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Barrier analysis to improve big data analytics capability of the maritime industry: A mixed-method approach

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ABSTRACT

The maritime industry is facing increasing challenges due to decarbonization requirements, trade disruptions, and geoeconomic fragmentation, such as International Maritime Organization (IMO) sets out clear framework to reach net zero emissions by 2050, Russia-Ukraine war disrupted maritime activities in the Black and Azov seas, and increased trade tensions between the United States and China. To enhance their sustainability, operational efficiency, and competitiveness, maritime organizations are therefore very keen to build big data analytics capability (BDAC). However, various barriers, mean that only a handful are able to do so. We adopt a mixed-method approach to analyze these barriers. Thematic analysis is used to identify five categories of barriers and 16 individual barriers based on empirical data collected from 26 maritime organizations. These are then prioritized using the analytic hierarchy process (AHP), followed by total interpretive structural modelling (TISM) to understand their interrelationships. Finally, cross-impact matrix multiplications applied to classification (MICMAC) is employed to differentiate the role of each barrier based on its driving and dependence power. This paper makes several theoretical contributions. First, China's hierarchical cultural value orientation encourages competition and obedience to rules, resulting in unwillingness to share knowledge, lack of coordination, and lack of error correction mechanisms. These cultural barriers hinder BDAC development. Second, organizational learning category barriers are found to be the most important in impeding BDAC development. This study also raises practitioners' awareness of the need to tackle cultural and organizational learning barriers.

1. Introduction

Big data analytics capability (BDAC) is an organization's capacity to process, visualize, and analyze data, thereby generating insights that support data-driven decision-making, planning, and execution (Dubey et al., 2019a). Successfully establishing and implementing BDAC enables businesses to identify useful information, uncover hidden patterns, discover market trends, and gain insights into unknown correlations (Mikalef et al., 2020). In recent years, businesses have accelerated applications of big data and associated technologies, with the aim of increasing profitability, smoothing operations, and enhancing market-based production, and ultimately achieving sustainable competitive advantage (Raguseo, 2018; Rialti et al., 2019). However, although 97.2 % of companies have invested in big data-related projects, only 24 % of these have transformed their organizations to become data-driven and thereby successfully achieve BDAC (Li et al., 2022; Brewis et al., 2023). One reason for this failure is that many firms have a shallow understanding of barriers to achieving BDAC, and therefore have difficulty allocating resources to tackle them effectively (Kumar et al., 2022a). For example, the percentage of firms identifying themselves as having successfully built BDAC declined from 37.1 % in 2017 to 31 % in 2019 (Bean and Davenport, 2019). We presume that this decline will have continued since 2019, given the effects of COVID-19.

China's maritime industry is playing an increasingly important role in global trading, employment creation, and environmental protection. For example, in 2021, it imported 11.9 % and exported 15.07 % of global merchandise, and its transportation services generated $833,510 million in value (UNCTAD, 2021). The industry's strong performance in

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handling merchandise relies heavily on maritime connectivity, a complex ecosystem comprising a range of service providers, satellite operators, hardware vendors, and integrators. In 2021, China's maritime connectivity achieved a score of 164 (ChinaPower., 2021), significantly higher than most other top countries, including Singapore (113), South Korea (108), the United States (106), and Malaysia (100). We believe that wide deployment of big data analytics (BDA) distinguishes China's maritime industry from those of other leading countries, since China initiated big data technologies for international shipping in 2015 (Port Technology, 2015). In other countries, only a handful of maritime companies currently have the capability to leverage big data (Trelleborg, 2022). For example, Maersk has tried to reduce its bunker costs by improving its BDAC, and Hyundai Heavy Industries has initiated BDAC development by extending its partnerships with world-leading technology suppliers such as Intel and Microsoft. Although BDAC promises a range of benefits for China's maritime industry, BDA is currently applied in only limited areas, including chartering and operations. It is seldom applied in areas such as technical management, fleet planning, voyage operations, and vetting, owing to various barriers (Zaman et al., 2017; Munim et al., 2020). For example, Jia and Cui (2021)'s analysis of barriers impeding the evolution of maritime port smartification indicates that insufficient government support for research and development is the most influential barrier. Chen et al. (2022) find that lack of a legal framework, cybersecurity, technical challenges, and small-scale big data applications are the main obstacles. These barriers impede China's maritime industry from improving its operational efficiency, environmental sustainability, productivity, and visibility. In particular, China has the world's largest shipping fleet, largest shipbuilding sector, is home to the biggest and most numerous ports, and its maritime industry is responsible for approximately 3 % of global greenhouse gas emissions (IMO, 2020; World Shipping Council, 2022). Analysis of millions of pieces of data-generated by vessel movements, ship construction, and port operations promises quicker routes and lower energy consumption for ships, greener ports, and more efficient shipbuilding (Senyo et al., 2021; Tijan et al., 2021). Thus, maritime businesses need a comprehensive understanding of barriers to BDAC development, in order to prioritize them to enable effective resource allocation, and gain insights into interrelationships between them, as tackling one barrier may introduce other barriers into the system. The barriers must also be accurately characterized before making major efforts to reduce their effects during the decision-making and implementation stages of BDA adoption (Senna et al., 2023). A proper investigation of barriers to achieving BDAC will help organizations to develop more effective strategies for development (Moktadir et al., 2019).

Several knowledge gaps are identified in existing research. First, previous analyzes of barriers, challenges, issues, problems, and hurdles to achieving BDAC and big data adoption focus mainly on manufacturing, healthcare, agri-food, and humanitarian industries (Bag et al., 2020; Chen et al., 2020; Gupta and Goyal, 2021; Kazancoglu et al., 2021; Raut et al., 2021a, 2021b). Few studies have examined the maritime industry (Zhang and Lam, 2019). Second, existing literature analyzing barrier to achieving BDAC uses various research methodologies, including theoretical and conceptual papers, literature reviews, case study and interviews, and surveys. For example, Sivarajah et al. (2017)'s review of literature on big data challenges and analytical methods confirms that case study and interviews, design research, and analytical, theoretical, and conceptual papers are frequently used research methodologies, whereas mixed methods are seldom used. Of the 243 studies they identify, only one uses a mixed-method approach, a clear research gap that needs to be filled. Further quantitative and qualitative research is required on this topic (Willetts et al., 2020). A multi-method approach involves of multiple forms of qualitative data or multiple forms of quantitative data in one study, whereas a mixed-method approach combines qualitative and quantitative data collection and analysis in one study (Creswell, 2015). A mixed-method approach has several unique advantages over a qualitative, quantitative, or multi-methods approach. First, it enables comprehensive assessment of a problem from different perspectives. For example, the results from qualitative interviews can be used to identify previously unknown explanatory variables, resolve mis-specified models, and understand incomprehensible statistical findings. Second, a mixed-method approach enriches the evidence and enables deeper questions to be asked. Third, combining qualitative and quantitative approaches helps to compensate for the limitations of each method (Kelle, 2006; Malina et al., 2011). Finally, few studies of the topic focus on China. Existing studies are based on data collected from either multiple industries or multiple countries, rather than being country- or industry-specific, thereby hindering practitioners' understanding.

To address the above-mentioned research gaps, this study draws on the resource-based view (RBV) to analyze barriers to achieving BDAC in China's maritime industry using a mixed-method approach. Three research questions are addressed: (1) what barriers impede China's maritime organizations from developing BDAC; (2) how can these barriers be prioritized and their interrelationships identified to develop BDAC efficiently; (3) what role does each barrier play in the system? To answer the first research question, we examined 26 maritime organizations that have applied BDA across China. The second question requires the recognized barriers to be prioritized and interrelated by applying analytic procedures and modelling techniques. For this purpose, we began by employing the analytic hierarchy process (AHP), a technique widely used to prioritize multi-criteria decision making (MCDM) problems (Emrouznejad and Marra, 2017). We then applied total interpretive structural modelling (TISM) to gain an understanding of interrelationships between the identified barriers. TISM enabled us to build interactions by allocating the barriers to various layers of a framework (Zhao et al., 2018). The final question aims to distinguish each barrier's role in the system, whether driving other barriers or depending on other barriers for its resolution. Thus, MICMAC analysis was selected to evaluate the TISM model and differentiate the barriers' roles.

This study makes several theoretical contributions to the RBV and organizational learning theory. First, it identifies 16 barriers to improving BDAC in China's maritime industry, including some scarcely mentioned by other scholars, such as lack of error correction mechanisms, lack of continuous assessment and improvement, lack of incentives for employees to test new knowledge, and lack of organizational memory. Second, it shows that organizational learning barriers are the most critical impediment to the development of BDAC. Unwillingness to share knowledge and lack of coordination are also identified as key barriers to BDAC improvement. Most existing work considers the key barriers to be lack of top management support, and technical, data, and financial barriers (Gupta and Goyal, 2021; Raut et al., 2021a; Jain and Ajmera, 2022; Tamvada et al., 2022). A novel contribution of our study is that our prioritization shows that organizational learning barriers are the most crucial category. This relates to the specific context of China because, since it initiated "Made in China 2025" in 2015, it has begun to equip various industries with advanced technologies, including the maritime industry. Thus, the key barriers identified in this study relate to the soft power of maritime organizations. Third, this study differentiates the barriers' roles based on their driving and dependence power. The results have managerial implications for ports' top management teams, managers of knowledge management departments, and government policymakers.

2. Literature review

In this section, we introduce the RBV, summarize the literature on BDAC, barriers hindering BDAC adoption, and the various MCDM methods used, and identify research gaps relevant to the present study.

2.1. Resource-based view

The RBV posits that a firm's sustained competitive advantage depends on its valuable, rare, and inimitable resources (Barney, 1991). These include technological and capital resources, infrastructure, reputational capital, knowledge, and human resources (Gunasekaran et al., 2017). Firms' capability to create or obtain these resources affects their competitiveness performance. We consider the RBV to be an appropriate theory to investigate this topic for two reasons. First, to embed BDAC at the organizational level, tangible resources (e.g. technology, finance, and data), intangible resources (e.g. organizational learning and data-driven culture), and human skills (e.g. technical and managerial skills) are all essential (Gupta and George, 2016). The RBV considers firms in terms of combinations of resources and capabilities that help to achieve competitive advantage and superior performance (Wernerfelt, 1984). Inability to acquire sufficient and necessary resources causes barriers to building BDAC. Second, the RBV has been used extensively to examine issues relating to big data. For example, Dubey et al. (2019b) use RBV and institutional theory to investigate big data and predictive analysis, and Mishra et al. (2019) use it to explore how organizational capabilities can enable the diffusion of big data and predictive analytics. Therefore, we chose to analyze barriers to improving BDAC in China's maritime industry through the theoretical lens of the RBV.

2.2. BDAC: Definitions, resources, elements, and adoption

Among various definitions, Wang et al. (2019) define BDAC as an organization's ability to generate, acquire, store, analyze, and visualize a large amount of data. Gupta and George (2016) frame it as an organization's capability to combine certain tangible, intangible, and human resources. Tangible resources include data (structured, unstructured, and semi-structured), technology (e.g., Hadoop, NoSQL, R programming, Data Lakes), and basic resources such as time and investment. Intangible resources include a data-driven culture and intensity of organizational learning. A data-driven culture, which is a critical resource, is defined as "the extent to which organizational members (including top-level executives, middle managers, and lower-level employees) make decisions based on the insights extracted from data" (Yu et al., 2021, p. 3). Its value for shaping business strategy, improving business performance, and sustaining competitive advantage is widely supported (Kamble and Gunasekaran, 2020). Organizational learning is critical in enabling organizations to achieve sustainable performance improvement and systematically incorporate new learning into organizational routines (Tortorella et al., 2020). New knowledge and experience can be acquired either through trial-and-error, or through an organizational knowledge repository embedded in working procedures and routines (Basten and Haamann, 2018). Human resources are also necessary, as BDAC must be planned and implemented by people, including business analysts, data scientists, and big data developers and engineers (Mauro et al., 2018).

Given the various benefits of BDA, such as predictability, valued knowledge, and strategic decision making, it has been widely deployed (Rammer and Es-Sadki, 2023). For example, in public areas, it can be applied to smart city development, in terms of urban informatics, digital public services, and citizen government e-interfaces, and to disaster/emergency management and policy-making for public services (Abuljadail et al., 2023). Iqbal et al. (2020) detail several applications of BDA in smart city development, including predicting taxi demand, personalizing health services, making business and economic policy recommendations for governments, analyzing population displacement and sentiment, detecting manufacturing faults, and applying biometrics and surveillance. Weerasinghe et al. (2022) highlight that BDA has great potential for population health management (e.g., precision medicine, preventive care, and technology-assisted clinical decision-making), but its implementation requires more engagement and participation in discussions of data quality across micro-, meso-, and macro-levels of healthcare. From a comparative analysis of BDA applications in public- and private-sector manufacturing, Gao et al. (2023) conclude that private enterprises can achieve better green innovation performance than government-owned BDA applications. Research on BDA applications in private areas is wide-ranging. For example, in their examination of four industrial applications, Corallo et al. (2023) illustrate that BDA plays a key role in promoting smart manufacturing, such as predictive maintenance for robots equipped with automotive industry-specific control systems. Xu et al. (2023) reveal that BDA can improve accuracy, response time, and flexibility in supply chain planning, and contributes significantly to process optimization and automation. Chatterjee et al. (2023) suggest that adoption of BDA may enhance decision-making and forecasting processes, and ultimately improve manufacturing firms' financial and operational performance. Finally, Saeed et al. (2022) find that BDA increases firms' legitimacy. Specifically, a 1 % increase in BDA is associated with an increase of approximately 27.4 % in firm legitimacy. A recent literature review (Huynh et al. 2023) reveals that studies relevant to BDA focus mainly on the research contexts of healthcare, supply chain management, manufacturing, the service sector, smart cities, and small- and medium-sized companies, but pay little attention to the maritime industry (Choi and Park, 2022; Tseng et al., 2022).

Maritime big data can be characterized in terms of the four "Vs" of volume, velocity, variety, and veracity (Koga, 2015). For example, the IMO (2012) requires all voyage data to be stored in a continuous and automatic manner, and to be retained for at least 30 days/720 h on a long-term recording medium and for at least 48 h on fixed and float-free recording media. This requires the generation and storage of high-volume of data. The maritime industry has various stakeholders, such as ship owners and operators, ports, ferries, tour boats, stevedores and terminals, marine services, and support services, who generate different types of data that can be used for analysis. For example, all passenger ships and other ships of 3000 gross tons or more are mandated to be equipped with voyage data recorders (VDRs), which are used mainly to record electronic data on each voyage (IMO, 2019). Up to 20 types of voyage-related data must be recorded and accumulated by VDRs, such as the ship's position and speed, wind speed and direction, engine and thruster order and response, water depth, accelerations and hull stresses, and audio communications (IMO, 2019). A significant amount of data relating to ships' performance and navigation is also recorded by automatic identification systems (AIS), which can also be used for analysis. A big data position paper published by DNV, a world-leading assurance firm, identifies six benefits of utilizing big data in the maritime industry: technical operations and maintenance, energy efficiency, safety performance, management and monitoring of accidents and environmental risks from shipping traffic, and commercial operations and automation of ship operations (Mirovic et al., 2018).

2.3. Empirical research relating to BDAC: Barrier identification and categorization

Both scholars and practitioners have realized the benefits of big data and have applied it to industries such as manufacturing, agri-food, healthcare, logistics, and smart industries. However, several barriers impede organizations from developing their BDAC. For example, Zhang and Lam (2019) consider nine cultural, managerial, and technical barriers that may hamper maritime organizations adoption of big data, the top three being lack of understanding of how to use BDA to improve the business, lack of executive sponsorship, and lack of skills to conduct BDA. Among Bag et al. (2020)'s 15 barriers that may influence BDAC establishment in humanitarian organizations, the key ones are multiple data formats, insufficient training and education, lack of focus on instilling modern management practices, scarcity of public-private partnerships, and failure to attract funding. Moktadir et al. (2019) show that in manufacturing, BDAC adoption is most significantly hampered by data-related barriers, followed by technology-related barriers. In smart industries, the barriers are different. For example, of the 12 barriers that Li et al. (2019) identify as hindering organizations from applying big data solutions, the key one is lack of understanding and strategic planning, because this may introduce six other barriers into the system.

Various taxonomies are used to categorize barriers to BDAC adoption. For example, Chen et al. (2020) classify 20 barriers into the five categories of expertise, operations, resources, regulation, and market access, whereas Konanahalli et al. (2022)'s four clusters are technological barriers, issues relating to data governance and management, inadequate preparedness for BDAC initiatives, and data quality and skills gaps. Alharthi et al. (2017) categorize barriers to BDAC adoption as technological, organizational, and human barriers, and Koga (2015) classify them in terms of sound competitive conditions, human resources, and technology. Based on previous studies and Gupta and George (2016)'s widely accepted framework for classifying big data resources, we followed four steps to categorize barriers to adopting BDAC into five categories: data and technology, basic resources, technological and managerial, cultural, and organizational learning. First, we searched Web of Science and Business Source Complete by entering relevant keywords to identify journal papers relating to barriers, challenges, issues, problems, hurdles or risks to BDAC adoption, big data, BDA and big data adoption. Web of Science and Business Source Complete were selected because they include a range of journals, cover all business disciplines, and have been extensively used in previous literature reviews (Zhao et al., 2022b). The initial search focused on management and business categories, resulting in 287 publications (148 from Web of Science and 139 from Business Source Complete). In our second step, two PhD students interested in big data and management were asked to check the abstract, introduction, and conclusion of each paper. We excluded publications focusing on drivers, enablers, and factors in BDAC adoption, literature review and conceptual papers, applications of other industry 4.0 technologies (e.g., blockchain, robotics, and artificial intelligence), business model establishment, and papers lacking a clear focus on big data. However, some publications focusing on disruptive, industry 4.0, or digital technologies (e.g. Annosi et al., 2021; Jain and Ajmera, 2022; Kumar et al., 2022b; Rathore et al., 2022; Tamvada et al., 2022) were included for analysis if they clearly distinguished the role of big data. This step resulted in only 24 publications remaining. Third, the two PhD students were asked to conduct a detailed analysis of the 24 publications, and identify and record the barriers. Finally, we consulted two professionals from the maritime industry to determine whether any other barriers should be added to our results. Table 1 shows the barriers to applying BDAC, listing the 24 relevant journal papers by author (s) (year), title, industry/country focus, barrier categorizations, and barriers identified. Following our synthesis of the literature and consultation of the two maritime professionals, we re-categorized the identified barriers into data and technology, basic resources, technological and managerial, cultural, and organizational learning. Some barriers identified were excluded from the new categorizations because they either have overlapping meanings or are too context-specific, such as financial constraints and lack of financial support.

2.4. MCDM methods used to evaluate barriers to BDAC adoption

Various MCDM methods have been used to evaluate barriers to BDAC adoption (see Table 2). For example, Raut et al. (2021b) apply a grey decision-making trial and evaluation laboratory (DEMATEL) approach and the analytical network process (ANP) to evaluate cause-effect relationships between 15 barriers to manufacturing firms' adoption of BDAC. Their results indicate that the key barriers are lack of data storage facilities, IT infrastructure, and organizational strategy, and uncertainty about the benefits and long-term usage. Khan (2022) employs the best-worst method (BWM) to prioritize 13 barriers to BDAC adoption in the context of smart city development. He proposes that data complexity and lack of a framework for BDAC adoption and appropriate technologies are crucial. Interestingly, Zhang and Lam (2019) suggest that lack of understanding of how to use BDAC should be given critical attention, as this is ranked first among 11 barriers to BDAC adoption in maritime organizations. Bag et al. (2020) implement TISM and fuzzy MICMAC analysis to investigate interactions between challenges to BDAC adoption. They find that poor data management and lack of funding are two driving barriers with the greatest capacity to elicit other barriers in the system.

2.5. Research gaps

Three research gaps identified from the literature review suggest avenues for further investigation.

First, several authors comment that barriers to BDAC adoption have been significantly less researched in the maritime industry than in other industries such as manufacturing (see Table 1). For example, Zhang and Lam (2019) highlight that maritime organizations' adoption of big data is lagging. Maheshwari et al. (2021) also find that existing studies focus on the education, telecommunications, finance, retail, governance, and healthcare industries, whereas the maritime industry seems to be neglected. Trelleborg (2022), a world-leading maritime infrastructure provider, states that many shipping and logistics service providers recognize the important role of big data in transforming their services, yet applications of big data in the maritime industry lag behind other sectors of the global economy. In view of this research gap, we explore barriers hindering maritime organizations from establishing BDAC.

Second, existing analyzes of barriers to BDAC adoption are based mainly on data from India and the UK, and significantly less attention has been given to China (see Table 1). For example, although we identify two studies focusing on China, Li et al. (2019) concentrate on smart industry and Chen et al. (2020) focus on healthcare. Among the 24 selected studies, none focuses on China's maritime industry. China is an important maritime power and initiated big data in its maritime industry in 2015 (Port Technology, 2015). New understandings can be gained from investigating this topic, focusing particularly on a country that has invested in big data in its maritime industry for many years.

Third, MCDM methods are widely applied to explore barriers to BDAC adoption (see Table 2). Frequently used methods include DEMATEL, ANP, ISM, and VIKOR. However, few studies have used a combination of AHP, TISM, and MICMAC. According to Cerneviciene and Kabasinskas (2022), applying different MCDM methods in a single study generates deeper insights, increases ability to structure complex evaluation tasks, and provides well-informed decisions for industry practitioners. Thus, this study explores the topic by integrating three MCDM methods: TISM, MICMAC, and AHP.

3. Research methodology

In this study, we adopted a mixed-method approach to analyze barriers impeding applications of BDA in maritime organizations. We did so for three reasons. First, a mixed-method approach supports depth and breadth of understanding by producing more complete evidence (Ostlund et al., 2011). For example, qualitative data provides subjective insights into barrier generation mechanisms, and quantitative data provides objective insights into barrier prioritization and categorization. Thus, exploring the issue from different angles enriches the evidence and provides deeper answers (Creswell and Clark, 2011). Second, a mixed-method approach enriches researchers' experience and strengthens interactions between scholars and practitioners, thereby enhancing interpretation and communication of the results (Bazeley, 2015). Third, combining qualitative and quantitative approaches compensates for the limitations of each method (Malina et al., 2011). For example, TISM is a qualitative modelling technique used to build interactions between different variables by allocating them to various layers of a framework. However, it neither prioritizes the variables, nor identifies the roles of

Table 1
Selected literature on barriers to applying BDAC.

Barriers' identification by checking relevant literatures				
Author(s) (year)	Paper/journal title	Industry/ country focus	Barrier categorization	Barrier identified
Ahmed et al. (2017)	The future of big data in facilities management: opportunities and challenges (Facilities)	Engineering and construction/ UK	ICT, external, and facilities management	Data security and compatibility issues, timely data processing for real-time systems, too many vendors selling many different products, fragmentation, lack of specific big data tools, effective integration of unstructured data from many different resources, ethical issues, the Data Protection Act, possible bias in data capturing and presentation, lack of available evidence/ cases of big data, lack of collaboration and data sharing, short-term thinking, low maturity of big data, consistency in data measurement and analysis, lack of knowledge and skills set, to obtain real value from extensive amount of volatile data
Alharthi et al. (2017)	Addressing barriers to big data (*Business Horizons*)	Not specified	Technological, human, organizational	Infrastructure readiness, complexity of data, lack of skills, privacy issues, cultural issues
Stylianou and Talias (2017)	Big data in healthcare: a discussion on the big challenges (*Health and Technology*)	Healthcare/ Cyprus	Not specified	Data quality, user training and information systems, economic, privacy and consent
Li et al. (2019)	Barriers of embedding big data solutions in smart factories: insights from SAP consultant (*Industrial Management & Data Systems*)	Smart/China	Technological and data-related, people, organization-wide barriers	Lack of understanding and planning, lack of top management commitment, lack of departmental collaboration and alignment, failure to identify big data analytical needs, lack of qualified consultants, lack of in-house scientists, immature CPS and IoT development, poor big data sets, poor big data management, information security threats, user resistance, lack of trust in big data analytical results
Moody et al. (2019)	Look before you leap: barriers to big data use in municipalities (*Information Polity*)	Government/ The Netherlands	Technical, informational	Insufficient infrastructure, loss of legitimacy, uninterpretable information
Moktadir et al. (2019)	Barriers to big data analytics in manufacturing supply chains: a case study from Bangladesh (*Computers & Industrial Engineering*)	Manufacturing/ Bangladesh	Technology-related, expertise- and investment- related, data-related, organization-related	Unavailability of specific BDA tools, lack of interest in implementing new technology, lack of skilled IT personnel, high costs of investment, lack of funding, lack of facilities to research and develop BDA tools, complexity of data integration, data quality, data security and privacy, performance and scalability, no policy to share data among organizations, lack of training facilities, time constraints, mindset in terms of big data
Shukla and Mattar (2019)	Next generation smart sustainable auditing systems using big data analytics: understanding the interaction of critical barriers (*Computers & Industrial Engineering*)	Agri-food/UK	Not specified	Poor business case, financial constraints, lack of top commitment, operational resistance to change, legacy systems in place, poor data quality, complexity of data management, data security concerns, legal and ethical challenges, lack of knowledge sharing, lack of infrastructure readiness, lack of skilled labour, immature technology, scalability challenges, risk of system failure
Zhang and Lam (2019)	A fuzzy Delphi-AHP-TOPSIS framework to identify barriers in big data analytics adoption: case of maritime organizations (*Maritime Policy & Management*)	Maritime/Multi-country	Cultural, managerial, technical	Difficult architecture of big data analytic system, current database software lacks in database analytics, scalability problem with big data, cannot make big data usable for end users, current database software cannot load data and process analytic queries fast enough, current data warehouse modelled for reports only, data security issues, inconsistent data quality, lack of understanding of how to use analytics to improve the business, lack of executive sponsorship, lack of staffing or skills for BDA, lack of management bandwidth due to competing priorities, difficulty forecasting costs and benefits, time consuming setting up the structure for using BDA in business decision making
Bag et al. (2020)	Big data analytics in sustainable humanitarian supply chain: barriers and their interactions (*Annals of Operations Research*)	Humanitarian/ African countries	Not specified	Poor data management, multiple data formats, lack of skills for data processing and correct interpretation, insufficient training and education, complexity, fear of new technology, infrastructure un-readiness,

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Table 1 (*continued*)

Barriers' identification by checking relevant literatures				
Author(s) (year)	Paper/journal title	Industry/ country focus	Barrier categorization	Barrier identified
				traditional mind-set of existing employees, difficulty changing entire organizational culture, low focus on new employee deployment, lack of focus on instilling modern management practices, poor infrastructure, poor information sharing, failure to attract funds, few public-private partnerships
Chen et al. (2020)	Big data management in healthcare: adoption challenges and implications (*International Journal of Information Management*)	Healthcare/ China (Taiwan)	Expertise, operations, resources, regulation, market access	Poor staff cooperation, data analysis ability, data application ability, multidisciplinary communication, data integration mechanisms, poor cooperation with patients, data approach ability, unwillingness to share, basic complementary measures, data creditability, high initial import costs, heavy staff workloads, regulatory limitations, data access, and utilization, responsibility for misdiagnoses, differences between divisions, protection of patient privacy, lack of incentives, limitation of value-added application
Annosi et al. (2021)	Digitalization within food supply chains to prevent food waste. Drivers, barriers and collaboration practice (*Industrial Marketing Management*)	Agri-food/Greece	Not specified	Collaboration among parties along the supply chain limited by small and medium-sized firms' capabilities to advance their systems to monitor food products, lack of knowledge of how digitalizing processes may substantially improve the environment and reduce food waste, smaller firms do not have resources to invest in digitalization, transition to digital technologies must involve people, lack of trust, psychological resistance, perception of new risks, lack of right personnel
Gupta and Goyal (2021)	Framework for implementing big data analytics in Indian manufacturing: ISM-MICMAC and fuzzy-AHP approach (*Information Technology and Management*)	Manufacturing/ India	Infrastructure & technology, organizational, operational, knowledge & skills, financial, data, management-related	Lack of infrastructure facility, unavailability of specific data tools, lack of training facilities, time constraints, no organizational data-sharing policy, lack of skilled IT personnel, lack of awareness of data analytics, lack of long-term vision, lack of management initiatives, lack top management commitment, high investment costs, lack of funding, data security and privacy, data quality, performance and scalability, complexity of data integration
Kazancoglu et al. (2021)	A fuzzy based hybrid decision framework to circularity in dairy supply chains through big data solutions (*Technological Forecasting & Social Change*)	Agri-food/Turkey	Economic, social and legal, environmental, technological, supply chain management, strategic	Lack of economic incentives, high investment costs for transformation, increased research and development costs, inadequacy of legal systems, inadequate knowledge transfer, lack of skilled workforce, lack of supplier commitment, insufficient environmental standards, inefficient use of resources, lack of incentives for green supply chain, issues relating to data security, integration, and privacy, technical infrastructure deficiency, lack of integration between technological processes and eco-efficiency, lack of implementation of emerging technologies, difficulty in balancing supply and demand, little understanding and knowledge of CE, inefficient information sharing, lack of transparency, inability to cope with dynamic nature and complexity, short product lifecycles, lack of enterprise policies and missions, inefficient top management commitment and support, lack of collaboration, coordination, and cooperation among stakeholders, lack of effective business models and frameworks, issues relating to cultural change during CE adoption
Pal et al. (2021)	Problems of big data adoption in the healthcare industries (*Asia-Pacific Journal of Health Management*)	Healthcare/ India	Not specified	Expertise, operational, resource, regulatory, and market access barriers

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Table 1 (*continued*)

Barriers' identification by checking relevant literatures				
Author(s) (year)	Paper/journal title	Industry/ country focus	Barrier categorization	Barrier identified
Raut et al. (2021a)	Big data analytics: implementation challenges in Indian manufacturing supply chains (*Computers in Industry*)	Manufacturing/ India	Not specified	Poor data quality and lack of trust in data, time-consuming activity, insufficient resources, lack of security and privacy, lack of financial support, behavioural issues, return on investment issues, lack of top management support, lack of skills, data scalability, lack of techniques or procedures, lack of data integration and management
Raut et al. (2021b)	Unlocking causal relations of barriers to big data analytics in manufacturing firms (*Industrial Management & Data Systems*)	Manufacturing/ India	Not specified	Lack of IT infrastructure, lack of data storage facility, lack of skilled workforce, IT illiteracy, employee resistance, lack of competitive ecosystem, lack of top management interest and support, lack of organizational strategy, uncertain about benefits and long-term usage, lack of data privacy, confidentiality, safety and security, lack of data authenticity and data accuracy, lack of financial support, poor returns on investment, lack of legal and ethical support by the government and state bodies
Alrahbi et al. (2022)	Challenges for developing health-care knowledge in the digital age (*Journal of Knowledge Management*)	Healthcare/ United Arab Emirates (UAE)	Not specified	Lack of motivation, lack of training strategy, lack of unified procedure, lack of coordination between health authorities, lack of marketing strategy, cost strategy, weak technology strategy, low standards, availability of technology, scope of telecoms infrastructure, technology life span, compatibility between old and new technology, technology maintenance, sensitivity of data, information security and privacy, information infrastructure, social awareness of big data, maturity of big data, staff learning behaviour, lack of global orientation, education background
Jain and Ajmera (2022)	Modelling the barriers of Industry 4.0 in India using fuzzy TISM (*International Journal of Business Performance Management*)	Manufacturing/ India	Not specified	Jobs disruption, excessive investments, need for specialized training and skills, data security and privacy concerns, lack of comprehensive network and IT facility, regulatory compliance issues, lack of uniform standards for information exchange, legal risk from external data use, insufficient maintenance support systems, organizational culture, government support, lack of digital strategy with resource scarcity, lack of top management support, employee resistance, unclear perceptions of IoT
Khan (2022)	Barriers of big data analytics for smart cities development: a context of emerging economies (*International Journal of Management Science and Engineering Management*)	Smart city/India	Privacy and security-related, technological, and management-related barriers	Lack of data privacy and security protocols, lack of data sharing, vulnerability to attack, lack of technologies to implement BDA, lack of computational power, heterogeneous environment, incompleteness, and interoperability, lack of big data processing platforms, data complexity, population diversity, lack of framework for BDA adoption, lack of collaboration, high investment costs
Konanahalli et al. (2022)	Drivers and challenges associated with the implementation of big data within UK facilities management sector: an exploratory factor analysis approach (*IEEE Transactions on Engineering Management*)	Facility/UK	Technological barrier, issues related to data governance and management, inadequate preparedness for BDAC initiatives, and data quality and skill gap	Poor quality data, concerns about security of data transmitted over the network, lack of clarity on how assets should be hierarchically grouped, inconsistent connectivity to handle bandwidth-intensive real-time applications, legal issues associated with aggregating massive amounts of data, ethical issues associated with data storage, ambiguity associated with ownership of big data, restricted rights to remotely access and control building management systems, closed protocols by product manufacturers, issues with legacy systems integration, lack of clear business cases for funding, lack of budget, lack of skilled talent, stakeholders resistance to change

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Table 1 (*continued*)

Author(s) (year)	Paper/journal title	Industry/ country focus	Barrier categorization	Barrier identified
Barriers' identification by checking relevant literatures				
Kumar et al. (2022a)	Analysis of barriers intensity for investment in big data analytics for sustainable manufacturing operations in post-COVID-19B pandemic era (*Journal of Enterprise Information Management*)	Manufacturing/ India	Not specified	Lack of policies for data security and privacy, absence of data-driven decision-making culture, high cost of developing digital infrastructure, ineffective performance framework for assessing the effectiveness of investments on new technologies, rigid organizational culture for making new investments on technologies, lack of confidence of return on investment in BDAC adoption, lack of research on applications of BDA tools, high cost associated in managing unstructured huge data, unavailability of specific BDA tools, absence of coordination among stakeholders, high cost associated in integrating data across the supply chain, inadequate data sharing policy among stakeholders, lack of competence for using BDA in resource optimization, lack of support from employees for implementing new technologies, high cost of hiring skilled big data analytic consultants, high cost of training programs, lack of trust and commitment among employees
Kumar et al. (2022b)	Fuzzy AHP approach for barrier to implement LSS in the context of Industry 4.0 (*International Journal of Productivity and Performance Management*)	Manufacturing /India	Not specified	High investment and implementation cost, employee fear and resistance to change, lack of top management commitment, unavailability of skilled manpower and need for enhanced skills, lack of awareness of data collection and analysis, cyber security and data privacy issues, lack of regulation, lack of data management system, lack of standards, legal issues and contractual uncertainty, lack of IT and organizational infrastructure, difficulty to identify process dimensions, seamless integration and compatibility issues, lack of availability of suppliers for embedded systems, low maturity level, lack of clarity about economic benefits, lack of leadership, advisory and monitoring, challenges in value-chain integration, lack of training and education, lack of integration of lean six sigma with smart tools, lack of good external consultant, lack of proper recognition and rewards, lack of effective communication, poor supply chain integration, ineffective model or road map of project implementation
Rathore et al. (2022)	Identification and analysis of adoption barriers of disruptive technologies in the logistics industry (*The International Journal of Logistics Management*)	Logistics/India	Not specified	Legal and data framework, resistance to change, infrastructure, data management, lack of trust, lack of communication, lack of top management support, lack of adequate resources, lack of advanced analytics skills, lack of reliability, privacy and security, technical issues
Tamvada et al. (2022)	Adopting new technology is a distant dream? The risks of implementing Industry 4.0 in emerging economy SMEs (*Technological Forecasting & Social Change*)	Manufacturing/ India	Financial, technological, operational, business, societal and environmental, supply chain, and cybersecurity	High investments, unclear economic benefit, long and uncertain amortization, risk of false investments, a decision in what to invest when, too late investments, risk of obsolescence of an investment in technology, personal cost, inadequate qualification of employees, redesign of facility layout, shifts of competencies, internal resistance and corporate culture, lack of expertise, low awareness, fear of employees, maintenance, infrastructure shortcomings, manufacturing process management-based risk, organizational risk, higher complexity, sabotage by employees, lack of standards, IT-interface problem, technical complexity and integration, lack of decision logic, low degree of maturity, availability of fast internet, power shifts, losing a competitive advantage, legal and political customers, job losses,

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Table 1 (*continued*)

Barriers' identification by checking relevant literatures				
Author(s) (year)	Paper/journal title	Industry/ country focus	Barrier categorization	Barrier identified
				mental stress, wastages, emissions, system overload, IT security, loss of suppliers
Re-categorization of barriers from synthesis of existing studies				
Category	**Barriers**			**Empirical identification from our study**
Data and technology barriers	Data security and compatibility issues, data integration issues, legal and ethical issues, privacy issues, complexity of data, possible bias in data capturing and presentation, immaturity of big data, lack of consistent in data measurement and analysis, immature of CPS and IoT development, information security threats, loss of legitimacy, data quality issues, scalability challenges, data credibility, lack of data storage facility, lack of data authenticity and data accuracy, compatibility between old and new technologies			Complexity of data, lack of a data integration approach, lack of parallel computing approaches
Basic resource barriers	Infrastructure unreadiness, high costs of investment, lack of funding, lack of facilities to research and develop BDA tools, time constraints, lack of government support			Lack of funding, limited access to data, time constraints
Technological and managerial barriers	Timely data processing for real-time systems, too many vendors selling many different products, lack of specific big data tools, lack of data analytics skills, lack of available evidence/cases of big data, short-term thinking, difficulty obtaining value from extensive amount of volatile data, lack of user training and information systems, lack of top management commitment, lack of understanding and planning, lack of qualified consultants, mistrust of big data analytics results, mindset in terms of big data, difficulty of architecture big data analytic systems, inability to make big data usable for end users, current database software lacking in database analytics, difficulty of forecasting costs and benefits, lack of management bandwidth due to competing priorities, lack of focus on instilling modern management practices, few public-private partnerships, market access barriers, lack of long-term vision, lack of economic incentives, lack of supplier commitment, uncompetitive ecosystem, lack of organizational strategy, technology maintenance, social awareness of big data, lack of computational power, vulnerability to attack, risk of false investments, redesign of facility layout, lack of advice and monitoring, high cost of training programmes, high cost of hiring skilled big data analytics consultants, absence of coordination among stakeholders			Lack of education and training, lack of data analytics skills, lack of capacity to anticipate future needs, lack of capability to interpret big data results
Cultural barriers	Cultural issues, user resistance, stakeholders' resistance to change, difficulty changing entire organizational culture, behavioural issues, internal resistance and corporate culture, absence of data-driven decision-making culture			Lack of error correction mechanisms, lack of continuous assessment and improvement, lack of coordination
Organizational learning barriers	Lack of collaboration and data sharing, lack of knowledge sharing, traditional mindset of existing employees, poor staff cooperation and learning behaviour, inadequate knowledge transfer			Unwillingness to share knowledge, lack of organizational memory, lack of incentives for employees to test new knowledge

each variable in the system. These limitations are alleviated by combining it with AHP and MICMAC analysis. Fourth, the results can be triangulated by employing a mixed-method approach (Zhao et al., 2020). For example, MICMAC analysis can be used to evaluate the results of TISM. Fifth, philosophically, a mixed-method approach allows investigation from both inductive and deductive perspectives, and consequently enables researchers to combine theory generation and hypothesis testing in a single study (Jogulu and Pansiri, 2011).

In this study, we conducted semi-structured interviews to collect data from experienced port practitioners, followed by thematic analysis to identify barriers impeding ports from establishing BDAC. The barriers identified through thematic analysis were then used as inputs for further analysis, using AHP to prioritize the categories of barriers and the barriers within each category and overall, TISM to build interrelationships between barriers, and MICMAC analysis to cluster the barriers based on their individual characteristics, for instance as driving or dependent barriers. The research methodology is illustrated in Fig. 1.

3.1. Data collection method

Semi-structured interviews were used to collect data by asking predefined questions around a thematic framework. Four primary considerations determined this choice of method. First, semi-structured interviews allow flexibility to ask probing research questions (Gugiu and Rodriguez-Campos, 2007). Second, a standardized interview schedule would not have accounted for the diverse educational, professional, and personal histories of the sample group (Barriball and While, 1994), and unstructured interviews would have been inappropriate to prompt responses specific to our questions. Third, semi-structured interviews elicit higher response rates than questionnaires (McIntosh and Morse, 2015). Finally, semi-structured interviews are well-suited to exploring participants' perceptions, knowledge, and opinions of an experience or phenomenon (Morse and Niehaus, 2009).

3.2. Data analysis methods

A combination of thematic analysis, AHP, TISM, and MICMAC analysis was employed in this study.

Thematic analysis is a qualitative approach widely applied to identify, describe, and report themes in a data set (Braun and Clarke, 2006). For several reasons, we selected this as the first method for analyzing the data collected from semi-structured interviews. First, it is helpful for generating unanticipated insights by highlighting similarities and differences across a data set. Second, it follows a well-organized structure, making it easier to summarize key features of a large data set (King, 2004). Third, it allows high flexibility, helping to generate rich and detailed accounts of data. Other qualitative data analysis techniques, such as grounded theory, narrative analysis, or discourse analysis, would have been unsuitable for this study owing to limitations in dealing with the variability and manifestations involved (Braun and Clarke, 2006).

AHP is a well-developed MCDM method for prioritizing alternatives in a complex decision-making problem (Saaty, 1980). It has been widely applied in various areas, including risk prioritization, supplier selection, and enterprise resource planning systems (Luthra et al., 2016; Bemmami and David, 2021). Other potential methods would have been inapplicable in this study owing to their various limitations. For example, the technique for order of preference by similarity to ideal solution (TOPSIS) technique has been criticized for its high subjectivity, ANP has limited applicability because of its complex process, and ELECTRE requires an additional threshold to be introduced when ranking alternatives (Sabaei et al., 2015; Yu et al., 2018). AHP has the advantages of wide applicability and ease of use (Emrouznejad and Marra, 2017), and was applied in this study to prioritize barriers impeding BDAC improvement in ports.

TISM is a qualitative modelling technique for building links between variables in a system. It helps to transform an unarticulated model into an unambiguous and straightforward model, and therefore helps to answer "what", "why", and "how" questions in theory building (Jena et al., 2017). Other methods, such as graph theory, structural equation

Table 2
MCDM methods used to evaluate barriers to BDAC adoption.

Author(s) (year)	Topic	MCDM methods used	Industry/ country focus	Number of barriers evaluated	Key barrier(s)
Moktadir et al. (2019)	Identifying and prioritizing barriers to big data analytics adoption	A Delphi-based AHP	Manufacturing/ Bangladesh	15	Lack of industrial facilities, high cost of investment, complexity of data integration, time constraints
Shukla and Mattar (2019)	Identifying and linking barriers	ISM-MICMAC	Not specified/ UK	15	Complexity of data management, immaturity of technology, lack of skilled labour
Zhang and Lam (2019)	Identifying and prioritizing barriers	Combination of Delphi, AHP and TOPSIS	Maritime/ Multi-country	11	Lack of understanding of how to use analytics to improve the business
Bag et al. (2020)	Identifying and linking barriers that impede BDAC adoption	Fuzzy TISM-MICMAC	Humanitarian/ Not applicable	15	Poor management of data generated from multiple sources and failure to attract funds
Chen et al. (2020)	Evaluating organization-driven barriers in implementing a big data-based healthcare information system	VIKOR	Healthcare/ Not applicable	20	Data application, data integration, data utilization, heavy staff workloads, and limited value-added applications
Gupta and Goyal (2021)	Identifying, ranking, and linking barriers to BDAC adoption	ISM-MICMAC-fuzzy AHP	Manufacturing/ India	16	Lack of top management commitment
Kazancoglu et al. (2021)	Uncovering and ranking potential barriers	Combination of fuzzy AHP-VIKOR	Agri-food/ Turkey	27	Economic barriers
Raut et al. (2021a)	Identifying and evaluating barriers to BDAC adoption	Combination of ISM and DEMATEL	Manufacturing/ India	15	Lack of top management support
Raut et al. (2021b)	Identifying barriers to BDAC adoption, and evaluating their cause-effect relationships	Combination of DEMATEL and ANP	Manufacturing/ India	15	Lack of data storage facilities, lack of IT infrastructure, lack of organizational strategy, uncertainty about benefits and long-term usage
Alrahbi et al. (2022)	Challenges for developing knowledge in digital age	Exploratory and confirmatory factor analysis	Healthcare/ UAE	16	Organizational strategy, technical barriers, readiness for big data and IoT, orientation
Jain and Ajmera (2022)	Modelling barriers to Industry 4.0	Fuzzy TISM	Manufacturing/ India	15	Lack of top management support
Khan (2022)	Investigating and prioritizing barriers to development of a smart city	BWM	Smart city/ India	13	Data complexity, and lack of framework and technologies for BDAC adoption
Kumar et al. (2022a)	Analysis of barriers to BDAC adoption for sustainable manufacturing operations	Graph theory matrix approach	Manufacturing/ India	17	Organizational barriers
Kumar et al. (2022b)	Analysis of barriers to implementing lean six sigma with big data analytics	Fuzzy AHP	Manufacturing/ India	27	Lack of leadership, advice and monitoring, lack of clarity about economic benefits
Konanahalli et al. (2022)	Ranking barriers to BDAC adoption	Exploratory factor analysis	Facility industry/UK	14	Data governance and management issues
Rathore et al. (2022)	Identifying and analyzing barriers to BDAC adoption	Fuzzy Delphi-ISM-MICMAC	Logistics/ India	12	Lack of top management support
Tamvada et al. (2022)	Analysis of barriers to adopting new technologies	Fuzzy-AHP	Not specified/ India	70	Financial and technological barriers

modelling (SEM), and interpretive structural modelling (ISM), can all be used to build interactions among variables, but each has limitations. For example, TISM only needs a small sample size, whereas a large sample is required for SEM (Tarka, 2018). Graph theory fails to indicate directions between two variables, whereas TISM does not suffer from this drawback (Agarwal et al., 2022). Finally, TISM has a critical advantage over ISM in providing explanations of links between variables (Sushil., 2012). Thus, in this study we applied TISM to build links between the barriers identified as impeding applications of big data technologies in ports.

Finally, we used MICMAC analysis to cluster the barriers and verify the TISM model. Two primary considerations were that it would provide deeper insights into the role of each variable in the system, and that it has been widely combined with TISM in previous studies (Raut et al., 2021a).

4. Empirical data collection

To develop an interview guide, we followed Gill et al. (2008)'s five-step process, comprising topic selection, defining different aspects of the topic, initial question formulation, final question determination through pilot tests, and determining the logical order of questions. Having reviewed relevant literature and conducted brainstorming sessions with two professors in data science and decision-making, we determined the topic, sub-topics, and initial questions, and evaluated the interview guide by conducting pilot tests with five maritime industry practitioners. This process indicated that we needed to improve our probing skills and give more examples during the interviews, such as citing examples of relevant software that might be used to perform BDA (e.g., Stata, Microsoft Power BI, IBM Watson Analytics). Our final interview guide consisted of six sections covering general questions, data and technology barriers, resource barriers, technological and managerial barriers, cultural barriers, and organizational learning barriers (see Appendix 1).

We employed purposive sampling and snowball sampling to collect empirical data from 26 ports in China (see Appendix 2). Chinese ports were selected for three reasons. First, in 2015, the Chinese government built its first big database for international shipping at Qingdao Port to facilitate modernization of the port and the shipping industry (Port Technology, 2015). More big databases have since been built across the country as a result of supportive policies and finance. Second, China has 17 ports listed in the top 50 container ports globally, based on their capacity to handle twenty-foot equivalent units (World Shipping Council, 2022). Third, the authors have deep connections with China's shipping and port industry resulting from participation and involvement in Horizon 2020 projects, making it easier for us to find suitable respondents. Purposive sampling is a method used to identify and select respondents most likely to yield useful and appropriate knowledge about the investigated phenomenon (Kelly, 2010). After several brainstorming sessions with the researchers involved in this study, we developed three criteria for identifying suitable respondents. First, to ensure the respondents' high-level knowledge and expertise, those selected should have more than ten years' working experience in ports and more than five years relating to big data. Second, to ensure adequate

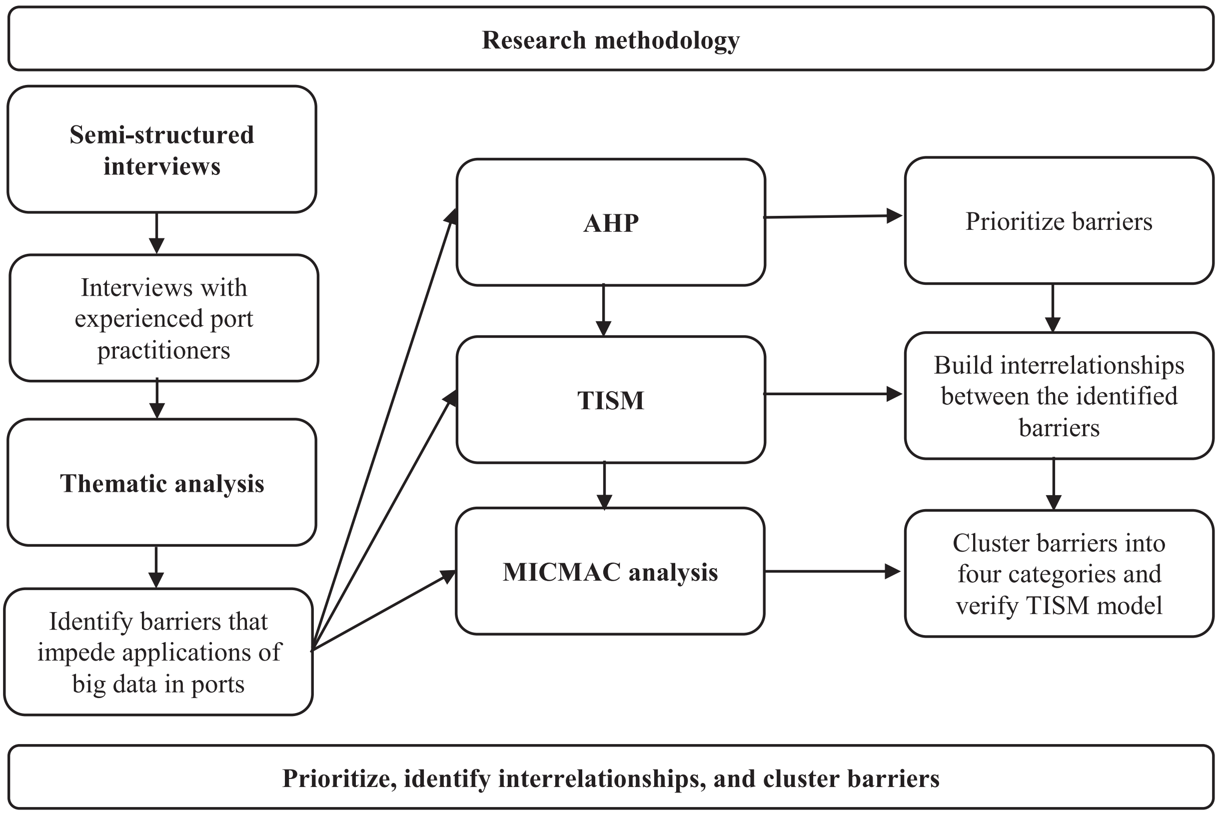

Fig. 1. Research methodology adopted.

knowledge relating to big data, respondents should be senior technicians, senior engineers, or other senior-level professionals. Third, the selected ports must have applied or be intending to apply BDA to assist their daily operations. Having participated in several maritime-focused projects funded by the Horizon 2020 Research, Innovation, Science, Expert (RISE) programme, we had built connections with several Chinese professors experienced in multimodal transportation, port management, and navigation technology who had been working with China's port and shipping industry for more than 30 years and therefore had wide-ranging connections. Based on their recommendations, we generated an initial list of 28 ports that might have applied BDA. After checking with relevant terminal operators and port authorities through WeChat and telephone, we confirmed that only 17 of these had applied BDA. We then began to search for relevant senior-level professionals from these ports, using our connections and the Chinese professors' recommendations, which resulted in 32 potential participants. Some did not have interests in our topic or did not fulfil our criteria owing to insufficient port- or big data-related working experience. This reduced our initial selection to 17 participants.

We sent participants an introductory email three days before their interviews to give them sufficient time to prepare their answers. Each interview was recorded with permission, and many probing questions were asked to seek clarification. The interviews lasted 75 min on average, allowing respondents to express their ideas and elaborate on their answers. At the end of each interview, we asked them whether they knew anyone with an interest in and willingness to participate in this research, a technique known as snowball sampling. In this way, another 15 potential respondents were identified, whom we contacted through WeChat and telephone to check their eligibility and availability. Nine of them satisfied the aforementioned selection criteria. We employed Yin (2009)'s proposed 24-h rule to analyze our qualitative data. Rapid data analysis helped us to determine when data saturation had been reached. After 23 interviews, key phrases such as "complexity of data" and "lack of data analytics skills" emerged frequently from analysis of our discussions with practitioners. We conducted three further interviews to check that no new themes emerged. Thus, the total sample size was 26. No universal rules are recommended for data saturation of sample sizes. For example, Hennink and Kaiser (2022) propose that the data saturation point tends to be reached after conducting between nine and 17 interviews or four to eight focus group discussions, particularly for studies that have narrowly defined objectives and relatively homogeneous populations. According to Bekele and Ago (2022), the most frequently mentioned range at which data saturation is reached in qualitative research is between 20 and 60 interviews. Scholars are not agreed on sample sizes for saturation because this depends on several factors, such as the aim of the research, the type of research questions, the analytical strategy, the quality of the dialogue, and the researcher's experience of conducting qualitative research (Francis et al., 2010; Bekele and Ago, 2022). Previous discussions of sample size in qualitative research are consistent with the 26 interviews conducted in our study.

5. Data analysis and findings

Four data analysis methods were employed in this study: thematic analysis, AHP, TISM, and MICMAC analysis.

5.1. Identifying barriers to BDAC adoption through thematic analysis

Thematic analysis was employed to identify barriers to BDAC adoption from the semi-structured interview data. First, the data were transcribed and edited. This involved word-for-word transcription of the interview audio files, and careful removal of irrelevant words and sentences from the transcripts. Second, immersive reading of the transcripts several times ensured that the coders were familiar with the data. The third step was coding and categorization. Using qualitative data analysis software (NVivo 13), we initially highlighted any words and sentences relevant to barriers to BDAC adoption. The codes extracted from the transcripts were then collapsed into themes, which were labelled with established constructs from the literature focusing on barriers to BDAC adoption. We further categorized the identified themes into different dimensions/categories, and finally employed King and Horrocks' (2010) framework to present the results (see Appendix 3).

Accordingly, 16 barriers are identified across five categories. In the data and technology category, we identify three barriers: complexity of data, lack of a data integration approach, and lack of parallel computing approaches. Among these, complexity of data received the most attention from our industry practitioners, and lack of parallel computing approaches the least. One interviewee stated *"Container ports include a range of stakeholders (e.g., port authority and terminal operators) and many digital systems (e.g., terminal operating system, truck appointing system, and port community system), which results in data that may originate from disparate sources and poses difficulties to analyze them."* In some situations, data may be available for analysis. However, the situation is exacerbated by lack of a data integration approach: *"Data analytics is a complicated process, which involves several basic steps such as extracting data from various sources, storing data appropriately, and integrating and transforming data with analytics."* There are three barriers in the basic resources category: lack of funding, limited access to data, and time constraints. Of these, lack of funding gained significant attention from the industry practitioners. We suppose this to be because establishing BDAC in container ports involves large investments in infrastructure. One interviewee said: *"BDA is an effective technological innovation that can improve port efficiency, but its successful deployment involves applications of many infrastructures, such as sufficient computational power and technology integration across port stakeholders."* In addition, access to data may be difficult: *"Sometimes, it is not easy to access data because of privacy issues, and companies fear disclosing their trade secrets."* In the technological and managerial category, we identify lack of training and education, lack of data analytical skills, lack of capacity to anticipate future needs, and lack of capacity to interpret BDA results. Interestingly, 69.23 % (18/26) of interviewees mentioned lack of training and education as a barrier. This is because most training and education is short-term and theoretically or conceptually based, whereas practical training is largely lacking. One interviewee stated: *"We have training and educational sessions about the latest development trends in container ports, port digitalization, port sustainability, carbon-neutral ports, and policy education. However, these training sessions are conceptually based. What we are lacking is practically-based training sessions such as data analytical skills improvement."* This is also why 88.46 % (23/26) of interviewees claimed that they lacked data analytics skills, and 80.77 % (21/26) mentioned lack of capacity to anticipate future needs. In the cultural category of barriers are lack of error correction mechanisms, lack of continuous assessment and improvement, and lack of coordination. In particular, lack of error correction mechanisms was frequently mentioned by interviewees. One stated: *"It is difficult to provide feedback or comments to managers even though they made mistakes."* We believe that the China's hierarchical cultural value orientation makes employees reluctant to propose their ideas and challenge their managers. Finally, we identify three barriers in the organizational learning category: lack of organizational memory, unwillingness to share knowledge, and lack of incentives for employees to test new knowledge. One interviewee stated: *"There are punishments for employees who make mistakes or errors. However, there are no incentives for employees to test new knowledge because we are a state-owned enterprise and keeping the enterprise smoothly running is our priority."*

5.2. Prioritizing identified barriers using AHP

AHP was implemented to prioritize the identified barriers. This involved the following steps.

1) *Definition of the aim of implementing AHP*: The aim of conducting AHP was to evaluate barriers to BDAC adoption in the maritime industry to determine their relative importance.
2) *Formation of pair-wise comparisons*: This step involved pair-wise comparisons of the identified barriers based on an expert's judgments. A professor in data science and decision making who had been collaborating with the maritime industry for more than ten years was asked to rate the relationships between pairs of barriers, based on Saaty (1980)'s work (see Appendix 4). Pair-wise comparison matrices for categories of barriers, specific barriers in each category, and their relative weightings are shown in Appendix 5.
3) *Calculation of priority of each criterion*: This step involved calculating the priority of each criterion in terms of its contribution to BDAC adoption in the maritime industry. First, we calculated a normalized pair-wise comparison matrix by adding all values in each column and dividing each barrier by its column total. We then computed priorities for each criterion by calculating the average of the values in each row of the normalized matrix (Luthra et al., 2016).
4) *Implementation of consistency analysis*: The aim of conducting consistency analysis was to ensure that the expert's judgments on pair-wise comparisons were consistent. A consistency ratio (CR) of less than 0.1 would confirm that the judgments and pair-wise comparisons were acceptable (Saaty, 1980), whereas if the consistency ratio was greater than 0.1, the expert would be asked to review the ratings. To obtain a CR, it is necessary to divide the consistency index (CI) by the random index (RI). The CI is determined by λ_{max}, which represents the maximum average value, and is calculated as follows. First, each value in a specific column of the pair-wise comparison is multiplied by the corresponding criteria weightings. Second, the weighted sum value is calculated by summing all values in a specific row. Third, the weighted sum values are divided by the corresponding criteria weightings of each criterion. Through this procedure, λmax can be obtained. CI is then calculated using the eq. $CI = (\lambda max - n)/(n-1)$, where n represents the number of elements. The AHP analysis results indicate the relative importance of categories of barriers, and of specific barriers in each category (see Table 3).

Organizational learning barriers are the top-ranked category, followed by resource, cultural, technological and managerial, and data and technology barriers. This means that organizational learning plays a significant role in improving maritime organizations' BDAC, requiring them to continuously acquire, disseminate, and use big data-related knowledge at individual, group, and organizational levels. Second, unwillingness to share knowledge is weighted highest among the identified organizational learning barriers. Knowledge hiding was a common phenomenon in the maritime organizations investigated, with most employees withholding what they knew (Connelly et al., 2012). The reasons for this may include highly competitive relationships between employees, lack of trust, and overreliance on other colleagues. To tackle this problem, maritime organizations should establish more cognitively complex roles, such as senior data scientists, data engineers, and data analysts. Those in such roles tend to share more knowledge because they need to process large amounts of information and solve complex problems (Gagne et al., 2019). Third, lack of funding is the top-ranked barrier in the resource category, while time constraints are ranked bottom. Fourth, lack of error correction mechanisms is ranked first in the cultural barriers category. We believe that China's hierarchical cultural value orientation (Schwartz, 2006) makes it difficult for ground-level and middle-level employees to discuss their ideas with the top management team, especially concerning big data-related decisions. Thus, common practices and mechanisms, such as communicating, detecting, analyzing, and correcting errors, should be embedded in organizational routines (Cusin and Goujon-Belghit, 2019). Fifth, lack of education and training is given the highest relative weighting of the four technological and managerial barriers. Previous research confirms that lack of training and education is an obstacle to building BDAC (Moktadir et al., 2019; Bag et al., 2020). Training and education are critical for successful improvement of organizations' BDAC (Dubey and Gunasekaran, 2015). Thus, reskilling and upskilling employees, for instance by equipping

Table 3
Global ranking of barriers to BDAC adoption.

Category of barriers	Relative weighting	Relative rank	Specific barrier	Relative weighting	Relative rank	Global weighting	Global rank
Data and technology barriers$_{(D)}$	0.073407	5	Complexity of data$_{(D1)}$	0.267964	2	0.017628	15
			Lack of a data integration approach$_{(D2)}$	0.194629	3	0.036425	11
			Lack of parallel computing approaches$_{(D3)}$	0.537407	1	0.023353	12
Basic resource barriers$_{(R)}$	0.275771	2	Lack of funding$_{(R1)}$	0.633411	1	0.103532	2
			Limited access to data$_{(R2)}$	0.260447	2	0.038619	10
			Time constraints$_{(R3)}$	0.106412	3	0.016517	16
Technological and managerial barriers$_{(T)}$	0.076506	4	Lack of education and training$_{(T1)}$	0.505089	1	0.067586	8
			Lack of data analytical skills$_{(T2)}$	0.148133	3	0.093427	5
			Lack of capability to anticipate future needs$_{(T3)}$	0.075895	4	0.021646	13
			Lack of capability to interpret big data analytics results$_{(T4)}$	0.270883	2	0.06689	9
Cultural barriers$_{(C)}$	0.143635	3	Lack of error correction mechanism$_{(C1)}$	0.647994	1	0.100457	4
			Lack of continuous assessment and improvement$_{(C2)}$	0.229814	2	0.070313	7
			Lack of coordination$_{(C3)}$	0.122191	3	0.103518	3
Organizational learning barriers$_{(O)}$	0.430682	1	Lack of organizational memory$_{(O1)}$	0.260447	2	0.021574	14
			Unwillingness to share knowledge$_{(O2)}$	0.633411	1	0.144712	1
			Lack of incentives for employees to test new knowledge$_{(O3)}$	0.106142	3	0.074002	6

them with hard skills (e.g., programming language, SQL and NoSQL databases, data structure, algorithms) and soft skills (e.g., passion, teamwork skills, interpersonal skills, positive attitude) are key to leveraging BDAC. Finally, of the three data and technology barriers, lack of parallel computing approaches is ranked first.

In the global ranking of barriers, the top three barriers are unwillingness to share knowledge$_{(O2)}$, lack of funding$_{(R1)}$, and lack of coordination$_{(C3)}$. However, based on the thematic analysis, the three barriers attracting the most support from maritime industry practitioners are complexity of data$_{(D1)}$ (26/26, 100 %), lack of funding$_{(R1)}$ (26/26, 100 %), and lack of data analytical skills$_{(T2)}$ (23/26, 88.46 %). This divergence may arise from the AHP prioritization being based on one professor's knowledge, and the thematic analysis results being based on industry practitioners' experiences, as the two sources differ in education, knowledge, expertise, and working experience. One interviewee stated: *"we had difficulties to find qualified data scientists even if high salaries were given."* Therefore, industry practitioners broadly agree that lack of data analytical skills$_{(T2)}$ and complexity of data$_{(D1)}$ should be given critical attention. However, with the professor's expertise in data science and decision making, he did not prioritize these two barriers not prioritized in the AHP.

5.3. Establishing interactions between the identified barriers through TISM

Investigating the joint impact of various barriers to BDAC adoption may result in better management of an organization's BDAC than tackling each barrier in isolation (Ho et al., 2015). AHP helped us to prioritize the identified barriers, highlighting which particular barrier types to alleviate and mitigate. However, this technique does not help to identify interrelationships and interdependencies between barriers, which may hinder BDAC improvement because mitigating one barrier may induce other barriers. Thus, we needed to explore interactions between the identified barriers. To do so, the following nine-step process was implemented for TISM:

1) *Barrier identification and definition*: This step involved identifying and defining the barriers to be modelled, using the barriers identified from our interviews with maritime industry practitioners as inputs into the TISM process.
2) *Determination of contextual relationships between pairs of barriers*: In focusing on building interrelationships between the 16 barriers identified, contextual relationships between two barriers were defined as "Barrier A will cause/induce Barrier B."
3) *Interpretation of relationships between pairs of barriers*: The expert was asked: (1) "do you think that barrier A will cause/induce barrier B"; and if yes, (2) "in what way will barrier A cause/induce barrier B." Through answers to these two questions provided deeper knowledge of barriers to BDAC adoption.
4) *Interpretive logic of pair-wise comparison*: This step involved individually comparing each barrier with all the other barriers. Thus, the total number of pair-wise comparisons for the 16 barriers was $n \times (n-1) = 16 \times (16–1) = 240$. An interpretive logic-knowledge base was developed based on the pair-wise comparisons. The experts' opinions were captured for each pair-wise comparison, coded "Y" to represent the presence of a relationship between two barriers, and "N" for no relationship. Relationships coded "Y", were then further interpreted.
5) *Development of initial and final reachability matrices*: An initial reachability matrix (see Appendix 6) was developed from the interpretive logic-knowledge base by transforming "Y" codes into "1" and "N" codes into "0". A transitivity check was then conducted to transform the initial reachability matrix into a final reachability matrix, using the rule "If barrier A relates to barrier B, barrier B relates to barrier C, which indicates barrier A necessarily relates to barrier C". The final reachability matrix is shown in Appendix 7.
6) *Determination of levels by partitioning the reachability matrix*: This step involved determining the levels of each barrier in the TISM model. Thus, it was important to determine the reachability set and antecedent set for each barrier based on the final reachability matrix. The reachability set for a particular barrier contains the barrier itself and any other barriers that it will cause/induce, and the antecedent set consists of the barrier itself and any other barriers that will cause/induce it. The intersection set is determined from the reachability and antecedent sets. This step was performed until the levels of all barriers were determined (see Appendix 8).
7) *Development of a digraph*: A digraph was developed by arranging all the barriers at their respective levels, and linking them through direct and transitive links (see Appendix 9). Only important transitive links were retained, based on the expert's recommendation.
8) *Interpretive matrix*: A binary interaction matrix was obtained by translating all interactions in the digraph into "1" in the respective cells. For cells with a "1" entry, relevant interpretations were extracted from the interpretive logic-knowledge base to form the interpretive matrix.

9) *Total interpretive structural model*: We formulated a TISM model of barriers to BDAC adoption to reveal their interdependencies and interactions (see Fig. 2).

The TISM analysis produced a hierarchical framework with ten levels (see Fig. 2). Lack of coordination$_{(C3)}$ is located at the lowest level of the TISM hierarchy, and lack of continuous assessment and improvement$_{(C2)}$ at the highest. The remaining 14 barriers are dispersed from levels II to IX. Coordination is critical in enabling maritime organizations to develop their BDAC, as multidisciplinary work is required to bring together various technical, analytical, and functional perspectives (Espinosa and Armour, 2016). However, lack of coordination exists widely at departmental and organizational levels in China. For example, lack of motivation to interact with higher-level governments to secure financial support for BDAC development may result in lack of funding$_{(R1)}$, and exacerbate lack of education and training$_{(T1)}$. Training and education are essential to enable employees to update their skill sets and knowledge relating to big data, such as applications of data visualization software, cloud services, programming languages, and understanding of the latest trends. However, education and training was commonly lacking in the maritime organizations investigated, potentially resulting in lack of error correction mechanisms$_{(C1)}$ and lack of parallel computing approaches$_{(D3)}$. Without parallel computing, different data analysis tasks and subtasks cannot be run simultaneously, giving rise to time constraints$_{(R3)}$ in big data projects. Lack of error correction mechanisms$_{(C1)}$ may also cause top management teams to make wrong decisions relating to big data. This may be due to unequal distribution of power, roles, and resources between the top management team and ground-level workers (e.g., software engineers, statisticians, and data architects), employees being expected to comply with rules and obligations attached to their roles, and difficulty in ground-level workers' comments, opinions, and knowledge reaching the top management team. Furthermore, employees may not be encouraged to trial and test new knowledge if financial resources are insufficient and punishments may be applied when they make mistakes. Therefore, lack of incentives for employees to test new knowledge$_{(O3)}$ and unwillingness to share knowledge$_{(O2)}$ were present in most of the organizations investigated.

The maritime industry generates around 100–120 million pieces of data per year (Trelleborg, 2022). These come from various sources, such as vessel movements, port operations, and transaction and financial records. To forecast equipment failures, conduct sustainable analysis of refrigerated containers, and streamline flows of goods, data scientists need to analyze structured, unstructured, and semi-structured data from various sources. Given the complexity of data$_{(D1)}$, they may lack sufficient data analytics skills$_{(T2)}$. Qualified data scientists must master a range of analytics skills, such as data cleaning and visualization, ability to use structured query language (SQL), NoSQL, and statistical programming languages (e.g., R, Python), and critical thinking and communication skills. Without sufficient and appropriate data analytics skills, they will find it difficult to analyze, interpret, and present data. Thus, lack of capability to anticipate future needs$_{(T3)}$ frequently arises from the difficulty of gaining deep insights from data. In congested ports, it is difficult to re-plan routes and vessel positions. Lack of a data integration approach$_{(D2)}$, lack of capability to interpret big data analytics results$_{(T4)}$, and lack of organizational memory$_{(O1)}$, make continuous assessment and improvement$_{(C2)}$ impossible.

5.4. Categorizing barriers through MICMAC analysis

MICMAC analysis was used to differentiate the role of each barrier in the system. We clustered the 16 barriers into four categories based on each barrier's driving and dependence power. Driving power was obtained by summing the values of each row in the final reachability matrix (see Appendix 7), and the corresponding dependence power was obtained by summing the values of each column. Based on their driving and dependence power, we plotted the barriers into four clusters (see Fig. 3). Higher driving power means a barrier has a greater opportunity to elicit other barriers in the system and occupies a lower level in the TISM hierarchy, whereas higher dependence power indicates that a barrier is more likely to be elicited by other barriers in the system and occupies a higher level in the TISM hierarchy.

➢ Independent barriers, characterized by high driving power and low dependence power, include lack of coordination$_{(C3)}$, lack of funding$_{(R1)}$, lack of education and training$_{(T1)}$, lack of incentives for employees to test new knowledge$_{(O3)}$, lack of error correction mechanisms$_{(C1)}$, lack of parallel computing approaches$_{(D3)}$, time constraints$_{(R3)}$, and unwillingness to share knowledge$_{(O2)}$. These act as drivers of the system, and therefore have more opportunities to elicit other barriers in the system. In particular, lack of coordination$_{(C3)}$ is located at the lowest level of the TISM hierarchy and has the highest driving power; therefore, tackling this should be a priority.

➢ No linkage barriers were identified in this study. Linkage barriers link lower-level independent barriers and higher-level dependent barriers in the TISM hierarchy, and are characterized by high driving and high dependence power.

➢ Autonomous barriers are characterized by less driving and dependence power. Only one barrier, limited access to data$_{(R2)}$, is categorized in this cluster. Autonomous barriers do not normally have many connections with the system. A majority of our interviewees stated that they had not experienced limitations in accessing data, with one commenting that "there are data from vessel movements, ships, transaction and finance records, credit reports, and bunker costs available for analysis."

➢ Dependent barriers, characterized by high dependence power and low driving power, are located at a relatively high level of the TISM hierarchy and are dependent on other barriers. The seven dependent barriers in our categorization are complexity of data$_{(D1)}$, lack of data analytical skills$_{(T2)}$, lack of capability to anticipate future needs$_{(T3)}$, lack of a data integration approach$_{(D2)}$, lack of capability to interpret big data analytics results$_{(T4)}$, lack of organizational memory$_{(O1)}$, and lack of continuous assessment and improvement$_{(C2)}$.

6. Discussion and contributions

In answering the three initial research questions, this study makes several contributions to the existing knowledge. First, 16 barriers across five categories (data and technology, resource, technological and managerial, cultural, and organizational learning) are identified as obstacles to improving BDAC in the maritime industry. Second, we prioritize these 16 barriers, providing a clearer understanding of their relative importance in impeding BDAC improvement. We also provide insights into interrelationships between the 16 barriers, which will guide their better management and elicit a systematic approach to tackling them. Third, this study establishes a categorization based on the role of each barrier in the system (independent, linkage, autonomous, dependent), which may help managers of maritime organizations to allocate resources more efficiently and effectively.

6.1. Theoretical contributions

The RBV is a well-developed theory and is widely used to investigate issues relevant to BDAC. Previous scholars using this approach to explore how resources can promote the performance of a firm, organization, institution, or supply chain, have confirmed that technological resources are necessary for BDAC (Alnuaimi et al., 2021; Ashaari et al., 2021; Saeed et al., 2022). However, what kind of technological resources may affect the adoption of BDAC in the context of container ports is less clear. Container ports differ from other organizations because they are constituted by a range of stakeholders, including the port authority and port terminal operators. Establishing BDAC at port

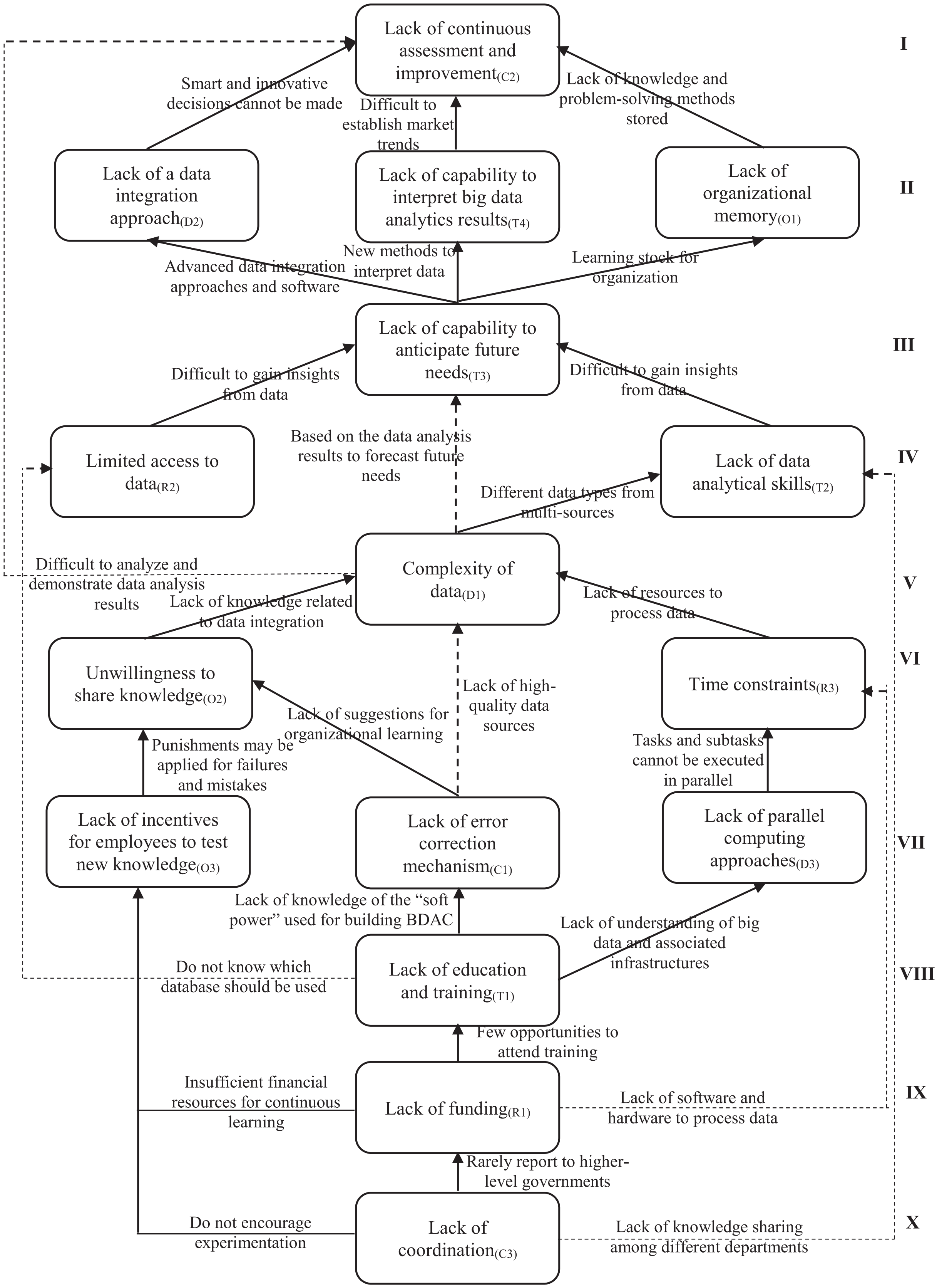

Fig. 2. TISM model of barriers to BDAC adoption.

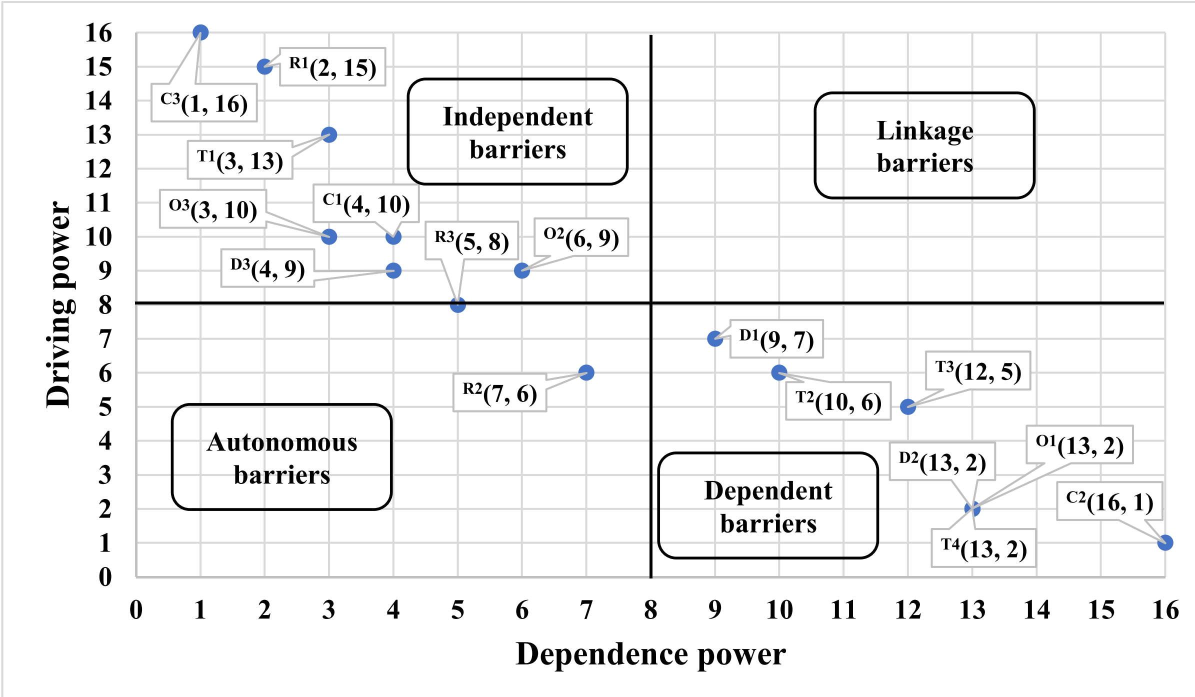

Fig. 3. MICMAC analysis of barriers to BDAC adoption.

community level is more difficult than building BDAC at the organizational level. Therefore, our study contributes to the RBV by highlighting that lack of technological resources such as a data integration approach, parallel computing approaches, and data analytical skills may raise obstacles to building container ports' BDAC. In a recent review of BDAC, Huynh et al. (2023) summarize seven big data-specific technological resources: data visualization, data provisioning, data processing, data aggregation, big data utilization, big data architectural components, and knowledge sharing of big data. However, they do not list parallel computing approaches, which is part of our contribution to the establishment of ports' BDAC. Moreover, our study is differ from previous work because we assume that BDAC adoption may be affected not only by a data-driven organizational culture, but also by the national cultural value orientation. In China, people are deeply affected by a hierarchical cultural orientation in which competition and obeying rules are viewed as good. As a result, they tend not to propose their ideas or challenge their leaders. The situation is even worse in some state-owned maritime enterprises, meaning that bottom-up feedback channels are ineffective. Therefore, it is difficult for the top management teams of maritime organizations in China to learn from frontline workers. This study extends application of the RBV to the area of barriers to BDAC adoption by identifying barriers from a cultural perspective. Finally, this study contributes to organizational learning theory in identifying that lack of organizational memory and lack of incentives for employees to test new knowledge are barriers to impede BDAC development. Although previous studies note the importance of organizational learning in building organizational BDAC (Gupta and George, 2016; Wamba et al., 2017; Calic and Ghasemaghaei, 2021), they do not clarify which specific elements of organizational learning may play an important role. Unlike other studies (Argote and Ren, 2012; Aissa et al., 2022; Lazar et al., 2022) that confirm the role of organizational memory systems at the team, departmental, and organizational levels, this study extends the research context to the port community level, highlighting that lack of an organizational memory system may raise obstacles to BDAC adoption.

Although previous studies have investigated barriers to adopting BDAC in various industries (Bag et al., 2020; Annosi et al., 2021; Kazancoglu et al., 2021; Raut et al., 2021a; Konanahalli et al., 2022; Tamvada et al., 2022), this study identifies several new barriers (see Table 1), including cultural barriers (lack of error correction mechanisms and lack of continuous assessment and improvement) and organizational learning barriers (lack of organizational memory and lack of incentives for employees to test new knowledge). However, several of our barriers support the existing literature. For example, Percin (2023) identifies 14 barriers impeding BDAC adoption in Turkey's agri-food industry, including barriers frequently mentioned by scholars, such as lack of financial resources, lack of top management support, complexity of data integration and management, and lack of skilled human resources. This study partially supports their results and confirms the presence of some of these barriers in China's maritime industry. Arunachalam et al. (2018) highlight two categories of barriers to adopting BDAC in supply chains: organizational barriers (time consuming, insufficient resources, privacy and security issues, behavioural issues, issues with returns on investment, and lack of skills) and technical barriers (data quality and scalability, and lack of techniques and procedures). This study reveals that time constraints, lack of data analytical skills, and data complexity are barriers that impede Chinese maritime organizations' adoption of BDAC. However, the maritime organizations involved in this study are state-owned enterprises that do not need to consider returns on investment, making a difference from Arunachalam et al. (2018)'s. Dehkhodaei et al. (2023) identify 34 barriers across seven categories in manufacturing industries, including barriers relating to data, technology, organizational issues, expertise and investment, governance, legal, and economic and business aspects. However, they do not mention any cultural- or organizational learning-related barriers. Qi et al. (2023) reveal several data- and technology-related barriers that challenge implementation of BDA in intelligent manufacturing systems, including data loss, leakage, offloading, data integration problems, and missing data streams. This study partially supports their view in identifying data complexity, lack of a data integration approach, and lack of parallel computing approaches as data- and technology-related barriers.

This study reveals that organizational learning is the most important category of barrier, while unwillingness to share knowledge and lack of coordination are the key individual barriers that most adversely influence BDAC improvement in the maritime industry. Our findings differ from those of most other studies in this area. Regarding prioritization of the categories of barriers to BDAC adoption, Percin (2023) identifies five categories and ranks with technological barriers as the first priority, followed by economic, social, environmental, and organizational barriers. In Moktadir et al.'s (2019) categorization, data-related barriers are ranked first, followed by technological, expertise and investment, and organizational barriers. Gupta and Goyal (2021) classify management, and infrastructure and technology-related-barriers as the main hurdles to implementing BDAC. However, in our findings, the organizational learning category is ranked first, whereas the data and technology category is last in the priority list. With regard to ranking individual barriers, our results also differ from existing work. Khan (2022) considers data complexity to be the most important of the 13 barriers identified. However, in our study, data complexity ranked only 15th of the 16 identified barriers. Bag et al. (2020) and Kumar et al. (2022a) indicate that lack of support from government and employees significantly impedes BDAC adoption. This study confirms that lack of coordination results in limited government funding, which further impedes BDAC deployment. Dehkhodaei et al. (2023) determine that lack of sufficient knowledge is the key barrier to establishing BDAC in a manufacturing industry. This study supports their view in confirming that unwillingness to share knowledge and lack of coordination are key impediments to the maritime industry's BDAC development. The study generates novel results that differ from existing studies conducted in countries with different economic, policy, and cultural environments. For example, in 2015, the Chinese government initiated its “Made in China 2025” programme to improve technological capabilities in ten key areas, including new information technology and new materials (Institute for Security and Development Policy, 2018). Several ports in China have already been equipped with big data technologies, including Qingdao, Guangzhou, Xiamen, Shanghai, and Shanghai Ports (Port Technology, 2015). Most of the ports investigated in this study seem to be equipped with the “hard power” (e.g., big data-related hardware) necessary to generate BDAC, but lack “soft power” in the form of forward and backward big data-related learning, knowledge, and skills across individual, group, and organizational levels. Our study appears to be the first to find that an organizational learning-related barrier (unwillingness to share knowledge) and a culture-related barrier (lack of coordination) are key barriers to BDAC development.

Finally, this study sheds light on the role of each barrier in the system. Eight barriers, including lack of coordination, lack of funding, and lack of education and training, are categorized as drivers that have the capability to elicit other barriers, one barrier (limited access to data) is classified as an autonomous barrier, and the remaining seven barriers are dependent barriers (e.g., lack of continuous improvement and assessment). Unlike other studies, we do not identify any linkage barriers. For example, Dehkhodaei et al. (2023) identify four linkage barriers to BDAC from data collected from Iranian companies: lack of top management support, weakness of data-driven decision-making, lack of funding, and lack of coherent planning. However, this study reveals that lack of funding is an independent barrier that may drive the system. This contrast shows that China's maritime industry is struggling to obtain government funding because China has the largest shipping fleet and shipping construction sector, and also has many of the world's top 50 container ports. To establish BDAC across all sectors of the maritime industry will be difficult and will require constant investment from the Chinese government. Bag et al. (2020) identify two driving barriers (insufficient training and education and poor management of data generated from multiple sources) among their 15 barriers to BDA adoption in the humanitarian industry. This study supports their finding since lack of training and education is classified in the independent barriers group. Raut et al. (2021b) find that six barriers drive challenges to the BDA of Indian manufacturing: lack of top management support, lack of financial support, lack of skills, lack of techniques or procedures, lack of sufficient resources, and data scalability. Our study partially supports their results.

6.2. Managerial implications

The results of this study have implications for tackling the organizational learning, basic resource, cultural, technological and managerial, and data and technology categories of barriers.

In our study, the organizational learning category (relative weighting of 0.430682) is ranked first among the five categories of barriers (see Table 3), indicating that tackling this category of barriers should be prioritized. Since establishing BDAC at port community level requires inputs from various port stakeholders to facilitate knowledge mobilization, we suggest that community-level transactional memory systems should be built to help understand individuals' expertise, promote trust among port stakeholders, and facilitate effective knowledge mobilization relevant to big data (Naqshbandi and Tabche, 2018; Aissa et al., 2022). This would alleviate organizational learning barriers such as unwillingness to share knowledge and lack of organizational memory.

The basic resource category of barriers (relative weighting of 0.275771) is ranked second among the five categories of barriers (see Table 3). To tackle the barriers in this category, port stakeholders must build relationships (*guanxi*) with key government officers who have power to allocate resources for their organizations' development because China is affected by the hierarchy cultural value orientation. Therefore, *Guanxi* plays a central role in the Chinese social order and is a social phenomenon peculiar to China (Xie and Li, 2021). This would alleviate barriers such as limited access to data, time constraints, and lack of funding.

We have two suggestions relating to cultural barriers. This category of barriers (relative weighting of 0.143635) is ranked third among the five categories of barriers (see Table 3), and lack of coordination$_{(C3)}$ is located at the lowest level of the TISM hierarchy (see Fig. 2) and has the highest driving power to elicit other barriers (see Fig. 3). Therefore, this category also requires critical attention from port managers. First, owing to the effects of China's hierarchical cultural value orientation (see Appendix 3), employees are expected to follow their leaders' ideas in conducting their work. Therefore, we suggest that ports' top management teams should implement a bottom-up approach to complement top-down management. The top management team should be responsible for formulating mid-term and long-term strategic goals for their company, while middle-management team members and ground-level workers should be responsible for developing steps to achieve the strategic goals, thereby improving collaboration, coordination, productivity, and employee morale (Conway and Monks, 2011). This would alleviate barriers such as lack of an error correction mechanism and lack of continuous assessment and improvement. Second, to strengthen coordination and collaboration among port community stakeholders (see Fig. 2), we suggest implementing cross-organizational workforce mobilization, whereby employees of one organization have multiple memberships of other organizations. The boundary-spanning role of these employees would strengthen cross-organizational interactions (Chau et al., 2017).

With regard to the technological and managerial category of barriers (relative weighting of 0.076506 and is ranked fourth among the five categories of barriers) (see Table 3), we suggest that conceptual and practical training should be implemented in parallel. Our interviewees were critical that all training and educational sessions are conceptually based, and that they lack practical training (see Appendix 3). Thus, for middle- and high-level managers responsible for making strategic decisions, conceptual training might be provided to help them to understand the latest trends in port development, the various advanced technologies that can be applied in ports, and relevant port policies. However, for ground-level data scientists, practical training might be provided to equip them with the latest data analytical skills.

Finally, the data and technology category of barriers is ranked last of the five categories (relative weighting of 0.073407) (see Table 3). The ports involved in this study should build relationships with leading technology providers in China to tackle data complexity, lack of a data integration approach, and lack of parallel computing approaches.

7. Conclusion, limitations, and future research directions

In this study, we adopted a mixed-method approach to identify and analyze barriers to BDAC adoption in China's maritime industry. Semi-structured interviews were conducted to collect data from 26 ports in China, followed by thematic analysis to identify barriers. AHP was then used to prioritize the barriers and determine their relative importance. Next, we applied TISM to build interactions between the 16 barriers. Finally, MICMAC analysis was implemented to differentiate the role of each barrier in the system. Our study responds to calls by Zhang and Lam (2019) and Munim et al. (2020) for more research on applications of BDAC in the maritime industry. This study enriches relevant literatures on the identification of barriers affecting BDAC adoption, expands the methodological approach used to analyze these barriers, and thereby contributing to the effective understanding and successful deployment of BDAC in the maritime industry. More specifically, this study makes several contributions to theory and managerial practice. Theoretically, this study extends the RBV and organizational learning theory by highlighting that lack of technological resources (e.g., parallel computing approaches, data analytical skills, and a data integration approach), the effects of national cultural value orientations, lack of community-wide organizational memory systems, lack of continuous assessment and improvement, lack of error correction mechanisms, and lack of incentives for employees to test new knowledge are obstacles to building ports' BDAC. Contributing to managerial practices, our findings on barrier prioritization, insights into interrelationships between barriers, and barrier clustering will help port managers to understand, analyze, and manage the barriers more effectively, and hence enhance BDAC adoption across the maritime industry.

7.1. Limitations and future research directions

This study has several limitations that might be addressed in future studies. First, this study focuses on China's maritime industry, which may limit generalization of our findings. Thus, we suggest using questionnaires to evaluate the results in other countries, such as Thailand, Iran, and India, that have a cultural value orientation similar to China (Schwartz, 2006). For example, our findings might gain generalizability by evaluating the various barriers, their prioritization, interrelationships, and categorization. Moreover, this study may have reliability issues because we involved qualitative data collection and analysis methods that are often criticized by researchers for lacking scientific rigour (Noble and Smith, 2015). To alleviate this issue, several strategies can be adopted in future research: (1) involving more researchers into qualitative data collection and analysis processes to reduce research bias; (2) sending interview transcripts and thematic analysis results to the interview participants for comments to examine whether the final themes reflect the phenomenon being investigated; and (3) having meticulous record to demonstrate clear decision trail and ensure data interpretations are consistent and transparent.

A second potential limitation is that we do not analyze enablers or driving forces to achieve BDAC in the maritime industry. Analysis of these may help maritime practitioners to understand the potential benefits of building BDAC, thereby contributing to a deeper understanding of the topic (Horvath and Szabo, 2019). Thus, future work might utilize our research methodology to understand what enablers or driving forces facilitate BDAC adoption in the maritime industry and provide a route for implementation by maritime practitioners.

Third, we collected data from 26 ports in China equipped with big data technologies. We selected ports that play an important role in the maritime system and act as linkages between sea- and land-side operations. However, we did not collect data from other stakeholders, such as ship owners and operators, marine services, and support services. This limits comprehensive understanding of the topic. Therefore, future work should collect data not only from ports, but also from other maritime stakeholders.

Fourth, AHP can be used to determine the relative importance of alternatives. However, it has been criticized for its limitations. First, Liu et al. (2020) observe that AHP is subjective in nature and over-relies on experts' inputs. The situation may be exacerbated if the prioritization results are based on a single expert's inputs (Mital et al., 2018). For example, in our study, a professor in data science and decision making was involved rating relationships between pairs of barriers. Second, it is difficult to use AHP to tackle large problems, particularly when those problems have more than four hierarchy levels (Saaty, 1980). In this study, three hierarchical levels were formulated to prioritize the categories of barriers, the barriers within each category, and their global ranking. Third, high computational capacity is required to tackle even a small problem (Salvia et al., 2019). Finally, the decision maker must have a comprehensive understanding of the problem, the purpose of the decision, and the criteria and sub-criteria used in decision making (Saaty, 2008). To alleviate the limitations of AHP, a group-based fuzzy AHP might be utilized in future research to analyze the problem by involving a group of experts with a deep understanding of both the topic and the decision-making process. This enables groups of experts to express their judgments independently in fuzzy linguistic terms, which has proved to be more realistic in tackling real-life decision-making problems (Groselj et al., 2015).

Fifth, TISM and MICMAC analysis were used in this study to determine interrelationships between barriers and cluster the barriers. However, these two techniques both have potential drawbacks. First, TISM has been criticized for failing account for the driving directions between two elements when modelling their interrelationships. Thus, future research might integrate the driving direction into the step 3 of the TISM analysis by asking the expert: whether element A positively or negatively influences element B if there is a relationship between the two elements. Sushil. (2018) provides detailed guidance on how to incorporate the polarity of relationships into TISM. Second, MICMAC analysis has been criticized for imprecision (Zhao et al., 2023). For example, in our study, relationships between two barriers are denoted as “1” to denote a relationship between two barriers, or “0” to denote that there is no relationship between them. However, other situations must also be considered, such as extremely weak, weak, strong, or very strong interrelationships (Zhao et al., 2022a). Thus, fuzzy set theory might be combined with MICMAC analysis in future research to improve the sensitivity analysis and provide more precise results on barriers' interrelationships and clusters.

CRediT authorship contribution statement

Guoqing Zhao: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Xiaotian Xie:** Supervision, Data curation. **Yi Wang:** Writing – review & editing. **Shaofeng Liu:** Writing – review & editing. **Paul Jones:** Writing – review & editing, Supervision. **Carmen Lopez:** Writing – review & editing.

Declaration of competing interest

No potential competing interest was reported by the authors.

Data availability

The authors confirm that the data supporting the findings of this study are available within the article [and/or] its supplementary materials.

Appendix 1. Interview guide

Part 1: General questions about the participant's background

(1) What is your role/position in your organization (e.g., senior manager, senior scientist, senior technician)?
(2) What is your highest educational attainment?
(3) How many employees work in your organization?
(4) How many years have you worked in the maritime industry?
(5) How many years of big data-related working experience have you had?

Part 2: Data and technology barriers

(1) Does your organization have access to very large, unstructured, or fast-moving data for analysis? If yes, please describe the data you have the right to access.
(2) Does your organization need to integrate multiple internal sources into a data warehouse or mart for easy access?
(3) Does your organization have sufficient facilities to perform big data analytics (e.g., data visualization software such as Microsoft Power BI and IBM Watson Analytics, or cloud services such as IBM Cloud and Amazon Web Services)?
(4) Other barriers/challenges that need to be specified…

Part 3: Resource barriers

(1) Does your organization have sufficient funding for big data analytics projects?
(2) Do you have enough time to achieve the desired result from a big data analytics project?
(3) Other barriers/challenges that need to be specified…

Part 4: Technological and managerial barriers

(1) Does your organization have training and education courses for employees?
(2) Do your organization's human resources have sufficient data analytics skills?
(3) Do you think your employees have appropriate data analytics skills to accomplish their jobs?
(4) Do you think the top management team can anticipate the future needs of other managers, suppliers, and customers?
(5) Other barriers/challenges that need to be specified…

Part 5: Cultural barriers

(1) Do you think that your organization has a data-driven culture?
(2) Other barriers/challenges that need to be specified…

Part 6: Organizational learning barriers

(1) Do you think your organization is actively searching for new and relevant knowledge?
(2) Do you think your organization is actively assimilating new and relevant knowledge?
(3) Do you think your organization has made concerted efforts to exploit existing competencies and explore new knowledge?
(4) Other barriers/challenges that need to be specified…

Appendix 2. Respondents' details

Port	Respondent role	Education	Working experience (years)	Big data experience (years)
A	Technical director	Graduate	19	7
B	Senior engineer	Graduate	14	5
C	Senior engineer	Postgraduate	12	5
D	Technology leader	Postgraduate	15	5
E	Intermediate engineer	Graduate	10	5
F	Senior computer engineer	Vocational education	15	6
G	Senior technician	Postgraduate	20	5
H	Senior technician	Graduate	15	6
I	Senior engineer	Graduate	28	5
J	Technical director	Postgraduate	20	7
K	Senior engineer	Postgraduate	10	5
L	Senior technician	Graduate	10	5
M	Senior technician	Postgraduate	15	7
N	Technical director	Postgraduate	22	7
O	Senior engineer	Graduate	16	5
P	Senior engineer	Graduate	18	6
Q	Senior technician	Diploma	10	5

(*continued on next page*)

(*continued*)

Port	Respondent role	Education	Working experience (years)	Big data experience (years)
R	Senior technician	Diploma	12	5
S	Senior human resource manager	Postgraduate	15	5
T	Human resource director	PhD	20	5
U	Senior finance manager	Postgraduate	10	5
V	Finance director	Postgraduate	13	6
W	Senior human resource manager	Postgraduate	14	5
X	Senior finance manger	Postgraduate	17	6
Y	President	PhD	16	7
Z	Vice-president	PhD	18	5

Appendix 3. Barriers identified from thematic analysis

First-order codes	Second-order themes	Support from industry practitioners (%)	Aggregate dimensions
"Large data sets from different sources that need many sources to process."	**Complexity of data (D1)**	A,B,C,D,E,F,G,H,I,J,K,L, M,N,O,P,Q,R,S,T,U,V,W,X,Y, Z (26/26, 100 %)	**Data and technology barriers (D)**
"It is difficult to integrate data from multiple internal sources into a data warehouse."	**Lack of a data integration approach (D2)**	A,B,C,D,E,F,J,K,L, M,N,O,P,Q,R,T,U,V,W,X (20/26, 76.92 %)	
"Our company has not adopted a parallel computing approach to big data processing."	**Lack of parallel computing approaches (D3)**	A,B,F,G,H,I,J,K,L, M,N,O,P,Q,R (15/26, 57.69 %)	
"We lack funding to do big data-related projects."	**Lack of funding (R1)**	A,B,C,D,E,F,G,H,I,J,K,L, M,N,O,P,Q,R,S,T,U,V,W,X,Y, Z (26/26, 100 %)	**Basic resource barriers (R)**
"We have limited access to very large and unstructured data."	**Limited access to data (R2)**	A,B,C,D,E,F,G,H,J,K,L, M,N,P,Q,R (16/26, 61.54 %)	
"We do not have enough time to achieve the desired result from a big data analytics project."	**Time constraints (R3)**	A,B,C,D,E,F,G,H,I,J,K,L, M,N,O,P,Q,R (18/26, 69.23 %)	
"Training related to applying relevant software is lacking in our company."	**Lack of education and training (T1)**	A,B,C,D,E,F,G,H,I,J,K,L, M,N,O,P,Q,R (18/26, 69.23 %)	**Technological and managerial barriers (T)**
"Sometimes, our analysts do not have appropriate skills to accomplish their jobs successfully."	**Lack of data analytics skills (T2)**	A,B,C,D,E,F,G,H,I,J,K,L, M,N,O,P,Q,R,T,U,V,W,X (23/26, 88.46 %)	
"Our analytics managers are not able to anticipate the future business needs of other managers, suppliers, and customers."	**Lack of capability to anticipate future needs (T3)**	A,B,H,I,J,K,L,M,N,O,P,Q,R, S,T,U,V,W,X,Y,Z (21/26, 80.77 %)	
"The manager sometimes cannot interpret the resources obtained using complex analyses."	**Lack of capability to interpret big data analytics results (T4)**	A,B,C,D,E,F,G,L,M,N,O,P,Q,R (14/26, 53.84 %)	
"Due to the hierarchical structure, it is difficult for us to correct manager's decisions."	**Lack of error correction mechanisms (C1)**	A,B,C,D,E,F,G,H,I,J,K,L,P,Q, R, T,U,V,W,X (20/26, 76.92 %)	**Cultural barriers (C)**
"Continuously assessing and improving the business activities in response to insights extracted from data is lacking."	**Lack of continuous assessment and improvement (C2)**	A,B,F,G,H,I,J,K,L, M,N,O,P,Q,R (15/26, 57.69 %)	
"Our analytics managers lack capability to coordinate big data-related activities in ways that support other partners."	**Lack of coordination (C3)**	A,B,C,D,E,F,G,H,I,J,K,L, O,P,Q,R (16/26, 61.54 %)	
"A knowledge repository has not been built."	**Lack of organizational memory (O1)**	A,B,C,D,G,H,I,J,K,L,M,N,Q,R (14/26, 53.85 %)	**Organizational learning barriers (O)**
"Obviously, employees lack willingness to share knowledge."	**Unwillingness to share knowledge (O2)**	A,B,E,F,G,H,I,J,K,L, M,P,Q,R (14/26, 53.85 %)	
"There are punishments for employees who make mistakes or errors."	**Lack of incentives for employees to test new knowledge (O3)**	A,B,C,D,E,F,G,H,I,J,K,L, M,N,O,P,Q,R (18/26, 69.23 %)	

Appendix 4. Numerical values used for pair-wise comparisons

Degree of preference	Numerical value
Equal importance	1
Moderate importance	3
Strong importance	5
Very strong importance	7
Extreme importance	9
Intermediate values between adjacent scale values	2,4,6,8

Appendix 5. Pair-wise assessment matrices

1. Pair-wise assessment matrix for categories of barriers to BDAC

	D	R	T	C	O	Relative weight	Rank
D (Data and technology barriers)	1	0.333	1	0.333	0.2	0.073407	5
R (Resource barriers)	3	1	5	3	0.333	0.275771	2
T (Technological and managerial barriers)	1	0.2	1	0.2	0.333	0.076506	4
C (Cultural barriers)	0.333	0.333	5	1	0.333	0.143635	3
O (Organizational learning barriers)	5	3	3	3	1	0.430682	1

Note: λmax = 5.218956, CI = 0.054739, CR = 0.04887411, RI = 1.12.

2. Pair-wise assessment matrix for "data and technology" category of barriers

	D1	D2	D3	Relative weight	Rank
D1 (Complexity of data)	1	2	0.333	0.267964	2
D2 (Lack of a data integration approach)	0.5	1	0.5	0.194629	3
D3 (Lack of parallel computing approaches)	3	2	1	0.537407	1

Note: λmax = 3.093853, CI = 0.046927, RI = 0.58, CR = 0.080909.

3. Pair-wise assessment matrix for "resource" category of barriers

	R1	R2	R3	Relative weight	Rank
R1 (Lack of funding)	1	3	5	0.633411	1
R2 (Limited access to data)	0.333	1	3	0.260447	2
R3 (Time constraints)	0.2	0.333	1	0.106412	3

Note: λ_{max} = 3.038166, CI = 0.019083, RI = 0.58, CR = 0.032902.

4. Pair-wise assessment matrix for "technological and managerial" category of barriers

	T1	T2	T3	T4	Relative weight	Rank
T1(Lack of education and training)	1	3	5	3	0.505089	1
T2 (Lack of data analytical skills)	0.333	1	2	0.5	0.148133	2
T3 (Lack of capability to anticipate future needs)	0.2	0.5	1	0.2	0.075895	4
T4 (Lack of capability to interpret big data analytics results)	0.333	2	5	1	0.270883	3

Note: λmax = 4.112693, CI = 0.037564, RI = 0.9, CR = 0.041738.

5. Pair-wise assessment matrix for "cultural" category of barriers

	C1	C2	C3	Relative weight	Rank
C1 (Lack of error correction mechanism)	1	3	5	0.647994	1
C2 (Lack of continuously assessment and improvement)	0.333	1	2	0.229814	2
C3 (Lack of coordination)	0.2	0.5	1	0.122191	3

Note: λmax = 3.003383, CI = 0.001691, RI = 0.58, CR = 0.002916.

6. Pair-wise assessment matrix for "organizational learning" category of barriers

	O1	O2	O3	Relative weight	Rank
O1 (Lack of organizational memory)	1	0.333	3	0.260447	2
O2 (Unwillingness to share knowledge)	3	1	5	0.633411	1
O3 (Lack of incentives for employees to test new knowledge)	0.333	0.2	1	0.106142	3

Note: λmax = 3.038166, CI = 0.019083, RI = 0.58, CR = 0.032902.

Appendix 6. Initial reachability matrix

	D1	D2	D3	R1	R2	R3	T1	T2	T3	T4	C1	C2	C3	O1	O2	O3
D1	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0
D2	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0
D3	1	1	1	0	0	1	0	1	1	1	0	1	0	1	0	0
R1	1	1	1	1	1	0	1	1	1	1	0	1	0	1	1	1
R2	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0
R3	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0
T1	1	1	1	0	0	0	1	1	1	1	1	1	0	1	1	0

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	D1	D2	D3	R1	R2	R3	T1	T2	T3	T4	C1	C2	C3	O1	O2	O3
T2	0	1	0	0	0	0	0	1	1	1	0	1	0	0	0	0
T3	0	1	0	0	0	0	0	0	1	1	0	1	0	1	0	0
T4	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0
C1	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1	0
C2	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
C3	0	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1
O1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0
O2	1	1	0	0	1	0	0	1	1	1	0	1	0	0	1	0
O3	0	1	0	0	1	0	0	1	0	1	0	1	0	0	1	1

Appendix 7. Final reachability matrix

	D1	D2	D3	R1	R2	R3	T1	T2	T3	T4	C1	C2	C3	O1	O2	O3	Driving power
D1	1	1	0	0	0	0	0	1	1*	1*	0	1*	0	1*	0	0	7
D2	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	2
D3	1	1	1	0	0	1	0	1	1	1	0	1	0	1	0	0	9
R1	1	1	1	1	1	1*	1	1	1	1	1*	1	0	1	1	1	15
R2	0	1	0	0	1	0	0	0	1	1*	0	1*	0	1*	0	0	6
R3	1	1	0	0	0	1	0	1*	1*	1*	0	1*	0	1*	0	0	8
T1	1	1	1	0	1*	1*	1	1	1	1	1	1	0	1	1	0	13
T2	0	1	0	0	0	0	0	1	1	1	0	1	0	1*	0	0	6
T3	0	1	0	0	0	0	0	0	1	1	0	1	0	1	0	0	5
T4	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	2
C1	1*	1*	0	0	1*	0	0	1*	1*	1*	1	1	0	1	1	0	10
C2	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1
C3	1*	1*	1	1	1	1	1	1*	1	1	1	1	1	1	1	1	16
O1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	2
O2	1	1	0	0	1	0	0	1	1	1	0	1	0	1*	1	0	9
O3	1*	1	0	0	1	0	0	1	1*	1	0	1	0	1*	1	1	10
Dependence power	9	13	4	2	7	5	3	10	12	13	4	16	1	13	6	3	

* Represents transitivity.

Appendix 8. Partitioning of the reachability matrix into levels

Barrier	Reachability set (RS)	Antecedent set (AS)	RS∩AS	Level
Iteration 1				
D1	D1, D2, T2, T3, T4, C2, O1	D1, D3, R1, R3, T1, C1, C3, O2, O3	D1	
D2	D2, C2	D1, D2, D3, R1, R2, R3, T1, T2, T3, C1, C3, O2, O3	D2	
D3	D1, D2, D3, R3, T2, T3, T4, C2, O1	D3, R1, T1, C3	D3	
R1	D1, D2, D3, R1, R2, R3, T1, T2, T3, T4, C1, C2, O1, O2, O3	R1, C3	R1	
R2	D2, R2, T3, T4, C2, O1	R1, R2, T1, C1, C3, O2, O3	R2	
R3	D1, D2, R3, T2, T3, T4, C2, O1	D3, R1, R3, T1, C3	R3	
T1	D1, D2, D3, R2, R3, T1, T2, T3, T4, C1, C2, O1, O2	R1, T1, C3	T1	
T2	D2, T2, T3, T4, C2, O1	D1, D3, R1, R3, T1, T2, C1, C3, O2, O3	T2	
T3	D2, T3, T4, C2, O1	D1, D3, R1, R2, R3, T1, T2, T3, C1, C3, O2, O3	T3	
T4	T4, C2	D1, D3, R1, R2, R3, T1, T2, T3, T4, C1, C3, O2, O3	T4	
C1	D1, D2, R2, T2, T3, T4, C1, C2, O1, O2	R1, T1, C1, C3	C1	
C2	C2	D1, D2, D3, R1, R2, R3, T1, T2, T3, T4, C1, C2, C3, O1, O2, O3	C2	I
C3	D1, D2, D3, R1, R2, R3, T1, T2, T3, T4, C1, C2, C3, O1, O2, O3	C3	C3	
O1	C2, O1	D1, D3, R1, R2, R3, T1, T2, T3, C1, C3, O1, O2, O3	O1	
O2	D1, D2, R2, T2, T3, T4, C2, O1, O2	R1, T1, C1, C3, O2, O3	O2	
O3	D1, D2, R2, T2, T3, T4, C2, O1, O2, O3	R1, C3, O3	O3	
Iteration 2				
D1	D1, D2, T2, T3, T4, O1	D1, D3, R1, R3, T1, C1, C3, O2, O3	D1	
D2	D2	D1, D2, D3, R1, R2, R3, T1, T2, T3, C1, C3, O2, O3	D2	II
D3	D1, D2, D3, R3, T2, T3, T4, O1	D3, R1, T1, C3	D3	
R1	D1, D2, D3, R1, R2, R3, T1, T2, T3, T4, C1, O1, O2, O3	R1, C3	R1	
R2	D2, R2, T3, T4, O1	R1, R2, T1, C1, C3, O2, O3	R2	
R3	D1, D2, R3, T2, T3, T4, O1	D3, R1, R3, T1, C3	R3	
T1	D1, D2, D3, R2, R3, T1, T2, T3, T4, C1, O1, O2	R1, T1, C3	T1	
T2	D2, T2, T3, T4, O1	D1, D3, R1, R3, T1, T2, C1, C3, O2, O3	T2	
T3	D2, T3, T4, O1	D1, D3, R1, R2, R3, T1, T2, T3, C1, C3, O2, O3	T3	
T4	T4	D1, D3, R1, R2, R3, T1, T2, T3, T4, C1, C3, O2, O3	T4	II
C1	D1, D2, R2, T2, T3, T4, C1, O1, O2	R1, T1, C1, C3	C1	
C3	D1, D2, D3, R1, R2, R3, T1, T2, T3, T4, C1, C3, O1, O2, O3	C3	C3	
O1	O1	D1, D3, R1, R2, R3, T1, T2, T3, C1, C3, O1, O2, O3	O1	II
O2	D1, D2, R2, T2, T3, T4, O1, O2	R1, T1, C1, C3, O2, O3	O2	
O3	D1, D2, R2, T2, T3, T4, O1, O2, O3	R1, C3, O3	O3	
Iteration 3				
D1	D1, T2, T3	D1, D3, R1, R3, T1, C1, C3, O2, O3	D1	

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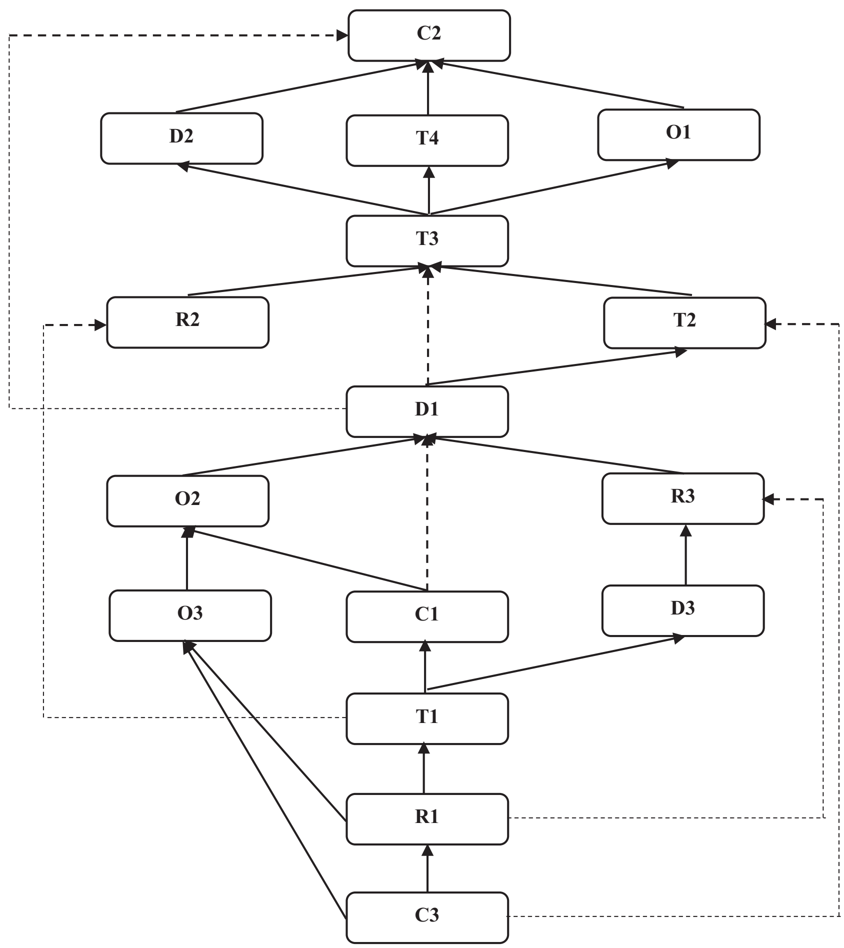
Barrier	Reachability set (RS)	Antecedent set (AS)	RS∩AS	Level
D3	D1, D3, R3, T2, T3	D3, R1, T1, C3	D3	
R1	D1, D3, R1, R2, R3, T1, T2, T3, C1, O2, O3	R1, C3	R1	
R2	R2, T3	R1, R2, T1, C1, C3, O2, O3	R2	
R3	D1, R3, T2, T3	D3, R1, R3, T1, C3	R3	
T1	D1, D3, R2, R3, T1, T2, T3, C1, O2	R1, T1, C3	T1	
T2	T2, T3	D1, D3, R1, R3, T1, T2, C1, C3, O2, O3	T2	
T3	T3	D1, D3, R1, R2, R3, T1, T2, T3, C1, C3, O2, O3	T3	III
C1	D1, R2, T2, T3, C1, O2	R1, T1, C1, C3	C1	
C3	D1, D3, R1, R2, R3, T1, T2, T3, C1, C3, O2, O3	C3	C3	
O2	D1, R2, T2, T3, O2	R1, T1, C1, C3, O2, O3	O2	
O3	D1, R2, T2, T3, O2, O3	R1, C3, O3	O3	
Iteration 4				
D1	D1, T2	D1, D3, R1, R3, T1, C1, C3, O2, O3	D1	
D3	D1, D3, R3, T2	D3, R1, T1, C3	D3	
R1	D1, D3, R1, R2, R3, T1, T2, C1, O2, O3	R1, C3	R1	
R2	R2	R1, R2, T1, C1, C3, O2, O3	R2	IV
R3	D1, R3, T2	D3, R1, R3, T1, C3	R3	
T1	D1, D3, R2, R3, T1, T2, C1, O2	R1, T1, C3	T1	
T2	T2	D1, D3, R1, R3, T1, T2, C1, C3, O2, O3	T2	IV
C1	D1, R2, T2, C1, O2	R1, T1, C1, C3	C1	
C3	D1, D3, R1, R2, R3, T1, T2, C1, C3, O2, O3	C3	C3	
O2	D1, R2, T2, O2	R1, T1, C1, C3, O2, O3	O2	
O3	D1, R2, T2, O2, O3	R1, C3, O3	O3	
Iteration 5				
D1	D1	D1, D3, R1, R3, T1, C1, C3, O2, O3	D1	V
D3	D1, D3, R3	D3, R1, T1, C3	D3	
R1	D1, D3, R1, R3, T1, C1, O2, O3	R1, C3	R1	
R3	D1, R3	D3, R1, R3, T1, C3	R3	
T1	D1, D3, R3, T1, C1, O2	R1, T1, C3	T1	
C1	D1, C1, O2	R1, T1, C1, C3	C1	
C3	D1, D3, R1, R3, T1, C1, C3, O2, O3	C3	C3	
O2	D1, O2	R1, T1, C1, C3, O2, O3	O2	
O3	D1, O2, O3	R1, C3, O3	O3	
Iteration 6				
D3	D3, R3	D3, R1, T1, C3	D3	
R1	D3, R1, R3, T1, C1, O2, O3	R1, C3	R1	
R3	R3	D3, R1, R3, T1, C3	R3	VI
T1	D3, R3, T1, C1, O2	R1, T1, C3	T1	
C1	C1, O2	R1, T1, C1, C3	C1	
C3	D3, R1, R3, T1, C1, C3, O2, O3	C3	C3	
O2	O2	R1, T1, C1, C3, O2, O3	O2	VI
O3	O2, O3	R1, C3, O3	O3	
Iteration 7				
D3	D3	D3, R1, T1, C3	D3	VII
R1	D3, R1, T1, C1, O3	R1, C3	R1	
T1	D3, T1, C1	R1, T1, C3	T1	
C1	C1	R1, T1, C1, C3	C1	VII
C3	D3, R1, T1, C1, C3, O3	C3	C3	
O3	O3	R1, C3, O3	O3	VII
Iteration 8				
R1	R1, T1	R1, C3	R1	
T1	T1	R1, T1, C3	T1	VIII
C3	R1, T1, C3	C3	C3	
Iteration 9				
R1	R1	R1, C3	R1	IX
C3	R1, C3	C3	C3	
Iteration 10				
C3	C3	C3	C3	X

Appendix 9. Digraph showing links between barriers to BDAC adoption



References

Abuljadail, M., Khalil, A., Talwar, S., Kaur, P., 2023. Big data analytics and e-governance: actors, opportunities, tensions, and applications. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2023.122612.

Agarwal, N., Seth, N., Agarwal, A., 2022. Evaluation of supply chain resilience index: a graph theory based approach. BIJ 29 (3), 735–766.

Ahmed, V., Tezel, A., Aziz, Z., Sibley, M., 2017. The future of big data in facilities management: opportunities and challenges. Facilities 35 (14), 725–745.

Aissa, N.B., Gurau, C., Psychogios, A., Somsing, A., 2022. Transactional memory systems in virtual teams: communication antecedents and the impact of TMS components on creative processes and outcomes. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2021.121235.

Alharthi, A., Krotov, V., Bowman, M., 2017. Addressing barriers to big data. Bus. Horiz. 60, 285–292.

Alnuaimi, B.K., Khan, M., Ajmal, M.M., 2021. The role of big data analytics capabilities in greening e-procurement: a higher order PLS-SEM analysis. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2021.120808.

Alrahbi, D.A., Khan, M., Gupta, S., Modgil, S., Jabbour, C.J.C., 2022. Challenges for developing health-care knowledge in the digital age. J. Knowl. Manag. 26 (4), 824–853.

Annosi, M.C., Brunetta, F., Bimbo, F., Kostoula, M., 2021. Digitalization within food supply chains to prevent food waste. Drivers, barriers and collaboration practices. Ind. Mark. Manag. 93, 208–220.

Argote, L., Ren, Y., 2012. Transactive memory systems: a microfoundation of dynamic capabilities. J. Manag. Stud. 49, 1375–1382.

Arunachalam, D., Kumar, N., Kawalek, J.P., 2018. Understanding big data analytics capabilities in supply chain management: unravelling the issues, challenges and implications for practice. Transportation Research Part E: Logistics and Transportation Review 114, 416–436.

Ashaari, M.A., Singh, K.S.D., Abbasi, G.A., Amran, A., Liebana-Cabanillas, F.J., 2021. Big data analytics capability for improved performance of higher education institutions in the era of IR 4.0: a multi-analytical SEM & ANN perspective. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2021.121119.

Bag, S., Gupta, S., Wood, L., 2020. Big data analytics in sustainable humanitarian supply chain: barriers and their interactions. Ann. Oper. Res. https://doi.org/10.1007/s10479-020-03790-7.

Barney, J., 1991. Firm resources and sustained competitive advantage. J. Manag. 17 (1), 99–120.

Barriball, K.L., While, A., 1994. Collecting data using a semi-structured interview: a discussion paper. J. Adv. Nurs. 19, 328–335.

Basten, D., Haamann, T., 2018. Approaches for organizational learning: a literature review. SAGE Open 8 (3), 1–20.

Bazeley, P., 2015. Mixed methods in management research: implications for the field. The Electronic Journal of Business Methods 13 (1), 27–35.

Bean, R., Davenport, T.H., 2019. Companies are failing in their efforts to become data-driven. Harv. Bus. Rev. https://hbr.org/2019/02/companies-are-failing-in-their-efforts-to-become-data-driven.

Bekele, W.B., Ago, F.Y., 2022. Sample size for interview in qualitative research in social sciences: a guide to novice researchers. Research in Educational Policy and Management 4 (1), 42–50.

Bemmami, K.E., David, P., 2021. Managing the use of simulation in systems engineering: an industrial state of practice and a prioritization method. Comput. Ind. https://doi.org/10.1016/j.compind.2021.103486.

Braun, V., Clarke, V., 2006. Using thematic analysis in psychology. Qual. Res. Psychol. 3, 77–101.

Brewis, C., Dibb, S., Meadows, M., 2023. Leveraging big data for strategic marketing: a dynamic capabilities model for incumbent firms. Technological Forecasting & Social Changes. https://doi.org/10.1016/j.techfore.2023.122402.

Calic, G., Ghasemaghaei, M., 2021. Big data for social benefits: innovation as a mediator of the relationship between big data and corporate social performance. J. Bus. Res. 131, 391–401.

Cerneviciene, J., Kabasinskas, A., 2022. Review of multi-criteria decision-making methods in finance using explainable artificial intelligence. Frontiers in Artificial Intelligence. https://doi.org/10.3389/frai.2022.827584.

Chatterjee, S., Chaudhuri, R., Gupta, S., Sivarajah, U., Bag, S., 2023. Assessing the impact of big data analytics on decision-making processes, forecasting, and performance of a firm. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2023.122824.

Chau, V.S., Gilman, M., Serbanica, C., 2017. Aligning university-industry interactions: the role of boundary-spanning in intellectual capital transfer. *Technological Forecasting & Social Change* 123, 199–209.
Chen, J., Chang, S., Zhang, P., Chen, Q., Peng, P., Claramunt, C., 2022. A critical examination for widespread usage of shipping big data analytics in China. Journal of Marine Science and Engineering 10 (12), 2009.
Chen, P.-T., Lin, C.-L., Wu, W.-N., 2020. Big data management in healthcare: adoption challenges and implications. Int. J. Inf. Manag. https://doi.org/10.1016/j.ijinfomgt.2020.102078.
ChinaPower., 2021. How is China influencing global maritime industry. Available at: https://chinapower.csis.org/china-ports-connectivity/. Accessed: 27/02/2023.
Choi, H.-Y., Park, J., 2022. Do data-driven CSR initiatives improve CSR performance? The importance of big data analytics capability. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2022.121802.
Connelly, C.E., Zweig, D., Webster, J., Trougakos, J.P., 2012. Knowledge hiding in organizations. J. Organ. Behav. 33 (1), 64–88.
Conway, E., Monks, K., 2011. Change from below: the role of middle managers in mediating paradoxical change. Hum. Resour. Manag. J. 21 (1), 190–203.
Corallo, A., Crespino, A.M., Vecchio, V.D., Gervasi, M., Lazoi, M., Marra, M., 2023. Evaluating maturity level of big data management and analytics in industrial companies. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2023.122826.
Creswell, J.W., 2015. A Concise Introduction to Mixed Methods Research. Sage Publications, Thousand Oaks, California.
Creswell, J.W., Clark, V.L.P., 2011. Designing and Conducting Mixed Methods Research. Sage Publications, Thousand Oaks, California.
Cusin, J., Goujon-Belghit, A., 2019. Error reframing: studying the promotion of an error management culture. Eur. J. Work Organ. Psy. 28 (4), 510–524.
Dehkhodaei, A., Amiri, B., Farsijani, H., Raad, A., 2023. Barriers to big data analytics (BDA) implementation in manufacturing supply chains. J. Manag. Anal. 10 (1), 191–222.
Dubey, R., Gunasekaran, A., 2015. Education and training for successful career in big data and business analytics. Ind. Commer. Train. 47 (4), 174–181.
Dubey, R., Gunasekaran, A., Childe, S.J., 2019a. Big data analytics capability in supply chain agility: the moderating effect of organizational flexibility. Manag. Decis. 57 (8), 2092–2112.
Dubey, R., Gunasekaran, A., Childe, S.J., Blome, C., Papadopoulos, T., 2019b. Big data and predictive analytics and manufacturing performance: integrating institutional theory, resource-based view and big data culture. Br. J. Manag. 30, 341–361.
Emrouznejad, A., Marra, M., 2017. The state of the art development of AHP (1979-2017): a literature review with a social network analysis. Int. J. Prod. Res. 55 (22), 6653–6675.
Espinosa, J.A., Armour, F., 2016. The big data analytics gold rush: A research framework for coordination and governance. In: 49th Hawaii International Conference on System Sciences (HICSS), pp. 1112–1121.
Francis, J.J., Johnston, M., Robertson, C., Glidewell, L., Entwistle, V., Eccles, M.P., Grimshaw, J.M., 2010. What is an adequate sample size? Operationalizing data saturation for theory-based interview studies. Psychol. Health 25 (10), 1229–1245.
Gagne, M., Tian, A.W., Soo, C., Zhang, B., Ho, K.S.B., Hosszu, K., 2019. Different motivations for knowledge sharing and hiding: the role of motivating work design. J. Organ. Behav. 40 (7), 783–799.
Gao, Q., Cheng, C., Sun, G., 2023. Big data application, factor allocation, and green innovation in Chinese manufacturing enterprises. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2023.122567.
Gill, P., Stewart, K., Treasure, E., Chadwick, B., 2008. Methods of data collection in qualitative research: interviews and focus groups. Br. Dent. J. 204, 291–295.
Groselj, P., Stirn, L.Z., Ayrilmis, N., Kuzman, M.K., 2015. Comparison of some aggregation techniques using group analytic hierarchy process. Expert Syst. Appl. 42 (4), 2198–2204.
Gugiu, P.C., Rodriguez-Campos, L., 2007. Semi-structured interview protocol for constructing logic models. Eval. Program Plann. 30, 339–350.
Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S.F., Childe, S.J., Hazen, B., Akter, S., 2017. Big data and predictive analytics for supply chain and organizational performance. J. Bus. Res. 70, 308–317.
Gupta, A.K., Goyal, H., 2021. Framework for implementing big data analytics in Indian manufacturing: ISM-MICMAC and fuzzy-AHP approach. Inf. Technol. Manag. 22, 207–229.
Gupta, M., George, J.F., 2016. Toward the development of a big data analytics capability. Inf. Manag. 53, 1049–1064.
Hennink, M., Kaiser, B.N., 2022. Sample sizes for saturation in qualitative research: a systematic review of empirical tests. Soc. Sci. Med. https://doi.org/10.1016/j.socscimed.2021.114523.
Ho, W., Zheng, T., Yildiz, H., Talluri, S., 2015. Supply chain risk management: a literature review. Int. J. Prod. Res. 53 (16), 5031–5069.
Horvath, D., Szabo, R.Z., 2019. Driving forces and barriers of industry 4.0: do multinational and small and medium-sized companies have equal opportunities? Technological Forecasting & Social Change 146, 119–132.
Institute for Security & Development Policy, 2018. Made in China 2025. Available at: https://isdp.eu/content/uploads/2018/06/Made-in-China-Backgrounder.pdf. Accessed: 14/11/2022.
International Maritime Organization, 2012. Adoption of revised performance standards for shipborne voyage data recorders (VDRs). Available at: https://wwwcdn.imo.org/localresources/en/KnowledgeCentre/IndexofIMOResolutions/MSCResolutions/MSC.333(90).pdf. Accessed: 01/03/2023.
International Maritime Organization, 2019. Voyage Data Recorders. Available at: https://www.imo.org/en/OurWork/Safety/Pages/VDR.aspx. Accessed: 01/03/2023.
International Maritime Organization, 2020. Fourth Greenhouse Gas Study 2020. Available at: https://www.imo.org/en/ourwork/Environment/Pages/Fourth-IMO-Greenhouse-Gas-Study-2020.aspx. Accessed: 07/10/2023.
Iqbal, R., Doctor, F., More, B., Mahmud, S., Yousuf, U., 2020. Big data analytics: computational intelligence techniques and application areas. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2018.03.024.
Jain, V., Ajmera, P., 2022. Modelling the barriers of industry 4.0 in India using fuzzy TISM. Int. J. Bus. Perform. Manag. 23 (4), 347–372.
Jena, J., Sidharth, S., Thakur, L.S., Pathak, D.K., Pandey, V.C., 2017. Total interpretive structural modelling (TISM): approach and application. Journal of Advances in Management Research 14 (2), 162–181.
Jia, X., Cui, Y., 2021. Examining interrelationships of barriers in the evolution of maritime port smartification from a systematic perspective. Transp. Policy 114, 49–58.
Jogulu, U.D., Pansiri, J., 2011. Mixed methods: a research design for management doctoral dissertations. Manag. Res. Rev. 34 (6), 687–701.
Kamble, S.S., Gunasekaran, A., 2020. Big data-driven supply chain performance measurement system: a review and framework for implementation. Int. J. Prod. Res. 58 (1), 65–86.
Kazancoglu, Y., Sagnak, M., Mangla, S.K., Sezer, M.D., Pala, M.O., 2021. A fuzzy based hybrid decision framework to circularity in dairy supply chains through big data solutions. Technological Forecasting & Social Changes. https://doi.org/10.1016/j.techfore.2021.120927.
Kelle, U., 2006. Combining qualitative and quantitative methods in research practice: purposes and advantages. Qual. Res. Psychol. 3, 293–311.
Kelly, S., 2010. Qualitative interviewing techniques and styles. In: Bourgeault, I., Dingwall, R., de Vries, R. (Eds.), The Sage Handbook of Qualitative Methods in Health Research. Sage Publications, Thousand Oaks.
Khan, S., 2022. Barriers of big data analytics for smart cities development: a context of emerging economies. Int. J. Manag. Sci. Eng. Manag. 17 (2), 123–131.
King, N., 2004. Using templates in the thematic analysis of text. In: C. Cassell & G. Symon (Edds). *Essential Guide to Qualitative Methods in Organizational Research*. Sage, London, UK, pp. 257–270.
King, N., Horrocks, C., 2010. Interviews in Qualitative Research. Sage Publications, London.
Koga, S., 2015. *Major Challenges and Solutions for Utilizing Big Data in the Maritime Industry*. MSc Thesis of World Maritime University. Malmo, Sweden.
Konanahalli, A., Marinelli, M., Oyedele, L., 2022. Drivers and challenges associated with the implementation of big data within UK facilities management sector: an exploratory factor analysis approach. IEEE Trans. Eng. Manag. 69 (4), 916–929.
Kumar, N., Kumar, G., Singh, R.K., 2022a. Analysis of barriers intensity for investment in big data analytics for sustainable manufacturing operations in post-COVID-19 pandemic era. J. Enterp. Inf. Manag. 35 (1), 179–213.
Kumar, P., Brar, P.S., Singh, D., Bhamu, J., 2022b. Fuzzy AHP approach for barriers to implement LSS in the context of industry 4.0. International Journal of Productivity and Performance. https://doi.org/10.1108/IJPPM-12-2021-0715.
Lazar, M., Miron-Spektor, E., Chen, G., Erez, M., Agarwal, R., 2022. Forming entrepreneurial teams: mixing business and friendship to create transactive memory systems for enhanced success. Acad. Manag. J. 65 (4), 1110–1138.
Li, L., Lin, J., Ouyang, Y., Luo, X., 2022. Evaluating the impact of big data analytics usage on the decision-making quality of organizations. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2021.121355.
Li, S., Peng, G., Xing, F., 2019. Barriers of embedding big data solutions in smart factories: insights from SAP consultants. Ind. Manag. Data Syst. 119 (5), 1147–1164.
Liu, Y., Eckert, C.M., Earl, C., 2020. A review of fuzzy AHP methods for decision-making with subjective judgements. Expert Syst. Appl. https://doi.org/10.1016/j.eswa.2020.113738.
Luthra, S., Mangla, S.K., Xu, L., Diabat, A., 2016. Using AHP to evaluate barriers in adopting sustainable consumption and production initiatives in a supply chain. Int. J. Prod. Econ. 181, 342–349.
Maheshwari, S., Gautam, P., Jaggi, C.K., 2021. Role of big data analytics in supply chain management: current trends and future perspectives. Int. J. Prod. Res. 59 (6), 1875–1900.
Malina, M.A., Norreklit, H.S.O., Selto, F.H., 2011. Lessons learned: advantages and disadvantages of mixed method research. Qual. Res. Account. Manag. 8 (1), 59–71.
Mauro, A.D., Greco, M., Grimaldi, M., Ritala, P., 2018. Human resources for big data professions: a systematic classification of job roles and required skill sets. Inf. Process. Manag. 54, 807–817.
McIntosh, M.J., Morse, J.M., 2015. Situating and constructing diversity in semi-structured interviews. Global Qualitative Nursing Research 2, 1–12.
Mikalef, P., Krogstie, J., Pappas, I.O., Pavlou, P., 2020. Exploring the relationship between big data analytics capability and competitive performance: the mediating roles of dynamic and operational capabilities. Inf. Manag. https://doi.org/10.1016/j.im.2019.05.004.
Mirovic, M., Milicevic, M., Obradovic, I., 2018. Big data in the maritime industry. International *Journal of Maritime Science & Technology* 65 (1), 56–62.
Mishra, D., Luo, Z., Hazen, B., Hassini, E., Foropon, C., 2019. Organizational capabilities that enable big data and predictive analytics diffusion and organizational performance: a resource-based perspective. Manag. Decis. 57 (8), 1734–1755.
Mital, M., Giudice, M.D., Papa, A., 2018. Comparing supply chain risks for multiple product categories with cognitive mapping and analytic hierarchy process. Technological Forecasting & Social Change 131, 159–170.
Moktadir, Md.A., Ali, S.M., Paul, S.K., Shukla, N., 2019. Barriers to big data analytics in manufacturing supply chains: a case study from Bangladesh. Comput. Ind. Eng. 128, 1063–1075.

Moody, R., Plat, V., Bekkers, V., 2019. Look before you leap: barriers to big data use in municipalities. Information Polity 24, 271–288.
Morse, J.M., Niehaus, L., 2009. Mixed-Method Design: Principles and Procedures. Left Coast Press, Thousand Oaks, CA.
Munim, Z.H., Dushenko, M., Jimenez, V.J., Shakil, M.H., Imset, M., 2020. Big data and artificial intelligence in the maritime industry: a bibliometric review and future research directions. Marit. Policy Manag. 47 (5), 577–597.
Naqshbandi, M.M., Tabche, I., 2018. The interplay of leadership, absorptive capacity, and organizational learning culture in open innovation: testing a moderated mediation model. Technological Forecasting & Social Change 133, 156–167.
Huynh, M.-T., Nippa, M., Aichner, T., 2023. Big data analytics capabilities: patchwork or progress? A systematic review of the status quo and implications for future research. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2023.122884.
Noble, H., Smith, J., 2015. Issues of validity and reliability in qualitative research. Evid Based Nurs 18, 34–35.
Ostlund, U., Kidd, L., Wengstrom, Y., Rowa-Dewar, N., 2011. Combining qualitative and quantitative research within mixed method research designs: a methodological review. Int. J. Nurs. Stud. 48 (3), 369–383.
Pal, S.K., Mukherjee, S., Baral, M.M., Aggarwal, S., 2021. Problems of big data adoption in the healthcare industries. Asia Pacific Journal of Healthcare Management 16 (4), 282–287.
Percin, S., 2023. Identifying barriers to big data analytics adoption in circular Agri-food supply chains: a case study in Turkey. Environ. Sci. Pollut. Res. 30, 52304–52320.
Port Technology, 2015. China to launch big data base for shipping. Available at: https://www.porttechnology.org/news/china_to_launch_big_data_base_for_shipping/. Accessed: 02/08/2022.
Qi, Q., Xu, Z., Rani, P., 2023. Big data analytics challenges to implementing the intelligent industrial internet of things (IIoT) systems in sustainable manufacturing operations. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2023.122401.
Raguseo, E., 2018. Big data technologies: an empirical investigation on their adoption, benefits and risks for companies. Int. J. Inf. Manag. 38, 187–195.
Rammer, C., Es-Sadki, N., 2023. Using big data for generating firm-level innovation indicators – a literature review. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2023.122874.
Rathore, B., Gupta, R., Biswas, B., Srivastava, A., Gupta, S., 2022. Identification and analysis of adoption barriers of disruptive technologies in the logistics industry. The international Journal of Logistics Management 33 (5), 136–169.
Raut, R.D., Yadav, V.S., Cheikhrouhou, N., Narwane, V.S., Narkhede, B.E., 2021a. Big data analytics: implementation challenges in Indian manufacturing supply chains. Comput. Ind. https://doi.org/10.1016/j.compind.2020.103368.
Raut, R.D., Narwane, V., Mangla, S.K., Yadav, V.S., Narkhede, B.E., Luthra, S., 2021b. Unlocking causal relations of barriers to big data analytics in manufacturing firms. Ind. Manag. Data Syst. 121 (9), 1939–1968.
Rialti, R., Zollo, L., Ferraris, A., Alon, I., 2019. Big data analytics capabilities and performance: evidence from a moderated multi-mediation model. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2019.119781.
Saaty, T.L., 1980. The Analytic Hierarchy Process: Planning, Priority Setting, Resources Allocation. McGraw-Hill, New York.
Saaty, T.L., 2008. Decision making with the analytic hierarchy process. International Journal of Services Sciences 1 (1), 83.
Sabaei, D., Erkoyuncu, J., Roy, R., 2015. A review of multi-criteria decision making methods for enhanced maintenance delivery. Procedia CIRP 37, 30–35.
Saeed, A., Riaz, H., Baloch, M.S., 2022. Does big data utilization improve firm legitimacy? Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2022.121847.
Salvia, A.L., Brandli, L.L., Filho, W.L., Kalil, R.M.L., 2019. An analysis of the applications of analytic hierarchy process (AHP) for selection of energy efficiency practices in public lighting in a sample of Brazilian cities. Energy Policy 132, 854–864.
Schwartz, S.H., 2006. A theory of cultural value orientations: explication and applications. Comp. Sociol. 5 (2–3), 137–182.
Senna, P.P., Roca, J.B., Barros, A.C., 2023. Overcoming barriers to manufacturing digitalization: policies across EU countries. Technol. Forecast. Soc. Chang. https://doi.org/10.1016/j.techfore.2023.122822.
Senyo, P.K., Effah, J., Osabutey, E.L.C., 2021. Digital transformation as public sector transformation strategy: a case of Ghana's paperless port. Technol. Forecast. Soc. Chang. https://doi.org/10.1016/j.techfore.2020.120387.
Shukla, M., Mattar, L., 2019. Next generation smart sustainable auditing systems using big data analytics: understanding the interaction of critical barriers. Comput. Ind. Eng. 128, 1015–1026.
Sivarajah, U., Kamal, M.M., Irani, Z., Weerakkody, V., 2017. Critical analysis of big data challenges and analytics methods. J. Bus. Res. 70, 263–286.
Stylianou, A., Talias, M.A., 2017. Big data in healthcare: a discussion on the big challenges. Heath and Technology 7, 97–107.
Sushil., 2012. Interpreting the interpretive structural model. Glob. J. Flex. Syst. Manag. 13 (2), 87–106.
Sushil., 2018. Incorporating polarity of relationships in ISM and TISM for theory building in information and organization management. Int. J. Inf. Manag. 43, 38–51.
Tamvada, J.P., Narula, S., Audretsch, D., Puppala, H., Kumar, A., 2022. Adopting new technology is a distant dream? The risks of implementing industry 4.0 in emerging economy SMEs. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2022.122088.
Tarka, P., 2018. An overview of structural equation modelling: its beginnings, historical development, usefulness and controversies in the social sciences. Qual. Quant. 52, 313–354.
Tijan, E., Jovic, M., Aksentijevic, S., Pucihar, A., 2021. Digital transformation in the maritime transport sector. Technol. Forecast. Soc. Chang. https://doi.org/10.1016/j.techfore.2021.120879.
Tortorella, G.L., Vergara, A.M.C., Garza-Reyes, J.A., Sawhney, R., 2020. Organizational learning paths based upon industry 4.0 adoption: an empirical study with Brazilian manufacturers. Int. J. Prod. Econ. 219, 284–294.
Trelleborg, 2022. Use of big data in the maritime industry. Available at: https://www.patersonsimons.com/wp-content/uploads/2018/06/TMS_SmartPort_InsightBee_Report-to-GUIDE_01.02.18.pdf. Accessed: 19/08/2022.
Tseng, H.-T., Aghaali, N., Hajli, N., 2022. Customer agility and big data analytics in new product context. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2022.121690.
United Nations Conference on Trade and Development, 2021. Maritime Profile: China. Available at: https://unctadstat.unctad.org/countryprofile/maritimeprofile/en-gb/156/index.html. Accessed: 27/02/2023.
Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.-F., Dubey, R., Childe, S.J., 2017. Big data analytics and firm performance: effects of dynamic capabilities. J. Bus. Res. 70, 356–365.
Wang, Y., Kung, L., Gupta, S., Ozdemir, S., 2019. Leveraging big data analytics to improve quality of care in healthcare organizations: a configurational perspective. Br. J. Manag. 30 (2), 362–388.
Weerasinghe, K., Scahill, S.L., Pauleen, D.J., Taskin, N., 2022. Big data analytics for clinical decision-making: understanding health sector perceptions of policy and practice. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2021.121222.
Wernerfelt, B., 1984. A resource-based view of the firm. Strateg. Manag. J. 5 (2), 171–180.
Willetts, M., Atkins, A.S., Stanier, C., 2020. Barriers to SMEs adoption of big data analytics for competitive advantage. In: 2020 Fourth International Conference on Intelligent Computing in Data Sciences, 21–23 October, Morocco.
World Shipping Council, 2022. The Top 50 Container Ports. Available at: https://www.worldshipping.org/top-50-ports. Accessed: 02/08/2022.
Xie, B., Li, M., 2021. Coworker guanxi and job performance: based on the mediating effect of interpersonal trust. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2021.120981.
Xu, J., Pero, M., Fabbri, M., 2023. Unfolding the link between big data analytics and supply chain planning. Technological Forecasting & Social Change. https://doi.org/10.1016/j.techfore.2023.122805.
Yin, R.K., 2009. *Case Study Research: Design and Methods*, 4th Eds. Sage, Thousand Oaks, CA.
Yu, W., Wong, C.Y., Chavez, R., Jacobs, M.A., 2021. Integrating big data analytics into supply chain finance: the roles of information processing and data-driven culture. Int. J. Prod. Econ. https://doi.org/10.1016/j.ijpe.2021.108135.
Yu, X., Zhang, S., Liao, X., Qi, X., 2018. ELECTRE methods in prioritized MCDM environment. Inf. Sci. 424, 301–316.
Zaman, I., Pazouki, K., Norman, R., Younessi, S., Coleman, S., 2017. Challenges and opportunities of big data analytics for upcoming regulations and future transformation of the shipping industry. Procedia Engineering 194, 537–544.
Zhang, X., Lam, J.S.L., 2019. A fuzzy Delphi-AHP-TOPSIS framework to identify barriers in big data analytics adoption: case of maritime organizations. Marit. Policy Manag. 46 (7), 781–801.
Zhao, G., Liu, S., Lu, H., Lopez, C., Elgueta, S., 2018. Building theory of Agri-food supply chain resilience using total interpretive structural modelling and MICMAC analysis. International Journal of Sustainable Agricultural Management and Informatics 4 (3/4), 235–257.
Zhao, G., Liu, S., Lopez, C., Chen, H., Lu, H., Mangla, S.K., Elgueta, S., 2020. Risk analysis of the Agri-food supply chain: a multi-method approach. Int. J. Prod. Res. 58 (16), 4851–4876.
Zhao, G., Liu, S., Wang, Y., Lopez, C., Zubairu, N., Chen, X., Xie, X., Zhang, J., 2022a. Modelling enablers for building Agri-food supply chain resilience: insights from a comparative analysis of Argentina and France. Prod. Plan. Control. https://doi.org/10.1080/09537287.2022.2078246.
Zhao, G., Olan, F., Liu, S., Hormazabal, J.H., Lopez, C., Zubairu, N., Zhang, J., Chen, X., 2022b. Links between risk source identification and resilience capability building in Agri-food supply chains: a comprehensive analysis. IEEE Trans. Eng. Manag. https://doi.org/10.1109/TEM.2022.3221361.
Zhao, G., Chen, H., Liu, S., Dennehy, D., Jones, P., Lopez, C., 2023. Analysis of factors affecting cross-boundary knowledge mobilization in Agri-food supply chains: an integrated approach. J. Bus. Res. https://doi.org/10.1016/j.jbusres.2023.114006.

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