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Port resilience to climate change in the Greater Bay Area

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ABSTRACT

As vital global supply chain nodes, ports are particularly vulnerable to risks caused by disruptions from climate-induced risks, e.g., extreme weather events, sea-level rise. Through incorporating the Objective Oriented Bayesian Network and Expectation Maximization approach, this paper develops a new framework which enables the assessment of port resilience to climate change across multiple dimensions. Taking the Greater Bay Area as an example, it is found that port systems are quite resilient under typical scenario, and the resilience could be enhanced with higher utilization rate and the implementation of recovery or adaptive measures with faster relative recovery speed. Key measures in improving the resilience of port systems from different perspectives are identified, including the advanced equipment, maintenance and reliability, and technology restoration in the future. Practically, such findings contribute to a deeper understanding of port resilience and offer industry practitioners and policymakers valuable implications to enhance sustainable and resilient port management.

1. Introduction

The Greater Bay Area (GBA), encompassing the towns of Hong Kong, Shenzhen, and Guangzhou, has emerged as a thriving hub for container visitors and port improvement in Asia. As one of the four key bay areas worldwide,[1] this southern coastal region of China has become a worldwide logistics centre because of its strategic location, well-evolved infrastructure, and favourable rules (Xu et al., 2023). For example, the Port of Shenzhen handled around 28.5 million TEUs in 2023, making it an essential gateway for an alternative between China and the rest of the world (Port of Shenzhen, 2024), while the Port of Hong Kong has also maintained its significance with the management of around 16.5 million TEUs in 2023 (Port of Hong Kong, 2024). This exponential boom has been fuelled by the enlargement of economies, the upward thrust of e-commerce, and the place's integration into worldwide delivery chains. Ports in the GBA have become essential nodes, facilitating the seamless motion of products and helping the place achieve financial prosperity (Wang et al., 2022).

However, along with the economic prosperity brought by the coastal areas, it is found that container ports are usually affected by climate related events, e.g., growing temperatures, sea-degree upward thrust, natural disasters, resulting in potential risks and threats

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[1] Four key bay areas refer to the San Francisco Bay Area, the New York Bay Area, the Greater Bay Area, and the Tokyo Bay Area.

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posed on critical port infrastructure systems (Wang et al., 2024a; Yang et al., 2018a). Such situation is particularly severe in the GBA, where the geographical location exposes it to many climate risks that have significant impacts on the regional development, evident by hundreds of published journal papers on climate risks in this region in recent years (e.g., Qin et al., 2024; Wang et al., 2024c; Zheng et al., 2024a).

Specifically, typhoons are the biggest climate risk that the ports in the GBA face, especially in the summer months. For example, in 2018, the hit of Typhoon Mangkhut caused a delay of over 300 container vessels in the Hongkong Port, resulting in huge economic loss (The Intergovernmental Panel on Climate Change, 2019). Statistically, in recent years, the annual number of typhoon warnings issued by Guangdong Province has witnessed an increase from around 10 in the past to 23 warnings in 2023 (Guangdong Meteorological Service, 2024). Such number is particularly higher than other key bay areas mainly due to the proximity to the tropical storm belt of the GBA. The rising frequency of typhoons and their increasing intensity are clear indicators of the growing climate risks faced by the coastal ports in the region. In addition, heavy rainfalls and storm surges are often connected with typhoons, which may put coastal ports at the risk of flooding, especially in low-lying port areas. As a result, coastal port systems will be largely affected, including the disruption of port logistics and the damage to port facilities. For instance, the storm surges and continuous heavy rainfall brought by Typhoon Mangkhut caused severe flooding in Guangdong Province, with the growth of water levels and the damage of port facilities in port areas (Sohu, 2018). Besides, other climate related risks, such as the rising sea levels and extreme temperatures, also affect the port management of the GBA to a certain extent in recent decades. Therefore, it is not difficult to find that ports in the GBA region are highly vulnerable to a wide range of climate related risks. Evaluating the port performance against these risks is essential for growing effective strategies and ensuring sustainable port resilience.

Within the context of port resilience, the Chinese government declared the "Dual Carbon Target" in 2020 and suggested an Action Plan for Carbon Dioxide Peaking before 2030 (Chen et al., 2023). Governments in the GBA region have responded to this call and implemented various policies aiming at mitigating the impacts of climate change and improving the port resilience performance, including the development of port adaptive strategies to withstand climate related risks in the formulation and amendment of Guangdong Province Climate Change Adaptation Action Plan, and the integration of climate change into the Port Master Planning. The implementation and continuous improvement of these standards is also a signal demonstrating the crucial importance of port resilience in achieving the sustainability goals locally and globally. Therefore, the GBA region is recognized as an emerging area where increasing climate risks (demand) meet the fast growth of climate adaptation policies (supply).

Driven by the demand for analyzing port resilience and the national strategies to promote sustainable port development, substantial research has been conducted with a particular consciousness on ports and weather extremes in the last decades (Wan et al., 2018; Wang et al., 2023b; Poo and Yang, 2024). However, significant research gaps have been found in current studies, i.e., the limitations of current applied approaches for the assessment of port network resilience to weather extremes, the demand for additional research studies on the resilience of ports in the GBA region where the effects of weather extremes can be extra severe, as well as the ignorance of experienced time of different port performance stages when facing climate related disruptions in the calculation of port resilience. More detailed information regarding these research gaps can be found in section 2.4.

To address these research gaps, this research aims to develop a comprehensive resilience assessment framework on port systems in the face of climate change using an Objective Oriented Bayesian Network (OOBN) model. Multidimensional factors that affect the resilience performance of port systems are considered, covering the disruptions, absorptive capacity, recovery capacity, and adaptive capacity. The questionnaire is designed to collect expert knowledge on the interdependencies among these factors, as well as to learn the parameters in the developed model. Taking the GBA as an example, the proposed OOBN model is proven to be effective in evaluating the preparedness of ports to withstand and recover from risks caused by disruptions dynamically, as well as calculating the exact port resilience value rationally. Sensitivity analysis is conducted to not only clarify the influence of different factors but more importantly to identify key factors that have significant influence on port resilience from different perspectives.

In this case, the research makes new contributions with regard to the following perspectives:

1) The OOBN model is, for the first time, applied for the port resilience analysis upon the authors' best knowledge. It is proved to have better performance than the standard BN model in terms of the expansion of network structure, especially for port resilience assessment where various factors from multiple aspects are considered. Further, the application of the Expectation maximization (EM) learning approach provides a new solution to addressing the data uncertainty issue (i.e., missing data or abnormal data) in the calculation of conditional probabilities in the BN model existing in the port resilience field, which is superior to the state-of-the-art Noisy-or approach. Such incorporation can also reinforce the current knowledge on the port resilience field.
2) The newly proposed assessment framework in this research takes into account the experienced time of the disruption stage and the recovery stage when assessing port resilience, which was ignored in previous research. Such consideration could provide a more reliable assessment result because the time ratio between the reduction and recovery is undoubtedly a signal reflecting the resilience performance of a port system, highlighting another novelty of this research.
3) Clarification of the climate resilience variation of port systems in the GBA along with the change of key parameters. To enhance the port climate resilience, port governments are suggested to improve the utilization rate of port facilities and implement recovery strategies with faster relative recovery speed simultaneously.
4) Redefinition and of the newly introduced key items influencing the performance of port systems in terms of different dimensions of port resilience via a comprehensive analysis work incorporating an improved mutual information analysis approach and the scenario analysis. 'Reduced navigational safety in port areas' is identified as the risk factor that has the highest influence on the occurrence of climate-related disruptions, while key measures in improving the port climate resilience are identified from port

capacities of absorption, recovery and adaption, including the advanced equipment, maintenance and reliability, and technology restoration in the future respectively.

5) The research provides new valuable practical implications for strengthening and managing resilience in port management for port governments. For example, the formulation of specific instructions on controlling serious climate-related risks on port disruptions, the implementation of effective measures identified via the comprehensive analysis across both the recovery and adaption aspects.

The remainder of this paper is organized as follows. Section 2 reviews the relevant studies focusing on port risk and resilience. Section 3 introduces the research framework, and the major methodologies applied in this work. The case of the GBA is utilized in Section 4 to illustrate how the model is developed based on the collected data. Section 5 provides an in-depth analysis of the model outputs containing the assessment of port resilience and the sensitivity analysis of the involved factors. Section 6 concludes this work.

2. Literature review

In this section, current studies regarding the port resilience under climate change are discussed, as well as the application of Bayesian network (BN) for the quantification of the port resilience.

2.1. Port resilience

Critical infrastructure structures, consisting of container ports, are crucial for assisting societal features and allowing international exchange. These structures are characterized by their interdependence, complexity, and the cap potential for cascading failures (Rinaldi et al., 2001; Panahi et al., 2021). Container ports, as crucial infrastructure, play a pivotal function inside the international logistics network, facilitating the motion of products and assisting monetary improvement. However, the criticality of ports additionally puts them at risk of disruptions, such as the ones due to climate change. Understanding container ports' specific traits and demanding situations as crucial infrastructure structures is important for growing powerful resilience strategies.

Traditionally, Port resilience is the performance of the port reacting and recovering from the risks associated with expected and unexpected disruptions, or in other words, the ability to prevent the exposure of the disruptions (Lau et al., 2024). It consists of four dimensions: disruption, absorptive capacity, recovery capacity, and adaptive capacity (Li et al., 2024a; Wang et al., 2023a).

Disruptions refer to those events that may cause negative impacts on the port, e.g., substantial financial losses, or severe imbalances of the port management system (Gu & Liu, 2023). These disruptive events could be viewed as associated risks threatening various aspects of the normal operations of coastal ports. The cap potential disruptions that ports may also face because of climate change are manifold and may have far-accomplishing consequences (Liu et al., 2023b). Sea-stage upward thrust, for example, can cause the inundation of port facilities, rendering them unusable and disrupting maritime supply chains (Becker et al., 2013). Extreme climate activities, consisting of hurricanes, typhoons, and hurricane surges, can cause extreme harm to port infrastructure, such as breakwaters, quay walls, and load coping with equipment. These disruptions to port infrastructure will have cascading consequences on international maritime supply chains, as ports function as crucial nodes inside the motion of products (Zhao et al., 2024). The failure of an unmarried port can cause delays, bottlenecks, and the disruption of exchange, with good-sized monetary consequences (Becker et al., 2018). Understanding the precise climate change-brought disruptions that ports face is crucial for growing powerful resilience strategies (Liu et al., 2023c). Besides, enhancing the resilience of ports in the face of climate change is important for ensuring the continuity of world exchange and monetary prosperity (Wan et al., 2024).

When disruptive events occur, the port performance will be affected. At this time, the intrinsic ability of the port will help absorb the negative impacts caused by these disruptions, which is called the absorptive capacity (Golan et al., 2020). This consists of measures consisting of infrastructure reinforcement, flood safety structures, and emergency reaction planning. For example, the Port of Rotterdam in the Netherlands has carried out a complete flood safety system, such as hurricane surge boundaries and dike reinforcement, to decorate its absorptive capability and face up to the effects of sea-stage upward thrust and excessive climate activities (Port of Rotterdam, 2022). Similarly, the Port of Los Angeles has invested in the improvement of shore electricity infrastructure, permitting ships to connect with the electric grid and decrease their emissions even at berth, thereby mitigating the environmental effect of port operations (Port of Los Angeles, 2021).

Subsequently, the port performance will recover from its lowest point gradually and steadily because of its recovery capacity (Wang et al., 2024b). The idea of recuperation potential and its importance in making sure to spark off recovery of port capabilities after disruptions must be discussed. The operation generally takes longer than what it undergoes in absorption. It may return back to its original condition, enhance to a higher condition, or attain a lower condition (Rehak et al., 2018; Gu et al., 2024). Examples of successful recuperation plans and techniques hired via way of means of resilient ports can offer precious insights. The Port of Singapore, for instance, has advanced a complete enterprise continuity plan that outlines tactics for the speedy recovery of port operations on the occasion of a disruption (Maritime and Port Authority of Singapore, 2022a; Maritime and Port Authority of Singapore, 2022b). This consists of the pre-positioning of crucial gadgets and the status quo of backup centres to ensure the continuity of shipment management and logistics services.

The port system will then maintain at the evolved steady level, and adapt to the disruptions it has experienced spontaneously, indicating it will learn from such progress and react or recover faster and more effectively next time in case similar disruptions happen (Xu et al., 2024). Case research highlighting powerful adaptive measures carried out via means of ports globally can indicate the improvement of complete resilience evaluation frameworks (Xia et al., 2024). The Port of Shenzhen in China, for example, has followed a proactive technique to weather trade adaptation, together with the implementation of inexperienced infrastructure, the diversification of strength sources, and the mixing of climate change issues into its long-term period planning (Port of Shenzhen, 2024). These measures have more advantageous the port's cap potential to develop to the evolving weather panorama and reduce the effect of destiny disruptions.

2.2. Assessment methods for port resilience

Recent years, a wide variety of approaches has been applied to assess port resilience, e.g., decision-making approaches (John et al., 2014), simulation analysis (Zhou et al., 2021), and other quantitative approaches. Among these methods, BN is a preferred one for the assessment of port resilience because of its ability in dealing with causal relationships and risk assessment (Yang et al., 2024a).

Incorporating the Fuzzy Analytical Hierarchy Process with the BN, John et al. (2016) presented a quantitative risk assessment model to assist port governments in implementing strategies for improving the resilience of port systems. Focusing on inland waterway ports, Hosseini & Barker (2016) proposed a useful tool based on the BN model in quantifying port resilience. Later, Hossain et al. (2019; Hossain et al., (2019, 2020) developed two BN models to assess the resilience of full-service deep-water ports and surrounding supply chain network of inland ports respectively. Similarly, Panahi et al. (2022) identified the key disruptions and strategies affecting the container terminals in Hongkong port. Wang et al. (2023a) constructed a port resilience assessment model, and they compared the performance of automated and non-automated terminals in Shanghai Yangshan port in China.

2.3. Adaptation and mitigation strategies in climate risk management for ports

Seaports play a critical role in global trade and are increasingly vulnerable to the impacts of climate change, including extreme weather events, sea-level rise, and natural disasters. To address these challenges, the literature highlights the need for adaptation and mitigation strategies to enhance seaport operations' resilience and sustainability (Morris, 2020). This review synthesises existing research on adaptation and mitigation (decarbonisation) in disaster management and climate risk analysis for seaports, emphasising both theoretical and practical contributions.

Adaptation strategies focus on increasing the resilience of seaports to climate-induced disruptions. Ng et al. (2018) highlight the importance of understanding sector-specific climate impacts to develop appropriate adaptation measures for commercial ports. They emphasise stakeholder collaboration, policy integration, and the alignment of adaptation goals with long-term business strategies. Jiang et al. (2020) distinguish between mitigation and adaptation strategies for seaports, underscoring the need to balance short-term disaster responses with long-term infrastructure resilience. Gong et al. (2020) extend this perspective by examining seaport investments in capacity expansion and natural disaster prevention, revealing that proactive investments can significantly reduce vulnerability to disasters while maintaining operational efficiency. Griese et al. (2021) construct a theoretical framework to analyze the acceptance phases for climate adaptation measures and disclose the key points for promoting the utilization of different adaptation measures. Wang et al. (2024b) develop an evaluation model to analyse the adaptation measures of ports in respond to typhoons, and reveal the inadequate supply of institutions and the absence of the main port stakeholders have higher probabilities leading to imperfections of port systems. Wu et al. (2024) explore how co-opetition with dry ports can enhance seaports' disaster adaptation capacities. Their findings suggest collaborative strategies involving interconnected transport nodes can improve disaster preparedness, resource sharing, and operational continuity during disruptions. Roukounis and Tsihrintzis (2024) also explore the effectiveness of different adaptation measures in enhancing port resilience.

Recent studies have also introduced the Climate Change Risk Indicator (CCRI) framework as a comprehensive tool for assessing climate risks in transport systems. Poo et al. (2021) focused on the application of CCRI for UK seaports, providing insights into the prioritisation of resilience measures and enabling more targeted adaptation strategies for port operations. Similarly, Wang et al. (2023b) apply the CCRI framework to a multi-modal transport system, highlighting its effectiveness in identifying and mitigating vulnerabilities posed by climate change. These frameworks offer valuable methodologies for integrating risk assessment into seaport disaster management and climate adaptation planning.

Mitigation strategies in seaport operations primarily focus on reducing greenhouse gas emissions and promoting sustainability. Masodzadeh et al. (2024) analyse the contribution of ports to shipping decarbonisation through incentive programs and the role of port state control. Their research demonstrates the potential of policy-driven initiatives to accelerate the adoption of low-carbon technologies and practices within the maritime sector. Alamoush et al. (2024) investigate the determinants of port decarbonisation implementation, using Implementation Theory to identify key enablers and barriers. Their study highlights the significance of regulatory frameworks, stakeholder engagement, and financial incentives in achieving decarbonisation goals. Similarly, Calderón-Rivera et al. (2024) address barriers to sustainable inland waterway transport, offering solutions that can inform broader decarbonisation efforts in the maritime industry.

A comprehensive approach to climate risk analysis often requires the integrity of both adaptation and mitigation strategies. Zheng et al. (2024) advocate implementing demonstrator projects to showcase effective adaptation measures for transport facilities, including seaports. Their research emphasises the importance of pilot initiatives in building stakeholder confidence and guiding large-scale implementation. Wu et al. (2024) highlight the interplay between adaptation and mitigation through collaborative initiatives with dry ports, suggesting that co-opetition frameworks can simultaneously enhance disaster resilience and reduce carbon footprints. This dual focus aligns with the broader trend of integrating climate adaptation and mitigation into seaport risk management strategies.

2.4 Research gaps

The relevant studies mentioned above contributed a lot to analysing port resilience from multiple dimensions. However, notable research gaps have emerged in the following aspects:

1) The limitations of current applied methods for port resilience assessment.

As indicated by previous research in this field, the standard BN model is the most popular method for the assessment of port resilience because of its capacities in dealing with risks and uncertainties. However, since the port resilience assessment is a complicated work involving various factors from multiple aspects, it will be intractable for the standard BN model to present a reliable network with expanded network structure (Fu et al., 2023). Therefore, new method is required to address this technical issue.

2) The demand for port resilience assessment in the GBA.

As stated in the introduction section, the port areas in the GBA region are largely affected by the climate risks due to its geographical location, hence making it necessary and significant to develop a systematic framework for quantifying the port resilience performance and analyzing the effect of risks on port systems brought by climate change. However, such topic is rarely discussed in previous works, making it a gap to fulfil in academic field.

3) The ignorance of experienced time of different stages.

Another research gap has emerged in the context of undertaking influenced time of different stages when calculating port resilience. Longer experience time in disruption and absorption stages or shorter experience time in recovery and adaption stages means better resilience performances of port systems. However, previous works ignored this point, which may affect the reliability of the assessment results.

Addressing these gaps could help enhance the understanding of port resilience against climate change for both the industrial and academic fields.

3. Methodology

This paper proposes a new idea of assessing resilience-constructing capability through three key dimensions: absorptive capability, recovery capability, and adaptive capability. The formulation of the idea is also supported by the real-world observations and previous studies against each dimension in a piecemeal manner. It is our intention to combine them in one holistic framework for comprehensive assessment of port climate resilience.

3.1. Quantification of port resilience

Through analysing the progress of port performance when disruptions occur, it is obvious that the whole process can be divided into two stages. In the first stage, because of the risks brought by disruptions and the absorptive capacity of the port system, port performance may experience a certain degree of loss; and in the second stage, the recovery capacity and the adaptive capacity will improve the port performance and reinvent the port system simultaneously. As a result, port resilience is commonly recognized as the ratio of the recovered performance (RP) to the lost performance (LP), as suggested by relevant studies in this field (Henry & Ramirez-Marquez, 2012; Hosseini & Barker, 2016; Panahi et al., 2022). In fact, since both the LP and the RP will occur only when certain conditions are satisfied, it is more appropriate to calculate the port resilience using the expected values of the LP and the RP considering the occurrence probabilities of corresponding conditions.

That is to say, let the port performance before the occurrence of disruption be x1, the performance after the disruption be x2, the occurrence probability of disruption be P1, the probability of absorptive capacity taking effect be P2. It is obvious that the port will lose performance ($x1 > x2$) only when the disruption occurs and the absorptive capacity of the port is unable to absorb such impacts, otherwise the lost performance would be zero as the disruptions are absorbed by the port ($x1 = x2$). Hence, the expected LP is calculated as:

$$LP = P_1(1 - P_2)(x_1 - x_2) \tag{1}$$

Further, during the port performance moves from x_1 to x_2, the recovery and adaptation abilities of the port system will consistently prompt the port performance to recover back to a normal operational status. Such recovery progress will occur only when either one of the recovery/adaptation abilities performs successfully, and the recover degree is set as α, which is the utilization rate of the port under regular operation situations. Besides, let the success rate of recovery capacity and adaptive capacity be P_3, and P_4 respectively, then the expected RP is calculated as:

$$RP = P_1(1 - P_2)\{[1 - (1 - P_3)(1 - P_4)] \times \alpha(x_1 - x_2)\} = [1 - (1 - P_3)(1 - P_4)] \times \alpha LP \tag{2}$$

As mentioned above, the traditional way to obtain the port resilience is to calculate the ratio of RP to LP subsequently. However, such classical expression utilized in previous research ignores one important element when assessing resilience, which is the influenced time at different stages. Under the condition of same disruption, a port system whose performance reduces slower in the first stage and rebounds or recovers faster in the second stage undoubtedly has stronger resilience than those systems with opposite trends. Therefore, it is necessary to take the influenced time at different stages into consideration when assessing port resilience.

In this research, let the performance reduction time be t_1, the recovery time till the steady status is t_2, then the port resilience is assessed by Equation (3), where it is proportional to t_1 and inversely proportional to t_2. The ratio t_1/t_2 is named as relative recovery speed (*rrs*), which represents the recovery speed comparing with the disruption speed.

$$Port\,Resilience = \frac{RP}{LP} \times \frac{t_1}{t_2}$$

$$Port\,Resilience = [1 - (1 - P_3)(1 - P_4)] \times \alpha \times \frac{t_1}{t_2} \tag{3}$$

3.2 Research framework

To achieve the assessment of port resilience, a research framework based on the novel application of the OOBN is proposed in Fig. 1. An incorporation of the Expectation Maximization (EM) approach and improved mutual information approach is utilized, and a

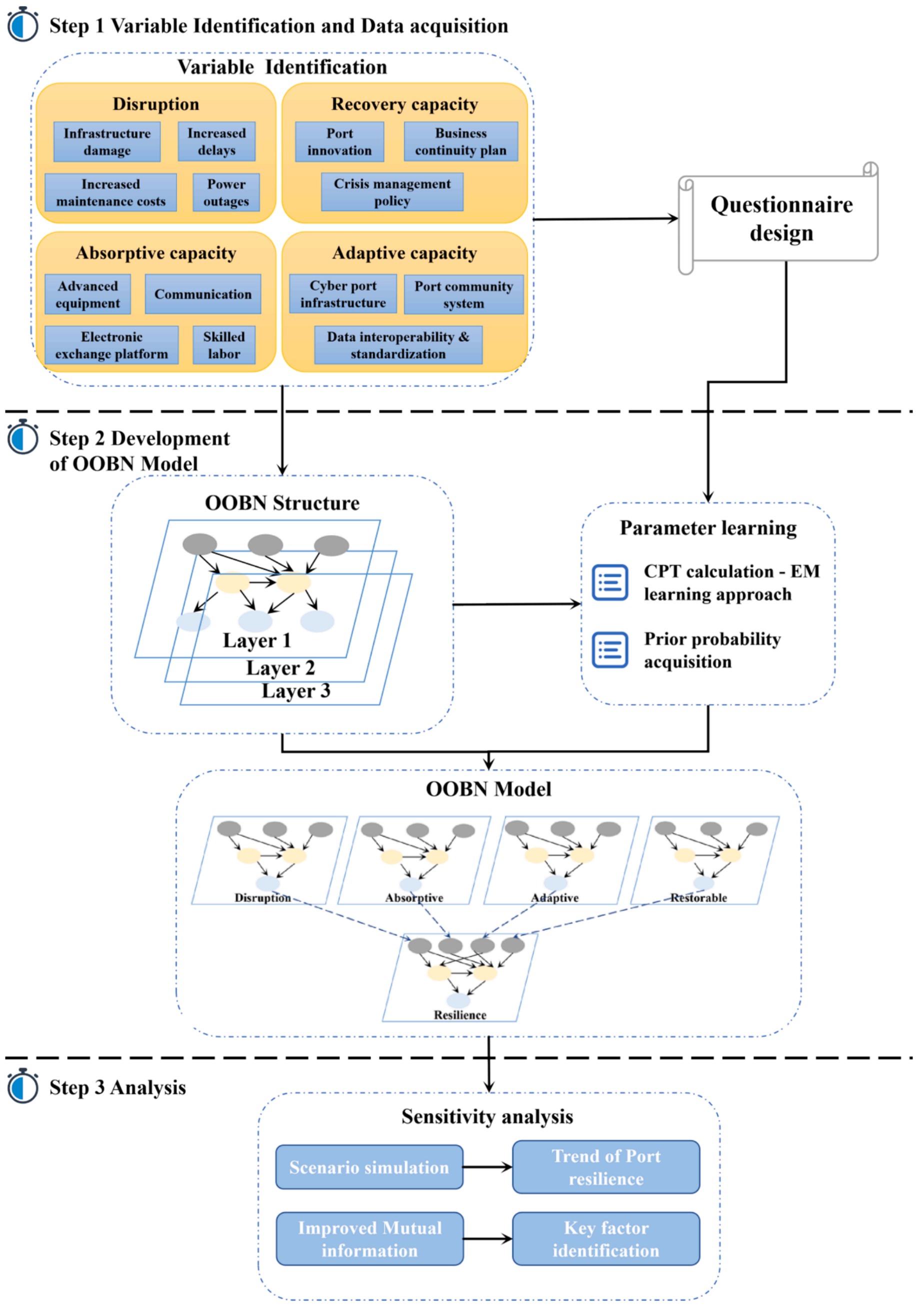

Fig. 1. Research framework for the port resilience assessment facing climate change.

detailed explanation of the framework is presented in the ensuing section.

3.2.1. Step 1: Variable identification and data acquisition

In this research, since the objective is to assess port performance in terms of the disruptions caused by climate change, relevant events and measures that may affect port resilience in this aspect are identified as the variables in the OOBN model from the literature. A questionnaire is then designed focusing on the causal relationships and dependencies among these variables corresponding to different aspects of port resilience. Various experts in this field are invited to express their opinions, which could help develop the subsequent model.

Since different experts have different research backgrounds, e.g., educational level, working experience, different weights should be assigned to these experts. In this research, the weight of each interviewed expert is calculated based on the following equation:

$$w_i = \frac{s_i}{\sum_{i=1}^{n} s_i}, i = 1, 2, ..., n \tag{4}$$

Where n is the number of all involved experts, w_i is the weight for the selected expert, s_i is the weight score of the selected expert calculated based on the criteria presented in Table 1, which is set according to many similar studies (Senol et al., 2015; Kuzu et al., 2019; Gürgen et al., 2023), and $\sum_{i=1}^{n} s_i$ is the total weight scores of all experts. In a word, the weight of each expert is calculated as the proportion of total weight scores. The determination of expert weights is able to help calculate the prior probabilities of root variables.

3.2.2. Step 2: Development of the OOBN model

As listed in literature review section, there have been several studies assessing port resilience using the standard BN in recent years. Because of its advantages in modelling risk and uncertainties through a probabilistic graphic network, the application of the BN is a proper way to assess and analyze port risk and resilience from both forward risk assessment and backward diagnosis (Yang et al., 2018b; Yang et al., 2023a).

However, because port resilience is a complicated problem involving influential factors from multiple aspects, i.e., risks and disruption, absorptive capacity, adaptive capacity, and recovery capacity, it is evident that the standard BN models are unable to manage the associated variables in a single network simultaneously in terms of the expansion of network structure (i.e., more involved factors) in this research.

To solve such an issue, an extended version of BN, called OOBN, is, for the first time, applied to port resilience analysis upon the authors' best knowledge. It is a complicated model consisting of several sub-models (Liu et al., 2016; Fu et al., 2023). Fig. 2 illustrates an example of an OOBN model. Each sub-model is a standard BN model, presenting the causal relationships among variables under this aspect. In each sub-model, there are three types of variables: input variable, internal variable, and output variable. For input variables and output variables, they work as the interfaces of each sub-network, or in other words, the input variables of the subsequent sub-network are linked with the output variables of the former sub-network, thus connecting the whole network. While for the internal variables, they are invisible and not allowed to connect with variables in other sub-networks. Additionally, the basic principle of the standard BN still applies to OOBN, which means loops are not allowed either in a single sub-network or the whole network.

Because of the distinctive features of OOBNs, it can achieve object-oriented modeling (Fu et al., 2023). Each sub-network is

Table 1
Weight scores for experts.

Constitution	Classification	Score
Current Job Position	Others	1
	Director/Analyst	2
	Manager	3
	Consultant	4
	Supervisor/Officer	5
	Others	1
Educational level	Bachelor	2
	Master	3
	Doctoral	4
Working Department	Others	1
	Research and Development	2
	Transportation	3
Company's Nature	Others	1
	Third-party logistics service providers/Freight forwarder	2
	Transport operators	3
	Port	4
	2–5 years	1
Working experience	6–9 years	2
	10–15 years	3
	16–20 years	4
	21–25 years	5
	26–30 years	6
	31 years or above	7

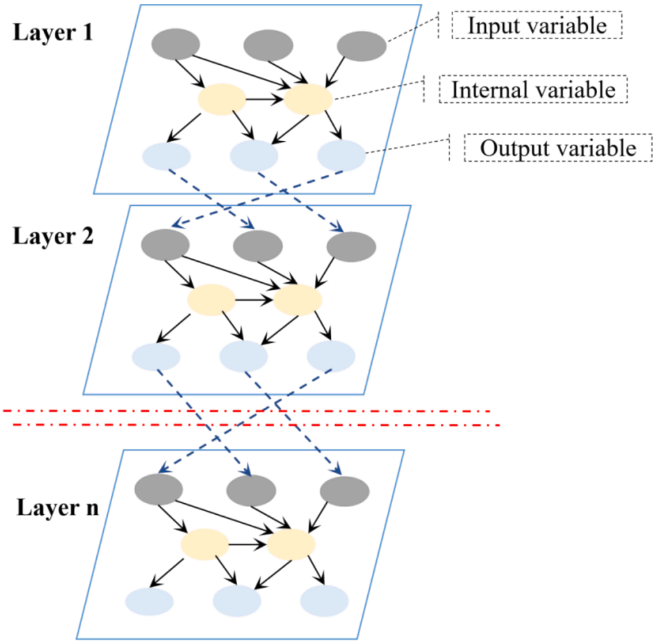

Fig. 2. An example of an OOBN model.

abstracted using an instance node, and the information of one sub-network is transmitted forward to the next one via the connections between input and output variables. Moreover, it also possesses the basic functions of the standard BN such as forward assessment and backward diagnosis. All of these natures make the OOBN a suitable modelling approach to the assessment of port resilience in this research.

To be specific, the development of the OOBN model in this research consists of two parts: structure determination and parameter learning.

(1) Structure determination

The determination of model structure is easy to achieve. Based on the identified variables in Step 1, the structure of each sub-network is obtained according to the discussions and opinions from invited experts, resulting in four sub-networks corresponding to the four dimensions of port resilience. Then the four target variables in four sub-networks are combined and act as the input variables for the final sub-network whose target variable is 'port resilience', as presented simply in Fig. 1.

(2) Parameter learning.

Once the structure of the OOBN model is determined, parameter learning is conducted to clarify the probability tables for each variable embedded in the model. There are two types of probability tables in the model, one is the prior probability tables (PPTs) for root variables (variables with no parent nodes), and the other is the conditional probability tables (CPTs) for target variables or internal variables with parent nodes. PPTs are relatively easy to acquire. Since each interviewee is asked to present their opinion on the occurrence probability of these root variables, hence the prior probabilities are calculated as the weighted average value of their answers, where the weights are determined based on the different backgrounds, experiences, and professionalism of the interviewees.

For the determination of CPTs, the traditional way to calculate conditional probabilities in previous research in the port resilience

Table 2
Parameters in the EM algorithm.

Parameters	Descriptions
$\boldsymbol{X_i}$	Variables
$\boldsymbol{x_{ik}}$	k^{th} state of X_i
$\boldsymbol{Parents(X_i)}$	parent nodes of X_i
$\boldsymbol{Parents(X_{ij})}$	j^{th} state of $Parents(X_i)$
$\boldsymbol{N_{ijk}}$	Number of cases involving x_{ik} and $Parents(X_{ij})$ in training data
$\boldsymbol{c_n}$	Specific case of x_{ik} and $Parents(X_{ij})$ in the training data, value range: $[1, N_{ijk}]$
$\boldsymbol{\alpha}$	Conditional probability of x_{ik} under the condition of $Parents(X_{ij})$
$\boldsymbol{\widehat{\alpha}}$	Estimation of α
$\boldsymbol{\widehat{\alpha}'}$	Updated value of $\widehat{\alpha}$
d	Data sample
d^*	Missing data sample
$\in$	Desired degree of precision

field is the Noisy-or approach (Hosseini & Barker, 2016). However, since there exists missing data or abnormal data if and when some interviewees may be unfamiliar with some aspects, the Noisy-or approach is incapable of modelling the associated uncertainty in data and hence not selected in this research. Instead, the EM learning approach, which is a deterministic approach to learning parameters asymptotically, is applied to calculate the conditional probabilities in the proposed model. It is again for the first time applied in the port resilience field, upon the authors' best knowledge, providing a new solution to the difficulty of accommodating high uncertainty in data in BN CPT of port resilience beyond the state-of-the-art methods (i.e., Noisy-or). Based on the probability distributions given by interviewees in the collected questionnaire data, a learning database containing simulated cases conforming to these probability distributions is generated accordingly, which could be utilized to achieve the CPT learning work via the application of the EM learning approach. It has been proven to be effective in dealing with incomplete data issues (Yang et al., 2024a; Yang et al., 2024b). The detailed information for the approach is introduced as follows.

The EM learning approach is briefly introduced as follows (Lauritzen, 1995). Table 2 presents the defined parameters utilized in the approach, while the subsequent procedures illustrate how the EM learning approach is achieved. More detailed information is documented in Yang et al. (2023b), including the detailed steps on how it is conducted for generating CPTs.

1) Set the value of $\widehat{\alpha}$ and ϵ arbitrarily.
2) The expected sufficient statistic for d^* is calculated through Equation (2)
3) The updated value $\widehat{\alpha'}$ for α is obtained following the rule of maximising $P(d^*|\widehat{\alpha'})$ using the calculated $E_{P(X_i|d,\hat{\alpha})}N_{ijk}$.

$$E_{P(X_i|d,\hat{\alpha})}N_{ijk} = \sum\nolimits_{n=1}^{N_{ijk}} P\left(x_{ik}, Parents\left(X_{ij}\right)|c_n, \widehat{\alpha}\right) \tag{5}$$

$$\widehat{\alpha'}_{ijk} = \frac{E_{P(X_i|d,\hat{\alpha})}N_{ijk}}{\sum_{k'} E_{P(X_i|d,\hat{\alpha})}N_{ijk'}} \tag{6}$$

Set $\widehat{\alpha'} = \widehat{\alpha'}_{ijk}$.

4) When $|\widehat{\alpha'} - \widehat{\alpha}| > \epsilon$, replace $\widehat{\alpha}$ with $\widehat{\alpha'}$.
5) Iterate this procedure until $|\widehat{\alpha'} - \widehat{\alpha}| \leq \epsilon$. The value of $\widehat{\alpha'}$ at this time is the learned value for the parameter.

Consequently, the calculated CPTs together with the obtained network structure constitute the final OOBN model.

3.2.3. Step 3: Analysis

Comprehensive analysis is conducted after the model is developed, which consists of the scenario simulation for the assessment of port resilience performance under various conditions, and sensitivity analysis for the identification of key variables that affect port performance in different aspects of resilience the most.

The scenario simulation is simply accomplished via inputting the relevant information into the proposed model, resulting in the corresponding value of port resilience under specific scenarios, while the sensitivity analysis is achieved based on the application of an improved mutual information analysis approach which is introduced as follows.

In information theory, mutual information is defined as the information shared by a pair of variables, which is an effective way to measure the strength of relationships between different variables (Fan and Yang, 2024; Li et al., 2024b; Zhou et al., 2024) . A higher value of mutual information is usually recognized as a signal of a strong relationship between the selected variables, thus help determining the key variables with significant influence on target variable.

However, considering the entropy of two variables is different, it would be one-sided to determine the strength of relationship based on the mutual information value if the difference of entropy value between X and Y is huge. Hence, in order to eliminate the entropy value differences of different variables, an improved mutual information (IMI) value is introduced in lEquation 7, which is able to clarify the relationships between attribute variables and target variable reliably and comprehensively.

$$IMI = \frac{I(X,Y)}{\sqrt{H(X) \times H(Y)}} \tag{7}$$

Where $I(X,Y)$ is the mutual information between variable X and Y, $H(X)$ and $H(Y)$ are the entropy of variable X and Y. After the calculation of the IMI value between each attribute variable and the target variable under the condition of the given data, variables with higher values are considered to have a greater influence on certain perspectives of the port resilience.

4. Model development — A case in the greater Bay Area

4.1. Data

A questionnaire is designed to gather relevant data used for the model development according to the approaches proposed by Iacobucci and Churchill (2010), which consists of seven steps: 1) Selecting the required necessary information from relevant literature; 2) Adopting a relevant question categorization and administrative manner; 3) Employing a relevant question layout and components; 4) Correctly organizing the question response; 5) Deploying precise wording in each question; 6) Selecting a practical and structured series of questions; 7) Generating a decision on the relevant design of questionnaire survey. After the adjustment and pre-testing work, a comprehensive layout of the questionnaire will be developed eventually.

The survey questions were discussed with relevant stakeholders including researchers, environmentalists, logistics associations, and industrial practitioners (e.g., logistics firms, terminal operators, and transport operators) to identify proper content, quantify the model, and question design. In doing so, it can increase the validity of the content and improve the correctness of the survey instruments. In particular, fuzzy wordings and duplex questions have been fully eliminated. A group of target survey respondents are also invited to conduct a pilot test of the survey. This step is commonly described as face validity (Ngai et al., 2008).

In general, the survey questionnaire is split into four key parts:

Part A: The profile of survey respondents is collected to give demographic or background information including gender, age, education level, current job position, the working department, the company's nature, and working experience in the logistics industry. The survey respondents were required to answer the seven items with close-ended questions.

Part B: In this part, major port disruptions associated with climate-related risks are identified. As described in the introduction section, port areas in the GBA are vulnerable to climate-related risks because of its geographical location. Among all possible risks that port areas may face, some of them are acute ones caused by extreme weather events such as the heavy rainfalls, storm surges, flooding, while others are chronic productions of long-term climate pattern changes like sea-level rise and temperature increase. Through a careful investigation on relevant pervious research focusing on these involved risks in two different types (e.g., Hosseini and Barker, 2016; Becker et al., 2018; Patel et al., 2018; Hossain et al., 2019; Hosseini et al., 2019; Verschuur et al., 2020; Izaguirre et al., 2021; Notteboom et al., 2021; Poo et al., 2021), nine major disruptions of port infrastructure were identified and verified to be relevant to the context of the GBA, including the disruption of maritime supply chains, damage to nearby ecosystems, damage to port infrastructure, increased maintenance costs, increased downtime and delays, increased risk of ship collision in port areas, reduced navigational safety in port areas, reduced cargo handling capacity, and power outages.

As such, survey respondents were asked to assign a probability of occurrence for each disruption based on their perception and/or experience about container ports in the GBA. Accordingly, the survey respondents were asked to indicate a probability of occurrence for every disruption ranging from 0 to 20 % – very low', 21 % to 40 % – 'low', 41 % to 60 % – 'medium', 61 % to 80 % – 'high', and 81 % to 100 % – 'very high'.

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Part C: In this part, the resilience-building capacities of ports in the GBA in response to the climate-induced risks are assessed. Aiming at reducing the vulnerability and enhancing preparedness of port systems, different measures are proposed from multiple dimensions, i.e., the absorption, recovery, and the adaptation. According to the guidelines for resilient port operations and adaptations against climate change formulated by various international organizations, e.g., International Maritime Organisation (IMO), World Meteorological Organization (WMO), United Nations Conference on Trade and Development (UNCTAD), International Labor Organization (ILO), these measures could be classified into several categories: technological measures, social and community measures, policy and planning measures, and operational measures. Focusing on these categories, associated measures from three dimensions are recognized from related previous research (e.g., Mansouri et al., 2010; Madhusudan and Ganapathy, 2011; Hosseini et al., 2019; Komugabe-Dixson et al., 2019; Panahi et al., 2021), resulting in five measures in the absorptive capacity, five measures in the recovery capacity, and seven measures from the adaptive capacity presented in the following Table 3a and b.

In response, survey respondents were asked to assign a probability of occurrence for each capacity based on their perception and/or experience about container ports in the GBA. Similar to Part B, survey respondents were asked to give a probability of occurrence for each measure ranging from 0 to 20 % – 'very low', 21 % to 40 % – low', 41 % to 60 % – 'medium', 61 % to 80 % – 'high', and 81 % to 100 % – 'very high'.

Part D: At last, related experts are invited to discuss the causal relationships among the identified factors from different perspectives. The pairs of factors that are supposed to have relationships will be linked in the model, constituting the structure of subnetworks and the finalized model.

Once the questionnaire is designed appropriately, a purposive sampling approach is selected to choose the proper population members for this research. The survey is distributed to target respondents online from December 2023 to January 2024, resulting in 100 valid questionnaires at last. The survey questionnaires were completed anonymously, and the responses were kept confidential and used only for academic purposes. The profile of respondents is summarized and presented in Appendix A. Specifically, 64 % of respondents were male and 36 % of respondents were aged between 26 and 35 years old. The majority of respondents (93 %) were well educated and acquired at a tertiary educational level (i.e., at least Associate Degree or Higher Diploma level). Moreover, 40 % of

Table 3a
Measures for improving resilience-building capacities.

Absorptive measures	Advanced equipment, Electronic exchange platform, Skillful emergency response team, Skilled labor with professional qualification, Communication
Recovery measures	Maintenance and reliability, Port innovation, Port health and safety management, Business continuity plan, Crisis management policy
Adaptive measures	Technology restoration, Port worldwide network, Port community system, Hinterland connection, Service restoration, Data interoperability standardization, Cyber port infrastructure

Table 3b
IMI value of influencing variables.

Perspective	Variable	IMI
Disruption	Reduced navigational safety in port areas	0.02362
	Disruption of maritime supply chains	0.01632
	Damage to nearby ecosystems	0.01271
	Increased maintenance costs	0.01155
	Increased downtime and delays	0.01067
	Reduced cargo handling capacity	0.00844
	Damage to port infrastructure	$2.80*e^{-10}$
	Increased risk of ship collision in port areas	$3.51*e^{-11}$
	Power outages	$4.55*e^{-13}$
Absorptive capacity	Advanced equipment	0.04533
	Electronic exchange platform	0.04403
	Skillful emergency response team	0.03761
	Skilled labor with professional qualification	0.01147
	Communication	0.01023
Recovery capacity	Maintenance and reliability	0.08039
	Port innovation	0.07652
	Port health and safety management	0.05885
	Business continuity plan	$8.21*e^{-11}$
	Crisis management policy	$5.03*e^{-11}$
Adaptive capacity	Technology restoration	0.06447
	Port worldwide network	0.04596
	Port community system	0.01723
	Hinterland connection	0.01677
	Service restoration	0.00988
	Data interoperability standardization	2.88*e-10
	Cyber port infrastructure	2.64*e-10

respondents were positioned at a managerial level. In addition, 37 % of respondents indicated that their working department is the transportation department, while 28 % of respondents expressed that their company nature is third-party logistics service providers. Furthermore, 34 % of respondents pointed out that they have worked for 2–5 years in the logistics industry.

4.2. Development of OOBN model

4.2.1. Development of sub-networks

The OOBN model consists of five sub-networks: S_1 (target variable: disruption), S_2 (target variable: absorptive capacity), S_3 (target variable: recovery capacity), S_4 (target variable: absorptive capacity), and S_5 (target variable: port resilience). As mentioned in section 3, the relationships among involving variables in each sub-network are figured out via the expert feedbacks.

Once the structure is determined, parameter learning is conducted subsequently. The prior probabilities of variables are calculated

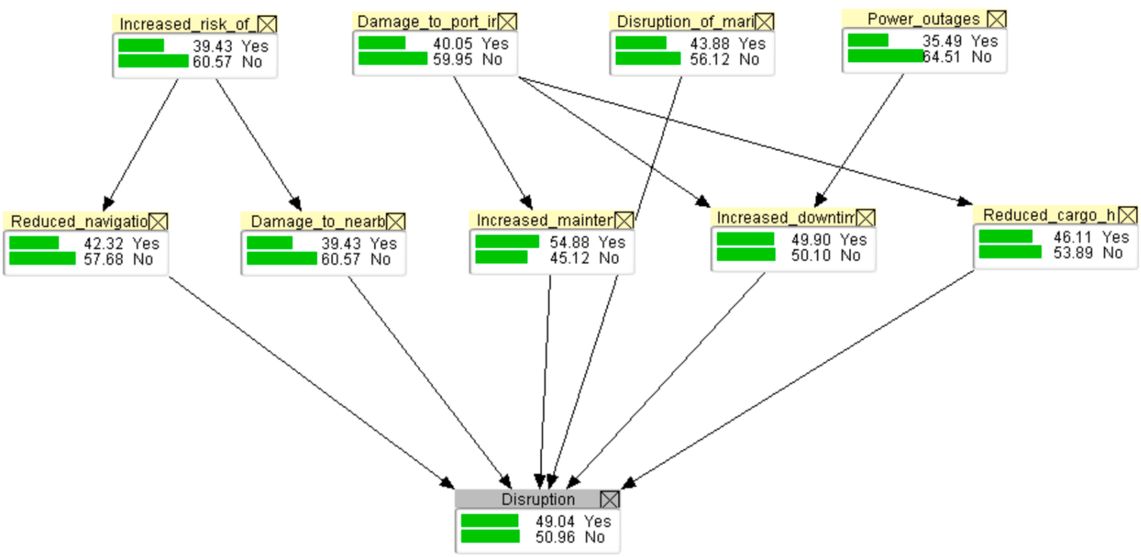


Fig. 3. Sub-network of ‘Disruption’.

as the weighted average of the interview outputs based on the weight calculation in Equation (4). As for the CPTs of other variables, they are acquired through the EM learning approach. Based on the calculated prior probabilities of each influencing variable, a data simulation process (Jensen and Nielsen, 2007) is conducted in the *Hugin* software to generate a learning database conforming to these numbers. EM learning approach is then applied to achieve the learning of CPTs existing in these sub-networks.

Consequently, the four sub-networks are presented in Figs. 3 to 6.

4.2.2. Development of finalized OOBN model

After the four sub-networks are determined, the finalized OOBN model is developed subsequently. Each target variable corresponding to each dimension in the above-developed four sub-networks is used as the input variable of the last sub-network, whose target variable is the 'port resilience'.

The last sub-network has three layers: four dimensions (i.e., disruption, absorptive capacity, recovery capacity, and adaptive capacity) of port resilience are located at the input layer, the LP and RP are set as the utility node in the internal layer, and the target variable 'Port resilience' is set as a function node putting at the last layer alone. The calculation of LP, RP, and Port resilience is achieved based on Equations (1) to (3) in Section 3.1. To be specific, the last sub-network is presented as follows in Fig. 7.

Consequently, by combining all sub-networks together, the finalized OOBN model for the assessment of port resilience in the GBA area is illustrated in Fig. 8.

Where each instance node (rounded rectangles in the figure) in the model represents the corresponding sub-network that is put forward in Sections 4.2.1 and 4.2.2, whose name is presented at the top of the rectangle. Meanwhile, the links in the model refer to the connections between the output variables and input variables of different sub-networks, conforming to the features of the OOBN model.

5. Results and analysis

5.1. Model results analysis

Through a thorough investigation of the proposed OOBN model, it is found that there is a 49.03 % chance that the disruption would occur in the port cluster in the GBA region, if and when a solid climate risk event occurs. Among all possible disruptions, the increased maintenance costs are identified as the risk factor that is most likely to happen (54.88 %), while power outages are the one that is most unlikely to happen (35.49 %). The occurrence probabilities of other disruption types fall within the range of 40 % to 50 %.

The structure of the absorptive capacity sub-network is the simplest one, with all influencing variables acting as independent nodes pointing at the absorptive capacity of the port. The port system in the GBA has a 69.37 % chance of success in absorbing the shocks and negative impacts caused by the disruptions, as indicated by the model results. All absorptive measures are recognized to have higher occurrence probabilities over 60 %. Of course, this result is based on the marginal probability, concerning the likelihood of all concern climate risk events. If and when a specific climate risk event is identified, such a result will be updated to better reflect specific cases (see Section 5.2).

For recovery capacity and adaptive capacity, both capacities have a success chance of around 70 % to achieve the recovery and adaptation of port performance. Considering the potential measures for these two perspectives, measures proposed for the adaptive capacity normally have higher occurrence probabilities, while those for the recovery capacity have a relatively lower chance. Data interoperability/standardization is viewed as the way that is implemented the most widely in terms of maintaining the adaptive capacity of ports, while three measures (i.e., maintenance and resilience, crisis management, and business continuity plan) have similar popularity about the recovery capacity, as reflected by the occurrence probabilities in the model.

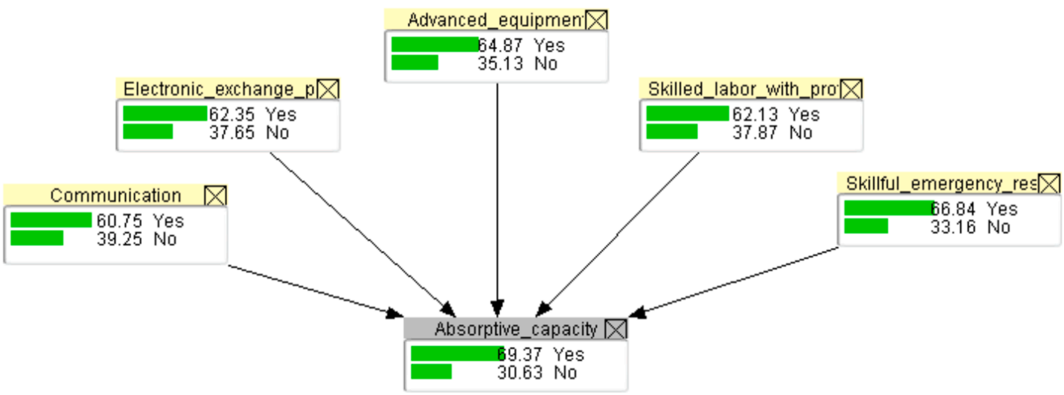


Fig. 4. Sub-network of 'Absorptive capacity'.

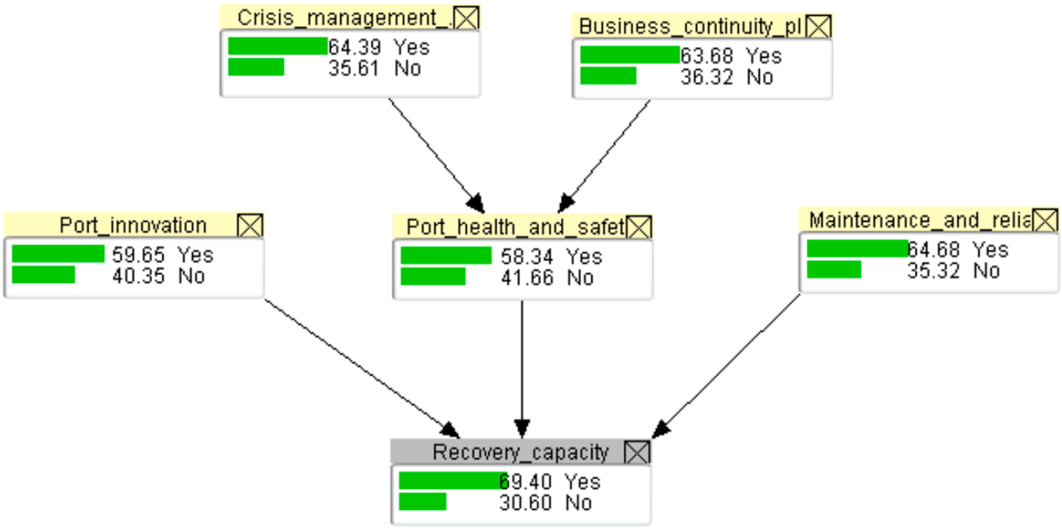


Fig. 5. Sub-network of 'Recovery capacity'.

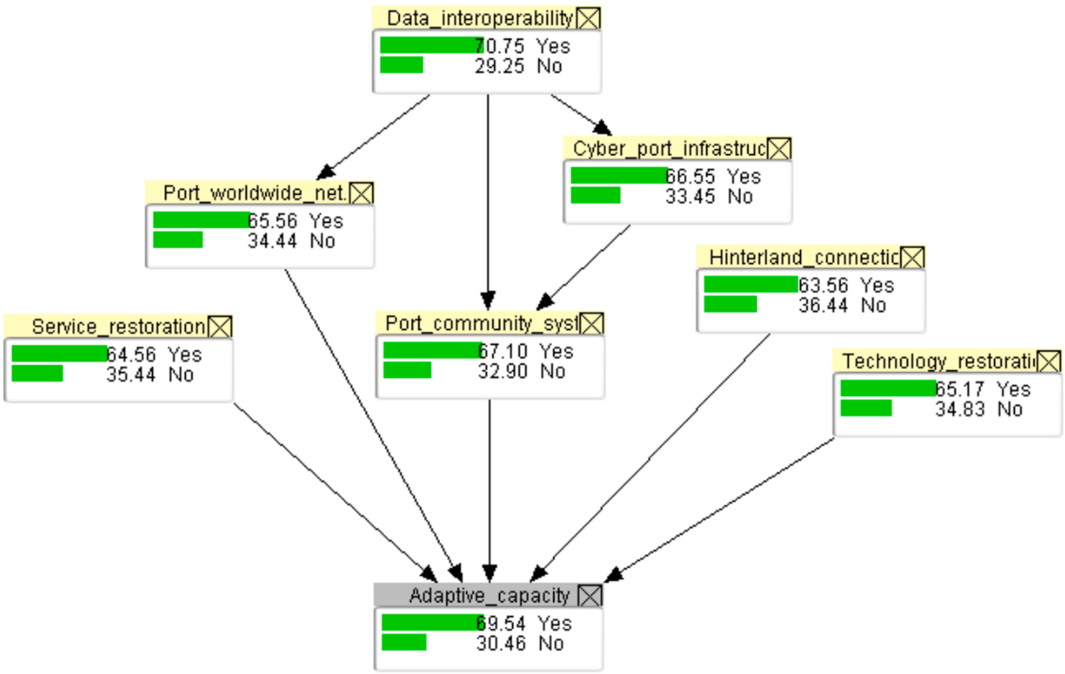


Fig. 6. Sub-network of 'Adaptive capacity'.

5.2. *Assessment and analysis of port resilience – scenario simulation*

In this section, port resilience is assessed via the proposed OOBN model, and an analysis is conducted to clarify the variation of port resilience under dynamic situations.

As suggested by relevant studies (i.e., Hossain et al., 2019; Hossain et al., 2020) and opinions collected from experts, the values of parameters in assessing port resilience in Equation (3) should conform to the following principles:

The recovery degree α, or the utilization rate, varies between 0.8 and 1.0; and

The recovery process in the second stage usually takes longer time than the performance reduction process in the first stage, indicating $t_1 > t_2$, or in other words, the ratio rrs (t_1/t_2) varies in the interval (0,1].

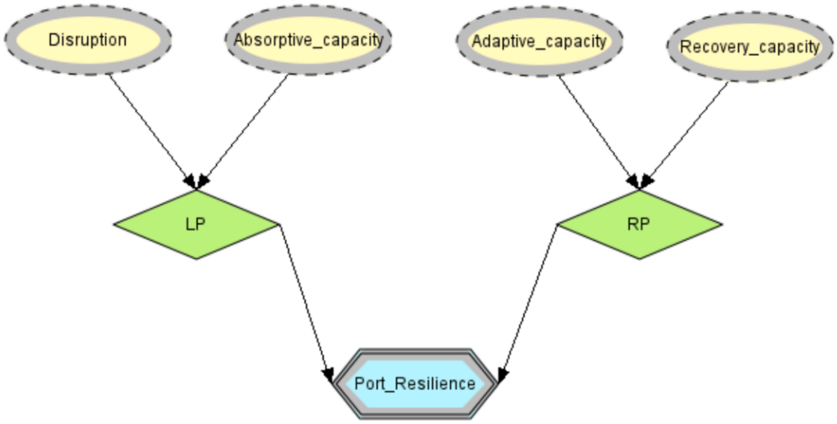


Fig. 7. Sub-network of 'Port resilience'.

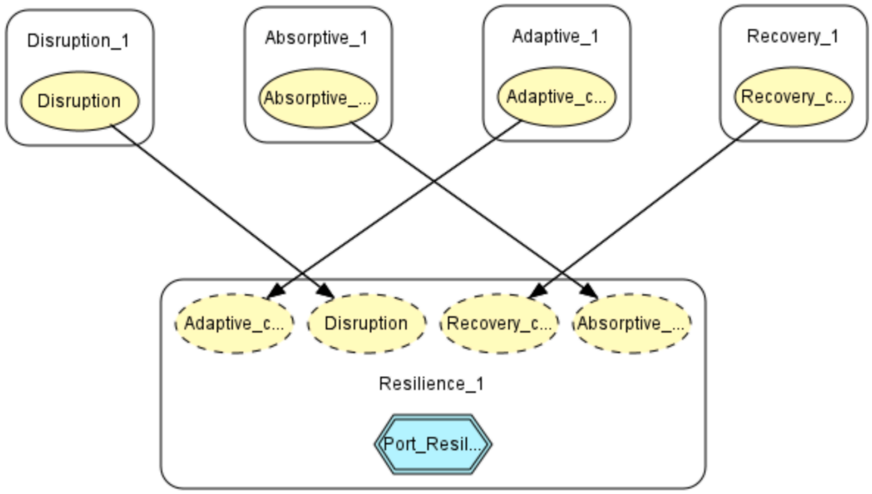


Fig. 8. The completed OOBN model for port resilience.

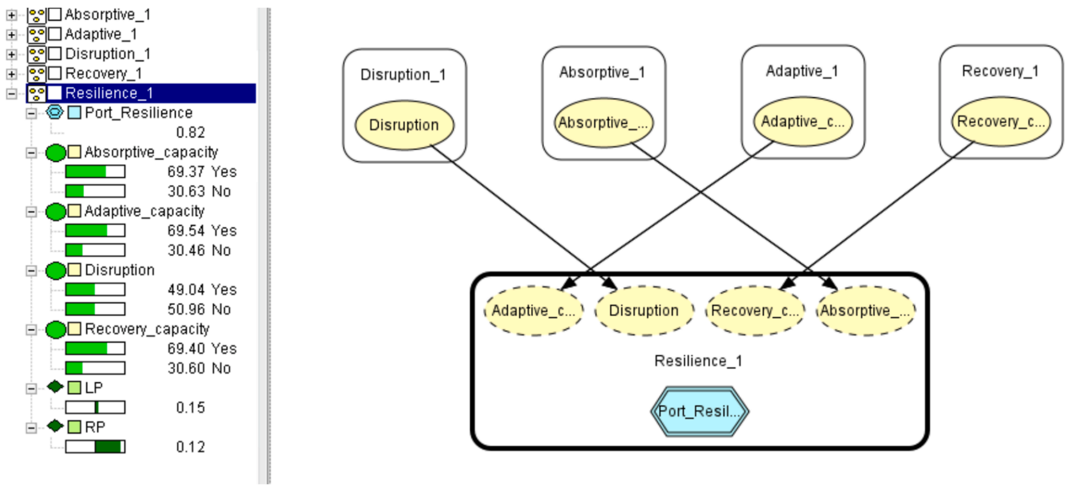


Fig. 9. The completed OOBN model for port resilience.

To demonstrate the assessment ability of the proposed OOBN model in this research, an example is illustrated in Fig. 9. The recovery degree α is set as the median value 0.9, and the *rrs* is set as 1 ($t_1 = t_2$), indicating the influenced time will not affect the final assessment result as the recovery time is equal to the lost time.

Once all information is put into the model, the panel on the left will present the calculated results. Under this scenario, it is found that port resilience is calculated as 0.82 under such conditions, along with the LP and RP calculated as 0.15 and 0.12, respectively. Port governments could follow this example to assess the port's resilience under their own conditions.

Further, as suggested by Equation (3), it is obvious that the port resilience is indeed affected by two parameters when the probabilities are determined by the OOBN model: the recovery degree (utilization rate) α and the *rrs* (relative recovery speed) β. The clarification of the variation of the port resilience value along with the change of these two parameters plays a significant role in understanding the trend of port resilience dynamically.

Matlab is utilized to draw the surface diagram that is able to reveal the trend of port resilience along with the change of these two parameters, which is illustrated in Fig. 10. In addition, the results of multiple scenario simulations under dynamic situations are presented in Fig. 11, where the value of one parameter is changed while the value of another value is kept unchanged.

From Figs. 10 and 11, several new findings are obtained as follows:

When both parameter α and β reach their maximum value '1′, the port system at this point will have the strongest performance against the negative impacts caused by the disruptions, whose resilience value is around 0.907; while on the other hand, if the recovery time last for infinitely long when comparing with the time of the first stage, the port resilience will approach zero. This finding well reflects the reality and in part verifies the model and the results.

In general, whatever the defined parameter is, its value increment will lead to the improvement of port resilience. The simultaneous increase of two parameters will further improve the port resilience to a greater extent. This finding provides valuable insights for port governments to focus not only on the utilization rate of port facilities, but also pay enough attention on the relative recovery speed of adopted recovery measures or adaptive ways.

Additionally, for a specific point on the surface diagram, it is not difficult to find that the higher the value of α and β it has, the larger the gradient it will have. Such phenomenon indicates the port resilience will be enhanced faster and faster along with the continuous increase of two parameters, indicating the faster *rrs* of adopted measures or higher utilization rate of port facilities should be the expected goals of port operations.

5.3. Sensitivity analysis

Sensitivity analysis is a widely applied measure to analyze the sensitivity of the resulting belief update of the target variable to the value variation of attribute variables. It can clarify the influence degree of different risk variables on the target variable and identify key variables that have stronger connections with the target variable, thus assisting the decision-makers in determining where they can improve, and how to formulate rational strategies.

As introduced in Section 3, mutual information analysis is applied in this research to figure out the influence magnitude of different variables. A basic principle of mutual information analysis is that a variable with a higher value of IMI is believed to have a greater influence on the target variable than one with a lower value. With the help of *Hugin* software, the results of IMI calculation in terms of different perspectives are presented in Table 3. Under each perspective, the influencing variables are listed in a descending order of value.

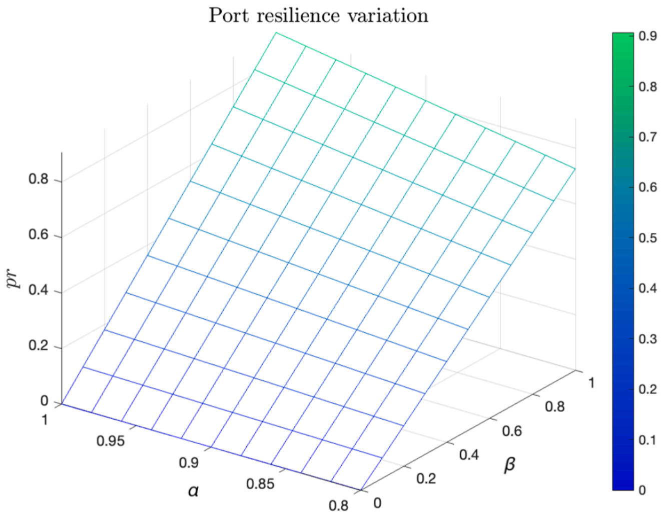
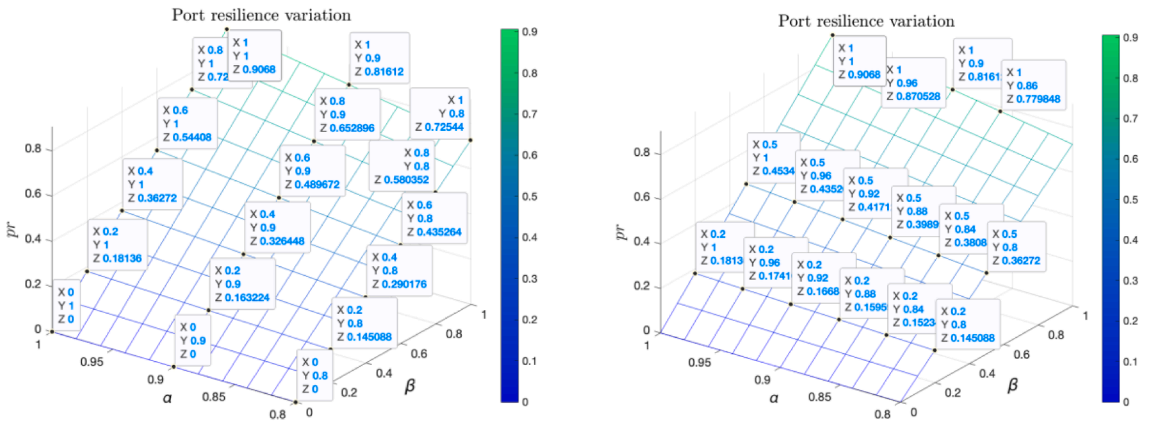


Fig. 10. Port resilience variation under different parameters.



a) Trend of port resilience along with the variation of α

b) Trend of port resilience along with the variation of β

Fig. 11. Trend of port resilience along with the variation of single parameter.

In terms of the disruption perspective, Reduced navigational safety in port area is the risk type brought by climate change that has the greatest influence to cause disruptions of the port system in the GBA region, whose IMI value is way higher than other types. Disruption of maritime supply chains is at the second place, indicating the emerging issues of maritime supply chains due to the climate change may disrupt the port resilience to a certain extent. Following these two risk types, Damage to nearby ecosystems, Increased maintenance costs, Increased downtime and delays and Reduced cargo handling capacity have similar but less influential impacts on port disruptions, while power outages, increased risk of ship collision in port areas and damage to port infrastructure' are among top three risk factors that have the least impact on the occurrence of port disruption.

As to the absorptive capacity, it is found that advanced equipment has the largest impact, which is followed by the electronic exchange platform and the skillful emergency response team. These three measures have a similar value of mutual information, indicating the improvement or implementation of these aspects could increase the absorptive capacity of the port system in the GBA region effectively. On the other hand, the other two measures, the skilled labor with professional qualification and communication, have limited impact on absorptive capacity, demonstrating the implementation and promotion of these two measures are not effective, thus not worth investing more resources.

Among the ways to recover the performance of port climate resilience, maintenance and reliability is proved to exhibit the maximum effect on improving the recovery progress of the port system. Either preventive measures or corrective ways are useful, with the preventive actions can reduce the failure rate and the corrective actions can alleviate the potential consequences. Port innovation have similar influence, and it is not difficult to understand that the application of innovative technologies (e.g., digital tools, intelligent facilities) is of crucial importance in speed up the recovery progress. Port health and safety management, the management of risky operations that may harm the safety and health of cargo or staffs, also has a considerable effect on enhancing the recovery ability of a port system, although a little bit less than the former two measures. When it comes to the last two measures, the business continuity plan and crisis management policy, their influence could be ignored because of the extremely low value of mutual information.

Concerning the adaptation, technology restoration in the future is no doubt the strategy that plays a crucial role in helping the port system maintain at new status in the GBA region. Port worldwide network has the second highest value of mutual information with adaptive capacity, and then followed by the port community system and hinterland connection. In a word, these four strategies are viewed as the major ones in withstanding the disruptions caused by climate change and improving the resilience of the port system. In fact, during the interview stage, many practitioners proved that the port connections and the implementation of advanced technology have top priorities in dealing with climate change. Since climate change may affect the operations of port clusters within the jurisdiction of the GBA region, the enhancement in port connection and technology innovation could unite local ports and help resist potential hazards and disruptions. Service restoration also has a certain impact on the adaptive capacity, although not significant but non-ignorable. In addition, besides the negative effects brought by climate change, the appearance of such disruptions could also be an opportunity to promote the development of new technologies, i.e., data interoperability standardization, and cyber port infrastructure. However, because of the immaturity of such technologies, the influence on maintaining adaptation and improving port resilience is limited currently, as reflected by the value in Table 3. Shortly, it is expected that these digital strategies could play an increasingly important role in reducing potential risks, maintaining healthy port management, restricting the negative impacts caused by disruptions, and improving port resilience.

5.4. Practical implications

Based on the analysis in the above sections, practical implications with regard to the enhancement of port resilience when facing climate-related risks can be put forward to help industry practitioner and port governments in port management.

(1) Formulation of specific instructions on controlling climate-related risks with significant impact on port disruptions.

When formulating regulations or rules, port governments should pay more attention on the identified climate-related risks with greater impacts on the occurrence of port disruptions, for example, the reduced navigational safety in port areas, the disruption of maritime supply chains, and the potential damage to nearby ecosystems. While for other risk types with less influence, i.e., increased maintenance costs and the increased downtime and delays, lower priorities should be assigned only when sufficient resources are possessed.

Specifically, when the navigational safety issue within port areas in the GBA region occurs, the occurrence probability of port disruptions will increase from 49.04 % to 59.72 %, as indicated by the proposed OOBN model. Similarly, this number will change to 57.33 % if the maritime supply chain is disrupted. Further, if both risks occur simultaneously, the occurrence probability will increase dramatically to 67.98 %. These changes indicate the likelihood of port systems being disrupted will be significantly increased under such conditions.

Therefore, port governments should formulate targeted instructions and implement countermeasures to control and reduce the likelihood of these identified climate-related risks. For example, it is promising to conduct the installation and improvement on monitoring system on vessel navigation safety within the port jurisdictions, and the development of digital early-warning system for the supervision of the real-time condition of maritime supply chain.

(2) Implementation of effective measures to enhance the port climate resilience across multiple aspects.

There are various measures applied to improve the port climate resilience across multiple perspectives, i.e., absorptive measures, recovery measures, and adaptive measures. However, through an in-depth analysis based on the proposed OOBN models in this research, it is found that not all of them are effective.

In terms of absorptive measures, the implementation of advanced equipment (e.g., automated equipment, facilities equipped with advanced technologies such as the internet of things, cyber infrastructure and the blockchain) in port management is found to be the most effective selection, which could improve the absorptive capacity from 69.37 % to 78.48 %, as estimated by the proposed OOBN model. Followed by the electronic exchange platform (e.g., single window, port community system), the application is proved to help transform the operation modes on port, leading to an increase in absorptive capacity probability to 77.48 %. In addition, a skillful emergency response team will also help absorb the potential climate-related disruptions to a certain extent, demonstrating the necessity of port authorities to build a team full of skillful and experienced personnel.

As to the recovery measures, maintenance and reliability of port systems is proved to be the most effective measure to help port system recover from potential disruptions, with a success rate of recovery capacity improved from 69.4 % to 80.24 %. Besides, the implementation of innovative technologies in port systems also have positive influence on speeding up the recovery progress, which is only slightly weaker than the maintenance and reliability (a success rate of 80.07 %). Meanwhile, port governments should keep an eye on the potential risky operations on ports and ensure the health and safety of cargo and staffs are guaranteed.

Eventually, to maintain a steady status, effective adaptive-related measures are suggested to be implemented, and the most recommended ones are the technology restoration and the port worldwide network. The technology restoration could help port government restore and reconstruct the port systems that may potentially affected by climate-related disruptions, as well as protect the port systems from suffering similar damage in the future again. As presented in the OOBN model, the implementation of the measure could effectively improve the adaptive capacity from 69.54 % to 79.13 %. In addition to this, port worldwide network is another effective adaptive measure. The development of port worldwide network involves the global container shipping network, port connectivity, port service, port supply chain, and other important components. The complicated network is proved to be effective in maintaining the port system at a steady status against possible climate change, as proved in the proposed model with an improvement from 69.54 % to 77.76 %. Other adaptive measures are far less effective on maintaining the steady status of port resilience performance than these two measures, for example, port community system, hinterland connection and service restoration are found to have limited influence, while the influence of data interoperability standardization and cyber port infrastructure is negligible.

In light of the above, port governments are advised to implement these identified effective measures from multiple perspectives to enhance the resilience performance of their port systems, which could make full use of possessed resources against possible climate-related disruptions and risks.

6. Conclusions

In the face of risks brought by climate change, ports are viewed as vulnerable infrastructures in dealing with potential disruptions from these extreme weather events, especially coastal ports in the GBA region, which are naturally vulnerable to such risks as sea level rise, typhoon and flooding. Understanding the resilience of ports when facing these risks is of essential importance to port management in the GBA region. Therefore, in this paper, a comprehensive resilience assessment framework is newly proposed via the development of a OOBN climate resilience model integrated with the EM learning approach, which could provide more reliable assessment results than traditional approaches. The influenced time of the disruption stage and the recovery stage, which are ignored in the previous research, is considered in the assessment of port resilience for the first time. Factors from multiple dimensions are selected, and a questionnaire is designed to collect relevant data and information about the GBA accordingly. Eventually, the obtained OOBN model containing five sub-networks is developed, which can assess the resilience of port systems dynamically.

Through an in-depth analysis of the developed model targeting the GBA, it is proved that the OOBN model could provide a comprehensible idea for coastal governments in evaluating the resilience and risk of port systems when facing climate change under various circumstances effectively and reliably. Moreover, it is evident that the port resilience to climate change will be enhanced with a higher utilization rate and a faster *rrs*. In addition, the influence of factors in different dimensions is clarified, especially the identification of those factors with significant impacts. Reduced navigational safety in port areas is identified as the risk factor that has the highest influence on the occurrence of port disruptions, while the advanced equipment, maintenance and reliability, and technology restoration in the future are viewed as the most effective measures in enhancing the resilience of port systems in terms of the absorptive capacity, recovery capacity, and adaptive capacity respectively.

Practically, these findings provide valuable insights and implications for port governments in developing effective port management plans and policies. It is advised that port governments should formulate targeted rules on identified high climate-related risks to control and reduce their occurrence likelihood, e.g., the development of digital real-time monitoring or early-warning systems on vessel navigation safety and maritime supply chain condition. Further, effective measures to help improve the resilience performance in different aspects are provided, which could assist the port authorities to make full use of possessed resources and enhance the port resilience to the maximum extent, i.e., the implementation of advance equipment and the electronic exchange platform in improving the absorptive capacity, the effort paid on port maintenance and innovative technologies in accelerating the recovery progress, and the application of the technology restoration and the port worldwide network in maintaining steady status of port performance when facing climate changes. Other measures should be placed at lower priorities only if there are extra resources available after the above prioritise measures being implemented.

In future research, our work will focus on the improvement of the applied methodology by introducing advanced data-driven machine-learning approaches, which could reduce the uncertainties caused by subjective judgment to a certain extent when developing the model structure. Besides, more areas will be included in the port resilience research, and a comparison analysis of port performance across different regions when facing climate change will be conducted, for example, the Southern East Asia (SEA) area to generate more empirical evidence in terms of rational of adaptation measures. This will help both academic researchers and industry practitioners better understand the resilience of port systems under different circumstances, thus promoting the proposal of rational port management strategies and regional collaborations among these closely linked areas.

CRediT authorship contribution statement

Zhisen Yang: Writing – review & editing, Writing – original draft, Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yui-yip Lau:** Writing – original draft, Data curation. **Mark Ching-Pong Poo:** Writing – original draft, Formal analysis, Data curation. **Jingbo Yin:** Writing – original draft. **Zaili Yang:** Writing – review & editing, Validation, Resources, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1
Description of Profile of Survey Respondents.

Demographics	Number of Respondents	Percentage
Gender		
Male	64	64
Female	36	36
Age Group		
18–25 years	16	16
26–35 years	36	36

(*continued on next page*)

Table A1 (*continued*)

Demographics	Number of Respondents	Percentage
36–50 years	31	31
51–60 years	9	9
Above 60 years	8	8
Educational Level		
Secondary School Level	4	4
Diploma/Certificate	3	3
Associate Degree/Higher Diploma	6	6
Bachelor's degree	54	54
Master's degree	32	32
Doctoral Degree	3	3
Current Job Position		
Supervisor/Officer	28	28
Consultant	8	8
Assistant Manager	10	10
Manager	29	29
Director	11	11
Analyst	5	5
Others	11	11
Working Department		
Procurement	4	4
Warehousing	4	4
Transportation	37	37
Inventory	3	3
Customer Service	19	19
Research and Development	16	16
Others	19	19
Company's Nature		
Third-party logistics service providers	28	28
Freight forwarder	17	17
Transport operators	16	16
Port	1	1
Warehouse	6	6
Trading	14	14
Others	20	20
Working Experience		
2–5 years	34	34
6–9 years	19	19
10–15 years	12	12
16–20 years	11	11
21–25 years	12	12
26–30 years	7	7
31 years or above	7	7

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