossain et al., 2019). Many Vietnamese ports provide employee training programs for continuing education and continuously improve working conditions and safety of employees, supporting community social activities and social equality (Roh et al., 2016). Puig et al. (2015) also point out that enhancing communication with communities could improve the relationship between port authorities and local communities, assisting ports in delivering environmental and economic benefits to the local communities. Therefore, social influence is a significant factor in port sustainability. Ports need to contribute to direct and indirect employment, maintaining relationships with the community and the liveability condition of the surrounding area.

2.4.3 Economic Dimension

Ports are vital for the economy. In addition to its own value-added production and job-creating benefits, the port is a national infrastructure that has a significant direct or indirect impact on business and the national economy (Stanković et al., 2021). Customers seek efficient and cost-effective port service. Roh et al. (2023) also indicate the importance of optimised operation planning in the economic dimension. By implementing a wide portfolio of digital tools, ports can perform accurate and rapid information processing and sharing, thus optimising the entire operational process to improve economic sustainability. For example, Huanghua port established a data-driven intelligent service platform to streamline the business process and facilitates the coordination between different entities in the supply chain, improving the sustainability of ports (Zhao et al., 2020).

However, few studies in the literature investigated port sustainability merely considering the economic aspect. Most of the literature considered both the economic and environmental dimensions of sustainability. Wang et al. (2019) stated that environmental management might mitigate the negative effects of environmentally unfriendly activities that can have a negative impact on companies' expected cash flows, such as lawsuits, clean-up costs of environmental mishaps, fines, reputation harm, and so on. Xing et al. (2021) also indicated that using more eco-friendly fuels like bioethanol could avoid emissions and help organisations achieve carbon neutrality. Moreover, Teschner (2019) argued that ports and other companies, such as residential developers and tourism developers, are increasingly competing for coastal land due to the hub statuses of trading and transportation of ports. Port developers should demonstrate the value, which includes economic benefits and environmental influence to be added by port investment projects compared to other developers.

Furthermore, Yang et al. (2013) note that businesses that incorporate environmental responsibility into their economic strategy may realise cost savings from resource reduction and increased efficiency while simultaneously increasing revenue from good image building. Roh et al. (2023) support the notion that cost saving is a significant sustainable port practice and point out that implementing cleaner technology port equipment can reduce operating costs and increase productivity. Sislian et al. (2016) also stated that ports would achieve greater economic stability and performance by implementing a policy of active and sophisticated environmental and social management to increase sustainability. Therefore, the concept of port sustainability demands the pursuit of economic growth, environmental quality, and social responsibility simultaneously. Port authorities must build an efficient and digitalised interaction system to adopt a sustainability SCM strategy with stakeholders to improve sustainability.

2.5 Summary

In conclusion, this chapter provided a review of the literature relevant to port development, port performance and port sustainability. First, a review of port development and related concepts has been conducted, including PSC, PSCI and the digitalisation of ports. Then, the definition of port performance and factors used for assessing port performance have been reviewed and stablished a deep understanding of port performance through a detailed analysis of the shifting role of ports in the supply chain. Finally, port sustainability and its related concepts are discussed. It is revealed that sustainability has shown great significance in the context of ports. The next chapter assessed the application of Big Data technologies in ports and provided details of BDAC.

Chapter 3 Big Data analytics capability

3.1 Introduction

This chapter reviewed existing literature related to Big Data application in ports, BDAC and RBT, as well as identified research gaps. This chapter consists of four sections. The first section reviews the existing literature related to Big Data, focusing on the main characteristics of Big Data. Then this section reviews the application of Big Data and its challenges in the shipping industries and supply chain, laying the foundation for evaluating how Big Data is seen in the port. Lastly, this section reviews the impact of Big Data technology on ports and identifies the challenges of applying Big Data technology to ports. Section two reviews existing literature on RBT and BDAC, including definitions and concepts. Drawing on the resource-based perspective, explore organisational resources that can be used for building BDAC. Section three reviews two types of structural equation modelling techniques: Partial Least Squares Structural Equation Modelling (PLS-SEM) and Covariance-Based Structural Equation Modelling (CB-SEM). This section discusses the key differences between these methods and their strengths and weaknesses. Finally, according to the literature review results, research gaps were summarised.

3.2 Big Data

The definition of Big Data has evolved over the past 15 years. IBM and other leading technology companies promote the concept of Big Data to various industries (Gandomi and Haider, 2015). The development of Big Data implies that the definition of Big Data has evolved rapidly. IBM, one of the major firms in the information sector, may have coined one of the simplest and most well-known terms for Big Data. Big Data, according to IBM, originates from sensors used to collect climatic data, social media posts, digital photographs and videos, buy transaction records, and cell phone

GPS signals, to mention a few examples (Al-Sai and Abdullah, 2019). TechAmerica Foundation's Federal Big Data Commission defined Big Data as “a term that describes large volumes of high velocity, complex and variable data that require advanced techniques and technologies to enable the capture, storage, distribution, management, and analysis of the information” (Mills et al., 2012, p.10). Vassakis et al. (2018) indicated that with the development of sensors such as speed meters, gyroscopes, smartphones, and digital cameras, the growth of Big Data increases daily and is hard to process rapidly. The following figure shows the main characteristics of Big Data.

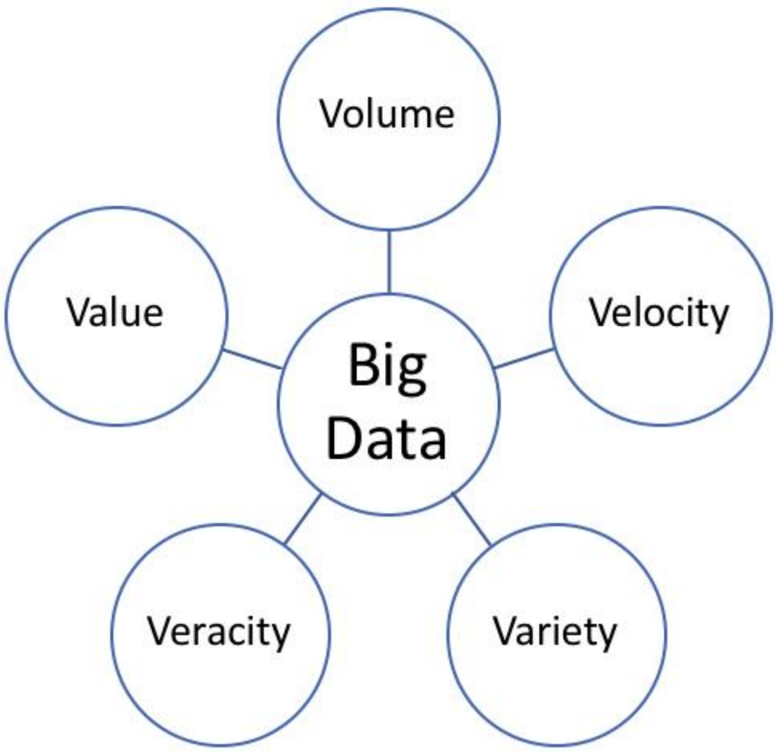

Figure 3.1 Five “V” of Big Data
Source: Gupta et al., (2018)

Figure 3.1 illustrates the features of Big Data. Big data has five main characteristics, which are referred to as the 5V: Volume, Variety, Velocity, Veracity and Value (Gupta et al., 2018, Bellini et al., 2022)

- Volume refers to the magnitude of data. The size of Big Data has been described in terms of terabytes, petabytes, or even zettabytes these days.

- Variety refers to the inherent heterogeneities of the structures, formats, and sources of data. The datasets in Big Data are stored in a variety of forms. Data variation differentiates Big Data from regular data.

- Velocity refers to the rate of data production and the speed at which the companies process and analyses.

- Veracity refers to the disorderliness or dependability of the data. For example, Twitter posts containing hashtags, abbreviations, typos, and slang are more difficult to manage for quality and accuracy than other forms of Big Data.

- Value refers to the relatively low-value density of a sheer volume of data. Valuable information hides amongst a larger body of non-traditional data.

In summary, the property of Big Data could be presented as “5V”, which includes Volume, Variety, Velocity, Value and Veracity.

3.3 Big Data in Ports

As discussed in Sections 2.2 and 2.3, early studies assumed that the various elements of the PSC network, including hinterland terminals, sea terminals and hinterland transport, have been further integrated into a single coherent port in order to maximise port value. To develop integration, the port should embed information flow from all parties (Paulauskas et al., 2021). A single supply chain may have hundreds of stakeholders, and each stakeholder has different priorities and viewpoints, which gather and create different types of information, implying that the port is the important node of the supply chain and that cargo transportation will become information-exchange hubs (Guo, 2020). Despite the strong appeal of the Big Data concept, there is limited understanding of the role of Big Data in port operation and management.

Port authorities who better understand the role of Big Data in ports are in a better position to exploit it. However, there has been substantial debate regarding the challenges and opportunities of Big Data in ports. Due to the port linkage between shipping and hinterland supply chain network, exploring the application and challenges of Big Data applications in maritime and supply chain could provide emerging insights to assist port authorities in investigating the role of Big Data in port.

3.3.1 Application of Big Data in Shipping Industries

Due to the current economic climate, variations in energy prices, and stringent environmental regulations, the shipping industry faces strong competition (Zaman et al., 2017a). Hence, shipping industries try to use new concepts and technologies to improve performance. Big Data, as an emerging technology, received wide attention from shipping industries since it presents huge potential in other areas such as healthcare, manufacturing and retailing (Galetsi et al., 2020, Dai et al., 2020, Bradlow et al., 2017, Wang and Hajli, 2017, Papadopoulos et al., 2022). Moreover, several researchers have evaluated the impact of Big Data on shipping industries and investigated the application of Big Data in shipping industries. The following table shows the application of Big Data in shipping areas.

Application of Big Data in shipping industries	Resource
Vessel Operation Management	Yang et al. (2018a); Perera and Mo (2017); Kim et al. (2020)
Predictive Maintenance System	Zaman et al. (2017b); Plaza-Hernández et al. (2020); Jimenez et al. (2020)
Environmental legislation monitoring	Molka-Danielsen et al. (2017);Vujičić et al. (2020)
Energy Management	Anan et al. (2017);Man et al. (2020)
Real-time decision support systems	Brouer et al. (2016); ; Lee et al. (2018a); Christos et al. (2020)
Condition monitoring	Brandsæter et al. (2016); Zaman et al. (2017b)
Vessel safety and Security	Mirović et al. (2018); Zaman et al. (2017a); Aslam et al. (2020)
Voyage Planning	Zhang et al. (2018); Han and Yang (2020)
Performance Monitoring and Optimisation	; Rødseth et al. (2016); Perera and Mo (2017); Perera and Mo (2020)
Intelligent Traffic Management	Fernández et al. (2016); Xiao et al. (2021)

Table 3.1 Application of Big Data in shipping industries

Table 3.1 demonstrates the wide application of Big Data in shipping industries. Big Data displays huge potential in improving shipping industries development, especially in the part of decision support, vessel performance monitoring and improvement, energy management and environmental protection.

Through the deployment of sensors, shipping industries could gather Big Data, including data on engine operation, pump operation, boilers operation, speed, location, etc. (Zaman et al., 2017b). Brouer et al. (2016) argued that applying BDA to analyse gathered data could predict future trends and support shipping industries in making great strategic decisions. Moreover, Perera and Mo (2017) point out that through handling vessel operational data, which are collected from sensors, ship performance and machinery performance could be monitored and controlled to avoid risks. Meanwhile, these data could be analysed to optimise vessel performance and forecast machine health. Furthermore, in the field of energy and environment, many researchers (Ang et al., 2017, Hasanspahić et al., 2021, Lee et al., 2018a) consider that BDA has huge potential to improve energy efficiency and environmental protection. Anan et al. (2017) showed that shipping industries could improve fuel efficiency and reduce greenhouse gas emissions by using BDA to analyse gathered ship operation data. Molka-Danielsen et al. (2017) indicated that shipping industries could monitor and visualise their air quality by implementing sensors network and Big Data and make decisions to reduce environmental influence via facilitating BDA. Therefore, Big Data plays an important role in shipping industries.

3.3.2 Challenges of Big Data in Shipping Industries

Due to the important potential of the application of BDA in shipping industries, BDA is widely used by shipping companies. However, although Big Data has huge potential to improve the performance of maritime industries, it also encounters many challenges. Numerous articles examining the challenges of Big Data in shipping industries proposed eight significant challenges that impact the development of Big Data in shipping industries (Man et al., 2020, Zaman et al., 2017a, Rødseth et al., 2016, Bao et al., 2018, Jović et al., 2019b). The following figure will show the key issues of BDA in shipping industries.

Figure 3.2 Key issues for application Big Data analytics in shipping industries

Source: Adapted from Bao et al. (2018) and Zaman et al. (2017a).

Figure 3.2 demonstrate eight key issues for using BDA in shipping industries. In shipping industries, the application of Big Data is still in the initial stage of development. Shipping companies face many challenges, not only at the level of technology but also at the level of management and society. Although the broad deployment of sensors brings a large amount of data to shipping companies, these data could not be analysed due to quality, transfer and integration issues (Man et al., 2020, Zaman et al., 2017a). Moreover, from the perspective of management, different data standards in different shipping industries, data ownership and the lack of Big Data professionals both limit the development of BDA in shipping industries (Zaman et al., 2017a, Rødseth et al., 2016, Jagadish et al., 2014, Sepehri et al., 2021). Furthermore, data security and privacy have always been the focus of social attention (Bao et al., 2018). Shipping industries transfer and manage vast amounts of data which include data of customers, ship owners, cargo, ports etc., which means shipping industries are exposed to data security threats and cyber-attacks. Shipping industries need to ensure data security to avoid economic losses and legal repercussions (Tam and Jones, 2018). Therefore, although the development of BDA in shipping industries has been hindered by some challenges, BDA still plays an important role in shipping industries and has huge potential to improve shipping performance.

3.3.3 Application of Big Data in Supply Chain Management

Researchers suggested that information and material flow are the core element of SCM (Min et al., 2019). Through the application of Big Data, supply chain participants enable to process and share gathered data by sensors to manage and monitor information and material flow (Ben-Daya et al., 2019). Moreover, several researchers have discussed the Big Data application in SCM and indicated that Big Data has huge potential to support SCM (Wamba et al., 2015, Addo-Tenkorang and Helo, 2016, Arunachalam et al., 2018, Kamble and Gunasekaran, 2020, Nguyen et al., 2018b, Raman et al., 2018). In the modern supply chain, the upstream side, which involves suppliers and manufacturers, and the downstream side, which involve logistics, distribution centres, retail and customers, are both significant sources of data (Addo-Tenkorang and Helo, 2016). These large amounts of data contain the huge value, and supply chain participants could extract useful information from these data through BDA tools. Lamba and Singh (2017) indicated that through BDA, supply chain managers could integrate data from different supply chain partners and analyse these data to predict demand and find the market trend. Arunachalam et al. (2018) argued that BDA not only helps supply chain manager forecast demand and market trend but also assist supply chain manager in gaining customer feedback to improve their service. Therefore, BDA is widely used by many supply chain managers to forecast demand and improve service.

Moreover, several researchers presented that many supply chain executives are keen to improve logistics performance with Big Data (Witkowski, 2017, Sanders, 2016, Moldabekova et al., 2021, Wang et al., 2016). Sanders (2016) indicated that logistics companies use the BDA tool to analyse real-time GPS and sensor data to optimise transportation routes and distribution centre locations to improve transportation efficiency and customer satisfaction. Kache and Seuring (2017) explored more opportunities for Big Data in logistics. They pointed out that Big Data capabilities could help logistics companies share information with other logistics service providers to build integration logistics service networks, supporting logistics managers in making strategic decisions. Hence, the application of BDA in logistics and transportation is significant.

Furthermore, Wamba et al. (2018) argued that gathering and sharing a large amount of data improve the transparency of the supply chain, which means supply chain managers could gain more information to support their decision-making in the extremely compound environment. By applying the BDA tool, supply chain managers could rapidly make better decisions to respond to market changes and improve operational efficiency (Gupta et al., 2019).

Consequently, the implementation of Big Data capabilities is crucial to SCM. Especially, BDAC can be seen as the main contributor to improving SCM performance. Supply chain participants, including suppliers, manufacturers, customers and logistics service providers, use BDA to support their business activities (Tiwari et al., 2018). In addition to the three main applications mentioned above, Big Data has a wide range of applications in the supply chain. The following table shows the application of Big Data in SCM.

Application of Big Data in SCM	Resource
Logistics	Kache and Seuring (2017); Wang et al. (2016); Lamba and Singh (2017); Borgi et al. (2017);Yan et al. (2019) Silva et al. (2021)
Inventory	Kache and Seuring (2017); Sanders (2016); Fernández-Caramés et al. (2019); Seyedan and Mafakheri (2020)
Responsiveness	Kache and Seuring (2017); Raman et al., (2018); Ageron et al. (2020)
Risk Management	Kache and Seuring (2017); Wu et al. (2017); Araz et al. (2020)
Financial implications	Kache and Seuring (2017); Zhong et al. (2016); Govindan et al. (2018)
Customer experience	Addo-Tenkorang and Helo (2016); Sanders (2016); Govindan et al. (2018); Gawankar et al. (2020)
Strategic sourcing	Tiwari et al. (2018); Sanders (2016); Lamba and Singh (2017); Seyedan and Mafakheri (2020)
Information management	Kache and Seuring (2017); Giannakis and Louis (2016); Maheshwari et al. (2021); Zhan and Tan (2020); Hader et al. (2022)
Product and market strategy	Kache and Seuring (2017);Wang et al. (2016); Govindan et al. (2018); Seyedan and Mafakheri (2020)
Integration and collaboration	Kache and Seuring (2017); Zhong et al. (2016); Manuel Maqueira et al. (2019); Maheshwari et al. (2021); Benzidia et al. (2021)
Innovation and product design	Kache and Seuring (2017);Wang et al. (2016), Raman et al., (2018); Seyedan and Mafakheri (2020); Bag et al. (2020)
Supply chain network design	Wang et al. (2016), Prasad et al. (2018), Tiwari et al. (2018); Maheshwari et al. (2021); Seyedan and Mafakheri (2020)
Supply Chain visibility and transparency	Kache and Seuring (2017); Kamble and Gunasekaran (2020); Ahmed et al. (2021)
Operations efficiency and maintenance	Kache and Seuring (2017); Raman et al., (2018); Addo-Tenkorang and Helo (2016); Lamba and Singh (2017); Maheshwari et al. (2021); Seyedan and Mafakheri (2020)
Demand management and production planning	Kache and Seuring (2017); Wang et al. (2016), Raman et al., (2018); Addo-Tenkorang and Helo (2016); Lamba and Singh (2017); Govindan et al. (2018); Seyedan and Mafakheri (2020)

Table 3.2 Application of Big Data in Supply Chain Management

3.3.4 Challenges of Big Data in Supply Chain Management

Despite emerging Big Data technologies making great contributions to SCM, the application of Big Data in SCM encounter some challenges. The challenges of Big

Data in SCM have been classified in this study. The following figure will illustrate the important challenges of applying Big Data in SCM.

Figure 3.3 Challenges of application Big Data in SCM

Source: Adapted from Zhong et al. (2016) and Arunachalam et al. (2018)

Figure 3.3. demonstrates the critical issue of Big Data in SCM. These eight issues in the age of Big Data -driven SCM are prime challenges. If these challenges are not appropriately addressed, Big Data will not receive much acceptance in the global supply chain. Compared with applying Big Data in shipping industries, SCM encounters more challenges in data collection methods and data analysis. Supply chain participants must develop new data collection methods to gather semi-structured and unstructured data. These data contain great potential values, which could provide more marketing information to supply chain managers and support them in making decisions (Choi, 2018). Moreover, traditional data analysis approaches may not process the increasing volume of data and support a broader range of applications

such as supply chain network design, product design and development, demand planning, inventory and logistics management (Yu et al., 2018). Hence, supply chain participants need to build BDAC to develop a relevant advanced data analysis approach which meets their strategy requirements (Zhong et al., 2016). Therefore, although Big Data plays an essential role in SCM, the application of Big Data in SCM still faces many challenges, especially the data analysis approach. Supply chain participants must build Data analytics capability to achieve a Big Data-driven supply chain and gain more competitiveness.

3.3.5 Big Data Application and Ports

Through a literature examination of the concept of Big Data and its application in shipping industries and SCM, a type of Big Data-related applications has been found and categorised based on Big Data's features and the viewpoints of researchers. For example, Addo-Tenkorang and Helo (2016) demonstrated five correlative and essential applications of Big Data in SCM: Big Data Acquisition, Big Data Storage, BDA, Big Data application and Big Data Value-adding. Arunachalam et al. (2018) presented the key element of BDA in the supply chain context to help organisations measure their current state of BDA. Moreover, given the revolution in supply chain and shipping industries, ports have entered a new era of smart ports. Several scholars have examined the technological scenarios in port digitalisation and advanced information and communications technology, revealing the main applications of Big Data technology that are significant for ports (Yau et al., 2020, Inkinen et al., 2021, Zarzuelo et al., 2020). The world's top 20 and European top 10 ports are examined by their websites and relevant reports to identify the application of Big Data in ports. The categorisation of Big Data applications and the specific Big Data used in ports may be integrated and extracted for use in the construction of the construct of Big Data applications in ports. As outlined in Table 3.3, based on the discussions of Addo-Tenkorang and Helo (2016); Arunachalam et al. (2018); Yau et al. (2020) and Inkinen et al. (2021), Big Data applications in ports have been divided into eight constructs: Data gathering, Real-time information monitoring, Data analysis and decision-making, Operation optimise, Information sharing platform, Predictive analysis, Innovation and Data integration and management.

Construct of application BD in port	**Port**	**Application Description**
Data Gathering	Port of Amsterdam	Port of Amsterdam deploys sensors in the port area in a more structured manner to gather data.
	Port of Hamburg	Port of Hamburg is developing a mobile GPS sensor to gather various data.
Real-time Information Monitoring	Port of Rotterdam	Port of Rotterdam developed an application called 'Pronto' to monitor all activities during a port call.
	Port of Amsterdam	Port uses sensors to measure which moorings are occupied.
	Port of Antwerp	Port of Antwerp uses an online tool, ‘Port+’, to offer precise and real-time information on the movement of vessels with the Antwerp port.
	Port of Hamburg	Port of Hamburg uses the software 'Port Monitor' to gather a variety of information and keep all the stakeholders in the port of Hamburg up to date.
Data analysis and decision-making	Port of Rotterdam	Port of Rotterdam offers an application 'Naviager' to analysis relevant data to assist customers in choosing best transport route.
	Port of Antwerp	Port of Antwerp uses the 'Port+' to analysis various data and offer a solution for intermodal transportation to customers.
	Port of Singapore	The Singapore maritime and port authority aims to use BDA platforms to complement its port management systems to improve planning processes.
Operation optimises	Port of Rotterdam	Port of Rotterdam developed an application, 'PortXchange', to efficiently organise, carry out, and keep track of all activities during a port call based on standardised data interchange.
	Port of Hamburg	Port of Hamburg gathers various data to ensure the traffic flows efficiently.
	Port of Felixstowe	Port of Felixstowe developed a PARIS computer system to analyse various data to optimise intermodal transportation services.
	Port of Los Angeles	Port of Los Angeles collaborate with GE transportation to improve port operation by delivering real-time data-driven insights.
Information shared Platform	Port of Rotterdam	All supply chain partners of the port of Rotterdam could use the Port Community System of Portbase to exchange data and share information efficiently.
	Port of Antwerp	Port of Antwerp share information and data with supply chain partners through the NxtPort Platform
	Port of Valencia	The port of Valencia employs the port community system to communicate with suppliers.
	Port of Jebel Ali	Port authorities develop a platform 'Dubai Trade' to share information and provider e-business services.

	Port of Shanghai, Port of Shenzhen, Port of Ningbo Zhoushan, Port of Qingdao, Port of Guangzhou, Port of Tianjin	Port of Shanghai builds a comprehensive information services network to share information with customers and offers some basic services.
Predictive analysis	Port of Rotterdam	Port uses BD and machine-learning algorithms to estimate the time of arrival more accurately.
	Port of Singapore	The Singapore maritime and port authority collaborated with IBM to forecast vessel arrival time through IBM Traffic Prediction Tool.
Innovation	Port of Rotterdam	Port of Rotterdam use PortXL to build a network among mentors, investors, companies, and sponsors to accelerate maritime innovations.
	Port of Antwerp	Port of Antwerp collaborates with the city of Antwerp, the University of Antwerp and the innovation hub to build a smart city and smart port with Big Data and other digital technology.
	Port of Shanghai	Port of Shanghai collaborates with Shanghai International shipping institute to investigate the role of big data in port.
	Port of Tianjin	Port of Tianjin collaborates with National Supercomputer Centre in Tianjin to investigate the application of Big Data.
Data integration and management	Port of Rotterdam	PortMaster uses big data and AI technologies to deliver information that is considerably more accurate than what is currently accessible.
	Port of London	Port of London manages and integrates various data to offer Vessel Traffic Services.
	Port of Ningbo Zhoushan	Port of Ningbo Zhoushan developed a platform to manage and integrate data.
Infrastructure Maintenance	Port of Hamburg	Port of Hamburg uses the sensor to monitor the infrastructure in the port to make the maintenance processes more effective and efficient.

Table 3.3 Application of Big Data technology in Port

Data gathering is related to the features of Big Data. Ports gather data from sensors and record port operation activities (Port of Amsterdam, 2022). Moreover, according to the classification of Addo-Tenkorang and Helo (2016), data integration and management are correlated with Big Data storage. Ports must manage and integrate data gathered in port operation activities to support data analytics and Big Data value-adding service (Port of London, 2022). In addition, Data analysis and decision-making and Predictive analysis both reflect the advanced analytics capability of Big Data. Arunachalam et al. (2018) investigated the application of Big Data in the supply chain from a data analytics capability perspective and classified five dimensions: Data generation, Data integration and management, Advanced analysis, Data visualisation and Data-driven culture. The most important stage of a Big Data application is data analytics, which may be divided into three categories: prescriptive, predictive and descriptive analytics (Roy et al., 2022). Thus, ports use data analytics to analyse various data to support decision-making and predictive vessel arrival time (Qronoport, 2022, Port of Rotterdam, 2022a). Fiaz et al. (2016) indicated that data visualisation is when organisations use tools and techniques to gather data and make it visuals to help managers underuse the data. Data analytics capability could be improved through data visualisation. Thus, Real-time information monitoring is related to data visualisation capability (Yau et al., 2020). Through real-time information monitoring, ports could offer timely data to stakeholders to support their data analysing (Hambury Port Authority, 2022). Furthermore, Operation optimises, Information shared platforms and Innovation both reflect the Big Data value-adding and Big Data application. Especially many ports have developed information-sharing platforms to share data and information with supply chain partners to increase port efficiency (Port of Rotterdam, 2022b, NxtPort, 2022, Yangshan terminal, 2022). Innovation and improved performance are significant dimensions of Big Data value creation (Grover et al., 2018). Port authorities apply Big Data to improve innovation and optimise operations to create more value (PrortXL, 2022, General Electric, 2022).

Therefore, in this report, the Big Data application in port is divided into eight constructs: Data gathering, Real-time information monitoring, Data analysis and decision-making, Operation optimise, Information sharing platform, Predictive analysis, Innovation and Data integration and management. Based on the above discussion, Big Data has a significant impact on ports, especially in aspects of Data analysis and decision-making, Operation optimises, Predictive analysis and Innovation. Many port authorities argued that these four applications (Data analysis and decision-making, Operation optimise, Predictive analysis, and Innovation) are the core applications of Big Data in ports, which could create significant value and improve port competitiveness. In order to develop these four main applications, ports need to build BDAC to help port managers understand the importance of Big Data and utilising Big Data resources.

3.3.6 Challenges of Big Data in Port Supply Chains

In section 3.3.5, the applications of Big Data in port are examined. Although Big Data show huge potential in ports, and some ports have started to use it to improve performance, port authorities cannot ignore the challenges of applying Big Data. The significant issues with applying big data in the supply chain and maritime industries are covered in sections 3.3.2 and 3.3.4. Because there is little study on big data in the PSC, recognising the problems with big data in the marine supply chain and looking at relevant port official reports could aid researchers in identifying the key drawbacks of using big data in the PSC. Based on the discussion in sections 3.3.2 and 3.3.4, this study presents the challenges faced by PSC in applying Big Data. The following figure 3.4 shows the main challenges of the application of Big Data in PSC.

Figure 3.4 Main Challenges of the Application of Big Data in PSC

Source: Adapted from Zhong et al. (2016), Arunachalam et al. (2018), Bao et al. (2018) and Zaman et al. (2017a).

Figure 3.4 illustrate eight challenges of the application of Big Data in PSC. The following sub-sections will give more details about the main challenges.

- Data Quality: SC involve different stakeholders and participants, and data is collected and exchanged by these organisations. Low-quality data will lead to errors in interpretation and affect the operation and decisions of many organisations. Moreover, some data have huge commercial and social implications, implying that some companies may gain benefits from misleading data. Thus, sensitive data must be examined before it is used (Rødseth et al., 2016). Therefore, gathering high-quality data is a vital element for enhancing PSCI and port digitalisation.
- Data collection method: With development ports, PSC becomes more complex and collected data with traditional data collection methods could not support ports to develop. Port wants to improve data collection methods to build smart

ports to improve accessibility and intelligence to enhance port digitalisation and sustainability (Yang et al., 2018b). Thus, some port implements relevant programs to gather more various data; for example, the Port of Amsterdam has started to work together with the sensor service provider 30Mhz to gather more various data to protect the environment and improve port development (Port of Amsterdam, 2017)

- Data analysis method: Enhancing port performance and sustainability rely on efficient data exchange and decision-making. Port authorities need to develop advanced systems or software to utilise data and share data efficiently. Port of Rotterdam developed a new system called PortXchange to improve PSC performance and sustainability. PortXchange could deduce ship arrival and departure time more accurately by using big data and machine-learning algorithms with information from the Automatic Identification System (Port of Rotterdam, 2022c). Port of Antwerp works together with Port + to develop an online application to offer port departure, port call and intermodal transportation solutions to improve PSCI (Portplus, 2022). Therefore, the data analysis method is a core enabler for applying Big Data to enhance PSCI and port sustainability.
- Data integration and standards: PSC network is complicated and involves different participant which use different information systems to gather various data. In order to combine unstructured and heterogeneous formats or create standards to increase data sharing and process efficiency, supply chain participants need advanced data processing techniques. For example, the Port of Rotterdam developed an application called Pronto to assist ship companies, agents, terminals and other service providers in optimising plans and

monitoring activities with standardised data exchange (Port of Rotterdam, 2018).

- Data Ownership: Data ownership is an elemental component of the application of Big Data in the PSC. Due to the limitation of technology, Big Data services of most ports are provided by the relevant business partner, such as the port of Antwerp works with Portplus, the Port of Felixstowe with PARIS, and the Port of Los Angeles collaborate with GE Transportation (Portplus, 2022, General Electric, 2022, PARIS, 2022). These business partners need the privileged of accessing various data sources to gather data and analyse. Moreover, with the increasing value of data, how to share or sell data without losing control is becoming important (Sarabia-Jácome et al., 2019a).
- Human Resource: In the domain of shipping industries and SCM, human resource has a significant impact on the application of Big Data. As an important part of the global supply chain network, human resource also is a vital enabler. Ports require a large number of technical personnel to use and develop emerging Big Data ports. Meanwhile, the ports and related supply chain staff will be trained to employ Big Data software and system.
- Innovation: Through accessing and analysing Big Data, firms could explore their products, customers and markets to extract new ideas. Meanwhile, BDA can help originations achieve business process innovation. Hence, Big Data is considered a significant driver of innovation by managers (Mikalef and Krogstie, 2020, Dong and Yang, 2020). In the domain of ports, ports share information with related institutions to develop new services to enhance PSCI and sustainability. For example, the port of Rotterdam established Rotterdam Logistics Lab to share ideas and data with partners to develop new information services (PrortXL, 2022). Port of Antwerp collaborated with IMEC, a world-

leading R&D and innovation hub in digital technologies, to develop smart ports (imec, 2017).

- Security: From the existing literature in shipping industries and SCM, it is evident that data security is a vital enabler of applying Big Data in PSC for PSCI and sustainability. With increasing supply chain participants' implantation of Big Data to exchange and utilise data, cybercriminals can choose more entry points for cyber-attack, which could cause supply chain interruption, impacting PSCI and sustainability. For example, the "NotPetya" cyber-attack destroyed the computer network of Maersk in June 2017, which interrupted multiple global terminals and logistics services of Maersk and caused a loss of roughly $300 million (Meyer-Larsen and Müller, 2018).

Like the challenges of Big Data application in shipping industries and SCM, Big Data application in the PSC also is limited by technology, management and society. Specifically, immature BDA methods and management concepts significantly limit the application of Big Data in the PSC. Although ports have various advanced technologies to choose from, digital transformation does not depend solely on technology strategy. To achieve the digital transformation and gain competitiveness from this transformation, port authorities need to develop a capability to utilise rich data resources of the port area (Munim et al., 2020). Hence, port authorities need to develop BDAC to help relevant managers further understand the role of Big Data in the port domain and port utilising Big Data technology. However, despite the strong appeal of utilising to port managers, there is a lack of consensus on the importance of port development BDAC. Even more, there is a limited understanding of though what mechanisms it contributes to port performance.

3.4 Big Data Analytics Capability

3.4.1 Defining BDAC

In section 3.3.2, attributes of Big Data have been described with 5Vs: Volume, Variety, Velocity, Veracity and Value. Jeble et al. (2018) proposed that BDA is a field which consists of Big Data, analytical tools and techniques to gain insights from a large amount of data. Hence, the term BDA is used by some researchers to emphasise the tools and processes which are applied to derive actionable insights (Mikalef et al., 2018). Based on this perspective, BDA is defined as “the application of multiple analytic methods that address the diversity of Big Data to provide actionable descriptive, predictive, and prescriptive results” (Lamba and Dubey, 2015, p.5). BDA is a sub-field of modern Data analytics and allows organisations to extract valuable insight from a massive, complex, and diverse data set (Gandomi and Haider, 2015). The innovation of BDA is mainly focused on dynamically converting unstructured and raw data into meaningful data sets (Arunachalam et al., 2018). It is an effective digital solution to tackle dynamic and unstructured problems without a predefined schema. The main distinction between BDA and traditional data analytics (TDA) techniques lies in the data types and processing capabilities (Vassakis et al., 2018). Traditional data analytics (TDA) is designed for structured databases and can effectively handle a large amount of structured data (Li and Lu, 2014). TDA relies on structured data stored in relational databases, which are usually pre-processed and structured to facilitate querying and reporting. In contrast, BDA does not require a pre-defined schema or data model (Kune et al., 2016). BDA can handle both structured and unstructured data, including social media, sensor, and multimedia data, which is impossible in TDA (Sivarajah et al., 2017). This flexibility and adaptability of BDA make it an ideal solution for solving dynamic and unstructured problems which cannot be easily addressed using traditional data analytics techniques.

Moreover, BDA enables organisations to process data in real-time, enabling them to detect and respond to emerging trends and issues quickly. BDA relies on distributed processing techniques, such as MapReduce and Spark, which enable organisations to process data in parallel across multiple servers (Kune et al., 2016). This distributed architecture allows BDA to handle massive amounts of data quickly and efficiently, making it well-suited for real-time decision-making (Yaqoob et al., 2016). In contrast, TDA is typically performed on historical data, making it less effective for real-time decision-making. Another key difference between BDA and TDA is using machine learning algorithms in BDA. Machine learning algorithms can help organisations discover hidden patterns and insights in data, enabling them to make more accurate predictions and decisions (Nti et al., 2022). TDA, on the other hand, relies on traditional statistical methods and pre-defined models, which may not be suitable for analysing large and complex data sets (Mannering et al., 2020). Therefore, BDA is a set of advanced techniques and tools that enable organisations to extract valuable insights from massive, complex, and diverse data sets.

BDA plays a more important role in firms and supply chains rather than merely as an analytics tool. Wang et al. (2016) presented that BDA has two perspectives: Big Data and business analytics. Big Data is the capacity to manage high-volume, high-velocity, and high-variety dynamic data sets. Business analytics refers to the ability to help organisations make better decisions and gain valuable business insights (Lai et al., 2018). Awan et al. (2021) and Wang et al. (2016) both indicated that BDA had become a crucial component of decision-making and a new enabler of competitive advantage. Therefore, BDA is defined as managing, processing and analysing the data with 5V features by holistic approaches to establish competitive advantages, create lasting value, and measure organisation performance (Wamba et al., 2017).

The capability closely related to BDA is called BDAC. From the capability perspective, BDAC is defined as " the organisational ability to utilise data assets in combination with physical IT assets and human resources to create competitive advantages" (Garmaki et al., 2016, p.4). Srinivasan and Swink (2018) defined BDAC from an analytics capability perspective in the supply chain context as organisations using tools and techniques to manage, process, visualise and analyse data to offer data-driven operational planning, decision-making and execution. Therefore, this paper defines BDAC in the context of the PSC as the ports' ability to gather pertinent data from the port operation, heterogeneous systems and business activities participants, then manage, process and analyse these data and visualise them intuitively to offer valuable business insights and support decision-making. Understanding and developing BDAC could help organisation managers deploy their Big Data strategies and support organisations to become data-driven organisations (Munir et al., 2022).

However, there is a limited investigation of the notion of BDAC in ports. Most research focused on the development of BDAC firms and evaluated its impact on firm performance (Cappa et al., 2021, Wamba and Akter, 2019, Ghasemaghaei and Calic, 2020). Hence, this study seeks to examine the resources needed to build BDAC in port and investigate how BDAC could contribute to port performance. Moreover, Arunachalam et al. (2018) indicated that different theoretical lenses, such as resource-based theory (RBT), organisational information processing theory (OPIT), contingency theory and knowledge-based view (KBV), could offer various frameworks to describe BDAC. According to OPIT, firms gather, analyse and manage information for informed decision-making in order to gain a competitive advantage (Zhu et al., 2022). The firm can gain a sustainable competitive advantage when the information processing capabilities match the firm's information processing needs (Srinivasan and Swink, 2018). Big data analytics involves the processing, analysis, and interpretation of large and complex datasets to discover patterns, trends, and insights that can inform decision-making and drive value. Based on OPIT, Big Data is seen as an information processing need of the business, and BDAC is seen as an important information processing capability for the business (Song et al., 2020). Contingency theory proposes that the effectiveness of a leader or manager's actions depends on how well they can adapt their behaviour to the needs of the scenario. By considering the external environment (e.g., cultural, political, economic, informational and technical factors), leaders can adapt the decision-making process, structure and practices to fit their specific circumstances (Wang, 2023). The theory can be applied to understand how Big Data can help organisations to adapt to environmental conditions. While contingency theory has gained attention from some Big Data scholars (Dubey et al., 2020, Vitari and Raguseo, 2020), contingency theory has lower explanatory power than RBT in explaining company performance in terms of revenue and profitability. KBV and RBT will be discussed in more detail below.

3.4.2 Knowledge-based view

The (KBV) is a theoretical framework that suggests that the knowledge possessed by an organisation is a critical resource that contributes to its competitiveness (Pereira and Bamel, 2021). Knowledge in this concept can be described as explicit and tacit knowledge, information and knowledge, technology, management and marketing, and many other appropriate concepts (Zotoo et al., 2021). Hence, organisations can create unique value propositions by accumulating, integrating, sharing, and using knowledge in their possession (Olabode et al., 2022). To effectively utilise the potential of big data and business analytics, organisations must build the proper methods to synchronise and integrate their knowledge and data (from both internal and external sources) (Qaffas et al., 2022). Business or domain knowledge is essential for the successful completion of big data and analytics-related operations, as well as the technical implementation of the system (Awan et al., 2021). Moreover, KBV highlights that the employee is the key driver in the creation of firm knowledge, and this knowledge resides within and across employees (Shamim et al., 2019). Organisations with high levels of staff knowledge and engagement can more effectively identify the need to modify existing resources and determine the steps required to accomplish these modifications. Ferraris et al. (2019) indicated that for better leverage of big data and business analytics, there is a growing need for employees with deep expertise in analytical, IT and communication skills. BDAC is considered a form of RBV because it relies heavily on knowledge. Hence, KBV is generally employed as an overarching theoretical framework for discussing BDAC (Qaffas et al., 2022, Shamim et al., 2020, Côrte-Real et al., 2017, Gupta et al., 2021).

However, KBV is not without its problems, as Erickson and Rothberg (2015) indicated that KBV emphasises the role of knowledge in obtaining a competitive advantage. KBV focuses on knowledge that may be a highly intangible or tract resource. However, considering knowledge alone is not comprehensive. Physical and capital resources (conventional factors of production), human resources, organisational processes, company traits, capabilities, social interactions (relational capital), and coordinating mechanisms are also among the strategic resources shown to increase firm competitiveness (Pereira and Bamel, 2021). The model constructed based on KBV is focused on capturing the impact of knowledge management and big data analytics talent capability on firm performance (Ghasemaghaei, 2019, Qaffas et al., 2022, Horng et al., 2022). Compared with KBV, RBT considers organisations as an aggregation of resources and offers a strong framework to demonstrate the relationship between organisational performance and organisational resources (Hutahayan, 2020). Another limitation of KBV is that it does not consider the importance of dynamic capabilities and ignores how companies can continuously update and develop their capabilities over time to remain competitive (Kaur, 2022). In contrast, RBT places a greater emphasis on the importance of dynamic capabilities, as well as the ability to acquire and integrate new resources and capabilities over time. Furthermore, KBV overlooks the importance of market positioning and strategic position. Firms must carefully examine their market positioning and strategically utilise their resources to maximise their competitive advantage. (Grant and Phene, 2022). RBT takes a more holistic view considering both internal capacity and external market conditions. Therefore, in this study, the RBT will be employed to constitute BDAC.

3.4.3 Resource-based Theory

Understanding firms' Big Data resources and determining the effective strategies to exploit them are crucial to establishing a completive advantage. This section focuses specifically on the relationship between RBT and BDAC. Following Barney (1991) seminal work, RBT has served as a crucial theoretical base for elucidating the significance of resources to sustained competitive advantage (Jeble et al., 2018). Barney et al. (2011) argued that firms could exploit a bundle of valuable, rare, inimitable and non-substitutable resources to achieve profitability in a highly competitive market. RBT emphasised two core components: resources and capabilities. Resources refer to tangible and intangible assets such as technology, human and organisational. Capabilities refer to a particular type of resource, which is also identified as tangible or intangible and aims to improve the productivity of other resources (Wang and Sengupta, 2016). After years of study and improvement, RBT has emerged as one of the most effective and well-known theories for analysing, describing, and forecasting organisational relationships and competitive advantages in many business disciplines (Gupta and George, 2016, Barney et al., 2011).

Gordon et al. (2005) investigated the competitiveness of the Port of Singapore by using the resource-based view and emphasised the contribution of IT to the Port of Singapore. Siregar and Sembiring (2013) used an RBT framework to analyse the information system and technique of Indonesia seaport company and point out the importance of IT to sustainable competitiveness. Moreover, RBT was utilised by Hyuksoo and Sangkyun (2015) to assess the container ports in different countries. Their research adds value by extending the use of RBT in ports and presenting five port resources, including traffic volume, infrastructure quality, linear shipping connection, operational efficiency, and institutional influence. De Martino et al. (2015) argued the importance and close relationship between port and hinterland, and they indicated that hinterland and intermodal services should be regarded as an important resource of ports. Hence, they used BRT to analyse the PSC and point out that ports must look beyond the port perimeter to collaborate with supply chain partners, related stakeholders, physical and knowledge-based resources to gain competitive advantage and value. Furthermore, the researches of Gordon et al. (2005), Siregar and Sembiring (2013), Hyuksoo and Sangkyun (2015) and De Martino et al. (2015) lack investigation of the impact of environmental resources. With the increasing environmental issues, port authorities need to evaluate the impact of environmental performance on port competitiveness. Cheon et al. (2017) employed RBT to explore the importance of environmental resources to port competitiveness, helping ports face mounting environmental pressures. These studies emphasised the significance of building a unique port.

Drawing on the RBT, many researchers consider BDAC to have the characteristics of value, rarity, imperfect inimitability and organisation and could be regarded as a significant source of organisation competitiveness (Queiroz and Telles, 2018, Kache and Seuring, 2017, Shan et al., 2019, Su et al., 2021). However, Gupta and George (2016) emphasised that BDAC, rather than Big Data, is regarded as the source of organisation competitiveness since most organisations will enable to collect a tonne of data from various sources. Moreover, building BACD needs to integrate different resources rather than merely rely on investments (Mikalef et al., 2018). Grant (2016) argued that organisations need to combine their physical, human, financial and organisational resources to create a capability. Capability building view complements the RBT and explains the process of creating unique and idiosyncratic (Wang and Hajli, 2017). In order to achieve turning inputs into valuable outputs, organisations should establish capabilities that will be challenging for competitors to duplicate by deploying, assembling, and integrating their resources. (Tallman et al., 2018). Port of Singapore created its IT capability by combining investment, infrastructure, government policies, human and IT management skills (Gordon et al., 2005). Hence, organisations need to reconfigure and integrate their resources to establish BDAC.

The above discussion shows that the resource-based theory could be applied to the evaluation of port BDAC. The RBT not only notes the importance of creating BDAC to firm competitiveness but also presents developing port IT capability by combining various port resources to improve port performance. Hence, using RBT could help people to understand and investigate the BDAC in ports.

3.4.4 Resources of the Big Data Analytics Capability

In sections 3.4.1 and 3.4.2, the BDAC and RBT are fully discussed. Port authorities need to integrate different resources to develop their BDAC to gain a competitive advantage. Drawing on the RBT logic, some studies (Gupta and George, 2016, Ciampi et al., 2020a, Lozada et al., 2019, Mikalef et al., 2019b) identify seven resources as the enablers of BDAC. The following Fig 3.5 shows the resources of BDAC. The tangible resources include data resources, technology resources and basic resources. Intangible assets involve data-driven culture and organizational learning. Human resources include managerial skills and technical skills.

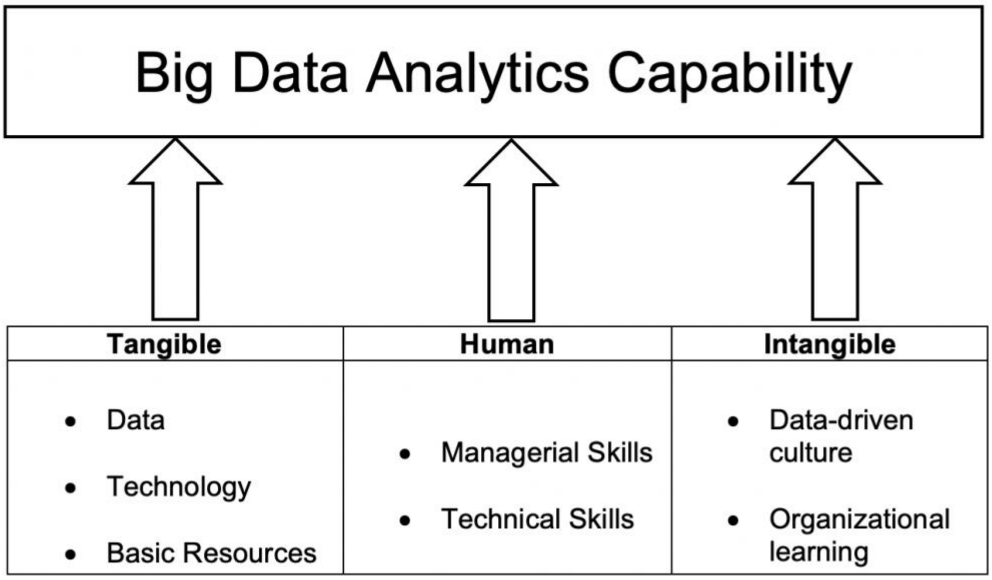

Figure 3.5 Resources of Big Data Analytics Capability

Source: Gupta and George. 2016.

3.4.5 Tangible Resources

According to Barney et al. (2011), tangible resources could be bought from the market, including buildings, IT infrastructure, equipment, equity, network, data sources, etc. Mikalef et al. (2018) indicated that more and more companies are trying to become data-driven companies, and they consider that data is the core driver of profitability in the data-oriented economy. Sheng et al. (2017) and Raguseo (2018) emphasised that organisations need to collect available data from various sources to help managers to gain more novel insights. Moreover, Bourreau et al. (2017) argued that it is common for firms to buy data from third parties to support their analysing and gain more insights. Hence, the core resource of BDAC is the data itself.

Data resources require advantageous technology to explore their value and meet the challenges. Grover et al. (2018) indicated that increasing organisational data exist in an unstructured format and require advantage analysis technology to create value. Ghasemaghaei (2020) also emphasised the importance of organisations' investment in sophisticated data analytics to explore insights from Big Data. Therefore, technology also is an important resource for developing BDAC.

Furthermore, utilising Big Data resources and developing new technology requires adequate investments. Raguseo (2018) pointed out that organisations need enough time to deploy and adapt invested new technologies to reap the full benefits. Thus, investments and time are referred to as two tangible resources which could support organisations creating BDAC.

3.4.6 Human Resources

Utilising data resources and new Big Data technology is highly dependent on human resources (Jeble et al., 2018). Lozada et al. (2019) indicated that technical skills and managerial skills are two essential aspects of human resources in creating BDAC.

Employing Big Data technologies requires people with specific skills and knowledge in, for example, scripting or programming language, cloud-based statistical platforms, and platforms used to track and understand website interactions (De Mauro et al., 2018). Tabesh et al. (2019) emphasised that organisations which lack data scientists will hardly realise the value of Big Data and develop BDAC. Furthermore, managerial skills also are a crucial component of human resources. Jeble et al. (2018) indicated that managers who have great management skills and experiences could help teams and firms achieve analytics projects. Additionally, the business will not benefit much from data analysis if managers cannot conclude from the results (Yasmin et al., 2020). As a result, the development of BDAC is said to require both technical and management expertise.

3.4.7 Intangible Resources

In contrast to tangible resources, intangible resources lack distinct and obvious bounds (Teece, 2014). Thus, intangible resources are not included in companies' financial statements, but they are regarded as a significant contributor to the company's performance (Monteiro et al., 2019). Lozada et al. (2019) argued that two intangible resources, namely Data-driven culture and Organisational learning, might assist a company in developing BDAC.

Organisational culture is an influential theory in organisation theory, and there is a lack of consistent definitions of this concept (Cao et al., 2015). A generally accepted definition of corporate culture relates to the values and beliefs that set norms for anticipated employee behaviour (Aboramadan et al., 2020). Dubey et al. (2019a) argued that organisational culture, not a lack of technology, is the fundamental reason for the failure of Big Data projects. Thus, firms require to develop a data-driven culture to support Big Data projects and gain novel insights from Big Data.

Organisation learning is considered to be the process of renewing knowledge assets and requires organisations to explore and learn new knowledge (Odor, 2018). Oh and Han (2020) indicated that in the rapidly changing internal and external environment, firms which continue developing and innovating with the latest knowledge would gain more competitive advantages. Therefore, data-driven culture and organisational learning are considered two important contributions to creating BDAC.

Therefore, this study considers BDAC an important capability for ports through RBT and Big Data studies. Developing BDAC requires organisations to combine data, technology, basic resources, managerial skills, technical skills, data-driven culture and organisational resources.

3.5 PLS-SEM and CB-SEM

Hair Jr et al. (2014) proposed that SEM has two techniques: covariance-based approach (CB-SEM) and variance-based partial least squares technique (PLS-SEM). The CB-SEM approach is undertaken when the research objective is theory testing and formation. This method determines the accuracy of a suggested theoretical model's estimation of the covariance matrix given a sample dataset (Sarstedt et al., 2014b). In contrast, the PLS-SEM method is employed when the purpose of the research is theory formulation and prediction. Babin et al. (2008) and Hair et al. (2012) indicated that although CB-SEM and PLS-SEM both were developed in 1980, CB-SEM became a broadly used approach in social science since the early development of Liner Structural Relations Statistical Software (LISREL). The statistical software package for CB-SEM can be obtained in Analysis of Moment Structures (AMOS), LISREL and Mplus (Afthanorhan, 2013). However, with analytics tools such as PLS-Graph software and SmartPLS software becoming available on the market, PLS-SEM gained the attention of the academic and research community (Ringle et al., 2015). This study chooses SmartPLS 3.0 as the analytics software since it is freely available to researchers and it has advanced reporting features (Wong, 2013). PLS-SEM experienced many methodological advances and disseminated to management and other disciplines continually. Many researchers (Patel et al., 2016, Calvo-Mora et al., 2016, Barroso-Méndez et al., 2016, Kurt et al., 2016) presented PLS-SEM application in the management research area. Therefore, PLS-SEM can be used to support researchers in the management area.

Furthermore, although CB-SEM and PLS-SEM both can analyse measurement theory and structural path models, each method is appropriate for a different research context. The following table shows the difference between CB-SEM and PLS-SEM.

Criterion	**PLS-SEM**	**CB-SEM**
Research Goals	Prediction of key target constructs, exploration or extension of an existing structural theory	Theory testing, Theory confirmation, Comparing alternative theories
Measurement Model Specifications	Can be modelled in either formative or reflective mode	Mainly reflective indicators
Model Complexity	Model is a large complexity	Model is small to moderate complexity
Indicators Per Construct	One or more	Ideally, 3-4 minimum to meet the identification requirement
Distribution Assumptions	Non-distribution	Normal distribution
Sample Size	Recommendations for the minimum sample size from 30 to 100.	Recommendation for the minimum sample size from 200 to 800

Table 3.4 Comparison of Partial Least and Covariance based Squares Structural

Source: Adapted from Sarstedt et al. (2014a)

Usakli and Kucukergin (2018) highlighted that the philosophy of measurement and the purpose of the analysis are the two determining factors when selecting between PLS-SEM and CB-SEM. PLS-SEM and CB-SEM follow different measurement philosophies. CB-SEM employs the common variance (the amount of variance shared by a collection of items) of the indicators and models the latent variables as common factors that explain the covariation between their related indicators. PLS-SEM, on the other hand, utilises the total variance (composed of common variance and unique variance) of the indicators to construct linear combinations of indicators (Rigdon et al., 2017b, Sarstedt et al., 2016). The following figure shows how total variance and common variance are related.

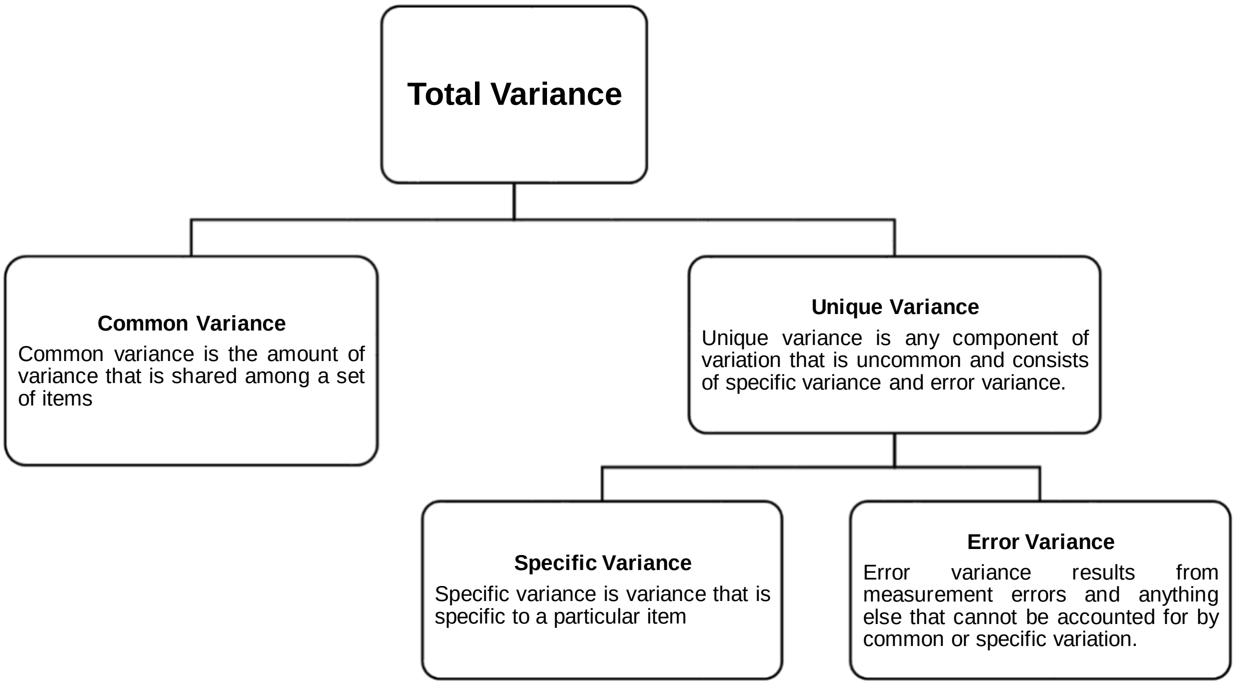

Figure 3.6The total variance and common variance

Source: Adapted from Sarstedt et al., 2016

Thus, compared with the CB-SEM estimation of the observed covariance matrix, the PLS-SEM approach enables the retention of more indicator variables to increase predictive accuracy and relevance (Hair et al., 2011). In addition, the study objective should be addressed while deciding between PLS-SEM and CB-SEM. Ali et al. (2018) and Richter et al. (2016) point out that the CB-SEM approach focuses on theory testing and confirmation. The PLS-SEM approach focuses on explanatory modelling and predicting key target constructs. Therefore, PLS-SEM is more suitable for undertaking this research based on the aim of this study.

3.6 Discussion of the research gaps

Based on the aforementioned analysis of the literature on BDAC, RBT, port sustainability, and port performance, some research gaps have been identified, which open avenues for further research:

1) Few existing studies have investigated the BDAC from port areas. According to a study of the pertinent literature, prior research has focused on examining the potential and problems that BDAC presents to financial organisations, information firms, manufacturing firms, and hospitals (Awan et al., 2021, Mikalef et al., 2020, Galetsi et al., 2020, Upadhyay and Kumar, 2020, Sabharwal and Miah, 2021, Maheshwari et al., 2021, Khanra et al., 2020). Recent literature review articles on the usage of Big Data analytics in the corporate context showed that most papers published in journals were on the subject of business, management, accounting, social science, decision, environmental science, energy, economics and finance, implying that there remains a gap in the literature about the impact of Big Data analytics on marmites and ports areas (Khanra et al., 2020). Moreover, Maheshwari et al. (2021) investigated the importance of Big Data analytics in SCM and illustrated key SCM areas employing Big Data analytics, such as education, finance, governance, healthcare, retail, and telecom. While it is generally agreed that ports play a

significant role in the supply chain, there is a lack of research investigating the potential of Big Data analytics in ports. Thus, it is evident that the impact of BDAC on ports needs more research.

2) Existing work on Big Data and ports has mainly focused on developing and applying new digital technology (Munim et al., 2020, Zarzuelo et al., 2020, Del Giudice et al., 2022, Inkinen et al., 2019). For example, the work of Zarzuelo et al. (2020) demonstrates several key technologies for port digitalisation, such as IoT, sensing solutions, cloud computing, energy solution, automation, and AI. Moreover, Munim et al. (2020) emphasise that when exploring the application of Big Data technologies in ports, more robust research on Big Data development in ports should also be conducted from a sociocultural and business research perspective. Meanwhile, more research is required to explore the impact of BDAC on ports, identifying the main drives for port digitalisation (Inkinen et al., 2021, González-Cancelas et al., 2020, Yau et al., 2020)

3) Little research has been conducted to develop a measurement model for constructing ports' BDAC. Although some scholars (Dubey et al., 2018a, Gupta and George, 2016, Yasmin et al., 2020, Awan et al., 2021) have explored what organisational resources are necessary for implementing Big Data initiatives, there is a lack of a universal model to evaluate the development of BDAC in the port area (Philipp, 2020, Brunila et al., 2021, Boullauazan et al., 2022). As an increasing number of ports shift to digital, port managers need a model to guide them in developing BDAC for driving digital transformation (Molavi et al., 2020, Heilig et al., 2017). Therefore, it is significant to understand the organismal resources and development process that ports require to build their BDAC (Vrakas et al., 2021).

4) Few existing studies have explored the mediating role of sustainability between BDAC and port performance. Although numerous scholars have revealed the benefit that BDAC brings to organisations, there is a limited body of understanding of the mechanisms through which BDAC can improve organisational performance (Mikalef et al., 2020, Wamba and Akter, 2019, Awan et al., 2021, Bahrami and Shokouhyar, 2021, Bahrami et al., 2022). Moreover, the current study focused on BDA as antecedents to sustainability (Jeble et al., 2018, Singh and El-Kassar, 2019, Dubey et al., 2019b, Raut et al., 2021, Xiao and Su, 2022). For example, Raut et al. (2021) highlight that BDA mediates the relationship between environmental practices and sustainable supply chain business performance. In addition, while the literature concerning ports and sustainability suggests that ports can create a sustainable completive advantage by applying RBT (De Martino, 2021, Yuen et al., 2019, Tran et al., 2020), little attention is paid to the impact of port sustainability as a mediator. Thus, there is a need to explore the mediation role of sustainability in the relationship between BDAC and port performance.

3.7 Summary

This chapter provides a review of Big Data, Big Data applications in ports, BDAC and RBT. First, the definitions of Big Data and its characteristics were reviewed; as a result, the five main characteristics of Big Data are clarified.

Second, Big Data applications in ports are discussed. A review of the literature has shown the Big Data application in the shipping industry and SCM, as well as highlighted the challenges of applying Big Data. Afterwards, examining the application of Big Data in port revealed that Big Data enjoy great potential to contribute to the development of ports. Then through a detailed analysis of Big Data in the shipping industry and SCM, a deep understanding of the challenge of Big Data in ports has been built.

Third, a review of BDAC and its related concepts has been conducted. Through a critical review of the literature relevant to RBT and BDAC, identifying seven organisational resources (data, technology, basic resources, technical skills, managerial skills, data-driven culture and organisational learning resources) for ports to build BDAC. Then, the significance of the seven resources was explored.

Furthermore, this chapter introduces two types of structural equation modelling techniques: Partial Least Squares Structural Equation Modeling (PLS-SEM) and Covariance-Based Structural Equation Modeling (CB-SEM). The key differences between these methods and their strengths and weaknesses were discussed, as well as highlighting situations where each method might be most appropriate.

Finally, four research gaps related to ports' BDAC, the relationships among BDAC, port sustainability, and port performance have been proposed based on the literature review after examining the key concepts and identifying indicators used in the measurement model. The following Chapter describes in detail how the theoretical model is constructed.

Chapter 4 Model and Hypotheses Development

4.1 Introduction

According to the literature in chapters 2 and 3, the crucial factors for achieving the research objective have been determined. It showed the new role of ports and the importance of integrating the sustainability concept into port development. It highlighted the impact of PSC and digitalisation on port performance. It also found that BDAC is an essential factor in improving ports. The research understands that the relationship between BDAC, port sustainability and port performance has yet to be tested in the research objective and conceptual framework context of port areas. Therefore, developing a theoretical model that illustrates the potential connections between the three conceptions is necessary.

This chapter aims to construct and defend a conceptual framework illustrating essential theoretical links between BDAC, port sustainability, and port performance. The measurement model for each variable will also be identified to demonstrate the factors contributing to these constructs. The chapter consists of three sections. It begins with a consideration of the direct relationship theories between constructs. The potential mediating effect of the model is then addressed. The chapter finishes with the conceptual model proposal.

4.2 Hypotheses of the direct relationships between constructs

4.2.1 The relationship between BDAC and port performance

As an integral part of the supply chain, port managers should focus on internal and external efficiency and meet stakeholder and customer perspectives and expectations (Ha et al., 2019). There is increasing discussion about the importance of BDAC in improving organisations' performance (Chen et al., 2015, Akter et al., 2016, Kache and Seuring, 2017, Lai et al., 2018, Jeble et al., 2018, Yasmin et al., 2020, Gu et al., 2021). BDAC is considered as a significant organisational information processing capability and could improve supply chain value creation (Chen et al., 2015). The study carried out by Akter et al. (2016) revealed that, drawing on the RBT, firms could improve firm performance through insights gained from building BDAC. The finding is congruent with the work of Wamba et al. (2017), who suggested that BDAC is a fundamental organisational competency that leads to a competitive edge in the Big data environment. Drawing on the RBT, in the Big Data and digitalisation environment, this research argued that port could improve competitiveness via integrating and deploying tangible (i.e., data, technology, basic resources), Human (i.e., managerial skills, technical skills), and intangible (i.e., data-driven culture, organisational learning) resources. Table 4.1 lists and defines individual sub-constructs that make up the BDAC affecting the port sustainability and port performance. Based on the literature review discussion, this study considers that these seven sources could help ports create BDAC and affect port sustainability and performance.

Moreover, Kache and Seuring (2017) pointed out that although the application of BDAC is still in its infancy stage, BDAC appears to have huge potential in information usage and decision-making at the supply chain level. Firm data can be better utilised when firms develop BDAC. They can improve their service offering, opportunity seizing, and value creation via data processing (Shou et al., 2019). Developing BDAC can help firms become data-driven in decision-making. Managers relying on data for decision-making make fast decisions, reducing reaction time and increasing productivity and profitability (Brinch, 2018). Drawing on the work of Brinch, Awan et al. (2021) highlighted that BDAC can drive decision-making quality and strengthen the business's value-added activities. BDAC not only can help organisations to integrate external relationships with customers and suppliers but also can improve internal processes to achieve information sharing and collaboration across departments of function within an organisation (Yu et al., 2021b). In addition, Lee (2018) argued that firms can re-design business processes by utilising Big Data to create new products and services for customers. Meanwhile, by analysing gathered data on customers and transactions, companies could improve service quality and tailor the requirements of customers (Cohen, 2018). Therefore, BDAC is one of the key organisational capabilities that affect competitive advantage in the big data environment.

Furthermore, as important supply chain nodes, ports are information-exchange hubs, managing volumes of data to share data between players in the PSC (Simoni et al., 2020). Given that ports deploy various sensors to achieve real-time monitoring and record port operation activities, they amass data that can be utilised to create value. The processing of these data by BDA technology can optimise operational efficiency and enhance the decision-making processes of ports (Jović et al., 2019b). Meanwhile, these data can also be applied by other stakeholders to become their new revenue source, eventually increasing the stakeholders and activity boundaries of ports (Cáceres et al., 2022). Bo and Meifang (2021) argued that Big Data and AI technology could help PSC members exchange their knowledge and relevant experience with each other, improving the performance of PSC participants and realise intelligent PSC. Other studies have identified a positive link between IT capability and port performance (Tseng and Liao, 2015, Bauk et al., 2018, Keceli, 2011)

While there is wide agreement that BDAC could enhance port performance, views differ on building BDAC in ports. Empirical evidence has supported the claim that traditional storage and analysing systems cannot manage massive data.

Organisations need to invest in technological infrastructure to gain advanced data management tools and additional data storage, increasing the financial pressure on the organisation (Al-Sai and Abdullah, 2019). Meanwhile, companies could lose control if existing staff lack sufficient experience to use advanced data management tools (González-Cancelas et al., 2020). Cappa et al. (2021) also point out that collecting large data volumes may eventually lead to infobesity, resulting in firms not extracting efficacious information. In addition, when ports undergo digital transformation, they face the threat of cyber-attacks which can seriously damage port operations (Gunes et al., 2021). Therefore, the effect of BDAC on port performance needs to be tested.

Based on the literature reviewed and general logic, the following hypothesis is proposed:

H1. Big Data analytics capability has a positive effect on port performance.

Construct	Definition	Source
Data	The extent to which organisations gather and integrate their internal and external data.	Akter et al. (2016); Jeble et al. (2018); Wamba et al. (2017); Lai et al. (2018), Mikalef et al. (2020); AlNuaimi et al. (2021)
Technology	The extent to which technological systems and platforms are available, used, and expected in organisations.	Jeble et al. (2018); Gupta and George (2016); Jha et al. (2020); Ashaari et al. (2021)
Basic Resources	The extent to which the organisations invest and spend time in BDA projects.	Akter et al. (2016); Gupta and George (2016); Jeble et al. (2018); Lai et al. (2018); Wang et al. (2016)
Managerial Skills	The extent to which managers understand and utilise BDA.	Akter et al. (2016); Jeble et al. (2018); Wamba et al. (2017); Lai et al. (2018); Jha et al. (2020); AlNuaimi et al. (2021)
Technical Skill	The extent to which employees have familiarised BDA skills.	Gupta and George (2016); Jeble et al. (2018); Wamba et al. (2017); Lai et al. (2018); Mikalef et al. (2020); Ashaari et al. (2021)
Data-driven Culture	The extent to which data-driven culture fosters decision-making, employee development and Big Data capability.	Jeble et al. (2018); Akter et al. (2016); Gupta and George (2016), Lai et al. (2018); Awan et al. (2021)
Organizational learning	The extent to which organisations offer knowledge	Akter et al. (2016); Jeble et al. (2018); Wamba et al. (2017); Lai et al. (2018), Arunachalam et al. (2018)

Table 4.1 Big Data Analytics Capability and Sub-constructs

4.2.2 BDAC and Port Sustainability

The need for sustainable development has been articulated widely. Most of the research (Lam and Li, 2019, Sislian et al., 2016, Cheon and Deakin, 2010, Kong and Liu, 2021, Lim et al., 2019) on port sustainability suggests a framework which involves the dimension of environment, society and economy, implying that ports not only need to contribute to the economy of nations and regions but also need to recognise their responsibility of the environment and build a harmonious port community. Table 4.2 lists individual sub-constructs that make up port sustainability performance. By examining the performance of these three performances, the outcome of port sustainability could be obtained.

Authorities and relevant organisations have recently turned their attention toward BDAC to improve sustainability (Song et al., 2017, Dubey et al., 2016, Jeble et al., 2018, Wu et al., 2016). Dubey et al. (2015) argued that BDA could support world-class manufacturing to balance its environmental, social and economic dimensions to achieve world-class sustainable manufacturing. Jeble et al. (2018) focused on the perspective of businesses and argued that Big Data and forecasting analytics capabilities might enhance the supply chain's sustainable performance. Given the potential of BDAC for enhancing sustainability, some ports employ Big Data technologies to seek a socially acceptable, environmentally friendly, and profit-maximising managerial approach. Ferretti and Schiavone (2016) presented that the Port of Hamburg tries to build an intelligent port by utilising Big Data to improve both the economic and ecological performance of the port. Ports primarily employ Big Data technology to accelerate digitisation and manage data from monitoring sensors (Heilig and Voß, 2017). Port authorities monitor the pollutant emission and gather relevant data from deployed air and water monitoring sensors, then use BDA to analyse these data to make informed decisions and improve environmental performance (Rathore et al., 2016, Casazza et al., 2019). In addition, Zhang et al. (2019b) reported that ports could analyse large AIS data to regulate the spatial-temporal dynamics of ship traffic in port waters, thereby avoiding ship collisions. Meanwhile, port authorities can utilise Big Data technology to forecast ship emissions by AIS and environmental data, thereby identification of emission reduction potentials and making the plane reduce emissions (Hensel et al., 2020).

Furthermore, IoT and Big Data technologies can help ports construct automated container terminals. Ports can analyse gathered data from vehicles, berth and quay cranes to optimise berth allocation and quay crane assignment strategies, reducing consumption of energy (Li et al., 2022). Port managers can monitor ports' equipment with IoT to maintain and repair them before failure, thus building a safe working environment for ports' employees (Hiekata et al., 2021). Besides, innovation can provide a solution to the main environmental issues. Burškytė et al. (2016) indicated that ports could improve environmental performance and remedy conflicts among ports and local communities by implementing eco-innovations. Big Data as a significant driver of innovation, could assist ports in eco-innovation. In addition, Santos et al. (2016) argued that online communication and information sharing could improve ports' environmental and social performance. Port could offer timely and wide online communication by using Big Data.

However, some previous studies (Bonilla et al., 2018, Furstenau et al., 2020) indicated that organisations need to replace obsolete equipment to deploy advanced Big Data technology, thus increasing resource waste and cost. Meanwhile, implementing advanced equipment and new systems caused the firm to dismiss unskilled labour, implying that the application of Big Data technology did not positively impact environmental, financial or social sustainability. Hence, to test the relationship, the following hypothesis is proposed:

H2. Big Data analytics capability positively influences the port sustainability performance.

Construct	Source
Environmental performance	Santos et al. (2016); Jeble et al. (2018), Rathore et al., 2016; Lim et al., 2019; Lam and Li, (2019); Chen and Pak (2017)
Social performance	Jeble et al. (2018); Lim et al., 2019, Lam and Li, (2019); Bjerkan and Ryghaug (2021); Oh *et al.* (2018)
Economic performance	Oh et al. (2018), Liu et al. (2016), Lim et al., (2019), Lam and Li, (2019), Ashrafi et al. (2020)

Table 4.2 Port Sustainability Performance and Sub-construct

4.2.3 Port sustainability and port performance

Given the increase in the environmental awareness of the public and port stakeholders, ports cannot ignore the negative impacts associated with the environmental and social issues within or near the port. Ports increasingly face social and regulatory pressures (Stanković et al., 2021). Consequently, attaining port sustainability is a crucial aspect of port competitiveness. Camilleri (2022) pointed out that organisations could gain a better positioning than their competitors by implementing their sustainable strategy.

Numerous scholars (Lu et al., 2016c, Parola et al., 2017, Lee et al., 2019, Hossain et al., 2021, Beleya et al., 2015) stressed the significance of developing port sustainability and argued that ports need to integrate sustainability concerns into their business strategies and operation to improve port performance. Zhang et al. (2019d) argue that sustainability can help firms improve organisational processes that enhance economic performance. By adopting environmental responsibility, ports can reduce the negative effects of environmental activities that can negatively impact their financial performance, such as lawsuits, fines, and reputational damage (Kronfeld-Goharani, 2018). Notteboom et al. (2020) note that implementing sustainability strategies can help ports meet the environmental requirements of business partners and achieve integration within a green supply chain, thus improving operational efficiency and reducing costs.

Moreover, economic sustainability can help ports build economic resilience and competitiveness (Vejvar et al., 2018). Further, sustainability improves not only the environment but also working and community conditions, which can enhance the operational performance of an organisation (Croom et al., 2018). Ports could extract and utilise tangible and intangible cultural values by considering the needs of local people and tourist communities, achieving better expansion and development (Carpenter et al., 2018, Zheng et al., 2020). In the meantime, port cities may improve port service quality and incubate additional value-added PSC service sectors by fostering port and city sustainability and interaction (Chen and Lam, 2018). Based on the literature review, five sub-dimensions are examined as the port performance measure. These are defined in Table 4.3.

However, while much literature supports the claim that pursuing sustainability improves firm performance, some studies (Adebanjo et al., 2016, Das, 2018) have not found significant relationships. Further, Magon et al. (2018) indicated that environmental and social practices might lead the firm to redesign the product to meet sustainability requirements, increasing the cost and time-to-market of new product development.

H3. Port sustainability performance positively influences the port performance.

Construct	Definition	Source
Service quality	The extent to which ports are able to offer safe and reliable services	Kim et al. (2016), Woo et al. (2013), Seo et al. (2016), Lu et al. (2016); Essel et al. (2022)
Cost	The extent to which ports are able to provide cost-effective service price	Kim et al. (2016), Woo et al. (2013), Seo et al. (2016), Ishii et al. (2013), Woo et al. (2011)
Operational efficiency	The extent to which ports are able to act quickly when faced with customers' requirements	Kim et al. (2016); Seo et al. (2016); Jiang et al. (2021); Zagloel (2019)
Value-added Services	The extent to which ports are able to add value to the services that it provides	Seo et al. (2016), Tseng and Liao (2015); Amonkar et al. (2021); Yang and Lirn (2017)
Customer Orientation	The extent to which ports are able to satisfy customers' needs.	Woo et al. (2011), Panayides (2017), Lee et al. (2016), Tseng and Liao (2015); Mwendapole and Jin (2021); (Le et al., 2020)

Table 4.3 Port Performance and Sub-construct

4.3 Mediation role of port sustainability

Some studies (Sarabia-Jácome et al., 2019b, Bauk et al., 2018, Munim et al., 2020) argue for a direct relationship between BDA technologies and port performance. Caldeirinha et al. (2020) note that ports enhance collaboration with supply chain partners via electronic data exchange platforms to improve service and operation performances. However, digitising port operations and building PCSs could help achieve sustainability to improve performance. Equally, port managers can optimise port operations, such as improving automated guided vehicles to reduce transportation times and reduce vessels' turnaround time through collected operational data, leading to improved economic sustainability and reduced cost (Del Giudice et al., 2022). Munim et al. (2020) claim that ports utilise massive operational data to reduce emissions and optimise energy efficiency, thus improving port environmental and economic sustainability. Strong port sustainability helps ports reduce environmental risk and improves port processes, enhancing performance (Yang et al., 2013, Ashrafi et al., 2019). Hence, sustainability could be significant in enhancing port performance. The following final hypothesis is as follows:

H4: Port sustainability mediates the relationship between BDAC and port performance.

4.4 Summary and conceptual model

Based on a survey of current literature on ports, sustainability, and BDAC research, a conceptual research model was established. Figure 4.1 and Table 4.4 illustrate a thorough model of the hypothesised relationships presented in this section. The proposed research model presented below illustrates our hypotheses and assumes that the port sustainability performance mediates the impact of BDAC on port performance. In the model, BDAC has seven first-order constructs: data, technology, basic resources, managerial skills, technical skills, data-driven culture, and organisational learning. Port sustainability has three first-order constructs: environmental, social and economic dimensions. Port performance has five first-order constructs: cost, service quality, operational efficiency, VAS, and customer orientation.

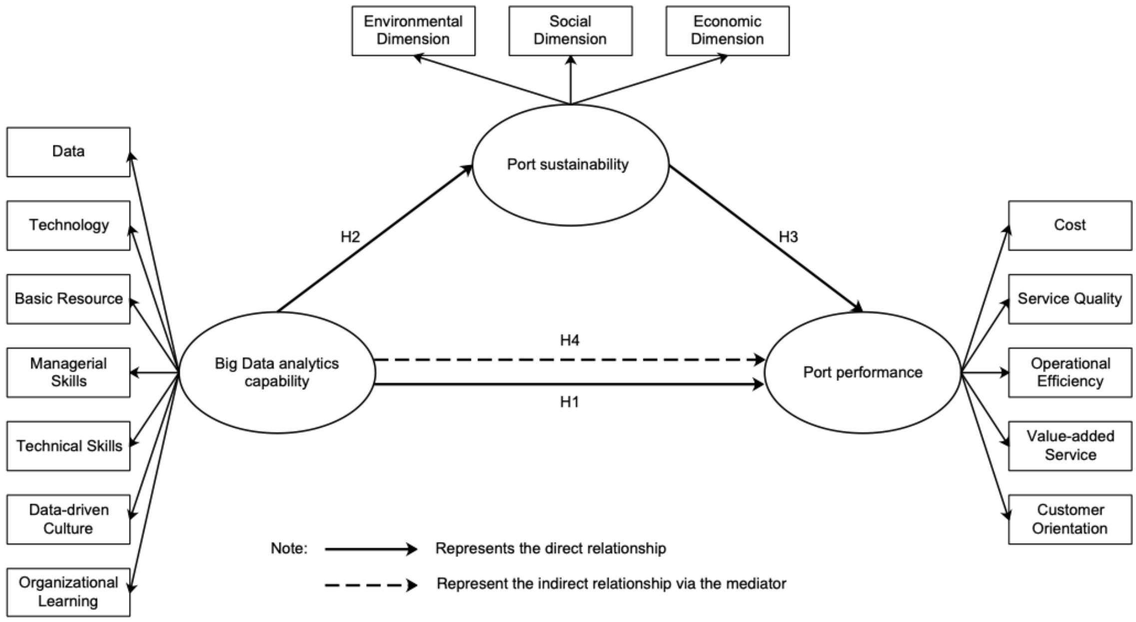

Figure 4.1 Conceptual model

Number	**Hypotheses**
H1	BDAC has a positive effect on port performance
H2	BDAC has a positive effect on port sustainability
H3	Port sustainability has a positive effect on port performance
H4	Port sustainability mediates the relationship between BDAC and port performance

Table 4.4 Summary of hypotheses

Chapter 5 Research design and methodology

5.1 Introduction

In the prior chapter, the conceptual model and hypotheses were introduced. This chapter outlines the design and methods of the research. This chapter starts by explaining the development of the research design, which was implemented through a quantitative method by questionnaire survey. This section also examines methodological aspects pertaining to research philosophies, research approaches, research strategy, research methodologies, research context, and the research process. The third section outlines how questionnaire surveys and other techniques of data collecting were conducted for this study. The fourth section introduces population characteristics and sampling methodology. The fifth section introduces the data analysis techniques employed in this study. The final section includes a chapter summary.

5.2 Research Philosophy and Approach

A research design is a plan and set of methods for conducting an investigation, depending on the nature of the research question or issues being investigated and the prior expertise of the researcher (Creswell, 2018). The research methodology explains to the reader how the researcher selected and implemented the available research methods. It should demonstrate that the research paradigm, research approach, research strategy, data collection methods, and data analysis are congruent with the whole process. Based on previous research (Amaratunga et al., 2002, Mkansi and Acheampong, 2012, Saunders et al., 2016), the following figure illustrates the stages of developing research.

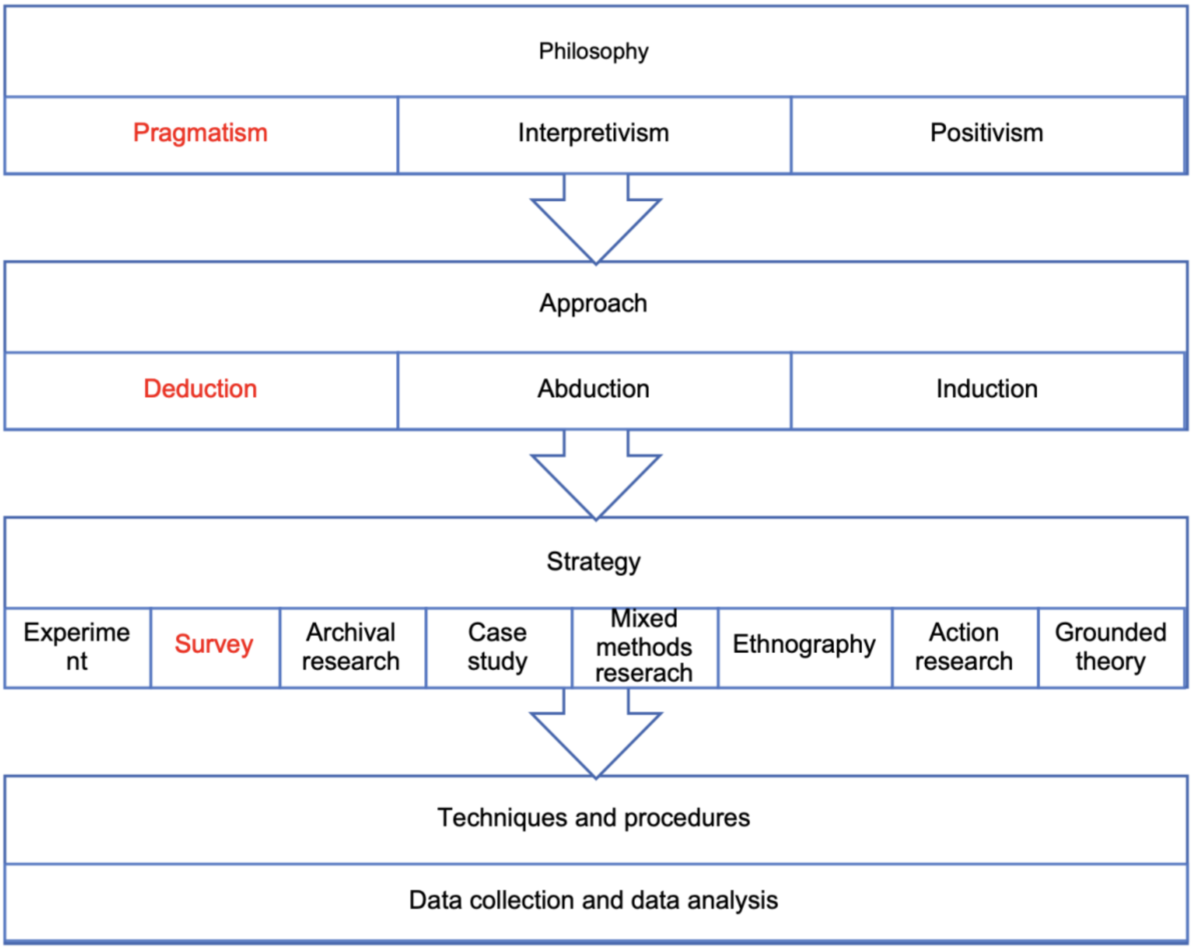

Figure 5.1 The research design

Source: Adapted from Mkansi and Acheampong (2012) and Saunders et al. (2016)

This study adopts pragmatism as its research philosophy and deductive reasoning as its research methodology. This research uses the survey to collect data and employs Structural Equation Modelling (SEM) approach to analyse gathered data. Following the order of philosophy, strategy, strategies, methods, research design, and sample techniques, the rationale for selecting the methodology for this study will be presented.

5.2.1 Research Philosophy

This section describes the available research philosophies and the one selected for this investigation. Data collection, analysis, and interpretation may be influenced by the research philosophy (Holden and Lynch, 2004). The research philosophy initially classifies how the world is perceived and demonstrates from which perspective the researcher views the problem and how the issue will be resolved. Research philosophy can influence how researchers perceive the world and subsequently understand it. The researcher will undertake their study following their comprehension of phenomena and the world (Sefotho, 2015). Hence, philosophy should become the driving force behind the whole research process.

The research philosophy can be distinguished by two main philosophical dimensions: ontology and epistemology (Wahyuni, 2012, Bunniss and Kelly, 2010, McLachlan and Garcia, 2015). Ontology and epistemology pertain to the nature of knowledge and the growth of that knowledge, respectively. The perspective of how the reality of one experience is ontology. According to Bryman et al. (2015), researchers should take a stance about their perceptions of how things actually are and function. On the other side, epistemology refers to the beliefs regarding the acceptable and proper means of generating, understanding and using knowledge. Scotland (2012) indicates that the focal question of epistemology is the nature of the relationship between the researchers and knowledge. Different research philosophies inherently contain differing ontological and epistemological views. The comparison and comprehension of research philosophies are summarised in Table 5.1.

Metatheoretical assumptions	Positivism	Interpretivism	Pragmatism
Ontology	Person and reality are separate	Person and reality are inseparable	Multiple realities can be investigated empirically
Epistemology	Research object has inherent qualities that exist independently of the researcher.	Knowledge of the world is internationally constituted through a person's lived experience.	Integrating different viewpoints to help interpret the data
Axiology	The research will be undertaken in a value-free way; the researcher is independent of the data	The researcher is part of what is being researched, cannot be separated and would be subjective	The researcher adopted both objective and subjective views
Data Collection Methods	Highly structured, large samples, measurement, quantitative, but can use qualitative	Small samples, in-depth investigations, qualitative	Mixed or multiple method designs; qualitative and quantitative

Table 5.1 Comparison of the Research Philosophies

Source: Adapter from Saunders et al. (2016)

Positivism aims to address big practical problems and identify precise causal linkages (McGregor and Murnane, 2010). Positivism argues that reality or knowledge is objective, independent, external and singular. Positivism supports the notion that the priority of research is scientific objectivity (Sefotho, 2015). To acquire objective and reliable data, researchers must separate the subject from the object, removing elements such as self, personal experiences, and feelings. Positivism is commonly employed in social research to provide more precise, quantifiable and objective data (Comte, 2015).

Interpretivism is a study technique focused on interpreting social occurrences in terms of their meanings (Goldkuhl, 2012). Instead of measuring and predicting occurrences, interpretivism emphasises the language, experiences, and perceptions of social actors.

Interpretivism seeks to comprehend not just what is occurring but also why. Chowdhury (2014) claimed that, given the complexity and uniqueness of business situations, social science research should consider influential contextual elements, personal experiences, and emotions that are sometimes disregarded in natural science study.

In addition, pragmatism also is a crucial philosophical viewpoint. Pragmatists claim that pragmatism is neither positivist nor interpretivism, and that it is feasible to deal with both ideologies (Yvonne Feilzer, 2010). Pragmatists argue that research issues and questions are more significant than the method's underlying philosophical assumptions (Giacobbi et al., 2005). In other words, pragmatists choose methods and theories which are more useful to tackle their research problems. Thus, Creswell (2018) and Venkatesh and Weatherspoon (2013) claim that pragmatism can integrate several methods. Both qualitative and quantitative research methods are feasible and well suited to generate complete evidence and power in a study than one method alone.

Based on the above discussion, this study is considered pragmatic. This research aims to investigate the impact of BDAC on ports. As the literature review above reveals, the current state of knowledge on the potential for BDAC to facilitate ports' performance and sustainability is currently in its infancy. Pragmatism allows researchers to analyse and synthesise extant knowledge while simultaneously exploring the possibilities of inventing new knowledge (Kaushik and Walsh, 2019). Considering that pragmatism is more suitable than other philosophies to investigate the impact of BDAC on ports. Previous research (Mendling et al., 2021, Kankam, 2019) has supported this opinion and indicated that pragmatism is a philosophy particularly suitable for research in the field of information systems. Moreover, this research needs to communicate with different PSC participants to explore knowledge related to BDAC, port sustainability and port performance. Pragmatism can help scholars to accept multi-faced viewpoints from different people and draw perspectives from multiple disciplines, ensuring a plurality of different perspectives and an ongoing integration of new ideas (Ockwell et al., 2019). Furthermore, pragmatism could avoid dualism, and pragmatists enable engagement in the process of trans-acting with others and things on an ongoing basis (Painter et al., 2019). Thus, the pragmatist's perspective could help the researcher to investigate how BDAC can change the port. As analysed above, this study follows a pragmatism philosophy. Pragmatism philosophy allows one method for specific research in the best possible manner (Iovino and Tsitsianis, 2020). In order to achieve the study aim, four research hypotheses were developed based on the literature review, and these hypotheses were tested using a quantitative methodology. The details of the method are further discussed in the following section.

5.2.2 Research approaches

There are two primary features of research approaches: deductive reasoning and inductive reasoning (Saunders et al., 2016). Deductive reasoning is a procedure for evaluating theories, which begins with an established theory or generalisation and strives to determine if the theory applies to particular situations. In contrast, Inductive reasoning is a theory construction process that begins with observations of particular examples and aims to establish generalisations about the investigated topic (Spens and Kovács, 2006). Nevertheless, as the differences between inductive and deductive research become smaller, abductive research, which mixes the two, is becoming increasingly popular. (Johnson et al., 2007). The advantages of the abductive research method include a deeper comprehension of a particular research issue.

Table 5.2 lists the characteristics of the deductive, inductive, and abductive research methodologies.

Feature	**Deductive**	**Inductive**	**Abductive**
Objective	To test theories, therefore validating true ones and eliminating false ones	To create descriptions of attributes and patterns	To comprehend social reality about the significance and motivations of social actors
Generalisability	Generalising from the general to the specific	Generalising from the specific to the general	Generalising from the interactions between the general and the specific
Contributions to theory	Theory verification or falsification	Theory building and generation	Theory building or modification
General process	Theory ↓ Hypothesis ↓ Data collection ↓ Findings ↓ Hypotheses confirmed or rejected ↓ Revision of theory	Observations ↓ Produce descriptions ↓ Relate these to research questions ↓ Theory building	Theory/Observation ↓ Generate or modify an existing theory ↓ Observation/date collection ↓ Relate these to research questions/data analysis ↓ Iterative theory development
Major research purposes	Explanation	Exploration Description	Exploration Description

Table 5.2 Feature of the three research approaches

Source: Author adapted by Bell et al. (2018)

The selection of research methods is contingent on the nature of the research problem and investigation. There are three different kinds of research objectives: exploratory, explanatory, and descriptive (Saunders et al., 2016). When a topic or phenomenon is little known and little research has been conducted on it, exploratory research is conducted (Stebbins, 2001). Explanatory research tries to test the prior theory or hypothesis, typically in the form of a causal relationship between various variables, whereas descriptive research aims to provide an objective description of the research subject (Nassaji, 2015, Gelo et al., 2008). From Table 2, explanation research is usually associated with the deductive research approach. By testing constructed hypotheses, this research investigates the relationship between BDAC, port sustainability and port performance. As a result, this study employs deductive reasoning as its method. As stated previously, pragmatism is the guiding philosophy, and deductive reasoning is the method employed in this study.

5.2.3 Research Strategy

This section shows what research strategy has been adopted in this study. Research strategy enables the scholar to investigate the research issues and guides the scholar to plan, execute, and monitor the study (Johannesson and Perjons, 2014). Creswell (2018) identifies three types of research methods: quantitative, qualitative, and hybrid. Quantitative research is the method that produces quantification and statistical analysis of data and seeks to demonstrate a cause-and-effect link between two variables via the use of mathematical, computational, and statistical approaches (Sürücü and MASLAKÇI, 2020). It adheres to the strict standards of logic, laws, prediction, and truth and is typically connected with positivist research philosophy (Mohajan, 2020). Apuke (2017) argued that quantitative methods could use to test theories and hypotheses and confirm the relationships between the factors.

Comparatively, qualitative research is an in-depth method that seeks to disclose individual beliefs, perceptions and attitudes to certain issues or sets of circumstances and attempts to interpret them (Mohajan, 2018). Qualitative approaches allow the researchers to investigate the original context of the phenomena under examination to capture the essential essence of a phenomenon (Castleberry and Nolen, 2018). Bansal et al. (2018) emphasised that qualitative research focuses on revealing the behaviour and perception of a target audience regarding a particular topic rather than using observation to produce measurements of a phenomenon or event. The definition of mixed methods research is when a researcher combines qualitative and quantitative research methodologies within a single study or a collection of closely connected studies (Creswell and Clark, 2017). Mengshoel (2012), Sandelowski (2014) and Van Griensven et al. (2014) propose three different types of mixed research designs. First, a quantitative method is applied first, followed by a qualitative method to explain the quantitative results. This design has been called explanatory. Second, a study in which a quantitative phase follows a qualitative phase has been called exploratory design. Finally, quantitative and qualitative approaches are applied simultaneously throughout the research process or at certain stages in parallel study design. Due to the aim of this study, this study applies a quantitative method to assess the relationship between variables. Some research (Mohajan, 2020, Johnson and Onwuegbuzie, 2004, Ramona, 2011, Lee, 2014, Ahmad et al., 2019) provided the advantages and weaknesses of quantitative research. The following table displays the advantages and challenges of using quantitative research methods.

Advantages	Disadvantages
• Results can be aggregated and are comparable across population groups. • Quantitative methods allow for the generalisation of research findings so long as the sample size is representative of the target population. • Quantitative research uses a randomised process to collect information, preventing bias from entering the data. • Quantitative methods can test the validity and reliability of data by using many different tools to ensure the results are accurate and highly objective. • Quantitative research can be used to test hypotheses in experiments because of its ability to measure data using statistics.	• Quantitative measurements must rely on the range and precision of a defined measuring scale. • The methods of calculation are complex. Without an automatic tool, the process can be difficult to implement. • Researchers cannot go back to participants after they have filled out a survey if there is more question to ask. • Research is unable to explore the behaviours and attitudes of respondents and may overlook potentially useful information and relationship as they are focused on numerical data. • The characteristics of the participants may not apply to the general population.

Table 5.3 Advantages and disadvantages of quantitative research methods

Source: Adapted from Mohajan (2020) and Ahmad et al. (2019)

Based on Table 5.3, using quantitative research methods have many advantages. Quantitative research methods allow scholars to investigate questions from the deductive perspective. Thus, quantitative research can be used to test and validate constructed theories and hypotheses (Ahmad et al., 2019). This study examined the relationship between BDAC, port sustainability and port performance. Quantitative research methods can help the researcher to confirm the relationship between the factors, producing findings independent of the researchers (Queirós et al., 2017). Moreover, by collecting data from many people, the studies can give the findings greater credibility and objectivity.

However, quantitative research methods also have a few shortcomings. Firstly, quantitative research needs the researcher to families the analytics method. In this study, although quantitative research methods increase the time of data analytics, they can improve the rigour and reliability of the results. Meanwhile, this study uses SmartPLS 3.0 software to assist the researcher in analysing collected data. In addition, quantitative measures must be dependent on the breadth and precision of the defined measurement scale (Lee, 2014). The study identifies the scope of the measurement scale, develops the hypotheses based on a literature review, and conducts a pilot study to ensure the validity and reliability of the measurement scale. Therefore, this study selects quantitative research methods as the research strategy.

In addition, specific to the research context of ports and BDA, there are much research adopted quantitative research methods (Mikalef et al., 2020, Awan et al., 2021, Wang et al., 2020, Dubey et al., 2018a, Lozada et al., 2019, Shamim et al., 2020, Ameen et al., 2020, Lin and Chang, 2021). For example, Mikalef et al. (2020) used quantitative analysis to investigate the relationship between Big Data analytic capability and competitive performance. Ameen et al. (2020) use a quantitative approach to assess the impact of organisational innovation on the financial performance of Dubai Port World. This study applies a quantitative research methodology to address the research questions and attain the research objectives. Within quantitative research strategies, the researcher has access to a variety of research methodologies. In this study, a questionnaire survey method was selected among various alternatives, which will be explained in further detail below.

5.3 Research Methods

5.3.1 Survey

This study adopted a survey-based approach and plans to use an online survey of a sample of port authorities, port managers and IT managers employed by the world's top ports. The following table will show the advantages and disadvantages of an internet questionnaire-based survey.

Advantages	Sources	Disadvantages	Sources
Low costs	Saunders et al. (2016), van Gelder et al. (2010)	Limited sampling and respondent availability	Marshall (2005), Jones et al. (2008)
Less time needed	Saunders et al. (2016), Jones et al. (2008)	Lack of conscientious response	Saunders et al. (2016), Bryman and Bell (2015)
Speedy result	Jones et al. (2008), Bryman and Bell (2015)	Differences in understanding and interpretation	Saunders et al. (2016), Jones et al. (2008)
Convenience for respondent	Saunders et al. (2016), Fricker and Schonlau (2002)	Respondents cannot be probed	Fricker and Schonlau (2002), Bryman and Bell (2015)
Reduction of Geographical dependence	Bryman and Bell (2015), Wright (2006)		
Online survey tools	Saunders et al. (2016), Bryman and Bell (2015)		
Avoidance skipped questions	Jones et al. (2008), Fricker and Schonlau (2002)		
Capable of collecting data from a large number of respondents	Saunders et al. (2016), Jones et al. (2008)		

Table 5.4 Advantages and Disadvantages of Internet Questionnaire Survey

Table 5.4 demonstrates the strengths and weaknesses of the Internet questionnaire. Internet questionnaires could be distributed to respondents through the Internet, and respondents could access the questionnaire through a hyperlink by the browser (Saunders et al., 2016). Thus, most researchers (Bell et al., 2018, van Gelder et al., 2010, Jones et al., 2008) stated that the Internet questionnaire is a more cost-efficient and time-saving data collection method than mail and postal questionnaires. Besides, Internet questionnaires using the Internet distribute questionnaires could prevent geographical dependence and distribute questionnaires to ports around the world. Moreover, the Internet survey could be distributed to many people with common characteristics and be returned rapidly (van Gelder et al., 2010, Wright, 2005). Hence, the Internet survey is suitable for collecting data with massive numbers of respondents.

Meanwhile, Saunders et al. (2016) indicated that Internet questionnaires could be conducted with online survey tools such as SurveyMonkey, Qualtrics and Snap Survey, and these tools could quickly turn collected data into results. Online survey technologies might prevent respondents from skipping questions by preventing respondents from proceeding to the next question if certain questions are skipped (Wamba et al., 2017). Furthermore, Pinsonneault and Kraemer (1993) suggested that the survey approach might capture causal links between components and produce generalisable assertions in the study context. The survey could measure the relationships between variables to answer theory-guided research questions and hypotheses (Creswell, 2018).

Despite these advantages, there are known to be three critical disadvantages of Internet questionnaires. The first is the sampling issue. Andrews et al. (2003) presented that due to the limited knowledge of respondents, assumptions about the sample may not be accurate. Thus, this study will conduct a pre-pilot study to identify the potential key informants and remove people without experience in Big Data and port management in large-scale data collection. The second disadvantage relates to response rates. Oppenheim (2000) argued that the Internet questionnaire has relatively high nonresponse rates than traditional modes of data collection. The third disadvantage is the lack of conscientious responses. Respondents may answer the question without thoroughly reading and thinking. For example, some respondents will make split-second choices that affect the data's validity (Jones et al., 2008). In order to overcome these two weaknesses, the questionnaire requires careful planning, design and create simple questions that are easy to answer (Bell et al., 2018). Therefore, although the Internet questionnaire has some drawbacks, these drawbacks could be controlled by careful design and examination.

Based on the above discussion, the type of study and the characteristics of respondents, the Internet questionnaire is a preferred data collection method in this study. This study adopts questionnaire item scales from previous studies to measure the causal conditions (Gupta and George, 2016, Woo et al., 2013, Cheon and Deakin, 2010, Kim et al., 2016). Respondents were requested to evaluate the extent of constructs on a 5-point Likert scale ranging from strongly disagree to strongly agree, with which their organisations practice the various aspects of measures. The collection of data involved two phases. Before the primary survey, a pilot study was done to assess the validity and reliability of the newly designed scales (Mikalef and Pateli, 2017). The first step of this pilot study is to seek comments and feedback from the five academics and five executives to ensure the newly developed scales are valid and reliable. The second part of the pilot study entails evaluating the questionnaire with 40 port managers to refine the newly developed measuring scales. Wamba et al. (2017) argued that the pilot study could evaluate the reliability of the developed scales and the data collection process. Finally, after the pilot study, the primary survey begins. In the large-scale data collection process, ports which be selected from the world's Top port list. The questionnaires were emailed to the key informants of these ports. In the end, the collected questionnaires were filtrated to exclude some responses from managers and employees without BDA experience. The detail of questionnaire development and the result of the pilot study are displayed in the next chapter.

5.3.2 Partial Least Squares Structural Equation Modelling (PLS-SEM)

SEM is a statistical method comprised of various mathematical models, computer algorithms, and causal modelling that takes a confirmatory approach to investigate a structural theory about a phenomenon (Byrne, 2016). Raykov and Marcoulides (2012) demonstrated that SEM consists of confirmatory component analysis, path analysis, partial least squares path modelling, and latent growth modelling. SEM is appropriate for assessing various and complicated causal links due to its examination of sophisticated research models with numerous observable, latent, and parameter variables (Hair Jr et al., 2014).

According to Wang and Rhemtulla (2021), SEM consists of two variables: the latent variable and the observable variable. The following figure illustrates the theoretical SEM and constructs.

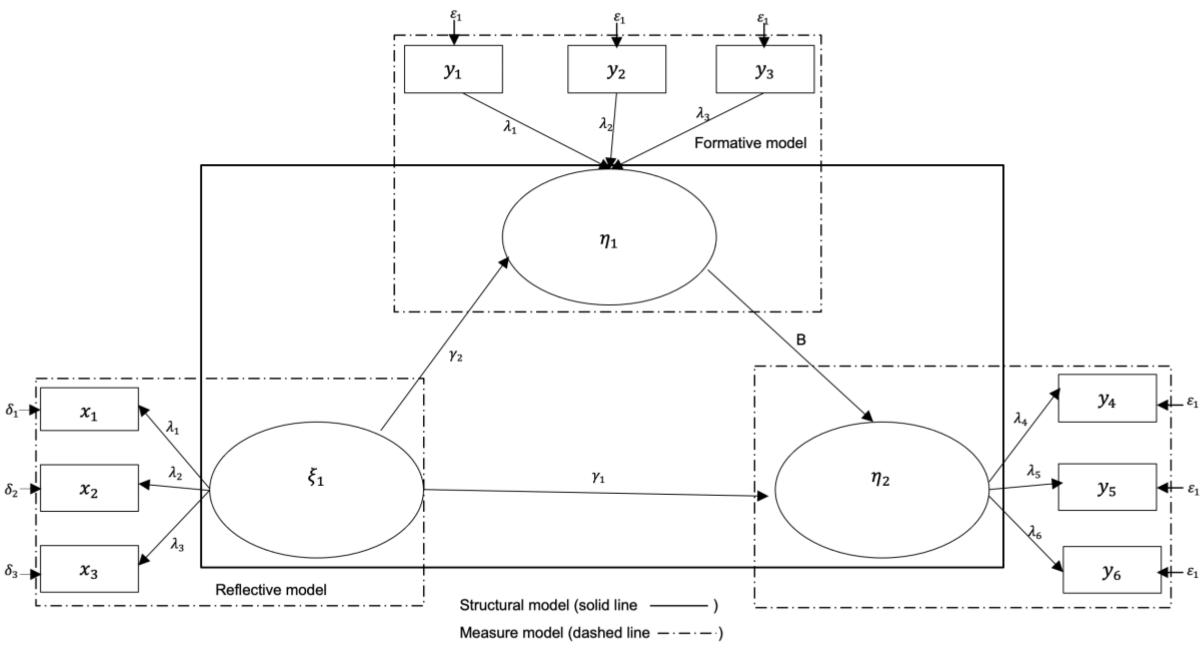

Figure 5.2 Theoretical SEM and constructs

Source: Adapted from Hair Jr et al. (2017a)

Latent variables are those that cannot be observed in the actual world, whereas observable variables are utilised as measurement items in questionnaires to assess latent variables. Each latent variable requires a minimum of two observed variables, and the combination of several latent and observed variables constitutes a single measurement construct. In addition, there are two types of latent variables: exogenous latent variables (ξ_1) and endogenous latent variables (η_1 and η_2). Exogenous latent variables impact other latent variables, but endogenous latent variables are either directly or indirectly influenced by other factors within the model; precisely, an endogenous variable may also be the source of another endogenous variable in the model (Ullman and Bentler, 2003). Consequently, SEM may detect multiple-dimensional causal linkages and latent variables that cannot be seen by other statistical methods (Lacobucci, 2010). Furthermore, Jarvis et al. (2003a) emphasised that SEM may distinguish between the measurement model, which links constructs to their corresponding measurements, and the structural model, which ties constructs to one another. The measurement model illustrates the links between latent and observable variables. The measurement models explain precisely how latent variables are evaluated in terms of observable variables, addressing their validity and reliability in assessing latent variables or hypothetical constructions (Wisner, 2003). The outer measurement model is structured differently depending on the type of measurement. In the formative model (η_1), the indicator variable causes the measurement of the construct. Thus, the arrows point from the indicator to the latent construct. In contrast, if the construct causes the measurement model of the indicator variables, the reflective model (ξ_1 and η_2) in which the direction of the arrow is from the construct to the indicator should be performed (Afthanorhan, 2014). The structural model explains causal links between latent variables (Mueller and Hancock, 2018). Path coefficients (γ_1, γ_2 and B) represent the strength of the relationships between latent variables, which are derived through regressions of each endogenous latent variable on its immediate predecessor construct.

The general structural model can be considered as some combination of multiple regression, including the relationship between observed variables with latent variables and links among latent variables. Hence, the general structural equation mode can be summarised into three matrix equations, two for the measurement part, which links latent variables to observed variables and one for the structural part linking latent variables to each other (Lam and Maguire, 2012, Ullman and Bentler, 2003, Kline, 2015). The structural part of the model can be written as Eq. (5.1).

$$\eta_i = \alpha + \mathrm{B}\eta_i + \Gamma\xi_i + \zeta_i \tag{5.1}$$

Where α is a vector of intercept for the equation, η_i is a vector of the latent endogenous variables for subject i , B is the matrix of coefficient giving the impact of the latent endogenous variables on each other, Γ is the matrix of coefficient giving the impact of the latent exogenous variables on the latent endogenous variables, ξ_i is the vector of latent exogenous variables for subject i, and ζ_i is the vector of disturbances for subject i.

The equation of measurement model can be written as

$$x_i = \nu + \Lambda_x\xi_i + \delta_i \tag{5.2}$$

$$y_i = \sigma + \Lambda_y\eta_i + \varepsilon_i \tag{5.3}$$

Where ν and σ are intercept vectors, Λ_x and Λ_y are the matrix of coefficient or loadings giving the impact of the latent ξ_i and η_i on x_i and y_i, δ_i and ε_i are vector of errors of measurement of x_i and y_i. The i subscript indexes the ith case in the sample. For simplicity, it is assumed that $\eta, \xi, \zeta, \delta, \varepsilon$ have zero expectation as well as ξ and ζ, ξ and δ, η and ε are uncorrelated.

Those equations play a key role in the presentation of the SEM. Equation 1 displays the structural model. The structural model reflects the hypotheses about how the different concepts relate to each other. Equation 2 and 3 illustrate the measurement model and link the latent to the observed responses.

5.3.3 Higher-order model (HOM)

In the previous section, the common SEM model is presented and discussed. In order to explore complicated theories and cause-effect relationships, the higher-order model (also known as the hierarchical component model) is used to establish more advanced and complex models. Cheung (2008) and Koufteros et al. (2009) indicated that HOM could give a framework for modelling a construct on an abstract dimension and its concrete subdimensions. It means that independent constructs can be integrated into a higher-order construct. Therefore, academics should decrease the linkages between different independent and dependent conceptions to develop models sparingly (Wetzels et al., 2009). Moreover, in the HOM, the researcher can develop a multidimensional construct to arrange indicators to avoid restatements of other indicators, reducing the collinearity among indicators (Matthews et al., 2018, Alsaad et al., 2015). Due to the advantages of HOM, this study employs HOM to measure constructs of BDAC, port sustainability and port performance.

According to Wong (2016), HOM consists of higher-order components (also known as second-order constructs) and lower-order components (also known as first-order constructs). A higher-order component (HOC) is a generic idea whose lower-order component (LOC) either represents or constitutes it. In order to establish HOM, the measurement items of LOC need to be identified, and the relationship between the HOC and LOC needs to be decided (Hooi et al., 2018). Hence, several scholars (Sarstedt et al., 2019, Afthanorhan, 2014, Becker et al., 2012) have suggested that four types of HOM, including reflective-reflective HOM, reflective-formative HOM, formative-reflective HOM, and formative-formative HOM. The following figure shows the four types of HOM.

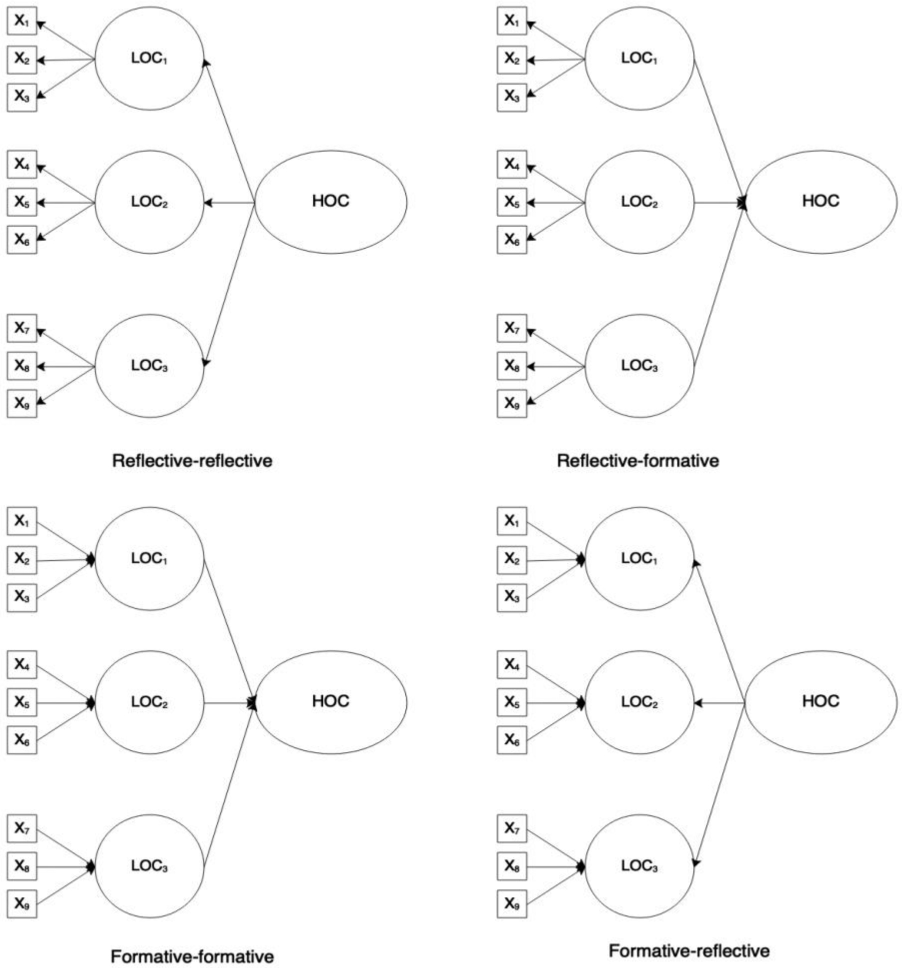

Figure 5.3 Four types of HOM

Source: Sarstedt et al. (2019)

Based on the literature review in this study, BDAC is conceptualised as a composite of seven dimensions, including data, technology, basic resources, technical skills, managerial skills, data-driven culture and organisational learning. Port sustainability performance includes three LOCs: environmental dimension, social dimension and economic dimension. Port performance is measured by five LOCs, including cost, service quality, operational efficiency, VASs and customer orientation. Moreover, according to Figure 5.3, all the measurement models in this study are reflective-reflective HOM. The reflective-reflective HOM has a reflective model for each first-order construct and a reflective model for the second-order constructs. The following figure presents the detail of reflective-reflective HOM. The equation of reflective-reflective HOM can be written as Eq. (5.4)

$$\xi_i = \gamma_i \eta + r_i \tag{5.4}$$

Where the construct η is conceptualised as a second-order latent variable upon which the first-order latent constructs ξ_i are dependent with measurement error r_i for each of these first order constructs and expected coefficients γ_i.

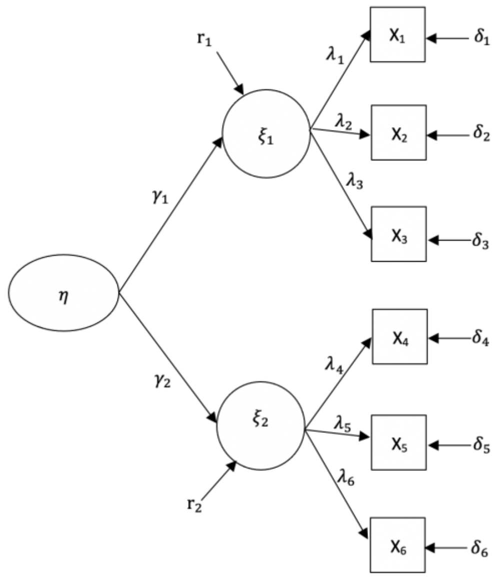

Figure 5.4 Higher-order reflective-reflective measurement model

Source: Adapted from Crocetta et al. (2021)

In conclusion, SEM enables to model and examine complex phenomena and provides validity and reliable measurement results (Lomax and Schumacker, 2004). HOM as an advantage technique of SEM has been widely used in the field of BDAC (Akter et al., 2016, Wamba et al., 2017, Mikalef et al., 2019b) and ports (Mira et al., 2019, Chen et al., 2018, Woo et al., 2011) in the field of ports. Thus, this study employs SEM as the primary data analysis technique to test proposed hypotheses.

5.3.4 Advantages and disadvantages of PLS-SEM

This part details the advantages and disadvantages of PLS-SEM. The advantages and disadvantages of PLS-SEM will be shown in the following table. Table 5.5 demonstrates the benefits and limitations of PLS-SEM.

Advantage	Source	Disadvantages	Source
Validity	Hair et al. (2016), Valle and Assaker (2015)	Net effects	Hair et al. (2016), Astrachan et al. (2014)
Complex Models	Sarstedt et al. (2014b), Henseler and Sarstedt (2012)	Convergence problem	Reinartz et al. (2009), Hair Jr et al. (2014)
Non-normal data	Hair et al. (2016), Reinartz et al. (2009)	Symmetrical causal relationships	Sarstedt et al. (2014b), Henseler and Sarstedt (2012)
Reliability/Measurement Error	Valle and Assaker (2015), Henseler and Sarstedt (2012)	PLS-SEM cannot test directionality in relationships.	Hair et al. (2016), Reinartz et al. (2009)
Analysing direct, indirect and total effects	Hair et al. (2016), Valle and Assaker (2015)		
Small samples size	Henseler and Sarstedt (2012), Reinartz et al. (2009)		

Table 5.5 Advantages and Disadvantages of PLS-SEM

The PLS-SEM method could provide some advantages for researchers. First, Goodhue et al. (2012) and Sharma et al. (2021) indicated that a range from 50 to 200 observations is the ideal sample size for SEM, and PLS-SEM could provide analysis efficiently with small sample sizes, which could help researchers to gather data with data collection constraints and low response rates. Second, compared with CB-SEM, PLS-SEM does not require normally distributed data, and it could be conducted in more areas where data are often non-normally distributed (Hair et al., 2016). Third, Rigdon (2012) and Thakkar (2020) stated that PLS-SEM offers the potential to evaluate models using hierarchically organised data at several levels. Due to the PLS-SEM assessment of the structural model based on accounting for explained variance in the endogenous, PLS-SEM could complete and simultaneously test all the constructs and relationships (Rigdon et al., 2017a). Moreover, PLS-SEM is a full-fledged approach that can test for exact model fit and could achieve more validity and reliable result when the research model is extremely complicated (Ajamieh et al., 2016, Peng and Lai, 2012, Kline, 2015).

However, although PLS-SEM has some advantages, it also has some limitations. Hair et al. (2016) pointed out that PLS-SEM cannot test directionality in the relationship. The directions of arrows in the structural equation model merely represent the hypotheses of causality within a system. Furthermore, many researchers (Astrachan et al., 2014, Tomarken and Waller, 2005, Woo et al., 2013) indicated that some drawbacks of PLS-SEM are attributable to the limitations of multiple regression analysis and structural equation modelling. Thus, convergence problems, symmetrical causal relationships and net effects have been observed.

Given the above description, PLS-SEM can handle a greater variety of problems than CB-SEM due to its ability to operate effectively with a considerably broader range of sample sizes and model complexity, as well as its less restrictive data assumptions (Hair Jr et al., 2014). In view of the identified constructs in this study and the need to explore the interrelationships between many dependent and independent variables concurrently, PLS-SEM is the appropriate approach.

5.3.5 PLS-SEM evaluation stages

Evaluating PLS-SEM results involves completing two stages. The following figure 5.5 demonstrates the two stages. From stage 1 to stage 4, the model was developed based on literature, and the data was gathered via the survey. In stages 5 and 6, measuring models are examined, with the analysis altering based on whether the model incorporates reflective or formative measurements or both. The structural model is evaluated if the measurement model provides satisfactory results (stage 7).

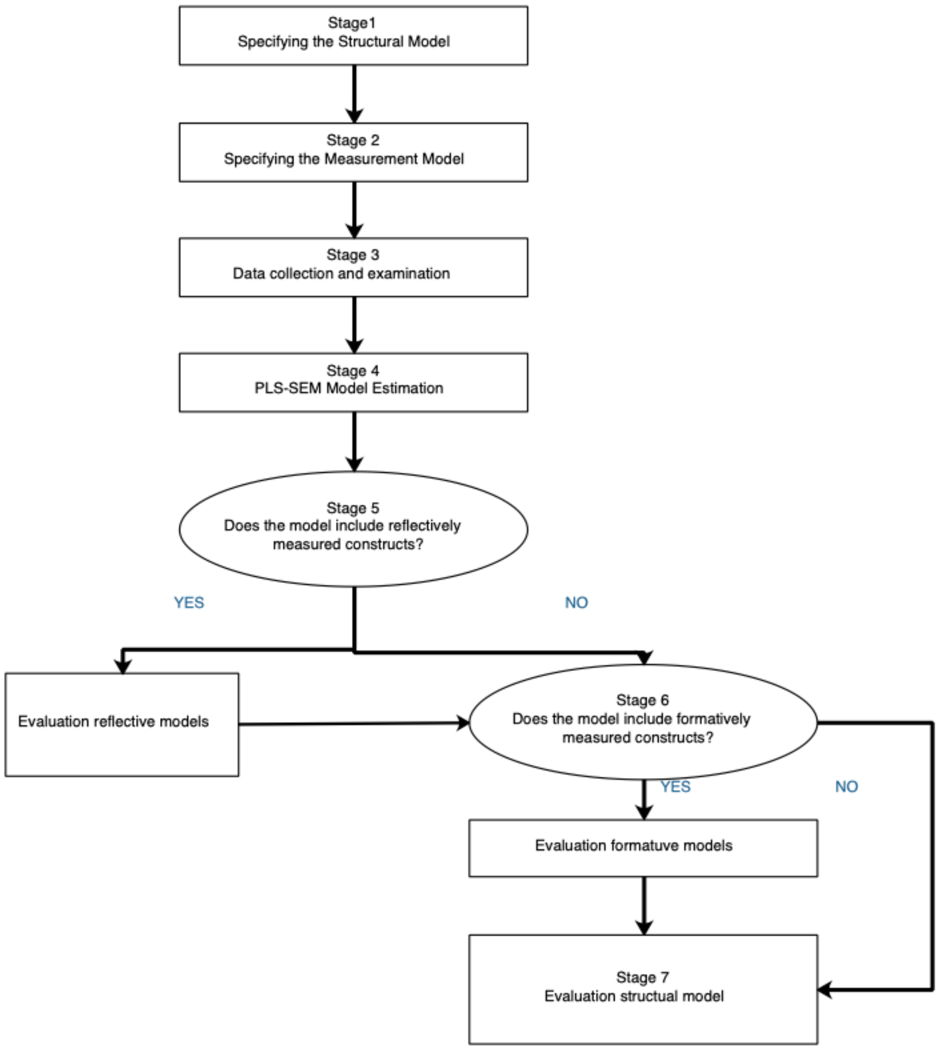

Figure 5.5 PLS-SEM evaluation stages

Source: Adapted from Sarstedt et al. (2022)

PLS-SEM relies upon rules of thumb to evaluate the results of the model estimation (Sarstedt et al., 2014b, Monecke and Leisch, 2012, Hair et al., 2016). The following Table 5.6 display the rule of reflective and formative measurement model assessment, and Table 5.7 show the rule of structural model assessment.

Reflective measure	Internal consistency reliability Indicator reliability Convergent validity Discriminant validity
Formative measure	Convergent validity Collinearity Significance and relevance of indicator weights

Table 5.6 Reflective and formative measurement model assessment

Source: Monecke and Leisch (2012)

Structural model measure	Coefficient of determination (R^2) Effect size (f^2) Predictive relevance (Q^2 and q^2), Significance and relevance of path coefficients

Table 5.7 Structural model assessment

Source: Hair et al., 2016

In this study, all first- and second-order constructs are reflective measurement models. Thus, the first criterion to be evaluated is internal consistent reliability. Sarstedt et al. (2017) argued that internal reliability is an indicator of the consistency of measurement items together in measuring the constructs of the measurement model. After evaluating the internal consistency reliability and indicator reliability, convergent validity is measured. Convergent validity refers to the degree to which a measure correlates favourably with different measures of the same construct. The average variance extracted (AVE) across all items linked with a certain concept is used to evaluate the convergent validity of an instrument (Monecke and Leisch, 2012). The final step of the evaluation reflective model is to assess the discriminant validity of the constructs. Discriminant validity measures the amount to which a concept is empirically different from other constructs in the route model, both in terms of how strongly it connects with other constructs and how clearly the indicators indicate just this particular construct. Fornell and Larcker (1981a) presented the Fornell-Larcker criterion to evaluate discriminant validity. This method compares each construct's AVE value with its squared inter-construct correlation (a measure of shared variance) with all other constructs in the structural model. In addition, due to the Fornell-Larcker criterion having some limitations, the heterotrait-monotrait ratio (HTMT) is used to evaluate discriminant validity further (Henseler et al., 2015). HTMT is the average correlation of indicators across constructs measuring distinct phenomena as compared to the average correlation of indicators inside the same construct.

After confirming the validity and dependability of the measurement model, the structural model is examined. The first step is to check the R^2 value of each endogenous construct. R^2 is the proportion of the variance in the endogenous construct, and it is a measure of the predictive accuracy of the model (Wong, 2013). Hair et al. (2016) emphasised that depending on the model complexity and research fields, the value of R^2 has different rules of thumb. Then, several scholars (Janadari et al., 2016, Al-Emran et al., 2018, Kumar and Purani, 2018) recommended testing f^2 to investigate the effect of the external construct on the endogenous construct. The next step is to evaluate the predictive relevance of the model (Q^2) and its effect size (q^2). The final phase involves assessing the importance and relevance of path coefficients for the hypothesised links between the constructs. The relevance of path coefficients vale is standardised on a range between -1 to +1. The coefficients closer to -1 represent strong negative relationships, while the coefficients closer to +1 represent strong positive relationships (Sarstedt et al., 2014b). In the chapter on data analysis, measurement model evaluation and structural model evaluation will be covered in further detail.

5.3.6 Sample size

A primary advantage of PLS-SEM over CB-SEM is that the PLS-SEM approach enables working with a small sample size. Many researchers (Hair Jr et al., 2014, Kock and Hadaya, 2018, Matthews, 2017) proposed that the minimum sample size for the PLS model should equal the larger of ten times the formative metric used to measure the maximum number of components or ten times the structural model route for the maximum number of components.

Despite the fact that the ten-fold rule provides a minimum sample size recommendation, researchers should evaluate sample size in light of the model and data characteristics (Hair Jr et al., 2014). Furthermore, many researchers(Sharma and Kim, 2013, Aibinu and Al-Lawati, 2010, Kock, 2015) indicated that PLS-SEM enables the analysis of non-normal distribution data. Hair et al. (2019) argued that social science studies usually work with non-normal distribution data. Non-normal data can lead the CB-SEM approach to produce abnormal results. Whiles PLS-SEM shows higher reliability in this situation. Therefore, PLS-SEM is preferable to undertake in this research.

5.4 Sampling

5.4.1 Sampling techniques

This section describes the prevalent sample categories and methodologies, as well as the one utilised for this study. Sampling is described as the process of selecting the most representative persons, objects, or events to represent the total population

(Sekaran and Bougie, 2016). The objective of sample collection is to generalise the survey population. In order to reduce potential bias and errors, researchers should select the appropriate sampling technique (Saunders et al., 2016). Several researchers (Easterby-Smith et al., 2018, Saunders et al., 2016, Malhotra and Birks, 2007) have observed that sampling procedures may be divided into probability and non-probability groups. Probability sampling is a popular approach used by researchers to ensure that the sample is indeed representative (El-Masri, 2017). Probability sampling gives an equal probability to each participant of being chosen from the sampling frame. Hence, probability sampling could ensure the generalisability of research findings (Easterby-Smith et al., 2018). Non-probability sampling differs from probability sampling in that researchers choose samples from a broader population without needing random selection. This means that not all individuals in the population have equal odds of being selected. Tansey (2009) indicated that the character of non-probability sampling is that the sample selection relies on subjective judgement. Thus, non-probability sampling might aid the researcher in controlling the selection process, despite the fact that findings of non-probability cannot be used to generalise the entire population. In addition, probability sampling may be subdivided into four techniques: simple random sampling, systematic sampling, stratified random sampling, and cluster sampling. Non-probability sampling strategies include convenience, purposive, quota, and snowball sampling. The following table shows the advantages and disadvantages of sampling techniques.

Method	Detail	Advantages	Disadvantages
Simple Random Sampling	Every sample entity has an equal chance of being part of the sample.	High generalizability; Readily comprehendible	Costly; Lower accuracy; Difficult to establish sampling frame
Systematic Sampling	Create a list of the population units of interest to the researcher.	Possible to increase representatives; simpler to install	Systematic biases are possible
Stratified Random Sampling	Take a basic random sample from each stratum after dividing the population into homogenous groups called strata.	Contains all essential subpopulations; Accuracy	Selecting stratification factors is difficult and costly
Cluster Sampling	Divide the population into clusters, and then sample each unit inside a cluster.	Simple to implement; Cheap	Results are imprecise and difficult to understand.
Convenience Sampling	Select representative units based on their accessibility.	Quick; Convenient; Less expensive	Lack of generalisability; Selection bias
Purposive Sampling	Researchers have a clear understanding of the sample units required and then contact potential sample members to determine if they match the eligibility requirements.	Cost-effective, Convenient, and perfect for exploratory research	Subjective; Not generalisable
Quota Sampling	Divide the appropriate population into groups, and then continue picking until each category has a sample of the desired size.	Samples might be managed for a variety of features	There is no promise that the sample will be representative
Snowball Sampling	Starting with one individual who fits the inclusion requirements for the research, they are asked to suggest further candidates.	Capable of estimating uncommon features	Time-consuming

Table 5.8 Advantages and disadvantages of sampling techniques

Source: Easterby-Smith et al. (2018) and Saunders et al. (2016)

Table 5.8 displays the benefits and drawbacks of sampling techniques. The research questions, aim, and objectives significantly impact the selection of sampling techniques (Saunders et al., 2016). This study aims to investigate the impact of BDAC on port performance and port sustainability. As the research focuses on international ports which deploy Big Data technology, port managers are also expected to have knowledge of Big Data or have work experience with Big Data to provide opinions. Hence, this study requires high-level port and Big Data relevant knowledge. In this situation, port managers with pertinent expertise may be regarded as acceptable participants for an online survey. Thus, non-probability sampling is more suitable for this study.

Using non-probability sampling, researchers can gain more accurate data and avoid misleading information. For example, participants who only drive trucks at the port and do accounting work may not contribute to this study. The following sub-sections will give more details about non-probability sampling.

Convenience sampling: Convenience sampling is frequently used when the initially targeted samples become inaccessible due to a lack of funding or time. Instead, potential samples with easier accessibility are contacted and asked to participate in the empirical study after receiving their consent. Tansey (2007) indicated that the researcher might select the sample in whichever method is most convenient. However, it also has some limitations. The variability and bias cannot be measured or controlled, and the result cannot be generalised beyond the sample (Acharya et al., 2013).

Purposive sampling: Purposive sampling refers to instances in which the researcher should pick certain cases and groups from whom he or she expects to obtain specific information, also known as expert sampling and judgement sampling. Purposive sampling can concentrate on people with particular characteristics who will help the relevant research (Etikan et al., 2016).

Quota sampling: When performing an empirical investigation, quota sampling necessitates collecting a variety of representative samples proportional to a certain proportion. Quota sampling is quicker and easier to conduct than probability sampling. Moreover, the quota sample improves the representation of particular strata within the population and ensures that these strata are not over-represented (Yang and Banamah, 2014). However, quota sampling also has some drawbacks. De Rada and Martín (2014) indicated that due to the sample selection without random, the sample might have a bias.

Snowball sampling: The snowball sampling technique entails finding an initial set of relevant respondents and then asking them to propose other possible subjects who have similar traits or are relevant to the subject of research (Noy, 2008). Snowball sampling could maximise the sample size and ensure the quality of the empirical study (Browne, 2005).

5.4.2 Sampling in this study

There are two sampling stages in this study, which include online surveys and a pilot study. The optimal strategy was determined to be a mix of snowball sampling and purposive sampling. The mix of purposive sampling and snowball sampling is employed since this study requires professional participants, and it is hard to find participants knowing both Big Data technology and port management area. Thus, port managers originally contacted are urged to refer to other port managers in the field in order to increase the size of the sample and get further insights (Etikan et al., 2016, Emerson, 2015).

To obtain online survey participants, ports which deploy Big Data technology and develop Big Data technology are screened via their websites, annual reports and professional social media. A search of the websites, annual reports and social media of the top 50 ports in the world revealed ports that have developed big data technologies. The following Table 5.9 shows the result.

The managers of the targeted port are then contacted through email and asked to recommend additional specialists in the sector. The spread of port managers could aid in locating more suitable participants within the field to fulfil the SEM survey request (Park, 2013). Moreover, the pilot study needs port managers and experts with Big Data technology knowledge and port working experience to examine the validity and reliability of the survey. Thus, port company managers, research institute researchers, university scholars researching relevant topics and government officers are taken as suitable participants because they have enough knowledge to provide more insights.

In summary, purposive sampling and snowball sampling are used in this study. These sampling techniques could help researchers to identify appropriate participants with relevant knowledge of Big Data technology and port working experience. Moreover, by using these two sampling techniques, the research could maximise the sample size to gain a more accurate and reliable result.

Ports	Main digital technology application	Technology type (BDA or TDA)	Source
Port of Shanghai	Integrated logistic information service platform	BDA	SIPG (2019)
Port of Singapore	Operation automation	BDA	Trelleborg Marine Systems (2018)
Port of Shenzhen	Integrated logistic information service platform	BDA	Yantian port Group (2018)
Port of Ningbo	Integrated logistic information service platform	BDA	Ningbo Zhoushan Port Company Limited (2019)
Port of Busan	Predictive analysis	BDA	PortNews (2017); Port Strategy (2019)
Port of Hong Kong	Data integration and management	BDA	Port Technology (2019); Opendatasoft (2018)
Port of Guangzhou	Integrated logistic information service platform	BDA	Xinhuanews (2019); SAFETY4SEA (2019)
Port of Qingdao	Operation automation	BDA	Smart maritime network (2019)
Jebel Ali Port	Data analysis and decision-making	BDA	DP World (2018)
Port of Tianjin	Integrated logistic information service platform	BDA	Liu, Gao and Wang (2018
Port of Malaysia	Data analysis and decision-making	BDA	Trelleborg Marine Systems (2018)
Port of Rotterdam	Innovation	BDA	Trelleborg Marine Systems (2018)
Port of Kaohsiung	Data analysis and decision-making	BDA	MOTC (2018)
Port of Antwerp	Integrated logistic information service platform	BDA	Port of Antwerp (2019)
Port of Dalian	Integrated logistic information service platform	BDA	Zhang (2017)
Port of Xiamen	Integrated logistic information service platform	BDA	Yang et al. (2018)
Port of Tanjung Pelepas	Vessel Traffic Management & Information System	TDA	PTP (2023)
Hamburg Port	homePORT	BDA	Port Technology Team (2021)
Port of Los Angeles	Operation optimisation	BDA	GE Transportation (2019)
Laem Chabang port	Data analysis and decision-making	BDA	Bangkok post (2019)
Port of Long Beach	Data analysis and decision-making	BDA	GE transportation (2018)

Port of Colombo	Container Terminal Management Syetem	TDA	Sri Lanka Ports Authority (2023b)
Port of Yingkou	Integrated logistic information service platform	BDA	PORTX (2019)
Saigon port	Data analysis and decision-making	BDA	Saigon newport corporation (2018)
Port of Suzhou	Integrated logistic information service platform	BDA	Suzport (2016)
Mundra port	Data analysis and decision-making	BDA	Adani (2019)
Port of Algeciras	Integrated logistic information service platform	BDA	Heilig, Schwarze and Voß (2017)
Port of Valencia	GREEN-C-PROJECT	BDA	Port Authority of Valencia (2019)
Port of Lianyungang	Integrated logistic information service platform	BDA	Port of Lianyungang (2019)
Port of Bremen	Integrated logistic information service platform	BDA	Bremenports (2018)
Port of Piraeus	Data analysis and decision-making	BDA	Greenport (2019)
NW Seaport Alliance	Data analysis and decision-making	BDA	The Northwest Seaport Alliance (2017)
Port of Santos	Data analysis and decision-making	BDA	Porto De Santos (2019)
Port of Manila	PPA Online	TDA	Philippine Port Authority (2023a)
Port Said	EDI message	TDA	PSCCHC (2023)

Table 5.9 Ports using Big Data technology

5.5 Research Design

This section gives a summary of the design and implementation of this research. The chosen research philosophy and approach significantly influence how a study is designed and executed (Leavy, 2017). As the discussion in 5.1.1 and 5.1.2, this research uses pragmatism as the philosophy and deductive reasoning as the approach. Depending on the determined philosophy and approach, the details of the research design are illustrated in Figure 5.6.

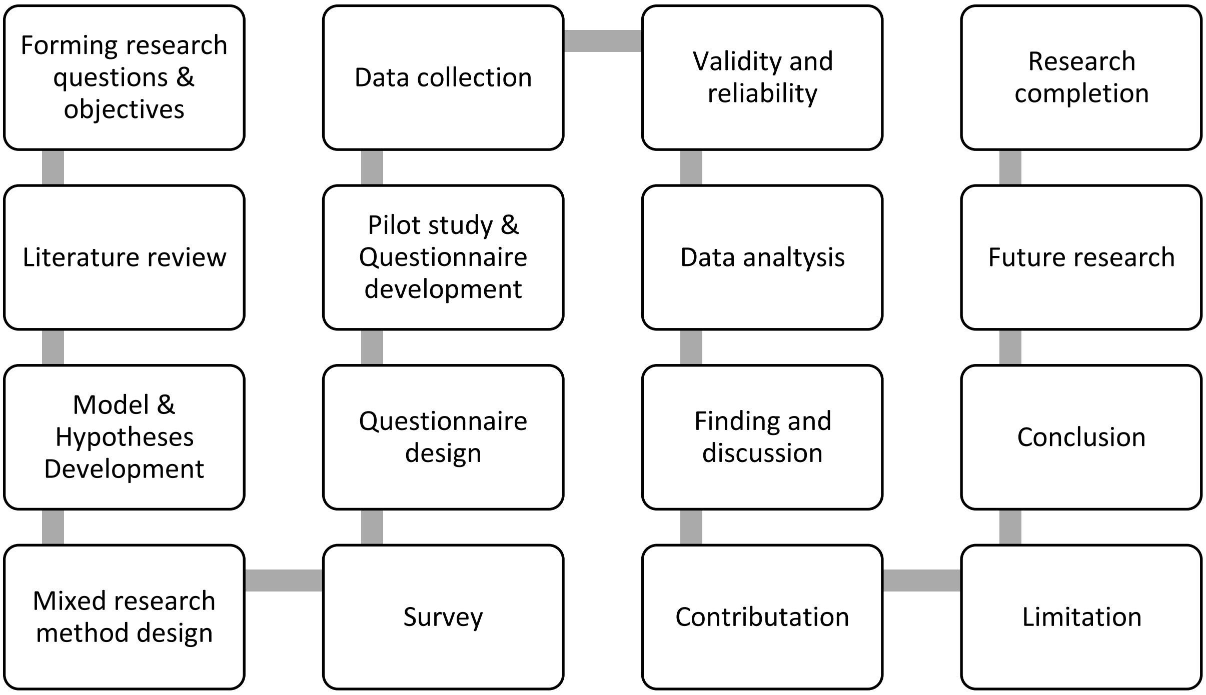

Figure 5.6 Research Design

This study consists of three stages: theoretical stage, quantitative stage and conclusion stage. The theoretical stage consisted of the literature review and hypotheses development. Understanding the study context and formulating the research questions, purpose, and objectives is the initial step in the theoretical phase. Then, a concentrated literature analysis is undertaken to examine the key concepts: port, Big Data, BDAC, port sustainability, and port performance. By the end of this stage, the initial research model and hypothesised relationships have been presented based on the literature review. The quantitative stage is considered the second stage. The second stage mainly aims to validate the hypothesised relationships and test the structural modal. The second stage uses an online survey to collect data from relevant port employees. Before conducting the major survey, a pilot survey is undertaken to evaluate the reliability of the components and assist the researcher in the ongoing development of the questionnaire. After testing the validity and reliability of collected survey data, the structural model is assessed to test hypotheses. Lastly, in addition to discussing the findings, contributions, and limits of the research, the conclusion section typically suggests possible future research possibilities.

5.6 Ethical Implications

This section assures that the study conducted meets ethical requirements. For this study, questionnaire and interview are conducted to collect data. Researchers have the responsibility to manage gathered data and ensure the privacy of participants and interviewees (Bell, 2014). Before beginning the study, the researcher filed for ethics permission to verify that no ethical limitations would be violated. The ethical approval (Ethical Approval Application No: FREIC1819.41) was evaluated and approved by the Faculty Research Ethics & Integrity Committee (FREIC).

All participants in this study were volunteers who were properly informed of the goal and intended application of the research. Participants were notified that they might withdraw at any moment from the empirical study. Guillemin and Gillam (2004) indicated that the confidential and anonymous treatment of participants' data is considered the norm for the conduct of research. Consequently, all participants were told throughout the questionnaire of the goal of the study and that all data collected would be treated anonymously.

Furthermore, all the collected data were protected based on the Data Management Plan (DMP). In order to improve data security, gathered data will be stored on an encrypted hard drive in a University of Plymouth institution laptop. Files created during this project will be encrypted so that only the principal investigator and researcher will be able to access them. In addition, due to confidentiality, any form of collected data related to this study will be destroyed no more than 12 months after the PhD viva.

5.7 Summary

This chapter has explained in detail the methodology this research adopted. This chapter discussed the research philosophy, research approach, data collection methods and data analysis methods. This study utilises pragmatism and deductive reasoning to answer the research question and accomplish its aims. Afterwards, the process of data collecting was described in depth. This study adopts a survey method to collect data. After describing the techniques of data collecting, the methods of data analysis are described. In this research, a quantitative approach is utilised. PLS-SEM is used to test constructed hypotheses. Section 5.3.5 justifies the selection of the SEM above other approaches based on its adaptability and ability to analyse simultaneous relationships.

Chapter 6 Pilot survey

6.1 Introduction

In chapter 5, the detail of the methodology, data analysing approach and data collection method are proposed. This chapter discusses the development of the questionnaire and the result of the pilot survey. The first section of this chapter presents the development of measurement items. The second part displays the result of the pilot survey.

6.2 Questionnaire development

Developing the questionnaire is a significant part of collecting data. In terms of design, the questions must be clear and related to the point that the researcher with to collect (Krosnick, 2018). The questionnaire must be designed with clear and simple words, with a logical structure and good formatting to collect a high response rate from the target audience (Song et al., 2015). If the questionnaire is too long, the rate of response will decrease. Current research (Jain et al., 2016, Saunders et al., 2016, Robinson and Leonard, 2018, Phillips et al., 2013) seems to indicate that there are six main types of survey questions.

Type of survey question	Description
Closed-end questions	Closed-ended questions are basically those questions that provide respondents with a predefined list of answer options to choose from.
Open-ended questions	Open-ended questions allow respondents to express themselves on their own terms.
Multipole choice survey questions	Multiple-choice questions let respondents pick one or more answers from a list of possibilities provided by the researcher.
Rating survey questions	Rating questions come with a scale of answer options where the respondents are asked to assess an issue based on an already predetermined dimension.
Likert scales survey questions	Likert scale is a question which is a five or seven or nine-point scale and used to gauge respondents' opinions and feelings.
Drop-down survey questions	A dropdown question allows respondents to choose an option from a list of options displayed in the dropdown menu.

Table 6.1 Six main types of survey question

Source: Author, based on Saunders et al. (2016) and Robinson and Leonard (2018)

This study applies Likert scales to develop the questionnaires. Because the Likert scale may offer the respondent a statement and allow the respondent to indicate how strongly they agree or disagrees with a statement along a rating scale, the Likert scale is a useful instrument for collecting quantitative data (Joshi et al., 2015). Although there have been debates on the number of points on the scale, most research (Lozada et al., 2019, Dubey et al., 2018a, Jeble et al., 2018, Dubey et al., 2018b, Mirahmadizadeh et al., 2018) on the BDAC area suggested that most popular number of points on response scales are 5. Chyung et al. (2017) indicated that the 5-point scale is easily understood by respondents and requires the shortest reaction time than the 7-,8-, and 9- point scales. It was determined that a five-point scale provides a dependable, consistent, and user-friendly alternative for assessing the outcomes of a large sample of responders (Joshi et al., 2015). Therefore, this study uses a 5-point Likert scale (1=Strongly disagree, 2=Disagree, 3= Neutral, 4=Agree and 5=Strongly agree) to collect data from employees and managers in ports. The questionnaire was developed in both English and Chinese. Researchers must pay attention to translating the questionnaire into another language since the inaccurate translation of the questions or responses will lead to erroneous results and conclusions (Jenn, 2006). The back-translation approach was utilised to guarantee that the language and its meaning were consistent. The research translates the questionnaire from English to Chinese; then, two independent translators back-translate the Chinese questionnaire to English again. The meaningful differences between the two are reconciled by comparing the back translation to the original text (Cha et al., 2007). Therefore, the questionnaire can avoid translation errors and confusion for the respondents.

6.2.1 The Questionnaire Structure

The questionnaire consists of four parts and an introduction. The rate of respondents will be affected by the introduction. Therefore, it is crucial to initially demonstrate and clarify the goal of the study (Saunders et al., 2016). This study employs a cover letter to explain and clarify the purpose and objectives of the research, as well as to illustrate how their involvement will benefit the study. Then reassures them that their information will be treated with a highly universal and ethical standard. The following figure 6.1 show the overall structure of the questionnaire.

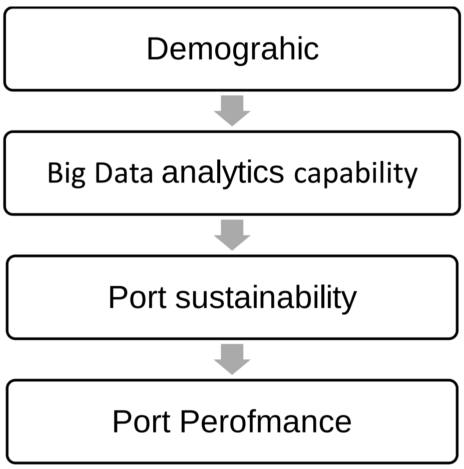

Figure 6.1 The layout of the Questionaire

The first part of the questionnaire was demographic questions. The second part focus on assessing the development of BDAC in the port. The third part asked the respondent to measure the impact of BDAC on port sustainability. In the last part, respondents were asked to evaluate the influence of the BDAC on port performance. Through literature review, the researcher identified validated and tested measurement scales. The three parts of the questionnaire use a five-point Likert scale rating (1=Strongly disagree, 2=Disagree, 3= Neutral, 4=Agree and 5=Strongly agree), and the initial questionnaire is shown in Appendix B & C.

6.2.2 Big Data analytics capability

According to the research of Lozada et al. (2019), Gupta and George (2016), Mikalef et al. (2018), and Mikalef et al. (2020), the construct of BDAC covers seven dimensions: data, technology, basic resources, managerial skills, technical skills, data-driven culture, organisational learning. Gupta and George (2016) identified seven resources that can build BDAC based on the resource-based theory and create measurement scales to evaluate the BDAC of companies. The seven resources of BDAC are supported by Mikalef et al. (2018), and they investigate and explain the BDAC of firms through a systematic literature review. Hence, based on their conceptualisation, this study develops the BDAC measurement items. The BDAC scale is presented in table 6.2.

Dimensions	Items	Source
Data	(1) We have access to very large, unstructured, or fast-moving data for analysis (2) We integrate data from multiple internal sources into a data lake for easy access (3) We integrate external data with internal to facilitate high-value analysis of our business environment	Akter et al. (2016), Gupta and George (2016), Mikalef et al. (2020)
Technology	(1) We have explored or adopted distributed computing approaches (e.g., Hadoop, Storm, Spark) to Big Data processing (2) We have explored or adopted different data visualization tools (3) We have explored or adopted cloud services (e.g., IBM Cloud, Amazon Web Services, Microsoft Azure, Google Cloud) for processing data performing analytics	Akter et al. (2016), Jeble et al. (2018), Dubey et al. (2018a), Mikalef et al. (2020)
Basic Resources	(1) Our Big Data analytics projects are adequately funded (2) Our Big Data analytics projects are given enough time to achieve their objectives	Gupta and George (2016), Jeble et al. (2018), Mikalef et al. (2020), Lozada et al. (2019)
Technical Skills	(1) Our port provides data analytics training to our own employees (2) Our port hires new employees that already have the data analytics skills (3) Our analysts have appropriate skills to accomplish their jobs successfully (4) Our analysts have the suitable work experience to accomplish their jobs successfully	Wamba et al. (2017), Akter et al. (2016), Mikalef et al. (2020), Jha et al. (2020)
Managerial Skills	(1) Our data analytics managers are able to work with functional managers, suppliers and customers to determine opportunities that Big Data might bring to our business (2) Our data analytics managers are able to coordinate Big Data-related activities in ways that support other functional managers, suppliers and customers (3) Our Big Data analytics manager are able to anticipate the future business needs of functional managers, suppliers, and customers (4) Our Big Data analytics managers are able to comprehend and assess the information extracted from big data	Akter et al. (2016), Gupta and George (2016), Gunasekaran et al. (2017), Mikalef et al. (2020)

Data-driven Culture	(1) We consider data a tangible asset (2) We consider data a tangible asset (3) We continuously assess and improve the business rules in response to insights extracted from data (4) We continuously coach our employee to make decisions based on data	Gupta and George (2016), Jeble et al. (2018), Mikalef et al. (2020), Shamim et al. (2020), Lozada et al. (2019)
Organisational learning	(1) We actively search for new and relevant knowledge (2) We assimilate new and relevant knowledge (3) We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge	Gupta and George (2016), Jeble et al. (2018), Mikalef et al. (2020), Lozada et al. (2019)

Table 6.2 Questionnaire items for the measurement of BDAC

From Table 6.2, the BDAC scale total has 23 items. In order to increase the accuracy of measurement items and make them more suitable for port environments, these 23 items have been adapted from much previous work (Akter et al., 2016, Dubey et al., 2018a, Wamba et al., 2017, Jeble et al., 2018). Their research focuses on examining the management, technological, and human capital capabilities of BDAC. In the management dimensions, they indicated that coordination across various apartments is considered the core resource of developing companies' BDAC. In the dimensions of technology, they point out that the connectivity and compatibility of Big Data technology are the main drivers of firms developing BDAC. In the data dimensions, Giebler et al. (2019) point out that traditional enterprise data analytics solutions based on data warehouses cannot handle the collected Big Data. In order to conduct comprehensive data analytics on these structured, semi-structured, and unstructured data, many researchers (Sawadogo and Darmont, 2021, Sarramia et al., 2022, Eichler et al., 2021) suggest that companies can use the data lake. In contrast to data warehouses, data lakes are databases that can handle batch and real-time streams as well as structured, unstructured, and semi-structured data from various sources (Sawadogo and Darmont, 2021). The Data lake can directly link to Hadoop and process data via MapReduce (Mathis, 2017). In the dimensions of talent capability, they emphasised that companies' related employees should have the technical knowledge, technology management knowledge and business knowledge to support the company establishing BDAC. In the dimensions of data-driven, both TDA and BDA can be used to create a data-driven culture, but they differ in their approach to data. As discussed in 3.4.1, TDA typically focuses on structured data, which is data that is organised into a predefined format, such as spreadsheets or databases. TDA relies on statistical and mathematical techniques to analyse this structured data and extract insights(Li and Lu, 2014). BDA can incorporate both structured and unstructured data, including raw data inputs and schema, as well as domain knowledge and experience. This approach involves using advanced technologies and techniques, such as machine learning and natural language processing, to extract insights from large volumes of data in various formats (Vassakis et al., 2018). When creating a data-driven culture, it is important to consider the specific needs and goals of the organisation. TDA may be the most appropriate approach for structured problems, such as measuring port performance. KPIs such as volume of cargo handled, vessel turnaround time, and berth occupancy rate are all measurable and structured data can be easily tracked and analysed using TDA techniques, providing valuable insights into performance metrics (Duru et al., 2020). However, for dynamic and unstructured problems, such as port sustainability, BDA may be the most appropriate approach. Sustainability is a complex and multifaceted problem involving various factors, including social, economic, and environmental considerations. Big data analytics can be useful in analysing unstructured data, such as social media feeds, satellite imagery, and weather data, to identify patterns and trends related to port sustainability (Vural et al., 2021, Yang et al., 2019). It is worth noting that sustainability is not exclusively an unstructured problem, and there may be structured data available that can be analysed using TDA techniques to identify opportunities for sustainable improvements. For example, port energy consumption data, emissions data, and waste disposal data are all structured data that can be analysed to identify opportunities for sustainable improvements (Molavi et al., 2020). Therefore, both approaches can be used together to create a comprehensive data-driven culture that leverages both structured and unstructured data. Furthermore, Jeble et al. (2018) presented the impact of BDAC on supply chain sustainability, providing a more comprehensive understanding of developing BDAC. This research develops a validated and reliable measurement instrument by integrating different measure items.

6.2.3 Port sustainability

In this study, the concept of port sustainability consists of three dimensions: the environmental dimension, the social dimension, and the economic dimension. Numerous scholars (Chiu et al., 2014, Chen and Pak, 2017, Oh et al., 2018, Lu et al., 2016a) have proposed measurement items to evaluate the sustainability performance of ports. The measurement items of this research were adopted from the study of Oh et al. (2018) since they investigated port sustainability specifically through aspects of the environment, economy and society. Moreover, Chiu et al. (2014) emphasised the ports' environmental performance and evaluated the effect of pollution, port community and port staff training on port sustainability. Chen and Pak (2017) also investigates the environmental performance indices of ports and highlights the influence of liquid pollution, air pollution and noise pollution. Through incorporating their measurement instrument, the environmental performance measurement items of this study become more validated and reliable. However, Chiu et al. (2014) and Chen and Pak (2017) have not demonstrated the social and economic impact of port sustainability performance in more detail. Lu et al. (2016a) proposed the effect of social and economic on sustainability performance and emphasised the importance of sustainable collaboration between ports and their partners, assisting the measurement instrument development. The scale for measuring port sustainability is shown in Table 6.3.

Dimensions	**Items**	**Source**
Environment	(1) Our port has adopted data analytics technology for reduction of air emissions. (2) Our port has adopted data analytics technology for reduction of wasted water. (3) Our port has adopted data analytics technology for reduction of noise. (4) Our port has adopted data analytics technology for reduction of oil consumption.	Jeble et al. (2018), Chiu et al. (2014), Lu et al. (2016a), Chen and Pak (2017), Dubey et al. (2019b)
Society	(1) Our port improves service quality by using data analytics technology. (2) Our port authority has improved the relationship with the neighbouring residents by building smart port. (3) Our staff's security and safety has improved by building smart port. (4) Our port provides support for employees' training and education.	Jeble et al. (2018), Chiu et al. (2014), Oh et al. (2018), Dubey et al. (2019b)
Economy	(1) Our port offers more employment opportunities. (2) Our port authorities multifunctional and efficient use of port areas by data analytics technology. (3) Our port authorities actively cooperate with industrial and economic development through building smart port. (4) Our port is driving the economic development of the area surrounding the port through developing data analytics technology.	Jeble et al. (2018), Oh et al. (2018), Lu et al. (2016a), Kang and Kim (2017)

Table 6.3 Questionnaire items for the measurement of port sustainability

6.2.4 Port performance

In this research, the port performance scale includes five dimensions: cost, service quality, operational efficiency, VAS, and customer orientation. The scale measuring port performance is mostly adapted from Woo et al. (2011), Kim et al. (2016), Tseng and Liao (2015) and Seo et al. (2016). In discussing the port performance in port integration into the global supply chain, Woo et al. (2011) argued that the primary aim of improving port performance is to meet the requirement of customers and supply chain partners. The finding is congruent with the work of Seo et al. (2016). However, the cost impact on port performance has not been sufficiently evaluated in their developed measurement items. The cost dimension is modified from Panayides and Song (2008) in order to increase the reliability and validity of the port performance scale. Moreover, service quality is a measure of how well a service meets or exceeds customer expectations. The SERVQAUL model is one of the initial and most widely used instruments for measuring service quality. It consists of five dimensions: tangibles, reliability, responsiveness, assurance, and empathy (Wang et al., 2015). However, when measuring port service quality, the SERVQAUL model does not consider the specifications of port operations, management and social responsibility (Lee et al., 2013, Thai, 2016). In particular, social responsibility is becoming increasingly important in the context of green initiatives that many ports around the world are trying to implement (Yeo et al., 2015). Hence, a number of studies (Phan et al., 2021, Pham and Yeo, 2019, Yeo et al., 2015) use the ROPMIS model, which was presented by Thai (2008) and created specifically to measure service quality in maritime transport. ROPMIS model consists of the following six dimensions: resources, outcomes, process, management, and image and social responsibility. In this study, the first and third question of service quality is related to the outcome dimension and reflects the ability of the service provider to deliver the service accurately and consistently. The second question about service quality is related to the management dimension and reflects the ability to understand customer needs and customer needs-oriented continuous improvement (Phan et al., 2021). The fourth question of service quality is related to the resources dimension and measures the convenience of cargo track and trace (Yeo et al., 2015). While some of these dimensions may have social aspects, such as image and social responsibility, service quality is primarily concerned with meeting the needs and expectations of customers in terms of the service provided. Social sustainability, on the other hand, relates to the broader social impacts of the port, such as its effects on the surrounding community, the well-being of its staff, and its contributions to sustainable development. So, unlike the questions about service quality, the first question regarding the social dimension focuses on measuring the ports' attitudes toward serving the surrounding community and their interactions with the community's requirements. The scale for measuring port performance is shown in Table 6.4.

Dimensions	Items	Source
Cost	(1) Through using data analytics technology, our port cargo handling charge is lower than our major competitor. (2) Through using data analytics technology, our port charges for intermodal transport are lower than our major competitor. (3) Through using data analytics technology, our port auxiliary service (pilotage, towage, customers) charge is lower than our major competitor.	Kim et al. (2016), Woo et al. (2013), Seo et al. (2016), Lu et al. (2016), Cho et al. (2010)
Service Quality	(1) Through using data analytics technology, our port handles cargo at quoted or anticipated times. (2) Through using data analytics technology, our port handles cargo on time according to customers requirement. (3) Through using data analytics technology, our port's service lead time is shorter than our major competitors. (4) Through using data analytics technology, our port provides shipment information accurately.	Kim et al. (2016), Woo et al. (2013), Seo et al. (2016), Yeo et al. (2015), Phan et al. (2021)
Operational Efficiency	(1) Through using data analytics technology, our terminal productivity is higher than our major competitor. (2) Through using data analytics technology, Port turn-around time is less (Ship waiting time due to congestion) than our major competitor. (3) Through using data analytics technology, our time for transportation mode transit is shorter than our major competitor.	Kim et al. (2016), Woo et al. (2013), Seo et al. (2016); Jiang et al. (2021); Yeo et al (2011)
Value-added Services	(1) Through using data analytics technology, our port has the capacity to handle different type of cargo. (2) Through using data analytics technology, our port has a variety of services to handle the transferring of cargo from one mode to another. (3) Through using data analytics technology, our port has the capacity to convey cargo through diversified routes/modes at the least possible time to the receiver. (4) Through using data analytics technology, our port has the capacity to launch new tailored services when the need arises.	Seo et al. (2016), Tseng and Liao (2015)
Customer Orientation	(1) Through using data analytics technology, our port is quick on making decisions regarding altering schedules, amending orders and changing design process to meet customers' demand. (2) Through using data analytics technology, our port can provide individual port services to our customers. (3) Through using data analytics technology, our port's response time for customer complaints is faster than that of our major competitors. (4) Through using data analytics technology, our port has smooth operational processes for port users.	Woo et al. (2011), Panayides (2017), Lee et al. (2016), Tseng and Liao (2015), Panayides and Song (2008)

Table 6.4 Questionnaire items for the measurement of port performance

6.3 Pilot survey

Before large-scale data collection, the newly developed questionnaires were further tested to ensure content and face validity. Wamba et al. (2017) point out that the results of the pilot study can provide valuable information about the reliability and validity of the measurement scales. Therefore, pilot research is conducted with the purpose of enhancing the measuring scales. Firstly, five port experts and five scholars were invited to examine the validity and reliability of the survey. The five port experts include two senior port managers and three IT managers who are employed by the port of Shanghai, the port of Rotterdam, the port of Shenzhen and the port of Piraeus. The five scholars focus on Big Data or Port areas. They checked the definition of the constructs and evaluated the relevance of each item to its theorised construct. Based on the questionnaire's evaluation and the feedback from experts and academics, a few suggestions for its enhancement were made. The following Table 6.5 show the suggestions and responses of the researcher.

Type of experts	Suggestions	Responses
Port IT manager	In the question of technology, offering some port-used software as an example to help respondents understand the questions. In the question of Basic Resources, the word “adequate funds” is difficult to judge.	Reworded question of technology to provide more port-specific software. Reworded question of basic resources to make it clearer.
Academic Researchers	In the part of port sustainability, improving the link between BDAC and port sustainability to make it clearer for respondents.	Reworded part of port sustainability to strengthen the link between BDAC and port sustainability.
Senior port manager	Making the part of port performance more interesting. Making the question of VAS and customer orientation clearer to understand.	Redesigned the part of the port performance to make it more presentable and easier to answer.
Academic professionals	Remove duplicated items of port performance. Providing more detail to the question of port performance.	Remove the duplicated item and reword some questions to make them more detailed and clearer.

Table 6.5 Suggestions of experts and responses from researchers

Specifically, based on the recommendations of the port IT manager, the researcher adapted the example given in the second question on technology to include commonly used software in ports, such as Sisense, Periscope Data, and Tableau. The port IT manager pointed out that the term “adequate funds” can be subjective and difficult to judge due to various factors and suggested modifying the first question of basic resources to "we have allocated large funds for Big Data project." This modification implies that the funding provided for the project is generous and substantial and can help participants respond more clearly.

Furthermore, the academic researcher pointed out that although the questions about port sustainability performance indicate that the port has taken steps to improve sustainability performance, the specific technologies used are not mentioned. For example, “Our port has adopted adequate measures for the reduction of air emissions” implies that the port has implemented a variety of actions or solutions to reduce air emissions, but the specific methods or technologies used are not mentioned. According to the suggestion of the academic researcher, this study adapted the question to “Our port has adopted data analytics technology for reduction of air emissions” and specifies that the port has employed data analytics technology specifically to reduce air emissions. The questions on sustainability were similarly modified to emphasise the big data technologies used to achieve this goal. The questions on port performance were also similarly modified to emphasise the enhancement of port performance enabled by Big Data technology.

Additionally, the academic professional recommended removing duplicated items of port performance and providing more details in the questions. Specifically, the three questions about value-added services appear to be very similar and contain similar ideas. They all emphasise the importance of value-added services in attracting cargo and mention the availability of facilities to provide such services. The research rephrased these questions and gave specific value-added services. For example, “value-added increase from value-added service” is changed to “Through using data analytics technology, our port has the capacity to convey cargo through diversified routes/modes at the least possible time to the receiver”. The changes to the value-added service section also respond to the recommendations of the port senior manager at the same time.

In addition, according to the comments of the senior port manager, the researcher reformulated the questions on customer orientation to make them more specific and clearer. For instance, “Our port has quick decision-making process” was changed to "through using data analytics technology, our port is quick on making decisions regarding altering schedules, amending orders and changing design process to meet customers’ demand”. The first sentence is more general and does not provide details about the specific methods or technologies used to facilitate quick decision-making. The second sentence provides more information about how our port achieves quick decision-making. Thus, according to the suggestions of port managers and scholars, the researcher reworked some questions and reorganised the questionnaire to make it clearer for respondents to answer.

Then the second draft of the questionnaire (shown in Appendix D & E) was evaluated. They indicated that the definition of the constructs is clear, and the measurement items are valid and reliable. After their review and evaluation, the pilot study was carried out before the primary data collection. The pilot questionnaire was emailed to 40 port management-level staff in 1. Qingdao Port, 2. Longkou Port, 3. Yingkou Port, and 4. Ningbo Port. The email includes a short introduction to detail this research and shows the definition of some terms. Finally, a total of 34 responses were obtained, and only 30 were complete with good quality. The collected data were processed and analysed by SPSS.

6.3.1 Internal Consistency

The purposes of this pilot survey are to test the reliability and validity of the newly developed scales. Most of the research on reliability suggests that internal consistency was chosen to assess reliability (Tavakol and Dennick, 2011, Henson, 2001, Streiner, 2003, Wong, 2013). Internal consistency can evaluate the reliability of survey or test items intended to measure the same concept (Henson, 2001). Thus, this study selected internal consistency as the assessment. Previous research (Francis and Katz, 2007, English and Keeley, 2014, Taber, 2018) points out that three commonly applied methods for testing internal consistency: split-halves test, Kuder-Richardson test and Cronbach's alpha test. The Split-halves test method is done by comparing the results of one half of a test with the results from the other half. If the result of each half is similar, the test has internal reliability (Feldt and Charter, 2003). The Kuder-Richardson test can provide an average correlation for all possible ways to divide a test into halves. Hence, the result of the Kuder-Richardson test is more accurate than the result of the split-halves test (Heale and Twycross, 2015). However, the split-halves and the Kuder-Richardson method require that answer to each question should be simple, which means they cannot analyse the multi-scale response and they require.

Cronbach's alpha could measure not only the average of all possible split-half correlations but also overcome the disadvantages of the Kuder-Richardson and split-halves approach (Tavakol and Dennick, 2011). So, Cronbach's alpha could measure the reliability of Likert scale surveys. Cronbach's alpha runs from 0 to 1, where 0 indicates no correlation between items on a scale and 1 indicates perfect correlation. Nair and Das (2012) and Aibinu and Al-Lawati (2010) both use Cronbach's alpha to test the reliability of the scale and point out that an alpha value greater than 0.7 are considered acceptable. However, the use of Cronbach's alpha also has some limitations. Tavakol and Dennick (2011) point out that the number of measure items can influence reliability. A small number of items tend to have a lower result, and vice versa. Moreover, Sijtsma (2009) argued that Cronbach's alpha assumes the questions are merely testing one latent variable or dimension. This implies that the test should be broken into different parts when measuring more than one concept or construct.

Therefore, based on the above discussion, Cronbach's alpha approach is more suitable for this study. Cronbach's alpha method is used to measure multi-scale responses and various concepts.

6.3.2 Construct validity

Validity refers to the extent to which the gathered data correctly reflect the phenomenon being examined (Noble and Smith, 2015). Past studies have demonstrated several ways of measuring validity, and the current investigation encompassed three types of validity: face validity, content validity, and construct validity. The following table shows their detail.

Validity	Definition	Source
Face validity	The extent to which a test appears to measure what it is intended to measure.	Leedy and Ormrod (2005)
Content validity	The extent to which an investigational inquiry is adequately covered by a certain metric.	Saunders et al. (2016)
Construct validity	The extent to which the measurements used actually tests the hypothesis or theory they are measuring.	Drost (2011)

Table 6.6 Descriptions of the approaches to assess validity

Table 6.6 demonstrates that both face validity and content validity have been evaluated. Specifically, through reviewing the literature and evaluating port managers and academics, the content and design of the questionnaire are improved and identified. Hence, this section focuses on measuring construct validity. This research selects the corrected item-total correlation (CITC) method to examine the construct validity of measurement scales. CITC is a technique for examining the homogeneity of a scale composed of multiple components (Hair et al., 2009). Many previous scholars (Tseng and Liao, 2015, Kim, 2014, Oruç and Tatar, 2017) utilised CITC to measure the validity of the construct and indicate that the CITC cutline is 0.5, which means any item with a lower value than this should be removed.

Therefore, based on the above discussion, this research analyses CITC and Cronbach's alpha to improve the reliability and validity of measurement items. The CITC and Cronbach's alpha is analysed through SPSS.

6.4 Result of the pilot study

Through using SPSS, the collected data were analysed. For each construct, Cronbach's alpha and CITC were analysed. The results are displayed below.

6.4.1 Big Data analytics capability

The BDAC construct consists of seven dimensions: data (D), technology (T), basic resources (BR), managerial skills (MS), technical skills (TS), data-driven culture (DDC) and organisational learning (OL). Table 6.7 presents the result of CITC and Cronbach's Alpha. All these analysis results suggest that all the items have strong reliability and validity.

Measures	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Cronbach's Alpha
D1	0.858	0.807	0.900
D2	0.765	0.887	
D3	0.784	0.872	
T1	0.852	0.928	0.938
T2	0.909	0.886	
T3	0.876	0.918	
BR1	0.813		0.897
BR2	0.813		
TS1	0.962	0.981	0.985
TS2	0.973	0.978	
TS3	0.963	0.980	
TS4	0.954	0.983	
MS1	0.980	0.991	0.993
MS2	0.972	0.994	
MS3	0.990	0.989	
MS4	0.988	0.989	
DDC1	0.932	0.954	0.967
DDC2	0.945	0.950	
DDC3	0.934	0.952	
DDC4	0.874	0.972	
OL1	0.978	0.977	0.987
OL2	0.978	0.977	
OL3	0.964	0.988	

Table 6.7 Big Data analytics capability

6.4.2 Port sustainability

This study considers three factors of port sustainability performance: environmental dimension (ED), social dimension (SD) and economic dimension (ECD). The CITC and Cronbach's alpha results are displayed in Table 6.8. Given the result, the values of Cronbach's alpha are both over 0.7, and the value of CITC is both over 0.5. Thus, no change is needed for this construct.

Measures	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Cronbach's Alpha
ED1	0.700	0.956	0.933
ED2	0.902	0.891	
ED3	0.905	0.894	
ED4	0.874	0.901	
SD1	0.543	0.898	0.867
SD2	0.786	0.802	
SD3	0.865	0.768	
SD4	0.697	0.839	
ECD1	0.637	0.918	0.898
ECD2	0.811	0.857	
ECD3	0.833	0.847	
ECD4	0.854	0.849	

Table 6.8 Port sustainability performance

6.4.3 Port performance

In this research, the port performance scale includes five dimensions: cost (C), service quality (SQ), operational efficiency (OE), value-added services (VAS) and customer orientation (CO). The item purification results are listed in Table 6.9. Based on the results, no improvement is needed for this construct.

Measures	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Cronbach’s Alpha
C1	0.902	0.957	0.962
C2	0.958	0.916	
C3	0.900	0.959	
SQ1	0.921	0.944	0.961
SQ2	0.937	0.939	
SQ3	0.927	0.942	
SQ4	0.834	0.968	
QE1	0.948	0.972	0.978
QE2	0.950	0.970	
QE3	0.963	0.960	
VAS1	0.875	0.957	0.961
VAS2	0.910	0.947	
VAS3	0.915	0.945	
VAS4	0.915	0.945	
CO1	0.928	0.947	0.977
CO2	0.947	0.968	
CO3	0.945	0.969	
CO4	0.949	0.968	

Table 6.9 Port performance

In conclusion, based on the results presented in Tables 6.7, 6.8 and 6.9, Cronbach’s alpha value for all constructs in this study was greater than 0.80. Hence, all measurement items have strong reliability. Moreover, based on the result, the ICTC in the pilot study ranged from 0.543 to 0.990, which means the questionnaire has great construct validity. The result of the pilot study indicates that the developed questionnaire has great quality and can be used in the primary survey.

6.4.4 Hypothesis testing

Figure 6.2 presents the estimates obtained through PLS-SEM analysis. Through analysing collected data from the pilot study, the model shows the path coefficients and explains the relationship between BDAC, port sustainability and port performance. In Figure 6.6, the path value between BDAC and port sustainability performance is 0.912; BDAC and port performance is 0.078; port sustainability performance and port performance are 0.903. Hence, BDAC is positively associated with port sustainability performance and port performance, and port sustainability is positively associated with port performance. Moreover, the explanatory power (R^2) of the endogenous construct is examined. The R^2 for port sustainability performance is 0.833, and R^2 for port performance is 0.949.

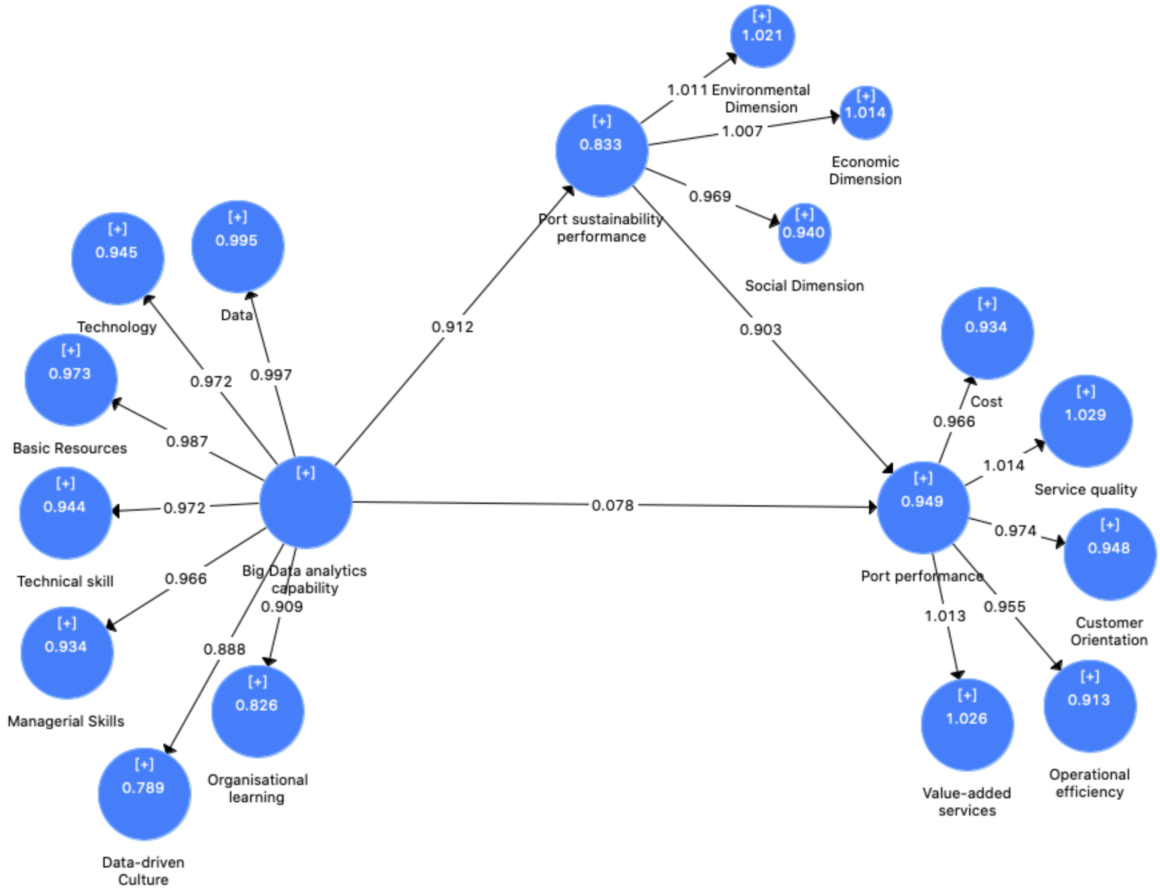

Figure 6.2 Structural model

The pilot study results show that all the hypotheses posited by this study are supported. However, due to the sample size, the relationships between the constructs of the proposed model have some limitations. Thus, the large-scale survey study will improve the reliability of the model and propose a deeper explanation.

6.5 Summary

This chapter showed the development of the questionnaire and pilot survey. The questionnaires used a 5-point Likert scale to explore the relationship between BDAC, port sustainability and port performance. Based on the literature review, the scale to measure cause-effect relationships between these variables is identified. The questionnaire was improved and modified by expert reviews. Then a pilot study was conducted to ensure the content validity of the questionnaire and the reliability of the constructs. The next chapter presents the result of the primary survey and the analysis of the collected data.

Chapter 7 Analysis and results

7.1 Introduction

This chapter describes the findings of the data analysis performed on the survey questionnaires. This chapter begins with a description of the respondents' demographic characteristics. Then the collected data were investigated to determine which data were acceptable and which had to be eliminated. It is followed by analysing the gained data to identify the reliability and validity of the results. Finally, the PLS-SEM procedures were used to test hypothesised relationships between constructs.

7.2 Demographic profiles of the respondents

The major data for this study were collected for approximately five months following the pilot survey, from February 2020 to June 2020. The top 50 ports in the Lloyd's List form the population of this study. 31 of the top 50 ports were identified as using Big Data technology. The detail of ports and their applied Big Data technology are presented in Table 5.10. Based on the list, an email including a link to the online surveys was sent to participants, including port management-level staff and IT department employees. Meanwhile, this email presented an abstract of this research to ensure participants understand the aims and significance of this study. In order to increase the response rate, a reminder email was sent to motivate and remind participants to complete the questionnaires. As a result, 207 questionnaires were collected, and participants without working experience in Big Data technology were excluded. Hence, 175 questionnaires were valid, and 32 questionnaires were disqualified. The valid response rate was 84.5%. Previous studies in the BDAC area presented lower responses rare, approximately 58% (Wamba et al., 2017) and 38% (Akter et al., 2016). So, this study achieved a high response rate. The following table displays the respondents' demographic characteristics.

Dimension	Category	Number	Percent
Age	22-28 years old	36	20.6%
	29-35 years old	61	34.9%
	36-42 years old	35	20%
	43-49 years old	22	12.5%
	50 years old or older	21	12%
Education	No formal qualification	0	0%
	College qualification (diploma /certificate)	33	18.8%
	Undergraduate degree	117	66.9%
	Postgraduate degree	25	14.3%
Big data working experience	1-2 years	105	60%
	3-4 years	50	28.6%
	5 years or more	20	11.4%
Occupation	Economist	33	18.8%
	Engineer	69	39.4%
	Technician	40	22.8%
	Marketing department	3	1.7%
	Supply chain department	11	6.3%
	Department Manager	5	3%
	Project department	6	3.4%
	Other	8	4.6%

Table 7.1 Demographic profile of respondents

Table 7.1 demonstrates that approximately 35% of respondents were between 29 and 35 years old. Regarding education, approximately 67% of respondents had an undergraduate degree, and 14.3% got a postgraduate one. Of the working experience, 11.4% of participants have five or more years of working experience using Big Data relevant knowledge and technique. 28.6% of respondents have 3-4 years of working experience, and all have at least one year. Hence, in this study, all respondents can understand the impact of the Big Data technique on their work and provide a reliable answer. Moreover, approximately 39% of respondents were engineers, and 22.8% of respondents were technicians. 18.8% of participants are economists that are analysing economic data of the port, while 6.3% of participants work in the supply chain department. Participants from different positions can provide various perspectives, increasing the reliability of the results.

7.3 Reliability and validity analyse

Before evaluating the model and hypotheses, the reliability and validity of the scale needs to be tested to ensure the reliability of the gathered data. Reliability refers to the dependability of the measuring device, whereas validity refers to the amount to which the obtained data accurately reflect the investigated phenomenon (Noble and Smith, 2015). Based on the discussion in chapter 6, this study uses Cronbach's alpha and CITC to evaluate reliability and validity. Nair and Das (2012) indicated that an alpha value greater than 0.7 are ideal, and greater than 0.5 can be acceptable. Hair et al. (2009) point out that the CITC cutline is 0.5. The following table shows the reliability and validity of the BDAC construct.

Measures	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Cronbach's Alpha
D1	0.749	0.802	0.863
D2	0.736	0.811	
D3	0.739	0.809	
T1	0.751	0.824	0.872
T2	0.776	0.800	
T3	0.740	0.835	
BR1	0.738		0.849
BR2	0.738		
TS1	0.761	0.879	0.901
TS2	0.822	0.856	
TS3	0.769	0.876	
TS4	0.766	0.877	
MS1	0.776	0.879	0.904
MS2	0.782	0.877	
MS3	0.783	0.876	
MS4	0.796	0.872	
DDC1	0.751	0.891	0.906
DDC2	0.769	0.885	
DDC3	0.809	0.872	
DDC4	0.825	0.865	
OL1	0.795	0.860	0.899
OL2	0.819	0.840	
OL3	0.788	0.867	

Table 7.2 Big Data analytics capability

Moreover, in this study, port sustainability performance includes three dimensions: environmental dimension (ED), social dimension (SD) and economic dimension (ECD). In Table 7.3, the CITC and Cronbach's alpha results are displayed. All the values of Cronbach's Alpha are over 0.8, and the value of CITC is over 0.5. Based on the results, no improvement is needed for this construct.

Measures	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Cronbach's Alpha
ED1	0.773	0.897	0.913
ED2	0.839	0.874	
ED3	0.837	0.874	
ED4	0.756	0.902	
SD1	0.628	0.860	0.864
SD2	0.731	0.819	
SD3	0.798	0.791	
SD4	0.702	0.832	
ECD1	0.601	0.892	0.877
ECD2	0.769	0.828	
ECD3	0.765	0.831	
ECD4	0.812	0.810	

Table 7.3 Port sustainability performance

Furthermore, in this research, the port performance scale includes five dimensions: cost (C), service quality (SQ), operational efficiency (OE), value-added services (VAS) and customer orientation (CO). The item results are listed in Table 7.4.

Based on the result of Tables 7.2, 7.3 and 7.4, Cronbach's Alpha for each construct was all above the threshold level of 0.7. It is concluded that all constructs are internally consistent and have acceptable reliability values. Moreover, the value of CITC was above the threshold level of 0.5, which means that the scale items have significant validity. Thus, all the scale items and collected data can move to the next phase to test the causal relationships between the research constructs.

Measures	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted	Cronbach's Alpha
C1	0.838	0.870	0.915
C2	0.861	0.852	
C3	0.790	0.911	
SQ1	0.763	0.884	0.904
SQ2	0.780	0.878	
SQ3	0.799	0.871	
SQ4	0.798	0.871	
OE1	0.690	0.796	0.842
OE2	0.729	0.759	
OE3	0.701	0.786	
VAS1	0.668	0.840	0.862
VAS2	0.761	0.801	
VAS3	0.696	0.829	
VAS4	0.710	0.823	
CO1	0.691	0.870	0.883
CO2	0.749	0.849	
CO3	0.746	0.850	
CO4	0.799	0.828	

Table 7.4 Port performance

7.4 Evaluation of the measurement models

According to several previous studies (Chen et al., 2015, Lai et al., 2018, Akter et al., 2016), the measurement model will be evaluated after examining the gathered data and scales. The measurement model enables researchers to check how developed latent variables fit together and the link between hypothetical constructs and their related indicators, thereby aiding in evaluating the validity and reliability of latent variables (Sarstedt et al., 2016).

Based on the discussion in section 5.2.3, the measurement model includes two types of models: the formative model and the reflective model. Hair et al. (2011) indicated that reflective and formative measurement models should be evaluated by different indicators. Furthermore, in this study, all measurement models are HOM (also known as hierarchical component models). According to the relationship between first-order latent variables and their variables and second-order latent variables, Jarvis et al. (2003b) and (Ringle et al., 2012) classify HOM into four categories: reflective-reflective HOM, formative-reflective HOM, reflective-formative HOM and formative-formative HOM. Hence, this study focuses on assessing the reliability and validity of the reflective-reflective HOM.

7.4.1 Reflective-reflective HOM assessment

Most of the research (Becker et al., 2012, Sarstedt et al., 2019, Crocetta et al., 2021, Cheah et al., 2019) on the investigation of HOM point out that there are two main approaches for analysing HOM are called repeated indicators approach and the two-stage approach. In the repeated indicators methodology, all lower-order component indicators are assigned to the higher-order component (Lohmöller, 2013). Thus, the repeated indicator approach can estimate all constructs simultaneously and produces smaller biases in the estimation of the HOM. Moreover, in their study of analysing different types of HOM, Becker et al. (2012) and Hair Jr et al. (2017b) found that the repeated indicators approach suits reflective-reflective HOM better. Hence, this study uses a repeated indicator approach to assess high-order measurement models.

7.4.2 Reliability assessment

Most of the research (Hair et al., 2011, Avkiran, 2018, Wong, 2013, Hair Jr et al., 2014) on the investigation PLS-SEM method suggests that reflective measurement models should be assessed with internal consistency, indicator reliability, convergent validity and discriminate validity. Internal consistency is traditionally assessed by using Cronbach’s Alpha. Based on the discussion in 6.2.1, Cronbach’s Alpha should have a value of 0.7 or higher. However, Wong (2013) and Sarnacchiaro and Boccia (2018) stated that Cronbach's Alpha has a drawback in that it incorrectly assumes that all indicators are equally trustworthy, hence tending to underestimate internal consistency reliability. Thus, recent research (Ali et al., 2018, Sarstedt et al., 2016, Ringle et al., 2020) has tended to show that composite reliability provides a more appropriate measure of internal consistency reliability. Composite reliability is more concerned with individual reliability and consideration of the varying factor loadings of the items. The composite reliability cutline is 0.7 (Lai et al., 2018). However, Hair Jr et al. (2016) point out that values above 0.95 may indicate that the items are redundant. Therefore, the value between 0.7 and 0.95 of composite reliability is acceptable. Ali et al. (2018) reported that numerous studies exhibit internal consistency reliability using both Cronbach's alpha and composite reliability. Therefore, both are used in this study to measure internal consistency reliability.

Furthermore, the indicator reliability is assessed using the outer loadings on the constructions. Avkiran (2018) and Aibinu and Al-Lawati (2010) suggested that the value of indicator loadings should be greater than 0.7. Hair et al. (2011) emphasised that if an outer loading is between 0.4 and 0.7, the composite reliability and convergent validity of these items need to be considered to decide whether to delete the item. If outer loadings are below 0.4, the reflecting indication must be removed. The following table displays the reliability of the reflective measurement model assessment.

Reliability	Criterion	Rules of thumb	Resource
internal consistency reliability	Cronbach’s Alpha	0.7 or higher	Sarnacchiaro and Boccia (2018)
	Composite reliability	between 0.7 and 0.95	Lai et al. (2018)
indicator reliability	Outer loadings	0.7 or higher between 0.4 and 0.7 need consideration other criterions	Avkiran (2018)

Table 7.5 Reliability in reflective measurement model assessment

The SmartPLS is used to analyse Cronbach’s Alpha, composite reliability and outer loading. The following two tables show an overview of the results. Table 7.6 displays the result of the first-order model, and Table 7.7 show the result of second-order constructs. Based on the analysis demonstrated in Tables 7.6 and 7.7, the values of Cronbach’s Alpha and outer loadings are all higher than 0.7. In addition, the composite reliability coefficients vary from 0.901 to 0.947, which is more than the required threshold value of 0.7 but lower than 0.95. Consequently, it can be concluded that the reliability of all measured latent variables and their associated items in this study is satisfactory.

Latent variable	Indicator	Loadings	Cronbach's alpha	Composite reliability
Data	D1	0.886	0.864	0.917
	D2	0.887		
	D3	0.887		
Technology	T1	0.894	0.873	0.922
	T2	0.894		
	T3	0.890		
Basic Resources	BR1	0.927	0.849	0.93
	BR2	0.937		
Technical Skills	TS1	0.863	0.901	0.931
	TS2	0.907		
	TS3	0.874		
	TS4	0.869		
Managerial Skills	MS1	0.875	0.904	0.933
	MS2	0.881		
	MS3	0.879		
	MS4	0.889		
Data-driven Culture	DDC1	0.863	0.906	0.934
	DDC2	0.876		
	DDC3	0.889		
	DDC4	0.906		
Organizational Learning	OL1	0.914	0.899	0.937
	OL2	0.918		
	OL3	0.905		
Environmental Dimension	ED1	0.870	0.913	0.939
	ED2	0.913		
	ED3	0.916		
	ED4	0.861		
Social Dimension	SD1	0.767	0.864	0.908
	SD2	0.870		
	SD3	0.897		
	SD4	0.834		
Economic Dimension	ECD1	0.746	0.877	0.916
	ECD2	0.884		
	ECD3	0.876		
	ECD4	0.909		
Cost	C1	0.932	0.916	0.947
	C2	0.941		
	C3	0.903		
Service Quality	SQ1	0.857	0.904	0.933
	SQ2	0.869		
	SQ3	0.900		
	SQ4	0.898		

Operational Efficiency	OE1	0.858	0.842	0.905
	OE2	0.880		
	OE3	0.877		
Value-added Service	VAS1	0.807	0.862	0.906
	VAS2	0.879		
	VAS3	0.830		
	VAS4	0.846		
Customer Orientation	CO1	0.895	0.883	0.919
	CO2	0.859		
	CO3	0.865		
	CO4	0.822		

Table 7.6 Reliability of first-order model

Second-order Construct	**Cronbach's alpha**	**Composite reliability**
Big Data analytics capability	0.950	0.911
Port sustainability performance	0.928	0.901
Port performance	0.941	0.907

Table 7.7 Reliability of second-order model

7.4.3 Validity assessment

After evaluating the reliability, the convergent and discriminate validity is examined to assess the validity of reflective-reflective high-order measurement models. Convergent validity assesses the extent to which a construct's indicators converge (Aibinu and Al-Lawati, 2010). In the reflective measurement model, convergent validity can be tested by the average variance extracted (AVE). AVE is defined as the grand mean squared loadings of the components associated with the construct. Many scholars (Shmueli et al., 2019, Al-Maroof and Al-Emran, 2018, Sarstedt et al., 2014b) supported using AVE to assess the convergent validity of the reflective measurement model and point out that the value of value should be at least 0.5 or higher. The following table shows the result of the AVE assessment. According to the result of

Table 7.8, the lowest AVE value is 0.707, and all AVE values exceed the recommended thresholds.

Second-order construct	AVE	Construct	AVE
Big Data analytics capability	0.767	Data	0.786
		Technology	0.797
		Basic Resources	0.869
		Technical Skills	0.772
		Managerial Skills	0.777
		Data-driven Culture	0.781
		Organisational leaning	0.832
Port sustainability performance	0.867	Environmental Dimension	0.793
		Social Dimension	0.711
		Economic Dimension	0.733
Port performance	0.812	Cost	0.856
		Service Quality	0.777
		Operational Efficiency	0.760
		Value-added Service	0.707
		Customer Orientation	0.741

Table 7.8 Value of AVE assessment

Furthermore, discriminant validity is assessed to support the validity of the reflective measurement model. The discriminant validity of each latent variable was evaluated to guarantee that each variable is subjectively distinct from other indicators. Recent research (Ab Hamid et al., 2017, Sarstedt et al., 2019, Wong, 2016, Barker and Ong, 2016) has tended to show that in the reflective measurement model and reflective-reflective high-order measurement model, discriminant validity can be assessed by Fornell-Larcker criterion and HTMT approach. Through the Fornell-Larcker criterion, the discriminant validity can be assessed by comparing the square root of the AVE for each construct to its correlations with all other constructs in the model (Fornell and Larcker, 1981b). Hair et al. (2011) and Cheung and Wang (2017) indicated that the square root of each construct's AVE should be bigger than its correlation with other latent variables in the outcome of the Fornell-Larcker Criterion. In addition, Sarstedt et al. (2019) emphasised that due to the high-order component repeating the indicators of its low-order components, the discriminant validity between high-order components and their low-order components is not needed to consider. Hence, the result of the Fornell-Larcker Criterion includes two parts: the result of high-order constructs and the result of low-order constructs. The following two tables present the result of the Fornell-Larcker Criterion. According to the results of Table 7.9 and Table 7.10, all the values of the diagonals are higher than those of the column.

	Basic resources	Cost	Customer orientation	Data	Data-driven culture	Economic dimension	Environmental dimension	Managerial Skills	Operational efficiency	Organizational learning	Service quality	Social dimension	Technical Skills	Technology	Value-added services
Basic resources	0.932														
Cost	0.527	0.925													
Customer orientation	0.554	0.566	0.861												
Data	0.673	0.442	0.451	0.887											
Data-driven culture	0.603	0.555	0.727	0.473	0.884										
Economic dimension	0.606	0.608	0.595	0.480	0.662	0.856									
Environmental dimension	0.635	0.528	0.589	0.462	0.573	0.689	0.890								
Managerial Skills	0.696	0.517	0.704	0.531	0.687	0.663	0.639	0.881							
Operational efficiency	0.550	0.658	0.683	0.471	0.649	0.642	0.612	0.580	0.872						
Organizational learning	0.484	0.506	0.630	0.388	0.753	0.563	0.536	0.565	0.596	0.912					
Service quality	0.461	0.617	0.529	0.372	0.504	0.583	0.488	0.452	0.668	0.416	0.881				
Social dimension	0.424	0.553	0.477	0.378	0.509	0.587	0.611	0.408	0.539	0.430	0.549	0.843			
Technical Skills	0.587	0.485	0.594	0.486	0.553	0.566	0.577	0.734	0.447	0.500	0.338	0.446	0.879		
Technology	0.506	0.347	0.431	0.400	0.386	0.435	0.371	0.424	0.366	0.338	0.382	0.305	0.299	0.893	
Value-added services	0.647	0.484	0.651	0.494	0.581	0.537	0.602	0.723	0.541	0.516	0.360	0.430	0.702	0.388	0.841

Table 7.9 Fornell-Larcker Criterion of first-order mode

	Big Data analytics capability	Port sustainability performance	Port performance
Big Data analytics capability	0.875		
Port sustainability performance	0.770	0.931	
Port performance	0.833	0.789	0.901

Table 7.10 Fornell-Larcker Criterion of second-order construct

Following the Fornell-Larcker Criterion method, the HTMT method is utilised to examine the discriminant validity. HTMT is the average correlation of indicators across constructs measuring distinct phenomena as compared to the average correlation of indicators inside the same construct. In discussing different validity assessment methods, Henseler et al. (2015) highlight that HTMT is able to achieve higher specificity and sensitivity rates than Fornell-Lacker Criterion. Their findings are supported by other scholars (Voorhees et al., 2016, Ab Hamid et al., 2017, Franke and Sarstedt, 2019), and they point out that the HTMT values should not exceed 0.85. The following two tables show the result of HTMT.

	Basic resources	**Cost**	**Customer orientation**	**Data**	**Data-driven culture**	**Economic dimension**	**Environmental dimension**	**Managerial Skills**	**Operational efficiency**	**Organizational learning**	**Service quality**	**Social dimension**	**Technical Skills**	**Technology**	**Value-added services**
Basic resources															
Cost	0.597														
Customer orientation	0.640	0.629													
Data	0.785	0.497	0.516												
Data-driven culture	0.684	0.607	0.811	0.530											
Economic dimension	0.700	0.678	0.670	0.552	0.737										
Environmental dimension	0.719	0.575	0.655	0.518	0.627	0.764									
Managerial Skills	0.793	0.568	0.788	0.601	0.756	0.740	0.702								
Operational efficiency	0.647	0.748	0.791	0.551	0.740	0.745	0.695	0.661							
Organizational learning	0.553	0.557	0.705	0.440	0.832	0.633	0.589	0.625	0.679						
Service quality	0.524	0.674	0.586	0.420	0.551	0.643	0.530	0.494	0.758	0.455					
Social dimension	0.483	0.621	0.541	0.430	0.566	0.667	0.675	0.453	0.625	0.479	0.615				
Technical Skills	0.669	0.532	0.665	0.549	0.608	0.633	0.635	0.813	0.509	0.553	0.369	0.497			
Technology	0.586	0.387	0.489	0.455	0.433	0.486	0.416	0.474	0.424	0.378	0.430	0.346	0.334		
Value-added services	0.756	0.544	0.745	0.573	0.652	0.610	0.679	0.818	0.631	0.583	0.401	0.493	0.795	0.447	

Table 7.11 HTMT of first-order components

	Big Data analytics capability	Port sustainability performance	Port performance
Big Data analytics capability			
Port sustainability performance	0.551		
Port performance	0.589	0.597	

Table 7.12 HTMT of second-order components

According to the result of Tables 7.11 and 7.12, all the values of HTMT are below 0.85. To conclude, with the assessments of the reflective-reflective high-order measurement model, all latent variables and their related items in this study have adequate reliability and validity. The following Table 7.13 show the assessment of the high-order model. Therefore, the examination can continue to the structural model stage.

Second-order Construct	Cronbach's alpha	Composite reliability	AVE	Dimensions	β	R	p-value
Big Data analytics capability	0.950	0.911	0.767	Data	0.700	0.490	<0.01
				Technology	0.567	0.322	<0.01
				Basic resources	0.816	0.665	<0.01
				Technical skills	0.798	0.636	<0.01
				Managerial skills	0.884	0.782	<0.01
				Data-driven culture	0.850	0.722	<0.01
				Organizational learning	0.757	0.574	<0.01
Port sustainability performance	0.928	0.901	0.867	Environmental dimension	0.896	0.804	<0.01
				Social dimension	0.825	0.680	<0.01
				Economic dimension	0.880	0.774	<0.01
Port performance	0.941	0.907	0.812	Cost	0.810	0.656	<0.01
				Service quality	0.784	0.614	<0.01
				Operational efficiency	0.866	0.751	<0.01
				Value-added service	0.747	0.558	<0.01
				Customer orientation	0.856	0.713	<0.01

Table 7.13 Assessment of high-order model

7.5 Structural model assessment

After establishing the validity and reliability of the measurement model, the structural model is analysed to test hypotheses. Most research (Lai et al., 2018, Avkiran, 2018, Akter et al., 2016, Hair et al., 2019) indicated that in the PLS-SEM, hypotheses are determined based on the coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2 and q^2), standardised beta coefficient (path value), t-statistic, and p-value significance.

7.5.1 Evaluation of coefficient of determination, effect size and predictive relevance

R^2 demonstrates the ability of the model to explain and predict the endogenous latent variables by measuring the degree of variance in the latent constructs that are explained by all its linked exogenous constructs (Zhang, 2017, Nagelkerke, 1991). According to Hair et al. (2019), R^2 values of 0.75, 0.50 and 0.25 are characterised as considerable, moderate, and weak, respectively. The following table shows the R^2 values of endogenous latent variables. Table 7.14 displays the R^2 values between 0.75 and 0.50, which means this model has acceptable prediction power.

Endogenous latent variables	$\boldsymbol{R^2}$ **value**
Port sustainability performance	0.748
Port performance	0.593

Table 7.14 R^2 of endogenous latent variables

After evaluating the R^2 values, f^2 is assessed to further measure hypotheses. Cohen (2013) indicated that f^2 can be used to assess the significant influence of the exogenous construct on the endogenous construct. Kock and Hadaya (2018) and Wong (2016) recommended that the f^2 values of 0.02, 0.15 and 0.35 should be regarded as modest, medium, and high impact sizes, respectively. The following table shows the result of f^2. According to Table 7.15, the exogenous variables have medium effect sizes on the endogenous variables.

Endogenous latent variables	$\boldsymbol{f^2}$ **value**
Port performance	0.210

Table 7.15 Value of f^2

Q^2 is used to evaluate the predictive relevance of the model in order to analyse the structural model (Cepeda-Carrion et al., 2019). Most previous research (Sarkar et al., 2001, Akter et al., 2011, Arnett et al., 2003, Hair Jr et al., 2016) on Q^2 value has pointed out that Q^2 value is obtained by using the blindfolding procedure in the PLS-SEM. Blindfolding is a strategy for reusing samples that deletes data points in a systematic manner and predicts their original values. When the value of Q^2 is larger than zero, it indicates that the structural model has predictive significance; otherwise, the model lacks predictive relevance. Moreover, the effect size q^2 is similar to effect size f^2. q^2 can assess the relative impact of predictive relevance, and the q^2values of 0.02, 0.15 and 0.35 are interpreted as small, medium, and large predictive relevance, respectively (Hair Jr et al., 2016). The following table displays the value of Q^2 and q^2 Table 7.16 shows that all Q^2 values are larger than zero, which means this structural model has predictive relevance. The value of q^2 is between 0.15 and 0.35, implying exogenous variables have medium predictive relevance on the endogenous variables.

Endogenous latent variables	$\boldsymbol{Q^2}$ **value**	$\boldsymbol{q^2}$ **value**
Port sustainability performance	0.317	
Port performance	0.358	0.031

Table 7.16 Value of Q^2 and q^2

7.5.2 Hypotheses test

After establishing the coefficient of determination and predictive relevance of the structural model, hypotheses are evaluated. In this study, three hypotheses are proposed, including H1 BDAC positively influences the port performance, H2 BDAC positively influences the port sustainability performance, and H3 port sustainability performance positively influences the port performance. The relationship between the structural model can be assessed by standardised path coefficients (Hoe, 2008).

Standardised path coefficients range between -1 and +1, with values of 0.10 indicating a little influence, 0.30 indicating a moderate effect, and 0.50 indicating a high effect (Hair Jr et al., 2014). Sarstedt et al. (2014b) and Kock (2018) recommend that the t-values and p-values must be determined after the path coefficients have been examined. The t-value is a test statistic and can determine the significant level of each relationship. The p-value is a quantitative way to show the result of hypothesis testing and represents the probability of obtaining an outcome that is at least as extreme as the observed data, assuming that the null hypothesis is true (Thiese et al., 2016).

Deliens et al. (2013) indicated that if a p-value is below a certain threshold (usually 0.05), then the corresponding hypothesis is assumed to be supported. If the p-value is less than 0.05, the results are considered statistically significant at the 95% confidence level. This means that there is only a 5% chance that the observed results occurred by chance, assuming the null hypothesis is true (Solla et al., 2018). If the p-value is less than or equal to 0.01, the result is considered highly statistically significant. McShane et al. (2019) indicated that a p-value<0.05 is considered to be strong evidence supporting a scientific theory and is necessary for a finding to be published. The following table shows the result of the hypotheses test. Table 7.17 shows all p-value is below 0.01. Thus, all results are considered highly statistically significant. Moreover, in PLS-SEM, repeatability refers to the degree of consistency or agreement among the responses to the questionnaire items (Sarstedt et al., 2017). High repeatability means that the respondents are giving similar responses to the questionnaire items. A possible reason for these similar responses might be the homogeneity of the sample. If the sample is highly homogeneous, meaning that the respondents share similar characteristics, such as age, gender, education, or occupation, they may have similar experiences and perceptions that lead to consistent responses (Bornstein et al., 2013, Burmeister and Aitken, 2012). As many of the ports in this study that used big data technology were in China, replies from many respondents were consistent since they had a common cultural background and set of perceptions. Another possible interpretation of these similar responses is social desirability bias. The respondents may give similar replies if they feel pushed to fit in or to provide socially acceptable comments in order to avoid coming out as unconventional or unsuitable (Larson, 2019). In sustainability-related questions, respondents tended to overstate their pro-sustainable intentions (Roxas and Lindsay, 2012). Thus, the high repeatability of this study may be due homogeneity of the sample and social desirability bias.

Hypotheses	$\boldsymbol{\beta}$	**t-value**	**p-value**
H1 BDAC—port performance	0.555	8.908	<0.01
H2 BDAC—port sustainability	0.770	21.295	<0.01
H3 Port sustainability—port performance	0.362	5.473	<0.01

Table 7.17 The result of hypotheses

Based on the result of table 7.17 and other evaluated results, the hypotheses can be identified. This hypothesis has a path coefficient of 0.555 in H1. It is supported by a t-value of 8.908 and a p-value below 0.05. The path coefficient in H2 for this hypothesis is 0.770. It is supported by a t-value of 21.295 and a p-value below 0.05. In H3, this hypothesis has a medium path coefficient of 0.326. It is supported by a t-value of 5,437 and a p-value below 0.05. Both reliability and validity were satisfactory. Therefore, it can confirm that in this study, all hypotheses are supported. In the next chapter, the data analysis results are discussed and explored in depth.

7.5.3 Mediation analysis

The study hypothesises that BDAC influences port performance indirectly through port sustainability. A mediating variable is defined as a variable that causes mediation in the independent and the dependent variables, such that the independent variable causes the mediation variable that causes the dependent (Mackinnon, 2015). Thus, the study considers port sustainability as a mediating variable. The analysis of the mediator can explain the relationship between the other two variables more precisely, allowing for a more thorough understanding of the mechanism of the direct relationship (Agler and De Boeck, 2017). Consequently, it is necessary to investigate and validate the potential mediating effects.

Certain prior studies (Wamba and Akter, 2019, Shou et al., 2019, Awan et al., 2021, Yu et al., 2021b) suggested that the bootstrapping approach could be employed to examine whether the impact of BDAC on port performance is mediated by port sustainability. Bootstrapping is a non-parametric resampling test. Demming et al. (2017) and Hadi et al. (2016) indicated that bootstrapping method does not rely on the assumption of normality and enables an accurate test of the indirect effect, and it is also fit for smaller sample sizes. Bootstrapping method also can produce confidence intervals for the analysis. Following the guidelines by Hair et al. (2016), the bootstrapping procedure with a 95% confidence level and 5,000 bootstrap samples are used to test the mediation hypothesis. The bootstrapping analysis of the mediated paths (BDAC-port sustainability-port performance) shows that $\beta = 0.278$ is significant, with a 5.082 t-value and <0.01 p-value. The indirect effect is a 95% confidence interval, ranging from 0.175 to 0.391 without 0, which means it is statistically significant (Memon et al., 2018). Hence, port sustainability played a partial mediating role between BDAC and port performance. Thus, the study supports H4. Table 7.18 shows the result of the direct and indirect effects of BDAC on port performance.

Paths	Mediator	Direct effect			Indirect effect		
		coefficient	p-value	t-value	coefficient	p-value	t-value
BDAC—Port performance	Port sustainability	0.555	<0.01	8.908	0.278	<0.01	5.082

Table 7.18 Bootstrapping test for mediation

Table 7.18 shows that both direct and indirect effects are significant. Different mediating types are found in the literature (Hair et al., 2016, Demming et al., 2017). The descriptions of various mediation types are detailed in Table 7.19. In this study, the relationship between BDAC and port performance is significant, and the indirect result is also significant. Hence, it could be concluded that this effect is a partial mediation rather than a full mediation. Meanwhile, the direct relationship remains significant upon the inclusion of the mediating. Therefore, port sustainability could be confirmed as being a significant mediator for the relationship between BDAC and port performance, and its effect is a complementary partial mediation. The final stage is to establish the strength of mediation after validating the relevance of the indirect impact. This method of assessment can be done using Variance accounted for (VAF=indirect effect/total effect). The work of Hair Jr et al. (2014) points out that VAF>80% indicates full mediation, 20% ≤ VAF ≤ 80% is characterised as partial mediation, and VAF < 20% indicates no mediation. In this study, the VAF of 0.334 were between 20% and 80%, which shows that a partial mediation effect has taken place. Therefore, 33.4% of BDAC's effect on port performance is mediated through port sustainability.

Type of mediation	Explanations
No effect (no mediation)	Neither the direct nor indirect effect are significant. The theoretical mode is invalid
Direct-only (no mediation)	The direct effect is significant but not the indirect effect
Indirect-only (full mediation)	The indirect effect is significant but not the direct effect
Competitive (partial mediation)	Both direct and indirect effects are significant but from opposite directions.
Complementary (partial mediation)	The indirect effect and the direct effect both are significant and point in same direction

Table 7.19 Type of mediation effects

Source: Adapt form Hair et al.(2016)

7.6 Summary

This chapter focuses on statistically evaluating the given research model and hypotheses to attain the research goals consistently. The researcher assessed the measurement and structural models by employing the PLS-SEM technique. In the initial phase, the validity and reliability of measurement models were tested. Internal consistency reliability was tested using Cronbach's Alpha, and composite reliability and indicator reliability was tested using outer loading to corroborate the reliability of the measurement model. The validity of the measurement model was confirmed by testing the AVE and HTMT. The assessment results show that measurement models satisfied the requirements of reliability and validity, and the structural model has sufficient predictive capabilities. In the second stage, the researcher completed the structural model analysis to evaluate the proposed hypothesis. The hypotheses are determined based on the coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2 and q^2), standardised beta coefficient (path value), t-statistic, and p-value significance. The result demonstrates that BDAC has a significant and positive effect on port performance, thus supporting hypothesis H1. The relationship between BDAC and port sustainability was also positive and significant, supporting hypothesis

H2. In addition, the outcome demonstrated a substantial and positive correlation between port sustainability and port performance, hence corroborating hypothesis H3.

Furthermore, mediating effects are confirmed; port sustainability mediated the relationship between BDAC and port performance, supporting hypothesis H4. Hence, the results confirmed that all hypotheses were accepted. The subsequent chapter will offer a more thorough analysis and explanation of the finding.

Chapter 8 Discussion

8.1 Introduction

This chapter discusses the results generated from Chapter 7. This chapter discusses the findings with proposed research questions and literature gaps to show that these objectives are accomplished. The first section briefly recalls the research aim and research objectives. Further, the following section will be split into several sections; each of the sections is fulfilling one research objective.

8.2 The research aims and research questions

This section reviews the research aim and research questions. The aim of this research is to examine the association between BDAC and port performance and explores the mediation role of port sustainability. In Big Data projects carried out by ports, assisting ports in sustainability has been one of the key applications. Improving sustainability could help organisations to enhance their performance, thus, investigating the role of sustainability in how the BDAC result in port performance takes on greater significance. Five research questions were developed to achieve the research aim. It would be useful to recall these questions to keep the purpose of the research in focus before discussing the findings. The following Table 8.1 show the research questions.

Number	**Research question**
RQ1	What are the core components of BDAC in the ports area?
RQ2	Is there a direct link between BDAC and port performance?
RQ3	Is there a direct link between BDAC and port sustainability?
RQ4	Is there a direct link between port sustainability and port performance
RQ5	Does the port sustainability mediate the relationship between BDAC and port performance?

Table 8.1 Research question

In the following subsequent sections, the finding of the research will be discussed in conjunction with the research question identified above and the hypotheses of this research. Table 8.2 displays the link between research questions and hypotheses.

Research Question	**Hypothesis**
RQ1	
RQ2	H1. BDAC has a positive effect on port performance.
RQ3	H2. BDAC has a positive effect on port sustainability.
RQ4	H3. Port sustainability has a positive effect on port performance.
RQ5	H4. Port sustainability mediated the relationship between BDAC and port performance.

Table 8.2 Relationship between research questions and hypotheses

The first section discusses the construct of BDAC. This will address research question 1. The second section discusses the impact of BDAC on port performance. This will address research question 2 and relates to hypothesis H1. The third section examines the relationship between BDAC and port sustainability, which link to RQ3 and the hypothesis H2. The fourth section addresses the relationship between port sustainability and port performance, linking to RQ4 and hypothesis H3. The final section discusses the influence of port sustainability as a mediator between BDAC and port performance. This will answer research question 3 and relates to hypothesis H4.

8.3 The core components of BDAC

The components of BDAC were developed based on the literature review and RBT. Drawing on these sources, the study develops BDAC construct with seven components and their associated measurement items. The result affirms the reliability and validity of the BDAC construct and shows that all components of this construct survived the same as the initially developed model. This outcome indicated that BDAC is developed by combining and deploying data, technology, basic resources, managerial skills, technical skills, data-driven culture, and organisational learning resources in the port environment. This finding is in line with other scholars' (Gupta and George, 2016, Ciampi et al., 2020a, Lozada et al., 2019) argument that BDAC as an organisational capability requires organisation orchestration of tangible, intangible, and human resources to create. This finding also distinguishes BDAC from IT in the port area. IT is considered as a technical capability in the port environment and focuses on the innovative application of technology (Attia, 2016). Unlike IT capabilities, BDAC is not merely a technical capability. BDAC is a unique capability created by combining several technical and non-technical resources and focusing on bringing a competitive advantage to the organisation.

Moreover, the findings show indicators' weights of BDAC, including data (0.70), technology (0.57), basic resources (0.82), technical skills (0.80), managerial skills (0.88), data-driven culture (0.85) and organisational learning (0.76). All the weights of indicators were statistically significant, and two indicators (managerial skills and data driven culture) were found that have higher value of weights. Hence, managerial skills and data-driven culture emerged as core components in developing BDAC. This outcome answers the first research question. The following table shows the result of the research question. Table 8.4 demonstrates the detail of the indicators' weights of the previous researchers.

Research question	Findings	Resource of support	Resource of not support
What are the core components of BDAC in the ports area?	Managerial skills and data driven culture emerged as core components in developing BDAC	Managerial skills: Mikalef et al. (2020); Henao-García et al. (2021); AlNuaimi et al. (2021); Lozada et al. (2019); Mikalef and Krogstie (2020)	Jeble et al. (2018); Gupta and George, (2016); Mikalef and Krogstie (2020)
		Data driven culture: Su et al. (2021); Mikalef and Krogstie (2020)	

Table 8.3 Result of research question 1

	Data	Technology	Basic resource	Technical skills	Managerial skills	Data-driven culture	Organisational learning
This study	0.7	0.57	0.82	0.80	0.88	0.85	0.76
Mikalef et al. (2020)	0.407			0.464		0.307	
Henao-García et al. (2021)	0.333			0.411		0.385	
AlNuaimi et al. (2021)	0.532			0.550			
Lozada et al. (2019)	0.340			0.429		0.358	
Su et al. (2021)	0.365			0.355		0.372	
Mikalef and Krogstie (2020)		When it comes to incremental process innovation capabilities, a stronger emphasis on technical skills and other basic resources are found to be core contributors.			For radical process innovation capabilities, it is striking to an observer that there is a shift toward managerial skills as a core condition.	For the remaining solution that corresponds to service industry firms, our findings highlight the importance of a data-driven culture	
Jeble et al. (2018)						Organisational learning and organisational culture also have a significant influence on building BDAC	
Gupta and George, (2016);	0.42			0.31		0.37	

Table 8.4 Result of indicators' weights

Table 8.3 shows that research obtained by Mikalef et al. (2020), Henao-García et al. (2021), AlNuaimi et al. (2021), Lozada et al. (2019) and Mikalef and Krogstie (2020) were consistent with this finding. Specifically, the work of Mikalef et al. (2020) provided convincing evidence that compared with tangible resources (weight=0.40) and intangible resources (weight=0.31), Human resources (weight=0.47) are the key component of BDAC. Organisations are paying more attention to managers with great management skills to help organisations leverage the potential of BDA. The empirical finding of this study reveals that with organisations applying advanced data analysis techniques and undertaking big data projects, it is important that managers have great management skills and experience to understand their operations and potential (Mikalef et al., 2019b). By improving the management skills of managers, ports can use BDA strategically. The result also indicated that managers with great management skills and data analytics skills enable to interpret the result obtained by analysing, assisting organisations in utilising Big Data and developing BDAC. Great management and data analytics skill can assist managers in forecasting future company demands of other managers, suppliers and customers Henao-García et al. (2021). Meanwhile, port managers can extract insights from the results of gathered data, thereby supporting port authorities in making decisions.

Furthermore, many previous works (AlNuaimi et al., 2021, Lozada et al., 2019) on the humane side of BDAC have focused on developing technical and relational knowledge to train experienced and mature managers. To date, very few studies evaluated managerial skills from a stakeholder perspective. This study revealed that managers must foster an ability to coordinate Big Data-related activities with supply chain partners. As a significant part of the supply chain, ports need to exchange data with supply chain partners, which means some big data projects need to collaborate with stakeholders. Successful cooperation depends on the interpersonal skills and trust-building abilities of managers (Cetindamar et al., 2021). Therefore, the finding of this study indicates that the important role of managerial skills in supporting ports in building BDAC. Port managers need to improve their BDA-related skills and knowledge to assist the port in developing BDAC.

In addition, the data provide convincing evidence of the importance of data-driven culture in creating BDAC. This finding is consistent with previous results (Su et al., 2021, Mikalef and Krogstie, 2020), showing that the development data-driven culture can help organisations use data better and widely. Specifically, Su et al. (2021) have argued that intangible resources (weight=0.372) contribute more than human skill (weight=0.355) and tangible resources (weight=0.365) toward BDAC. According to the findings of this study, port managers who operate in a data-driven atmosphere are encouraged to make decisions based on statistics rather than intuition. Developing data-driven culture can stimulate the organisation to leverage data and asset organisation in developing the data application process, supporting organisations building BDAC (Yu et al., 2021a).

Moreover, this study reveals that establishing a data-driven culture can stimulate organisational employees to continuously improve business activities by extracting insights from data. Evidence from the work of Mikalef and Krogstie (2020) argued that the data-driven culture and how people view the value of information could improve innovation capabilities, thereby improving product quality and creating new products. Developing data-driven culture can break down organisation silos and integrate information from a different departments (Ciampi et al., 2020a). A strong data-driven culture can stimulate organisational managers to analyse gathered data and collaborate across multiple departments to utilise extracted insights, improving business activities and BDAC. Therefore, data-driven culture and Managerial skills were identified as core components of building BDAC.

In addition, due to the research context of this study being ports, the result differs from previous research (Gupta and George, 2016, Jeble et al., 2018) on other industries such as manufacturing, computer/software and financial services industries. The work of Gupta and George (2016) demonstrates that tangibles resources (weight=0.42) contribute more than human resources (weight=0.31) and intangible resources (weight=0.37) to the BDAC. The data provide convincing evidence that tangibles resources, including data, technology and basic resources, are fundamental to Big Data success. Organisations may not achieve BDAC without adequate investment of finance and effort (Lozada et al., 2019). With continuously financial support, organisations can employ the right talents and improve BDA infrastructures, thus supporting organisations to leverage big data. Investments in the Big Data initiative need to take some time to create measurable value (Mikalef et al., 2020). Thus, basic resources such as time and investment are necessary. However, compared with ports, computers, financial services and manufacturing industries face more financial pressures. Ports often receive policy support and government investment. For instance, with the support of the Belt and Road policy, COSCO cooperates with the Tianjin and Qingdao ports to invest in their operation, shipping, multimodal transportation and port aviation (Song et al., 2018). Successive governments of Ghana promote four digital platform transformation reforms for the port of Ghana, improving the intelligence of ports (Senyo et al., 2021). Thus, although this study also highlighted the importance of basic resources, port managers focus more on managerial skills and data-driven culture.

Moreover, Gupta and George (2016) emphasised the significance of data and technology resources. While in this study, an interesting finding was that the technology component has a lower impact on building BDAC of ports than other components. This result concurs with the work of Henao-García et al. (2021) and Mikalef et al. (2019b), who presented that technology has a limited impact on BDAC. The findings of Gupta and George (2016) are less surprising if we consider that most respondents are chief information officers, chief technology officers, vice presidents of technology, and directors of IT and analytics managers. Unlike chief information/technology officers, many managers might have a relative lack of technological awareness (Jha et al., 2020). Due to the technologies, software and terms used in BDA evolving fast, some port managers may not realise they are using advanced techniques. Especially, managers use some advanced analytics techniques which come from built-in systems. For example, the port of Antwerp uses the NxtPort data usage platform to share data among the participants of ports. NxtPort was developed by a private company, and it integrates various applications to help user to utilise the data pools easily (Caldeirinha et al., 2022). Although the finding of Gupta and George (2016) reveals the significance of tangible resources, they also emphasise the necessity for organisations to hire personnel with big data-specific technical and administrative capabilities and to cultivate a data-driven organisational culture.

Furthermore, although this study indicated that port authorities improve the BDAC by exploitation of existing competencies and exploration of new knowledge, organisational learning have a peripheral in developing BDAC. This position appears to be somewhat contrary to some works. For example, Jeble et al. (2018) established a link between Big data and predictive analytics capability on supply chain sustainability. They revealed that organisation learning is the crucial component of building Big data and predictive analytics capability. A possible reason for this discrepancy might be that organisational learning can help firms to gain economic sustainability in an uncertain environment. In a competitive market, organisations need continuous learning to gain a sustainable competitive advantage and keep pace with the change in the external environment (Odor, 2018). Organisational learning is seen as a prerequisite for innovation, and organisations need to train their employees to help them learn advanced knowledge, thereby continually improving their products and service (Amarakoon et al., 2018). Thus, Jeble et al. (2018) emphasised that organisational learning is the essential resource that contributes toward Big data and predictive analytics capability. Ports keep changing with the liberalisation of world markets, technological and organisational change. These changes force the port to continually learn to enhance customer expectations and respond to the changing demands. However, Pantouvakis and Karakasnaki (2018) indicated that in order to assist ports in better accommodating customer needs, focusing merely on organisational learning is not enough. Ports should also have the agility to reorganise their internal structures and reengineer their services based on new knowledge. In alignment with previous studies, the finding of the study could hint that developing organisational learning could help organisational acquire Big Data-related knowledge and diffusing knowledge but may not utilise gathered data. After that, it is the data-driven culture and management skills of managers that assist organisations in utilising Big Data. Therefore, although in this research the data provide convincing evidence that organisational learning plays an important role in build DBAC of ports, this research highlighted that the managerial skills and data-driven culture resources have greater impact on building BDAC in port areas.

It could be argued that organisational managers develop different strategies in building BDAC according to the different business process and business environment faced by the organisations. Organisations should prioritise certain resources when developing BDAC. In summary, managerial skills and data-driven culture had been noted as core components of BDAC in port environment.

8.4 BDAC and port performance

In order to answer research question 2, the relationship between BDAC and port performance was evaluated and tested through PLS-SEM. The results show that BDAC has a positive effect on port performance (coefficient=0.555, t=8.908 and p<0.01). This outcome answers the second research question and H1. The following Table 8.5 shows the result of research question 2. Table 8.6 demonstrates the detail of the findings of previous works.

Research question	**Hypothesis**	**Finding**	**Resource of support**	**Resource of not support**
Is there a direct link between BDAC and port performance?	BDAC has a positive effect on port sustainability. (Supported)	The effect of BDAC on port performance is positive	Akter et al. (2016); Wamba et al. (2017); Ferraris et al. (2019); Dubey et al. (2018a); Su et al. (2021); Upadhyay and Kumar (2020); Wamba and Akter (2019); Yadegaridehkordi et al. (2020); Rialti et al. (2019)	Ghasemaghaei and Calic (2020); Liu et al. (2020); Cappa et al. (2021); Gunes et al. (2021)

Table 8.5 The result of research question 2

Research	Finding
Akter et al. (2016)	BDAC have a positive impact on firm performance (path coefficient=0.709, t=13.265)
Wamba et al. (2017)	BDAC has a significant positive effect on firm performance (path coefficient=0.56, t=7.19, p<0.001)
Ferraris et al. (2019)	The greater the firm's BDAC, the higher the firm performance is (path coefficient=0.59, t=3.84, p<0.01)
Dubey et al. (2018a)	Data analytics has a positive impact on an organisation's competitive advantage (path coefficient=0.28, p<0.01)
Su et al. (2021)	Tangible resources of BDAC have a significant positive effect on organisational performance (path coefficient=0.365, p<0.01) Human skills of BDAC have a significant positive effect on organisational performance (path coefficient=0.355, p<0.01) Intangible resources of BDAC have a significant positive effect on organisational performance (path coefficient=0.372, p<0.01)
Upadhyay and Kumar (2020)	BDAC positively influence a firm's performance (path coefficient=0.431, t=6.603, p<0.0001)
Wamba and Akter (2019)	Supply chain analytics capability has a significant impact on firm performance (path coefficient=0.386, t=3.9581)
Yadegaridehkordi et al. (2020)	Big data adoption has a positive effect on firm performance (path coefficient=0.804, p<0.001)
Rialti et al. (2019)	Organisational BDAC is positively related to superior performance (path coefficient=0.768, p<0.01)
Ghasemaghaei and Calic (2020)	Data volume does not significantly impact innovation performance (path coefficient=-0.033, p>0.05)
Liu et al (2020)	Cost is a factor, as SMEs are not always in a position to spend big sums of money on Big Data tools; even if they could, they may not have the personnel to configure, operate, and maintain such a system.
Cappa et al. (2021)	Big data volume has a negative effect on firm performance.
Gunes et al. (2021)	The digital transformation of the port has brought cyber security gaps and threats to business processes.

Table 8.6 The findings of previous research

The findings showed that ports could reduce cost, improve service quality and operational efficiency, as well as provide superior VAS by developing BDAC. This result seems plausible; nevertheless, no published studies in the field of ports and supply chains have demonstrated a positive association between port building BDAC and port performance. Hence, several studies from various contexts have been consulted to confirm the relationships between BDAC and port performance. Previous studies (Akter et al., 2016, Gupta and George, 2016, Wamba et al., 2017, Ferraris et al., 2019, Dubey et al., 2018a, Su et al., 2021, Upadhyay and Kumar, 2020) have found the same result in different samples and environmental. For instance, Akter et al. (2016) proposed a BDAC model drawing on RBT and confirmed the positive impact of BDAC (coefficient=0.709, t=13.265) on firm performance. Wamba and Akter (2019), investigating the relationship between supply chain analytics capability and firm performance, found that supply chain analytics capability has a positive impact on firm performance (coefficient=0.386, t=3.9581). However, while there is broad agreement that developing BDAC can improve organisational financial performance, operational efficiency and service quality (Akter et al., 2016, Ferraris et al., 2019, Ghasemaghaei and Calic, 2020, Yadegaridehkordi et al., 2020, Wamba and Akter, 2019), the link between BDAC and VAS and customer orientation is rarely implied in the literature. One notable exception to this is the work of Wamba et al. (2017), who indicated the impact of BDAC on market performance. The results of this study yielded additional evidence of the relationship between BDAC, VAS and customer orientation. Developing BDAC can help ports to improve the multimodal transport service. Originations can exchange information and communicate more effectively with supply chain participants by developing information communication technologies (Queiroz et al., 2019). Ports can gain data from various transportation service providers and optimise services by building BDAC to transport cargo via diversified routes to customers in the least possible time. Meanwhile, ports can analyse the demand of the market to offer new tailored services.

Moreover, the findings highlight that ports can quickly respond to customer requirements by developing BDAC. Utilising Big Data technology, ports can catch and integrate a wide variety of customers' data. Through analysing gathered customers' data, ports can deeply understand customers' expectations and complaints, thereby quickly making decisions to meet the requirements of customers (Anshari et al., 2019). Furthermore, from the customers' perspective, the results of this work indicated that ports could provide greater customer experiences by building BDAC. Big data technology and data-driven culture can break information islands and accelerate data transmission (Yan et al., 2019). Port authorities can collect data from different departments of port and supply chain partners. Meanwhile, port authorities can process gathered data and integrate them into mobile apps and websites for the customer. Therefore, this study confirmed the link between BDAC, VAS and customer orientation.

The positive relationship between BDAC and port performance can be interpreted by RBT. Reviewing the relevant literature in RBT, RBT indicated that firms could exploit various valuable, rare, inimitable, and non-substitutable resources to achieve profitability in a highly competitive market (Barney et al., 2011). Port authorities build BDAC by integrating data, technology, basic resources, managerial skills, technical skills, data-driven culture and organisational learning resources. Thus, BDAC is considered as superior, rare and inimitable capabilities. According to RBT, ports can enhance performance by utilising BDAC. Ferraris et al. (2019) also corroborate this view, who argued that firms could integrate and deploy serval resources to create BDAC, achieving better customer retention and higher profitability.

A related idea that might explain the positive relationship between BDAC and port performance is the entanglement view of the dimensions of BDAC. Specifically, the dimensions of BDAC need to work together and not act in isolation (Akter et al., 2016).

It means that an organisation with a mature BDAC should have a data-driven culture, great technical staff, experienced managers, and data analytics techniques. Employees of ports can utilise gathered data by applying data analytics techniques to improve service quality and optimise operation (Shou et al., 2019). Port managers with greater managerial skills can make a decision rapidly based on data analysis, reducing reaction time and increasing productivity and profitability (Brinch, 2018). Consequently, it is understandable that by building BDAC, port authorities can reduce cost, improve service quality, and optimise operation, which enhances port performance.

A further interpretation of the present result is that BDAC can assist organisations in making decisions related to organisational operations from a strategic perspective. BDAC can support organisations' strategic decisions and assist organisations in pursuing innovative corporate strategies, thereby seizing new market opportunities and improving performance (Ciampi et al., 2020b). In addition, Shamim et al. (2020) highlighted the potential of BDAC in decision-making and indicated that BDAC could help managers transform data into actionable insight to achieve effective and efficient decision-making, enhancing organisational performance. Therefore, it seems reasonable that developing BDAC can assist ports in making a decision rapidly and adjusting operation strategies, improving operational efficiency and, offering more customer benefit, enhancing port performance.

Furthermore, a positive relationship between BDAC and organisational performance has been found in studies by Rialti et al. (2019), Dubey et al. (2018a), Bag et al. (2021) and Gupta et al. (2020). Rialti et al. (2019) considered the BDAC and dynamic capabilities of organisations and indicated that BDAC can improve organisational performance in the dynamic market. Gupta et al. (2020) argued that BDAC can help organisations to reaction market change and adapt their services to meet the requirement of customers, giving a competitive advantage to the organisations. Consequently, a significant connection between BDAC and port performance is well supported by evidence from a wide range of scholarly sources.

In addition, as shown in table 8.6, the work of Wamba and Akter (2019) demonstrated a medium correlation between supply chain analytics capability and firm performance. Hair Jr et al. (2014) pointed out that the value of path coefficients < 0.10 suggest a minor influence, around 0.30 indicates a medium effect, and ≥ 0.50 indicates a high effect. A related idea that might explain this phenomenon is that the realisation of a sustained competitive advantage by a firm not only depends on the firm's analytics technologies and capability but also requires agility in the context of the BDA environment. If an organisation lacks agility, it will not be able to integrate, grow, and reconfigure strategic resources and capabilities at the optimal time to maximise the benefits of adopting BDA (Barlette and Baillette, 2022). Wamba and Akter (2019) also highlighted the importance of supply chain agility. Supply chain analytical capability can improve firm performance by enhancing supply chain agility. Thus, supply chain analytics capability has a medium positive impact on firm performance.

However, this result differs from studies by Ghasemaghaei and Calic (2020), Liu et al. (2020), Cappa et al. (2021) and Chang (2021), which indicated that the negative impact of BDA on firm performance. Contrary to our expectations, while the findings of Ghasemaghaei and Calic (2020) indicated that data variety and data velocity have a significant influence on firm performance, they highlight that the path from data volume to firm performance was not significant (coefficient=0.016, $p > 0.05$). Drawing on the work of Ghasemaghaei and Calic (2020), Cappa et al. (2021) has advanced the hypothesis that Big Data volume negatively affects firm performance and point out that simply focusing on collecting large amounts of data cannot help organisations to improve performance. Collecting large volumes of data may eventually lead to infobesity, resulting in firms cannot extract efficacious information (Whitler, 2019). Meanwhile, Big data volumes require firms to investment technological infrastructure to collect and manage data, increasing the cost of deploying the Big Data initiative. Thus, organisations should gather various types of data and integrate them timely. In port operation, port managers can collect different types of data, such as traffic data, cargo data, weather data and machinery data (Jović et al., 2019b). The data also provide evidence that port authorities can manage and integrate different types of data. It means that port authorities can integrate gathered different types of data timely, enhancing port performance. Moreover, Liu et al. (2020) highlight that cost limits the application of BDA in small and medium-sized enterprises. Advanced information systems and software come with costs that can obstruct firms from creating value from Big Data. Different from small and medium-sized enterprises, the sample of this study is chosen from the world. The top 50 ports generally have sufficient funds to implement BDA projects. Meanwhile, the development and digitalisation of ports are usually supported by the government and stakeholders (Haezendonck and Langenus, 2019, Senarak, 2020). Therefore, the findings of this study indicated that ports could build BDAC to create value and enhance port performance. Furthermore, according to Gunes et al. (2021), when ports undergo digital transformation, ports face the threat of cyber-attacks which can lead breakdown of the port operation. By applying big data technology, ports can share information across organisations and better cooperate with PSC partners, which means cyberattacks on ports could affect others within the supply chain (Zarzuelo, 2021). Cyber-attacks on ports can cause great financial losses; for instance, the Maersk NotPetya incident was a 10 days outage that cost roughly

$200M (Weaver et al., 2022). Although little explanation is offered in this paper, the development of BDAC necessitates the application of advanced information systems and the collection and interchange of data, which may introduce cyber dangers and security weaknesses. Especially the weakness of multiple infrastructures, sensors and systems interconnected in the port digitisation provides manifold gates for hacktivist groups to materialise their attacks (Senarak, 2021). Ports should employ experienced technicians and use reliable information systems to avoid cyber security threats.

8.5 BDAC and port sustainability

The association between BDAC and port sustainability was investigated to address question 3 of the research. The results show that BDAC has a positive effect on port sustainability (coefficient=0.770, t=21.295 and p<0.01). This finding answers the third research question and H2. The following Tables 8. 7, and 8.8 displays the result of research question 3 and the findings of previous research

Research question	**Hypothesis**	**Finding**	**Resource of support**	**Resource of not support**
Is there a direct link between BDAC and port sustainability?	BDAC has a positive effect on port sustainability. (Supported)	The effect of BDAC on port sustainability is positive	Heilig et al. (2017), Wu et al. (2016), Ferretti and Schiavone (2016); Munim et al. (2020); Song et al. (2017); Dubey et al. (2019b); Bjerkan and Seter (2019); Mageto (2021)	Bonilla et al. (2018), Zhao et al. (2017); Hämäläinen and Inkinen (2019); Brunila et al. (2021); Saunila et al. (2019)

Table 8.7 The result of research question 3

Research	Finding
Heilig et al. (2017)	Digital technologies and information systems have implications on the behaviour and decision of individual actors to fulfil new requirements for addressing environmental problems.
Wu et al. (2016)	There is no doubt that the emergence of big data would have a high potential to support green targets in an environmentally friendly future and sustainable development.
Ferretti and Schiavone (2016)	IoT technologies redesign and improve the performance of all the main business processes of the port, enhancing the economic and ecological performance of the port.
Song et al. (2017)	Through utilising the tools of Big Data, the improvement of natural resource utilisation, energy efficiency, environmental protection, and sustainability could all be achieved.
Dubey et al. (2019b)	The Big Data & predictive analytics capability is positively related to perceived social performance. (Path coefficient=0.726, $p<0.001$) The Big Data & predictive analytics capability is positively related to perceived environmental performance. (Path coefficient=0.854, $p<0.001$)
Bjerkan and Seter (2019)	Port can assess footprint, reduce energy consumption and improve environmental risk management by monitoring emissions.
Munim et al. (2020)	In the maritime context, environmental impacts can be reduced by utilising Big Data and AI in decision-making.
Mageto (2021)	Deploying BDA can enhance economic, social and environmental performance, which results in better sustainable SCM.
AlNuaimi et al. (2021)	BDAC has a positive influence on environmental performance. (Path coefficient=0.596)
Bonilla et al. (2018)	Industry 4.0 need to involve the disposal of obsolete equipment that cannot be integrated into new systems, hence increasing electronic waste. In addition, the production of product-related ICT is anticipated to result in an increase in primary energy consumption.
Hämäläinen and Inkinen (2019)	Big Data and disruptive innovation can improve decision-making to achieve low environmental and emissions impact. But implementing cross-implementation project to gather and analyse data from different contexts are often costly.
Saunila et al. (2019)	No significant correlations were obtained between smart technologies and environmental sustainability. (Path coefficient=0.012) No significant correlations were obtained between smart technologies and social sustainability. (Path coefficient=0.095) Smart technologies are positively related to economic sustainability. (Path coefficient=0.152, $p<0.05$)
Brunila et al. (2021);	The digitalisation of ports may face resistance from different actors and stakeholders since it often leads to high investment costs and a reduction in the need for a human workforce.

Table 8.8 The findings of previous research

This result was consistent with several prior research (Heilig and Voß, 2017, Wu et al., 2016, Ferretti and Schiavone, 2016, Munim et al., 2020, AlNuaimi et al., 2021) that proposed ports can apply Big Data technology to enhance port sustainability. For example, the results obtained by AlNuaimi et al. (2021) are consistent with our findings, demonstrating that BDAC positively influences environmental performance in e-procurement. The findings of this study provide preliminary evidence for suggesting that BDAC is one of the important organisational capabilities that can help ports enhance environmental performance. Port authorities can monitor environmental conditions by utilising big data technology. For instance, the port of Hamburg deployed air and water monitoring sensors to monitor emissions and pollution (Ferretti and Schiavone, 2016). Ports can gather vast and rich sources of environmental data from various sensors. Compared with the traditional environmental data collection approach, port authorities can gain more accurate environmental data in real time by implementing Big Data technology. Some previous work (Casazza et al., 2019, Lee et al., 2020, Abualhaija et al., 2021) on Big Data technology and port environment indicated that port managers could understand the pollution level and gain the capability to predict environmental risk with the help of BDAC. This study provides preliminary evidence that managers not only can monitor environmental pollution but also could utilise BDAC to unearth the value of gathering environmental data further to improve environmental performance, offering further support for this. Organisations can set emission targets and define emission-reducing measures by utilising BDAC to coordinate and reuse data (Zhang et al., 2019a). In the port area, environmental data are collected from different sources such as transportation, production and emissions. Port managers can utilise BDAC to integrate these information sources to accelerate decision-making and prescribing solutions for pollution management.

Meanwhile, organisational managers can utilise BDAC to analyse gathered environmental data, thereby proposing an innovative digital solution to solve environmental challenges (Hämäläinen and Inkinen, 2019). Through analysing integrated data, the management of ports can gain new insights to redesign the business process and steer ports towards higher environmental responsibility. Moreover, BDAC can assist port managers in utilising rich vessel movement data provided by the automatics identification systems. By adapting and optimising maritime traffic information, ships can reduce fuel consumption and emissions (Bjerkan and Seter, 2019). Therefore, BDAC has a positive effect on ports' environmental performance.

In addition, most of the research (Cetindamar et al., 2022, Jeble et al., 2018, Hossain et al., 2019, Bjerkan et al., 2021) on developing economic performance indicates that it is primarily connected to reducing expenses related to energy consumption, waste discharge, and disposal. For example, Del Giudice et al. (2022) indicated that ports that develop BDAC have the ability to integrate and analyse different types of data about the port operation. Port managers can optimise port operations, such as improving automated guided vehicles to reduce transportation times and reduce vessels' turnaround time by these data, leading to reduced energy consumption and cost. Through further investigating the impact of BDAC on creating jobs, the national economy and the development of port cities. The result yielded additional evidence that BDAC can improve the port's economic sustainability. BDAC can facilitate the integration of ports into the supply chain and create new business models, which could attract more firms to establish plants and offices close to the ports, thereby bringing more job opportunities and revenue to the city (Moeis et al., 2020).

Moreover, BDAC can help ports efficiently use port areas. Kang and Kim (2017) pointed out that port authorises could better develop and plan in a port to efficiently utilise the valuable port area via building a stronger relationship with stakeholders. Port can share information and strategies with stakeholders from building BDAC, enhancing cooperation with stakeholders. Our study also found that BDAC can drive the economic development of the area surrounding the port and actively cooperate with city development. Some previous studies (Hein and Laar, 2020, Teschner, 2019, Acciaro et al., 2020a) have demonstrated that the change in port activities and operations leads to an increasing separation between the city and ports. This study argued that digital and intelligent technologies can break down the barrier between ports and cities, making the two identities mutually interdependent and influential. Ports that develop BDAC can help policymakers, urban planners, and administrators efficiently manage the flow of data, information and resources within port cities, promoting the economic growth of cities (D'Amico et al., 2021). Ports can integrate into urban planning to balance ports and cities' interests, adapting to changing needs and opportunities to improve city development. Therefore, the BDAC of ports makes a notable contribution to ports' environmental and economic sustainability.

Furthermore, scant studies have focused on the relationship between BDA and social sustainability, which is surprising considering the increasing importance of social sustainability for port development. In previous studies, scholars point out that BDAC can enhance firm social sustainability by improving employment conditions, improving safety and increasing employment (Dubey et al., 2019b, Jeble et al., 2018). Specifically, the work of Dubey et al. (2019b) demonstrates that Big Data and predictive analytics have a positive impact on social performance. In order to build BDAC, ports need new employees and provide training to staff, which means ports can improve employment conditions and provide job opportunities to society. Meanwhile, ports can improve employee safety by monitoring the work environment. Therefore, port BDAC can enhance social sustainability. Moreover, Santos et al. (2016) indicated that Big Data technology can support ports in building port community systems, which can help port managers better collaborate with stakeholders to improve social performance. Improving the integration of stakeholder objectives and information from the perspective of a PSC could result in more robust and supported strategic planning outcomes for the local community. However, making the strategies and policies of port city development does not usually involve port employees and community groups. Their voices and complaints seem to be neglected by researchers in investigating the relationship between ports and residents (Lam and Yap, 2019). This study considered the relationship between port development BDAC on residents and indicated that port BDAC can help achieve harmony between ports and residents. In a port city that is deeply nested with information and digital technologies, residents can direct cooperation with port authorities, port managers and stakeholders to integrate sustainability aspects into decision-making processes (Gurzhiy et al., 2021). Therefore, it is indicated that port BDAC plays an important role in enhancing port sustainability.

Nevertheless, some previous studies (Bonilla et al., 2018, Zhao et al., 2017, Brunila et al., 2021, Saunila et al., 2019) proposed different results and indicated that the application of Big Data technology was not found to have a positive impact on exploitation capabilities. Particularly, the study carried out by Saunila et al. (2019) showed that no significant correlations were obtained between smart technology and social sustainability, and no significant correlations were obtained between smart technology and environmental sustainability. A possible reason for this discrepancy might be that smart technology alone is not sufficient to improve the social and environmental sustainability of organisations. Organisations need related technicists, experienced managers and organisational culture to utilise smart technologies (Yasmin et al., 2020), thereby gaining advantages for society and a sustainable environment. In port areas, port authorities integrate technology resources and various resources, especially managerial skills and data-driven culture, to build BDAC. Therefore, port managers can improve port sustainability by developing BDAC.

Moreover, Bonilla et al. (2018) point out that in the short term, organisations need to dispose of obsolete equipment and implement new equipment to achieve the applications of Big Data technology in supporting sustainability. The replacement of a lot of equipment increases resource waste. As a significant part of the supply chain, ports need to be equipped with sufficient equipment to face the current development trend (Jeevan et al., 2021). Thus, ports need to update equipment to support digital transformation, thereby aligning with the requirements and technological changes of supply chain partners. In the long term, the digitalisation of equipment can help ports to reduce energy consumption and emission, improving port sustainability. Moreover, the implication of advanced equipment and new system cause the firm dismissal of unskilled labour (Furstenau et al., 2020). This could lead to conflict between the port and labour unions, as labour unions tend to believe digitalisation leads to a decrease in the need for the workforce (Brunila et al., 2021). Nevertheless, the finding of this study shows that BDAC has a positive effect on port sustainability as port authorities provide training to employees, and most of the ports are in the early stages of digitisation did not cause a lot of resource waste (Inkinen et al., 2019). Another possible reason for this might be that most participants work in IT departments in this study, meaning they may not be familiar with equipment purchasing and replacement.

8.6 Port sustainability and port performance

In order to address the fourth question, the relationship between port sustainability and port performance was tested. The result shows that port performance is positively influenced by port sustainability (coefficient=0.362, t=5.473 and p<0.01). This finding answers the fourth research question and H3. The following Tables 8. 9, and 8.10 display the result of research question 4 and previous research findings.

Research question	**Hypothesis**	**Finding**	**Resource of support**	**Resource of not support**
Is there a direct link between port sustainability and port performance	Port sustainability has appositive effect on port performance. (Support)	The effect of port sustainability on port performance is positive	Lu et al. (2016c), , Yang et al. (2013), Kang and Kim (2017), Croom et al. (2018), Pedersen et al. (2018)； Wang et al. (2020); Khan et al. (2021)	Das (2018), Magon et al. (2018)，Dam and Petkova (2014)

Table 8.9 Result of research question 4

Research	Findings
Lu et al. (2016c)	Improving port sustainability can help the port to obtain benefits such as a potential increase in business due to a green reputation, cost savings and faster turnaround.
Yang et al. (2013)	In the context of container transportation, green performance correlates favourably with company competitiveness (Path coefficient=0.246, $p<0.05$).
Kang and Kim (2017)	In a highly competitive economy, implementing sustainability strategies and practises can improve the durability of competitive advantage and boost competitiveness.
Croom et al. (2018)	The social sustainability orientation has a positive effect on operational performance. (Path coefficient=0.223, $p<0.05$)
Pedersen et al. (2018)	There is a positive relationship between sustainability performance and corporate financial performance. (Path coefficient=0.115, $p<0.01$)
Wang et al. (2020)	Green SCM is positively related to firm performance (Path coefficient=0.80, $p<0.001$)
Khan et al. (2021)	Environmental performance has a positive impact on organisational performance. (Path coefficient=0.125, t=5.187, $p<0.05$) Economic performance has a significant and positive impact on organisational performance. (Path coefficient=0.758, t=7.162, $p<0.001$)
Das (2018)	The construct environmental management practices do not have any significant association with operations performance (Path coefficient=0.182, t=1.473, p=0.141).
Magon et al. (2018)	Environmental practices might negatively affect costs, time-to-market, and new product development.
Dam and Petkova (2014)	Firms which announce participation in environmental supply sustainability programs will have a marginally significant negative stock price.

Table 8.10 The findings of previous research

This finding resonates with Lu et al. (2016c), who argued that ports reducing unfriendly environmental activities can avoid a negative impact on port financial performance. Moreover, the findings show that port sustainability not only influences port financial performance but also impacts port operational efficiency. This finding is consistent with Kang and Kim (2017) and Yang et al. (2013). They argued that improving sustainability could assist ports in meeting the environmental requirement of their business partners and achieving integration with a green supply chain, which can improve operational efficiency. Furthermore, this study focuses on the impact of social sustainability on port performance, which remains rare in previous research into the ports. Croom et al. (2018) point out that pursuing sustainability can stimulate the organisation to improve working and community conditions, enhancing organisation performance. In this study, work and community conditions were considered indicators of port social sustainability. Thus, the outcome demonstrates that port social sustainability contributes to port performance, which is supported by Croom et al. (2018). Consequently, with all of this backing from a vast array of research, it is clear that there is a positive correlation between port sustainability and port performance.

However, the study contradicts the research findings of Das (2018), who demonstrate that there is no positive relationship between environmental management practices and operations performance. A possible reason for this different result might be that the relationship between environmental management practices and operations performance differs according to contextual elements. Different industries and their location have different environmental practices and operations processes (Magon et al., 2018). The study of Das (2018) merely focuses on Indian firms. Thus, this study supports the finding that port sustainability has a positive effect on port operations. Furthermore, from the financial perspective, this finding appears contrary to previous studies, which indicated that organisations motivated environmental practices might result in increased costs due to upgrade production processes and extra environmental investment. A related idea which might explain why ports' financial performance is not affected by implementing a sustainability strategy is that many nations and organisations set various decrees and economic incentives to encourage ports to become more sustainable. For example, the EU port policy promotes the charging of environmental cost by seaports and provide financial support for green port infrastructure (Du et al., 2019).

8.7 The mediating role of port sustainability in the relationship between BDAC and port performance

In order to answer the fifth question, the impact of BDAC on port performance through the mediation role of port sustainability was investigated. The results show that the relationship between BDAC and port performance is mediated by port sustainability (coefficient=0.278, t=5.082 and p<0.01). More precisely, the mediation effect contributed to 33.4% of BDAC's total effect on port performance. This outcome answers the fifth research question and shows that H4 is accepted. The following Tables 8.11 and 8.12 display the result of research question 5 and the findings of previous research.

Research question	**Hypothesis**	**Finding**	**Resource of support**
Does the port sustainability mediate the relationship between BDAC and port performance?	Port sustainability mediated the relationship between BDAC and port performance (Support)	Relationship between BDAC and port performance is mediated by port sustainability	Zhang et al. (2019d); Oláh et al. (2020); Zahid et al. (2021); Khan et al. (2021); El-Khalil and Mezher (2020)

Table 8.11 Result of research question 5

Research	Findings
Zhang et al. (2019d)	In a volatile market, management innovation and technological innovation can assist businesses in achieving environmental success, which in turn shapes high performance. Sustainability mediates the relationship between management innovation and organisational performance. (Path coefficient=0.066, p=0.01). Sustainability mediates the relationship between technological innovation and organisational performance. (Path coefficient=0.110, p<0.001).
Oláh et al. (2020)	Organisations can integrate automation and digitisation with organisational sustainability development goals to promote environmental sustainability, improving competitive advantage.
Khan et al. (2021)	Using Blockchain technology to execute circular economy principles can boost both economic and environmental performance, which ultimately enhances organisational performance.
Zahid et al. (2021)	Environmental sustainability will mediate the relationship between workplace sustainability and the firm financial performance.
El-Khalil and Mezher (2020)	Sustainability mediates the relationship between agility and operational performance. (Path coefficient=0.072, t=2.444, p=0.015).

Table 8.12 The findings of previous research

The findings show that both the direct and indirect effects of BDAC and port performance are significant and positive. Not only does the mediation improve the overall effect of the association between BDAC and port performance, but it also expands the explanation of how and why BDAC contributes to performance. Although no existing studies in the big data and port contexts address the mediating role of sustainability between BDAC and port performance, the mediating role of sustainability has been acknowledged through the review of multiple studies, for example, in the relationship between customer awareness and sustainable supply chain (Jermsittiparsert et al., 2019); organisational strategic and corporate environmental performance (Xing et al., 2019, Wijethilake, 2017); environmental regulation and financial performance (Xing et al., 2020). Unlike previous studies, this study focused on the impact of BDAC on sustainability. Saunila et al. (2019) have yielded some important insights that corporate sustainability strategy can mediate the effect of smart technologies on environmental sustainability. This means that corporate can take better advantage of smart technology through sustainability strategy to create benefits. Our study further extends the work of Saunila et al. (2019) in that we have examined the mediation role of sustainability between BDAC and port performance, further understanding that port can enhance port performance through building BDAC because BDAC of ports can stimulate the integration of sustainable development strategies into port operation.

Moreover, the result indicated that ports could attain more benefits from building BDAC by enhancing sustainability. This finding resonates with Zhang et al. (2019d), who investigated similar themes and identified the mediation role of sustainability between management innovation, technological innovation and organisational performance. The work of Zhang et al. (2019d) demonstrated that the relationship between technology innovation and organisation performance is mediated by sustainability (coefficient=0.11 and p $p<0.01$), and the relationship between management innovation and organisation performance is mediated by sustainability (coefficient=0.016 and $p<0.01$). This study extends the study of Zhang et al. (2019d), as Big Data technology is becoming the critical basis for creating the new business model, products and services. Our results provide convincing evidence that compared with developing technology innovation and management innovation, building BDAC through integrating various organisational resources organisations can better help the organisation to improve performance via acquiring valuable resources that configure sustainability.

In addition, unlike many of the prior studies (Raut et al., 2021, Xiao and Su, 2022) indicated that the mediating role of BDA on sustainability, our study advances the current knowledge by providing new evidence that port managers can leverage port sustainability to catalyse the impact of BDAC on port performance. BDAC is expected to have a positive impact on enhancing organisational performance by improving economic, environmental and social performance. Moreover, this finding appears contrary to the work of Raut et al. (2021), who highlight that BDA mediates the relationship between environmental practices and sustainable supply chain business performance. A possible reason for this discrepancy might be that BDA has a role to play in environmental practices to improve sustainable supply chain performance by analysing data to avoid environmental accidents. BDA can help firms better implement sustainability practices (Dubey et al., 2016). Thus, BDAC not only can assist organisations in improving sustainability performance but is also the cornerstone of their implementation of sustainability time. Additionally, there are other situations in the literature concerning Big Data technology and seaports that highlight sustainability as a crucial enabler without overtly referring to it as a mediating variable. (Muller et al., 2018, Oláh et al., 2020, Inkinen et al., 2019, Christodoulou and Cullinane, 2019). Therefore, it is understandable that the relationship between BDAC and port performance is mediated by port sustainability.

In conclusion, this section addresses the fifth research question by discussing the mediation role of port sustainability with H4. In conjunction with earlier analyses in this study, port sustainability is shown to have a beneficial effect on port performance and to operate as a mediator between BDAC and port performance.

8.8 Summary

This chapter reviewed the research aim, research gaps, conceptual model, and hypotheses employed in this investigation. Then the study findings considering the five research questions are discussed. The main findings of each question were discussed in the context of the literature. Identified and justified possible explanations for the findings that were inconsistent with prior studies. First, the present research identifies the components of BDAC, including data, technology, basic resource, managerial skills, technical skills, data-driven culture, and organisational learning resources. The research indicated that managerial skills and data-driven culture had been noted as core components of building BDAC. Second, the research highlights the great contribution of BDAC to port performance. Third, the results show that port build BDAC can enhance port sustainability and indicate the effect of BDAC on port social sustainability. Fourth, the relationship between port sustainability and port performance has been addressed. The result revealed that ports with greater sustainability were able to enhance their performance. Finally, the research responds to the ability of sustainability to mediate the association between BDAC and port performance. Alongside the end of the discussion of the theoretical model and the examination of the model's direct and indirect connections, Figure 8.1 presents an updated version of the theoretical model.

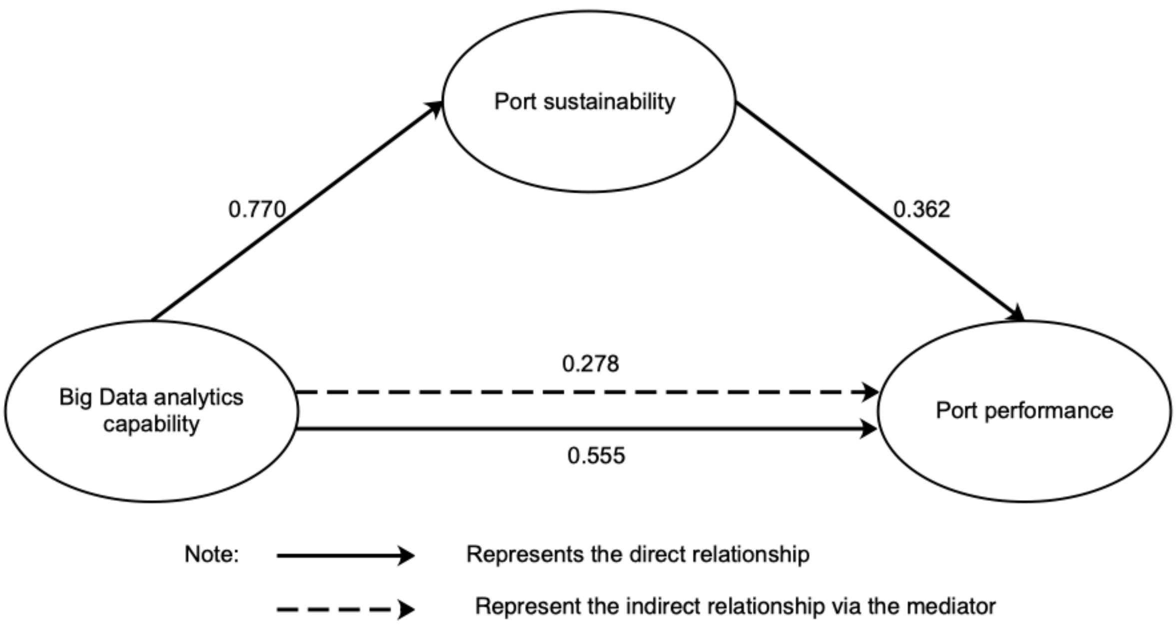

Figure 8.1 Updated theoretical model

The next chapter concludes the study and provides some concluding remakes for the research aim, research objectives and research questions. Then the theoretical and practical implications were discussed. Finally, it points out the limitations and potential future research.

Chapter 9 Conclusion

9.1 Introduction

This chapter provides an overview of the key findings and discusses the contributions of this study. This chapter consists of three sections. Firstly, this chapter shows the key findings linked to the aims and objectives of the research. In addition, this chapter highlights the study's theoretical and managerial contributions. Finally, the study's shortcomings and ideas for further research are discussed.

9.2 Key findings

The aim of this research is to examine the association between BDAC and port performance and explore the mediation role of port sustainability. To achieve this aim, this study sets out five research objectives. This section presents the key findings and discusses how these findings have addressed the respective research objectives. The following Table 9.1 shows the research objectives and how they were achieved.

Research objectives	**Discussion chapter**	**Relational sections in Chapter 8**	**Objective achieved**
To develop a structural model for BDAC, port sustainability and port performance, and create relevant measurement.	Chapter 3,4 & 6		Yes
To identify the key components of BDAC in port area.	Chapter 7 & 8	Section 8.3	Yes
To assess the direct relationships presented within the proposed structural model	Chapter 7 & 8	Section 8.4 & 8.5	Yes
To examine the mediatory role of port sustainability on the relationship between BDAC and port performance	Chapter 7 & 8	Section 8.6 & 8.7	Yes
To provide recommendations for port managers to develop BDAC and improve performance	Chapter 9		Yes

Table 9.1 Research objectives summary

9.2.1 To develop a structural model for BDAC, port sustainability and port performance, and create relevant measurement.

This study found the applicability of Big Data technology in the port sector after conducting a comprehensive literature review, including Data gathering, Real-time information monitoring, Data analysis and decision-making, operation optimise, Information sharing platform, Predictive analysis, Innovation and Data integration and management. Table 4.3 present a summary of Big Data application in ports. It shows that the application of Big Data technology is the trend in port development. However, in port areas, applying Big Data technology is limited by organisational readiness, management support and technological competence. Hence, port authorities must develop BDAC to help better port managers utilise Big Data technology. A systematic review of BDAC and RBT identifies three key research gaps: firstly, research on BDAC and organisational performance remains in its infancy; secondly, few studies have examined the influence of BDAC on ports, especially within the context of RBT; thirdly, there is limited understanding through what mechanisms BDAC contributes to port performance.

In order to address research gaps, a preliminary theoretical model was built in accordance with the literature review and RBT. There were four theories developed in chapter 5. H1 and H2 showed that BDAC has a positive effect on port performance and port sustainability. The third hypothesis was that port sustainability enhances port performance. The association between BDAC and port performance was mediated by the sustainability of ports, according to Hypothesis 4. In terms of the mediating effect, a relational review of Chapters 4 and 5 revealed that some scholars consider there is an indirect or mediated relationship between BDAC. Chapters 4 and 5 also found that improving sustainability can enhance the port operation and show that ports widely employ Big Data technology to assist port sustainability. Thus, the researcher included port sustainability in the model to investigate how BDAC improves port performance.

A pilot study was done to offer actual support for the construction of the theoretical model. In Chapter 6, the researcher developed the questionnaire and analysed the pilot survey. Based on the pilot study result, the measurement scales were valid and reliable. Moreover, according to the feedback of participants, the questionnaire was updated to ensure content and face validity.

9.2.2 To identify the key components of BDAC in the port area.

Based on the literature review and RBT, this study ascertained the resources that can be used to develop BDAC, including Data resources, technology resources, Basic resources, technical skills resources, managerial skills resources, data-driven culture resources and organisational learning resources. In order to provide a comprehensive view of developing BDAC in a port setting, this study evaluated these seven resources that, when combined, build BDAC. The critical components of building BDAC in port were revealed through the analysis. The study suggested that, amongst the seven resources, managerial skills had the most decisive influence on building ports' BDAC. Specifically, it is important that managers have great management skills and experience to utilise advanced techniques and gain insights from the data when ports deploy Big Data technologies. Managerial skills in the current study are not limited to utilising Big Data to improve port operations. It also implies that managers can coordinate Big Data resources to support supply chain partners. Moreover, the study also shows the importance of data-driven culture in creating ports' BDAC. By developing data-driven culture, organisations could break down the organisational silos and integrate information from different departments, utilising data better and widely.

In addition to these two components, another significant component is basic resources, followed by technical skills, organisational learning, data, and technology. It is interesting to note that although technology resource is the cornerstone of implementing Big Data technologies, their impact on BDAC development in port areas is limited. A possible interpretation of this finding is that technologies, software and terms used in BDA are evolving fast. Managers might have a relative lack of technological awareness and may not realise that they are using advanced techniques. Therefore, the study shows that intangible and human resources are more critical than technology resources in assisting ports in developing BDAC.

9.2.3 To assess the direct and indirect relationships presented within the proposed structural model

The researcher utilised the research finding from Chapter 4 to create higher-order models for the PLS-SEM analysis in Chapter 7, where the researcher assessed the proposed hypotheses. The relationship between the BDAC, port sustainability and port performance was identified by analysing the structural model. More specifically, the PLS-SEM analysis evaluated and identified the impact of BDAC on port sustainability and port performance. The results show that the BDAC had a direct positive relationship with port sustainability and port performance. In other words, port authorities can enhance port performance and sustainability by developing BDAC. Additionally, the findings demonstrated that port sustainability had a favourable impact on port performance. This means that improving port sustainability helped enhance port performance.

In addition to confirming the direct impact of BDAC and port sustainability on port performance, this study also discovered that BDAC not only directly impacted port performance but also diverted some positive impact through the construction of port sustainability. The study found that the association between BDAC and port performance was mediated by port sustainability. More precisely, the mediation effect contributed to 33.4% of BDAC's total effect on port performance. Not only does the mediation improve the entire effect of the link between BDAC and port performance, but it also elucidates how and why BDAC contributes to port performance.

9.2.4 To provide recommendations for port managers to develop BDAC and improve performance

Following the holistic evaluation of BDAC development in ports and examining the impact of BDAC on port sustainability and port performance, some insights can be extracted and offered to port authorities. According to these insights, port managers can better develop BDAC in ports and make greater strategies to apply Big Data technology to e

The specific recommendations are offered in Section 9.3.2, which analyses the study's practical ramifications.

9.3 Contribution of the study

In section 9.2, the main findings and results of the study were summarised. The findings of this study also make significant contributions to several user groups; this is especially true for port managers and academic society. The theoretical implications and managerial implications are described in the following sub-sections.

9.3.1 Theoretical implications

This study investigates the direct impact of BDAC on port performance and the indirect impact through port sustainability capabilities. This study developed a theoretical model based on RBT and adopted a quantitative research method, including an online survey, SEM, and PLS-SEM to assess. The key findings of this study have produced various theoretical implications and contributed to the existing body of knowledge, which will be discussed in the following.

Firstly, this study contributes to enhancing the scholars' knowledge and understanding of the relationship between BDAC and port performance. Specifically, this study uses RBT as the theoretical lens to explore the impact of BDAC. A review of the literature showed that many studies investigate the concept of BDAC and its impact, but most of the studies focus on one dimension of BDAC (Hao et al., 2019, Dubey et al., 2018a, Awan et al., 2021, Yu et al., 2021b, Wang et al., 2020, Olabode et al., 2022). For example, Dubey et al. (2018a) and Yu et al. (2021b) argued that BDAC is an organisational facility and investigated its impact from the technology dimension. This study presents a theoretical framework of BDAC consisting of three dimensions and highlights the importance of human resources and intangible resources, including technical skills, managerial skills, data-driven culture, and organisational learning. Consequently, the contribution of this study is the evaluation of BDAC from seven resources and the empirical validation of the effect of BDAC on port performance. Moreover, some studies (Wamba et al., 2017, Akter et al., 2016, Ferraris et al., 2019, Mikalef et al., 2018) investigated the impact of BDAC based on the relationship between IT capabilities and firms' competitive advantages using RBT. Although these studies of BDAC take advantage of the RBT, they do not distinguish BDAC from IT capabilities. This study points out that BDAC is different from IT capability. In particular, IT capability focuses on supporting firms' business processes and strategies in the IT literature (Li and Chan, 2019, Guo et al., 2021). Unlike IT capability, this study suggested that the value of BDAC lies primarily in gaining new insight from different sources and making decisions based on newly gleaned intelligence. This finding is consistent with the study of Mikalef et al. (2020), who argue that BDAC can help firms identify opportunities and threats and reinforce managers' decisions. Furthermore, compared with regular IT staff, BDA professionals might have significantly different roles, responsibilities, knowledge and skills (Gupta and George, 2016). Consequently, the findings of this study can also help illuminate the distinction between BDAC and IT competence.

Second, this research contributes to the current literature by providing new insights into the mediating effects of port sustainability on the relationship between BDAC and port performance. Specifically, if BDAC benefits the port performance, organisations need to find a way to use their resources efficiently. While a substantial body of research has explored the association between BD and port performance, little is known about the mechanisms by which a BDAC can affect organisational performance (Mikalef et al., 2020, Wamba and Akter, 2019, Awan et al., 2021, Bahrami and Shokouhyar, 2021, Bahrami et al., 2022). Moreover, the current study focused on BDA as antecedents to sustainability (Jeble et al., 2018, Singh and El-Kassar, 2019, Dubey et al., 2019b) and called for research on the outcome of sustainability. Thus, the model presents port sustainability as a mediator to help explain how BDAC affect port performances. Moreover, the current study. The research indicates that port sustainability, as the mediator of the relationship between BDAC and port performance, not only improves the overall effect of the interactions but also provides a deeper knowledge of the mechanisms behind BDAC-port performance correlations. This study contributes to the literature on BDAC by providing evidence that developing BDAC could help ports achieve sustainability which induces high performance.

Third, this study develops a port performance model based on the RBT theory and identifies key constructs, explaining the relationships among the BDAC, port sustainability and port performance. Previous works on port performance have focused on defining port performance, identifying enablers for building port performance and exploring port competitive advantage strategies (Vaggelas, 2019, Ha et al., 2019, Ridwan and Noche, 2018, Duru et al., 2020, Nguyen et al., 2018a). Although there are few studies to formulate the port performance model (Rezaei et al., 2018, Ridwan and Noche, 2018, Caldeirinha et al., 2018, Mira et al., 2019), these models in the literature are inadequate, which confirms the emerging need for this research. Specifically, the interdependencies and interrelationships among the constructs of BDAC, port sustainability and port performance in relation to ports are currently inadequate in the past studies. Thus, this study fills this research gap by presenting a model with the interrelationships of the three constructs to help researchers understand port performance.

Fourth, this study made various theoretical contributions to the literature by developing valid and reliable measurement scales for the structural model. Specifically, this contribution is focused on developing a measurement scale for the construction of ports' BDAC and port performance. Due to much previous work on BDAC has focused on financial firms, information firms and manufacturing firms (Akter et al., 2016, Wamba et al., 2017, Gunasekaran et al., 2017), there was a lack of measurements to assess the BDAC of ports. Thus, by developing a measurement for the BDAC of ports covering the tangibles resources, intangibles resources and human resources. Researchers may enrich and add to the extant literature by using these measurements to measure the BDAC of ports.

Last, this work contributed to BDAC research pertaining to seaports. This study specifically addressed the information gap about the significance of BDAC in developing ports and the impact of constructing BDAC in ports. As it has been noted, most recent research work on BDAC has focused on financial firms, information firms, manufacturing firms and hospitals (Akter et al., 2016, Wamba et al., 2017, Gunasekaran et al., 2017, Wang et al., 2020, Yu et al., 2021b, Shamim et al., 2020, Upadhyay and Kumar, 2020). In contrast, port-related research is still in its infancy. Most researchers working in the area of ports have tended to investigate the role of digital technology and automation technology such as BDA, IoT, automation, AI and robotics in port performance (Acciaro et al., 2020b, Yang et al., 2018b, Sun et al., 2018, Durán et al., 2021, Tsolakis et al., 2021). There is no empirical study investigating the impact of BDAC on port performance; thus, by exploring the impact of BDAC on port performance, this study made contributions to fill a research gap in the literature.

9.3.2 Managerial implications

Besides the contribution to theory, the findings also provide several practical implications for port authorities, port managers, and stakeholders of the PSC. Consequently, the final purpose of the research has been addressed in this section. The managerial implications of this study will be discussed in the following:

First, the finding of this study could guide port managers' decisions to deploy and invest in the BDAC of port managers. Especially this study could help port managers who are either planning to build BDAC or who have already started and are in the early stages of implementing Big Data technologies. In recent years, BDAC has been considered an essential organisational capability to assist firms in gaining a competitive advantage in a highly connected and dynamic global environment (Pinochet et al., 2021). Through building BDAC, managers could analyse gathered data to derive insights for decision-making, enhancing operational efficiency and organisational performance (Awan et al., 2021). This study identified the relationship between BDAC and port performance and suggested that BDAC is a significant enabler of improved port performance. Thus, this research helps port managers better understand the role of BDAC and formulate port development strategies.

Second, the finding of this study may help port managers to make effective strategies for building BDAC of ports. The outcome of this study enlightens port managers that building BDAC is much more than merely making investments, collecting vast amounts of data and having access to advanced technology. Mikalef et al. (2020) indicated that technical and managerial skills are required to gain value from Big Data initiatives. Port managers need to recruit people with good Big Data technical and managerial skills, improve the intensity of organisational learning and embed big data decision-making into the organisational culture. Thus, port managers and HR departments need to hire talent with Big Data technical skills or offer training to employees to analyse and manage gathered data. Meanwhile, port authorities need to employ managers with solid management skills and experience with Big Data to plan, implement and manage Big Data-related processes and initiatives. It is important that these managers should understand how Big Data can be applied to different areas in the organisation (Lozada et al., 2019). Furthermore, this study highlights the importance of data-driven culture. Cetindamar et al. (2022) also argued that developing a data-driven culture can stimulate the organisation to leverage data and encourage port managers to make data-driven decisions. Hence, ports should take a long-term view and recognise the importance of cultural change to build BDAC. Ports managers and authorities should make an effort to build a data-driven culture in ports to achieve cross-functional distribution of data, realising the full potential of Big Data owned by ports.

Third, this study can assist port managers in developing an evaluation instrument for evaluating the strengths and shortcomings of their ports' BDAC by identifying the seven essential resources utilised to construct BDAC. Port managers can apply the survey instrument presented in this study to ascertain which resources they have in abundance and which resources they lack. Particularly, port managers can apply the assessment tool to measure intangible and human resources, making strategies to improve them. Therefore, this study can help managers identify the gap in BDAC and consider how to fill the gap.

Fourth, the findings reveal that building BDAC can benefit port sustainability. It is important to note that BDAC not only can improve environmental and economic performance but also can enhance social sustainability in the port (D’Amico et al., 2021, Santos et al., 2016). This study makes port managers aware that Big Data technologies can improve employment conditions, help port managers better collaborate with stakeholders and achieve harmony between port and residents to improve social performance. Therefore, this study aids port administrators who must constantly balance social, economic, and environmental performance standards. Our results point out that BDAC offers significant benefits to both dimensions of port sustainability.

Fifth, a significant insight from this study is how a great proportion of the effect of BDAC on port performance is impacted by the mediation of port sustainability. Previous studies equally highlight the value BDAC can deliver to the organisation via mediating effect (Shabbir and Gardezi, 2020, Ciampi et al., 2020a, Wamba and Akter, 2019). Therefore, port managers should consider port sustainability as a significant strategic objective and better leverage BDAC to improve it to achieve high-level port performance. Through a comprehensive understanding of the relationship between BDAC, port sustainability and port performance, port managers can shape their policies and strategies for sustainability and port performance.

9.4 Limitation and recommendations for further research

9.4.1 Limitation

While the study brings important implications for both researchers and managers, this study also has several limitations. First, the main limitation of this study is selecting the top 50 global ports as the sampling frame restricted the data collection. The researcher collected data from the top 50 global ports implementing Big Data technologies. The selection of these ports was mainly based on these ports playing a significant role in world trade and showing their strategies for building intelligent ports. Concerns might be raised that the world's top ports can gain more support and attract more talent than small and medium ports when implementing Big Data-related initiatives. Although the quality of participants is high, it is still possible to gain different results if the study collected data from more ports.

The location of data collection was cited as the second constraint. While this study collected data from the 50 leading global ports that implement Big Data technologies, 28% of the top 50 ports are located in China (Nightingale, 2020). Meanwhile, most of them have strategies for utilising state-of-the-art digital technologies, leading to biased results. Thus, the research finding should be generalised with caution. However, most studies that use a survey-based approach usually do not avoid generalisability issues (Dubey et al., 2018a).

Third, the measurement scales of the research model have inherent limitations. The assessment scales for this study were adapted from prior research and tested in a pilot study. However, there are still concerns that some factors cannot fully be captured in the research model.

The fourth limitation relates to the data collection method. This study collected data merely from five-point Likert-scale questionnaires. Although the researcher undertakes many approaches to ensure data quality, using perceptual performance measures to evaluate organisation performance may induce measurement errors (Ketokivi and Schroeder, 2004). Deposit much quantitative research collected data through questionnaire survey, collecting data from multiple data sources may enhance the validity of outcomes.

The last limitation of this research is merely one mediator in it. This study focuses on port sustainability as a moderator to investigate the effect of BDAC on port performance. This may pose a limitation for this study since other factors may matter in the relationship between BDAC and port performance.

9.4.2 Directions for Future Research

According to the outlined contributions and limitations of this paper, this section proposes several research directions. First, as with the limitations mentioned above, the research targets of this study are the top 50 global ports, ignoring some perceptions of medium and small ports. Thus, further research could expand the scope of this research by considering the participants from medium and small ports. This could provide further insights and a more comprehensive understanding of the impact of BDAC on ports, as each port has its unique position in the global supply chain.

Second, further research could conduct investigation across various countries of ports and apply the model to explore the impact of BDAC on them. Different countries may have different policies to support port developments and different cultures for implementing state-of-the-art technologies. For instants, port authorities in Europe focus on setting-up energy policies to optimise port energy consumption (Sdoukopoulos et al., 2019). Port authorities in China focus on setting-up policies to improve port integration, avoiding overcapacity and excessive competition (Notteboom and Yang, 2017). Thus, further research should collect data from ports in different countries and compare the result to ensure the generalisability of the research result.

Third, since the report about the port performance is a self-report from port managers, it may undermine its objectivity. Thus, forthcoming studies could employ secondary data to measure port performance to improve these deficiencies. Moreover, further studies could use qualitative methods adopting a case study approach or interviews to derive broader and more profound implications.

Fourth, this research focused on investigating the direct impact of BDAC on port performance and the mediating effect of port sustainability. In future research, the BDAC could be researched more thoroughly in port areas and how port authorities use BDAC to improve port performance. Researchers could incorporate innovation, competitive pressure and risk management (Acciaro et al., 2018, Cheon et al., 2018) into the conceptual model to assess the role of these capabilities on the relationship between BDAC and port performance. It would help researchers understand the mechanisms through which a BDAC can improve organisational performance.

Lastly, a potential route for future research could be to obtain perspectives from port stakeholders and people who use port services. Currently, most of the studies on the role of BDAC gain insights from the service provider. Hence, the opinions of the port's stakeholders and clients can help researchers to extract novel insights and achieve a comprehensive understanding of the effect of BDAC.

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Appendix A: Ethical Approval

UNIVERSITY OF PLYMOUTH
Faculty of Business

Date: 19 June 2019

Dear Xiaotian,

Ethical Approval Application No: FREIC1819.41

Title: Investigating the impact of Big Data analytics capability on port performance, port sustainability and port supply chain integration

Thank you for your application to the Faculty Research Ethics & Integrity Committee(FREIC) seeking ethical approval for your proposed research.

The committee has considered your application and is fully satisfied that the project complies with Plymouth University's ethical standards for research involving humanparticipants.

Approval is for the duration of the project. However, please resubmit your application tothe committee if the information provided in the form alters or is likely to alter significantly.

The FREIC members wish you every success with your research.

Yours sincerely
(Sent as email attachment)

Mr Derek Shepherd
Chair

Faculty Research Ethics & Integrity CommitteeFaculty of Business

Derek Shepherd, Chair, Faculty Research Ethics & Integrity Committee, Faculty of Business, Cookworthy, University of Plymouth, DrakeCircus, Devon PL4 8AA, United Kingdom

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Appendix B Initial questionnaire (English version)

UNIVERSITY OF PLYMOUTH

Questionnaire

Dear Sir or Madam

Thanks indeed for participating this survey about Big Data analytics capability and port performance. This research defines **Big Data analytics capability in context of the port area as the ability of port organisations to collect and gather relevant data from the port operation, heterogeneous systems and business activities participants, then managing, processing and analysing these data and visualising them intuitively to offer valuable business insights and support decision-making**. Based on this definition, please fill the questionnaires.

Please provide your opinion based on your firms' perspective. You only need to fill the question once.

General Information

Education:

Respondent Title:

Tenure:

Total Big Data experience (years):

Company/port name:

Number of employees:

IT related investment:

I. Big Data Analytics Capability

Based on your organization evaluate the following statements by selecting one of the answers, from 1 to 5

(1=Strongly Disagree… 3=Neither Disagree nor Agree… 5=Strongly Agree)

1. Data

We have access to very large, unstructured, or fast-moving data for analysis

1	2	3	4	5

We integrate data from multiple internal sources into a data lake for easy access

1	2	3	4	5

We integrate external data with internal to facilitate high-value analysis of our business environment

1	2	3	4	5

2. Technology

We have adopted distributed computing approaches (e.g., Hadoop, Storm, Spark) to Big Data processing

1	2	3	4	5

We have adopted different data visualization tools (e.g., Microsoft Power BI, IBM Watson Analytics, MATLAB, SAP HANA)

1	2	3	4	5

We have adopted cloud services (e.g., IBM Cloud, Amazon Web Services, Microsoft Azure, Google Cloud) for processing data performing analytics

1	2	3	4	5

3. Basic Resources

We have allocated adequate funds for Big Data project.

1	2	3	4	5

We have enough time to achieve desired result from Big Data analytics projects

1	2	3	4	5

4. Technical Skills

We provide data analytics training to our own employees

1	2	3	4	5

We hire new employees that already have the data analytics skills

1	2	3	4	5

Our analysts have appropriate data analytics skills to accomplish their jobs successfully

1	2	3	4	5

Our analysts have suitable education to fulfil their jobs.

1	2	3	4	5

5. Managerial Skills

Our analytics managers are able to coordinate Big Data-related activities in ways that support other partners.

1	2	3	4	5

Our analytics managers are able to anticipate the future business needs of other managers, suppliers and customers.

1	2	3	4	5

Our analytics managers have good sense of where to use Big Data.

1	2	3	4	5

Our analytics managers can interpret the analyses obtained using complex analyses and offer inputs which are useful for swift decision making.

1	2	3	4	5

6. Data-driven Culture

We consider data a tangible asset.

1	2	3	4	5

We base our decisions on data more than instinct.

1	2	3	4	5

We are willing to override our own intuition when data contradict our viewpoints.

1	2	3	4	5

We continuously assess and improve the business activities in response to insights extracted from data.

1	2	3	4	5

7. Organisational learning

We actively search for new and relevant knowledge

1	2	3	4	5

We assimilate new and relevant knowledge

1	2	3	4	5

We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge

1	2	3	4	5

II. Port sustainability performance

1. Environmental Dimension

Please indicate your level of agreement with the following statements by selecting one of the answers, from 1 to 5

(1=Strongly Disagree… 3=Neutral… 5=Strongly Agree)

Our port has adopted adequate measure for reduction of air emissions.

1	2	3	4	5

Our port has adopted adequate measure for reduction of wasted water.

1	2	3	4	5

Noise in our port areas has significantly reduced.

1	2	3	4	5

Our port has adopted adequate measure for reduction of oil consumption.

1	2	3	4	5

2. Social Dimension

Please indicate your level of agreement with the following statements by selecting one of the answers, from 1 to 5

(1=Strongly Disagree… 3=Neutral… 5=Strongly Agree)

Our port authorities' services quality has improved.

1	2	3	4	5

The relationship between neighbouring residents and our port authorities is getting better.

1	2	3	4	5

Our staff's security and safety has improved.

1	2	3	4	5

Our port provides support for employees' training and education.

1	2	3	4	5

3. Economic Dimension

Please indicate your level of agreement with the following statements by selecting one of the answers, from 1 to 5

(1=Strongly Disagree… 3=Neutral… 5=Strongly Agree)

Our port offers more employment opportunities.

1	2	3	4	5

Our port authorities multifunctional and efficient use of port areas.

1	2	3	4	5

Our port authorities actively cooperate with industrial and economic development

1	2	3	4	5

Our port is driving the economic development of the area surrounding the port.

1	2	3	4	5

III Port performance

Please indicate your level of agreement with the following statements by selecting one of the answers, from 1 to 5

(1=Strongly Disagree… 3=Neutral… 5=Strongly Agree)

1. Cost

Our port cargo handling charge are reasonable and competitive.

1	2	3	4	5

Our port charges for intermodal transport are reasonable and competitive.

1	2	3	4	5

Our port auxiliary service (pilotage, towage, customers) charge are reasonable and competitive.

1	2	3	4	5

2. Service Quality

Please indicate how your port performs compared to your **major competitors**, from 1 to 5. (1 = much worse, 2 = worse, 3 = no difference, 4 = better, 5 = much better)

Our port handles cargo at quoted or anticipated times.

1	2	3	4	5

Our port handles cargo on time as customers require.

1	2	3	4	5

Our port's service lead time is short.

1	2	3	4	5

Our port provides shipment information accurately.

1	2	3	4	5

3. Operational Efficiency

Please indicate how your port performs compared to your **major competitors**, from 1 to 5. (1 = much worse, 2 = worse, 3 = no difference, 4 = better, 5 = much better)

Our terminal productivity is high.

1	2	3	4	5

Port turn-around time is short (Ship waiting time due to congestion).

1	2	3	4	5

Our time for mode transit is short.

1	2	3	4	5

4. Value-added Services

Please indicate how your port performs compared to your **major competitors**, from 1 to 5. (1 = much worse, 2 = worse, 3 = no difference, 4 = better, 5 = much better)

Cargo is attracted by value-added services.

1	2	3	4	5

Value added increase from value-added service.

1	2	3	4	5

We have adequate facility for value-added service.

1	2	3	4	5

5. Customer Orientation

Please indicate how your port performs compared to your **major competitors**, from 1 to 5. (1 = much worse, 2 = worse, 3 = no difference, 4 = better, 5 = much better)

Our port has quick decision-making process.

1	2	3	4	5

Our port provides customised port services to our customers.

1	2	3	4	5

Our port could respond promptly to the need of customers.

1	2	3	4	5

Our port has easy and fast operational processes for port users.

1	2	3	4	5

Appendix C Initial questionnaire (Chinese version)

调查问卷

这个研究是为了调查大数据分析能力在促进港口供应链整合，港口可持续性和港口业绩方面的表现。该研究旨在开发一个模型，以探索大数据分析能力，港口供应链整合，港口可持续性和港口业绩之间的关系。**这项研究将港口的大数据分析能力定义为“港口组织从港口运营，操作系统和业务活动参与者中收集相关数据，然后管理，处理和分析这些数据并对其进行可视化，以提供有价值的业务见解并支持决策的能力”**。根据此定义，请填写调查表。

请根据您公司的观点提供您的意见。该调查问卷仅用于学术研究。填写的信息永远不会透露给他人。请放心，您的姓名和个人回复将保密。因此，您提供的所有信息都无法由论文的读者确定。如果您能参与这项研究，我将非常感谢。

基本信息

年龄：

教育程度：

职称：

任期：

大数据相关的工作经验（年）：

公司/港口名称：

地理位置：

在职员工人数：

港口/企业对 IT 相关项目投入的资金：

一、大数据分析能力

根据您的港口/企业/组织的实际情况，对以下陈述进行评估。其中（1=非常不同意.....3=中立....5=非常同意）

1. 数据

我们港口企业组织可以对大量的、非结构化的、快速传输的数据进行分析

1	2	3	4	5

我们可以将来自不同内部源的数据整合到数据仓库以便于访问

1	2	3	4	5

我们港口/企业组织可以整合外部数据与内部数据，以促进我们业务环境的分析

1	2	3	4	5

2. 科技

我们港口/企业/组织采用并行计算方法（例如 Hadoop、Storm、Spark）来处理大数据

1	2	3	4	5

我们港口/企业/组织使用了不同的数据可视化工具（例如，Microsoft Power BI、IBM Watson Analytics、MATLAB、SAP HANA）

1	2	3	4	5

我们港口/企业/组织已经使用云服务来处理和分析数据 （例如 IBM Cloud, Amazon Web Services, Microsoft Azure, Google Cloud）

1	2	3	4	5

3. 基本资源

我们港口/企业/组织为大数据项目划拨了充足的资金

1	2	3	4	5

我们港口/企业/组织提供了足够的时间来实现大数据分析项目的预期结果

1	2	3	4	5

4. 技术能力

我们港口/企业/组织为雇员提供大数据分析技术的培训

1	2	3	4	5

我们港口/企业/组织雇佣已具有大数据分析技术的人员

1	2	3	4	5

我们港口/企业/组织的分析师具有适当的大数据分析技巧，以成功完成他们的工作

1	2	3	4	5

我们港口/企业/组织的分析师接受了适当的教育足以完成他们的工作

1	2	3	4	5

5. 管理能力

我们港口/企业/组织的数据分析管理者可以协调大数据相关的业务来帮助合作伙伴

1	2	3	4	5

我们港口/企业/组织的数据分析管理者可以预测供应商、顾客未来的需求

1	2	3	4	5

我们港口/企业/组织的数据分析管理者对在哪里使用大数据技术有着很好的认知

1	2	3	4	5

我们港口/企业/组织的数据分析管理者可以理解使用复杂分析方法获得的结果，并且提供对快速决策有用的信息

1	2	3	4	5

6. 数据驱动文化

我们港口/企业/组织认为数据是一种有形资产

1	2	3	4	5

我们干港口/企业/组织更依赖数据做出决策而不是直觉。

1	2	3	4	5

当数据与我们的观点相矛盾的时候，我们愿意推翻我们的直觉

1	2	3	4	5

根据从数据中提取的见解，我们港口/企业/组织不断地评估和改进业务活动

1	2	3	4	5

7. 组织学习

我们港口/企业/组织积极的寻求新知识

1	2	3	4	5

我们港口/企业/组织吸纳新的知识

1	2	3	4	5

我们港口/企业/组织致力于开发现有的能力和探索新知识

1	2	3	4	5

二、港口可持续能力

根据您的港口/企业/组织的实际情况，对以下陈述进行评估。其中（1=非常不同意.....3=中立....5=非常同意）

1. 环境

我们港口已采取适当措施来减少废气排放。

1	2	3	4	5

我们港口已采取适当措施来减少水资源浪费

1	2	3	4	5

我们港口地区的噪音已大大降低。

1	2	3	4	5

我们港口已采取适当措施来减少燃料消耗

1	2	3	4	5

2. 社会

根据您的港口/企业/组织的实际情况，对以下陈述进行评估。其中（1=非常不同意.....3=中立....5=非常同意）

我们港务局的服务质量有所提高。

1	2	3	4	5

港口和周边居民的关系变得越来越好了。

1	2	3	4	5

我们员工的安全保障得到了提升。

1	2	3	4	5

我们港口为员工提供培训和教育

1	2	3	4	5

3. 经济

根据您的港口/企业/组织的实际情况，对以下陈述进行评估。其中（1=非常不同意.....3=中立....5=非常同意）

我们港口提供了很多的工作岗位。

1	2	3	4	5

我们港口可以多功能和高效地利用港口土地。

1	2	3	4	5

我们港口积极配合产业和经济发展。

1	2	3	4	5

我们港口驱动了港口周边的经济发展。

1	2	3	4	5

三、港口业绩

根据您的港口/企业/组织的实际情况，对以下陈述进行评估。其中（1=非常不同意.....3=中立....5=非常同意）

1. 成本

我们港口的货物装卸费合理且具有竞争力。

1	2	3	4	5

我们港口的多式联运收费合理且具有竞争力。

1	2	3	4	5

我们港口的辅助服务（引航、拖航、客户）收费合理且具有竞争力。

1	2	3	4	5

2. 服务质量

与主要竞争对手相比您的港口表现如何，对以下陈述进行评估。其中（1=非常不同意.....3=中立....5=非常同意）

我们港口可以在预期时间内处理货物。

1	2	3	4	5

我们港口可以根据顾客的要求及时处理货物。

1	2	3	4	5

我们港口的服务前置时间（service lead time）更短。

1	2	3	4	5

我们港口提供准确的货物信息。

1	2	3	4	5

3. 运营效率

与主要竞争对手相比您的港口表现如何，对以下陈述进行评估。其中（1=非常不同意.....3=中立....5=非常同意）

我们港口的生产能力更高。

1	2	3	4	5

我们港口的港口周转时间(由于拥堵导致的船舶等待时间)更短。

1	2	3	4	5

我们港口的运输方式转换时间更短。

1	2	3	4	5

4. 增值服务

与主要竞争对手相比您的港口表现如何，对以下陈述进行评估。其中（1=非常不同意.....3=中立....5=非常同意）

我们港口用增值服务吸引货物。

1	2	3	4	5

我们港口的通过增值服务提高价值。

1	2	3	4	5

我们有足够的设施提供增值服务。

1	2	3	4	5

5. 以顾客为导向

与主要竞争对手相比您的港口表现如何，对以下陈述进行评估。其中（1=非常不同意.....3=中立....5=非常同意）

我们的港口可以快速做出决策。

1	2	3	4	5

我们的港口可以为我们的客户提供个性化的港口服务。

1	2	3	4	5

我们港口可以可以及时响应客户的需求。

1	2	3	4	5

我们的港口为用户提供简单快捷的操作流程。

1	2	3	4	5

Appendix D: Questionnaire for the pilot study and primary study (English version)

UNIVERSITY OF PLYMOUTH

Questionnaire

Dear Sir or Madam

Thanks indeed for participating this survey about Big Data analytics capability and port performance. This research defines Big Data analytics capability in context of the port area as “the ability of port organisations to collect and gather relevant data from the port operation, heterogeneous systems and business activities participants, then **managing**, **processing** and **analysing** these data and **visualising** them intuitively to offer **valuable business insights** and **support decision-making**”. Based on this definition, please fill the questionnaires.

Please provide your opinion based on your firms’ perspective. You only need to fill the question once.

General Information

Education:

Respondent Title:

Tenure:

Total Big Data working experience (years):

Company/port name:

Number of employees:

IT related investment:

I. Big Data Analytics Capability

Based on your organization evaluate the following statements by selecting one of the answers, from 1 to 5

(1=Strongly Disagree… 3=Neither Disagree nor Agree… 5=Strongly Agree)

1. Data

We have access to very large, unstructured, or fast-moving data for analysis

1	2	3	4	5

We integrate data from multiple internal sources into a data lake for easy access

1	2	3	4	5

We integrate external data with internal to facilitate high-value analysis of our business environment

1	2	3	4	5

2. Technology

We have adopted distributed computing approaches (e.g., Hadoop, Storm, Spark) to Big Data processing

1	2	3	4	5

We have adopted different data visualization software (e.g., Sisense, Periscope Data, Tableau, Microsoft Power BI, IBM Watson Analytics,)

1	2	3	4	5

We have adopted cloud services (e.g., IBM Cloud, Amazon Web Services, Microsoft Azure, Google Cloud) for processing data performing analytics

1	2	3	4	5

3. Basic Resources

We have allocated large funds for Big Data project.

1	2	3	4	5

We have enough time to achieve desired result from Big Data analytics projects

1	2	3	4	5

4. Technical Skills

Our port provides data analytics training to our own employees

1	2	3	4	5

Our port hires new employees that already have the data analytics skills

1	2	3	4	5

Our analysts have appropriate data analytics skills to accomplish their jobs successfully

1	2	3	4	5

Our analysts have suitable education to fulfil their jobs.

1	2	3	4	5

5. Managerial Skills

Our analytics managers are able to coordinate Big Data-related activities in ways that support other partners.

1	2	3	4	5

Our analytics managers are able to anticipate the future business needs of other managers, suppliers and customers.

1	2	3	4	5

Our analytics managers have good sense of where to use Big Data.

1	2	3	4	5

Our analytics managers can interpret the resources obtained using complex analyses and offer inputs which are useful for swift decision making.

1	2	3	4	5

6. Data-driven Culture

We consider data a tangible asset.

1	2	3	4	5

We base our decisions on data only not on instinct.

1	2	3	4	5

We are willing to override our own intuition when data contradict our viewpoints.

1	2	3	4	5

We continuously assess and improve the business activities in response to insights extracted from data.

1	2	3	4	5

7. Organisational learning

We actively search for new and relevant knowledge

1	2	3	4	5

We assimilate new and relevant knowledge

1	2	3	4	5

We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge

1	2	3	4	5

II. Port sustainability performance

Please indicate your level of agreement with the following statements by selecting one of the answers, from 1 to 5

(1=Strongly Disagree… 3=Neutral… 5=Strongly Agree)

1. Environmental Dimension

Our port has adopted data analytics technology for reduction of air emissions.

1	2	3	4	5

Our port has adopted data analytics technology for reduction of wasted water.

1	2	3	4	5

Our port has adopted data analytics technology for reduction of noise.

1	2	3	4	5

Our port has adopted data analytics technology for reduction of oil consumption.

1	2	3	4	5

2. Social Dimension

Our port improves service quality by using data analytics technology.

1	2	3	4	5

Our port authority has improved the relationship with the neighbouring residents by building smart port.

1	2	3	4	5

Our staff's security and safety has improved by building smart port.

1	2	3	4	5

Our port provides support for employees' training and education.

1	2	3	4	5

3. Economic Dimension

Our port offers more employment opportunities.

1	2	3	4	5

Our port authorities multifunctional and efficient use of port areas by data analytics technology.

1	2	3	4	5

Our port authorities actively cooperate with industrial and economic development through building smart port.

1	2	3	4	5

Our port is driving the economic development of the area surrounding the port through developing data analytics technology.

1	2	3	4	5

III Port performance

Please indicate your level of agreement with the following statements by selecting one of the answers, from 1 to 5

(1=Strongly Disagree… 3=Neutral… 5=Strongly Agree)

1. Cost

Through using data analytics technology, our port cargo handling charge is lower than our major competitor.

1	2	3	4	5

Through using data analytics technology, our port charges for intermodal transport is lower than our major competitor.

1	2	3	4	5

Through using data analytics technology, our port auxiliary service (pilotage, towage, customers) charge is lower than our major competitor.

1	2	3	4	5

2. Service Quality

Through using data analytics technology, our port handles cargo at quoted or anticipated times.

1	2	3	4	5

Through using data analytics technology, our port handles cargo on time according to customers requirement.

1	2	3	4	5

Through using data analytics technology, our port's service lead time is shorter than our major competitors

1	2	3	4	5

Through using data analytics technology, our port provides shipment information accurately.

1	2	3	4	5

3. Operational Efficiency

Through using data analytics technology, our terminal productivity is higher than our major competitor.

1	2	3	4	5

Through using data analytics technology, Port turn-around time is less (Ship waiting time due to congestion) than our major competitor.

1	2	3	4	5

Through using data analytics technology, our time for transportation mode transit is shorter than our major competitor.

1	2	3	4	5

4. Value-added Services

Through using data analytics technology, our port has the capacity to handle different type of cargo

1	2	3	4	5

Through using data analytics technology, our port has a variety of services to handle the transferring of cargo from one mode to another.

1	2	3	4	5

Through using data analytics technology, our port has the capacity to convey cargo through diversified routes/modes at the least possible time to the receiver.

1	2	3	4	5

Through using data analytics technology, our port has the capacity to launch new tailored services when the need arises.

1	2	3	4	5

5. Customer Orientation

Through using data analytics technology, our port is quick on making decisions regarding altering schedules, amending orders and changing design process to meet customers' demand.

1	2	3	4	5

Through using data analytics technology, our port can provide individual port services to our customers.

1	2	3	4	5

Through using data analytics technology, our port's response time for customer complaints is faster than that of our major competitors

1	2	3	4	5

Through using data analytics technology, our port has smooth operational processes for port users.

1	2	3	4	5

Appendix E: Questionnaire for the pilot study and primary study (Chinese version)

调查问卷

这个研究是为了调查大数据分析能力在促进港口供应链整合，港口可持续性和港口业绩方面的表现。该研究旨在开发一个模型，以探索大数据分析能力，港口供应链整合，港口可持续性和港口业绩之间的关系。**这项研究将港口的大数据分析能力定义为“港口组织从港口运营，操作系统和业务活动参与者中收集相关数据，然后管理，处理和分析这些数据并对其进行可视化，以提供有价值的业务见解并支持决策的能力”**。

根据此定义，请填写调查表。

请根据您公司的观点提供您的意见。该调查问卷仅用于学术研究。填写的信息永远不会透露给他人。请放心，您的姓名和个人回复将保密。因此，您提供的所有信息都无法由论文的读者确定。如果您能参与这项研究，我将非常感谢。

基本信息

年龄：

教育程度：

职称：

任期：

大数据相关的工作经验（年）：

公司/港口名称：

地理位置：

在职员工人数：

港口/企业对IT相关项目投入的资金：

一、大数据分析能力

根据您的港口/企业/组织的实际情况， 对以下陈述进行评估。其中（1=非常不同意.....3=中立....5=非常同意）

1. 数据

我们港口企业组织可以对大量的、非结构化的、快速传输的数据进行分析

1	2	3	4	5

我们可以将来自不同内部源的数据整合到数据仓库以便于访问

1	2	3	4	5

我们港口/企业组织可以整合外部数据与内部数据， 以促进我们业务环境的分析

1	2	3	4	5

2. 科技

我们港口/企业/组织采用先进的的数据处理软件来处理大数据

1	2	3	4	5

我们港口/企业/组织使用多种数据可视化工具

1	2	3	4	5

我们港口/企业/组织已经使用云服务来处理和分析数据

1	2	3	4	5

3. 基本资源

我们港口/企业/组织为大数据项目划拨了大量资金

1	2	3	4	5

我们港口/企业/组织提供了足够的时间来实现大数据分析项目的预期结果

1	2	3	4	5

4. 技术能力

我们港口/企业/组织为雇员提供大数据分析技术的培训

1	2	3	4	5

我们港口/企业/组织雇佣已具有大数据分析技术的人员

1	2	3	4	5

我们港口/企业/组织的分析师具有适当的大数据分析技巧，以成功完成他们的工作

1	2	3	4	5

我们港口/企业/组织的分析师接受了适当的教育足以完成他们的工作

1	2	3	4	5

5. 管理能力

我们港口/企业/组织的数据分析管理者可以协调大数据相关的业务来帮助合作伙伴

1	2	3	4	5

我们港口/企业/组织的数据分析管理者可以预测供应商、顾客未来的需求

1	2	3	4	5

我们港口/企业/组织的数据分析管理者对在哪里使用大数据技术有着很好的认知

1	2	3	4	5

我们港口/企业/组织的数据分析管理者可以理解使用复杂分析方法获得的结果，并且提供对快速决策有用的信息

1	2	3	4	5

6. 数据驱动文化

我们港口/企业/组织认为数据是一种有形资产

1	2	3	4	5

我们干港口/企业/组织根据数据作出决策，而不是根据直觉作出决策

1	2	3	4	5

当数据与我们的观点相矛盾的时候，我们愿意推翻我们的直觉

1	2	3	4	5

根据从数据中提取的见解，我们港口/企业/组织不断地评估和改进业务活动

1	2	3	4	5

7. 组织学习

我们港口/企业/组织积极的寻求新知识

1	2	3	4	5

我们港口/企业/组织吸纳新的知识

1	2	3	4	5

我们港口/企业/组织致力于开发现有的能力和探索新知识

1	2	3	4	5

二、港口可持续能力

根据您的港口/企业/组织的实际情况，对以下陈述进行评估。其中（1=非常不同意.....3=中立....5=非常同意）

1. 环境

我们港口应用数据分析技术去减少空气污染

1	2	3	4	5

我们港口应用数据分析技术来减少水资源浪费

1	2	3	4	5

我们港口应用数据分析技术来减少噪音

1	2	3	4	5

我们港口应用数据分析技术来减少燃料消耗

1	2	3	4	5

2. 社会

应用数据分析技术并很大程度上的提高我们港口服务

1	2	3	4	5

通过打造智慧港口，港口和周边居民的关系变得更好了

1	2	3	4	5

通过打造智慧港口，员工工作时的安全得到了提升

1	2	3	4	5

我们港口为员工提供培训和教育

1	2	3	4	5

3. 经济

我们港口提供了很多的工作岗位

1	2	3	4	5

我们港口通过数据分析技术，多功能和高效地利用港口土地

1	2	3	4	5

通过打造智慧港口，我们港口积极配合产业和经济发展

1	2	3	4	5

通过发展数据分析技术，我们港口驱动了港口周边的经济发展

1	2	3	4	5

三、港口业绩

根据您的港口/企业/组织的实际情况，对以下陈述进行评估。其中（1=非常不同意.....3=中立....5=非常同意）

1. 成本

通过应用数据分析技术，与我们的主要竞争对手相比，我们港口的货物处理费用（cargo handling fee)更低

1	2	3	4	5

通过应用数据分析技术，与我们的主要竞争对手相比，我们港口的多式联运费用更底

1	2	3	4	5

通过应用数据分析技术，与我们的主要竞争对手相比，我们港口的辅助服务（引航，拖航）费用更低

1	2	3	4	5

2. 服务质量

通过应用数据分析技术，我们港口可以在预期时间内处理货物

1	2	3	4	5

通过应用数据分析技术，我们港口可以根据顾客的要求及时处理货物

1	2	3	4	5

通过应用数据分析技术，与我们的主要竞争对手相比，我们港口的服务前置时间（service lead time）更短

1	2	3	4	5

通过大数据分析技术，我们港口提供准确的货物信息

1	2	3	4	5

3. 运营效率

通过应用数据分析技术，与我们的主要竞争对手相比，我们港口的生产能力更高

1	2	3	4	5

通过使用数据分析技术，与我们的主要竞争对手相比，我们港口的港口周转时间(由于拥堵导致的船舶等待时间)更短

1	2	3	4	5

通过使用数据分析技术，与我们的主要竞争对手相比，我们港口的运输方式转换时间更短

1	2	3	4	5

4. 增值服务

通过使用数据分析技术, 我们港口有能力处理不同类型的货物

1	2	3	4	5

通过使用数据分析技术，我们的港口可提供多种服务来处理从一种模式到另一种模式的货物转移

1	2	3	4	5

通过使用数据分析技术，我们的港口有能力在最短的时间内通过多种路线/模式将货物运送到客户手中

1	2	3	4	5

通过使用数据分析技术，我们的港口有能力在需要时推出新的定制服务

1	2	3	4	5

5. 以顾客为导向

通过使用数据分析技术，我们的港口可以快速做出有关更改时间表、修改订单和更改设计流程的决定，以满足客户的需求

1	2	3	4	5

通过使用数据分析技术，我们的港口可以为我们的客户提供个性化的港口服务

1	2	3	4	5

通过使用数据分析技术，与我们的主要竞争对手相比，我们港口可以更快的处理顾客的反馈

1	2	3	4	5

通过使用数据分析技术，我们港口为顾客提供了顺畅的操作流程

1	2	3	4	5