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Quantitative analysis of the impact of COVID-19 on ship visiting behaviors to ports- A framework and a case study

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ABSTRACT

Corona Virus Disease 2019 (COVID-19) outbreak leads to a significant downturn in the global economy and supply chain. In the maritime sector, trade volume slumped by 3.8% in 2020 compared with 2019. To explore the impacts of COVID-19 on ship visiting behaviors, a framework is proposed to analyze the impact of COVID-19 on port traffic using Automatic Identification System (AIS) data. Firstly, a ship travel behavior-based model is proposed to identify the vessel anchoring and berthing. Then, the diversity in vessel anchoring and berthing time are analyzed, reflecting the impact of COVID-19. The port congestion caused by COVID-19 is quantified by accounting for the number of visiting ships and their residence time. Finally, a case study is carried out on vessels in the Beibu Gulf, China, operating from 2019 to 2020. The results show that the average anchoring time and berthing time increase by 62% and 11% for cargo ships and by 112% and 63% for oil tankers after the outbreak of COVID-19 compared with that before COVID-19. And the density of ships increases in the port area in 2020. Accordingly, the relevant improvements and countermeasures are proposed to reduce the adverse impact of the pandemic on the port navigation system. The paper has the potential to provide a reference for port management and improving port navigation efficiency in the post-pandemic era.

1. Introduction

Ports are an essential part of the global maritime trade. It plays a vital role in global resource allocation. Statistics show that the maritime trade accounts for around 80% of the worldwide trade and is the backbone of the world economy (Wang et al., 2021; Zhang et al., 2022; Fu et al., 2022), making maritime port performance and resilience crucial to sustaining global economic growth (Wan et al., 2016). The prevalence of COVID-19 has become a global health and socio-economic crisis, which profoundly impacts the way we perceive the world and daily life (Perillo et al., 2021; Armenio et al., 2021). A series of chain reactions caused by the outbreak of COVID-19, such as factory shutdown, logistics disruption, and shipping price changes, have direct or indirect impacts on the shipping market and port operation. An increase of 1% of the coronavirus reported cases globally would decrease the Baltic Dry Index by 0.03% and the Baltic Dirty Tanker Index by 0.046% (Michail and Melas, 2020), where the Baltic Sea Index as a barometer of the international dry bulk transport market is closely related to the quality of the global economy (Xu et al., 2022). Port is an important import and export channel with a high risk of transmission, and an increasing number of countries are taking strict measures to reduce the spread of COVID-19 in imports and export (Notteboom et al., 2021). Strict quarantine measures can effectively reduce the risk of infection, and strong isolation measures can quickly control the epidemic, but they also have a massive impact on global maritime trade and shipping (Chinazzi et al., 2020).

To date, studies of the impact of covid-19 on shipping have focused on the reduction of maritime traffic at the macro level and the changes in port services at the micro level. From the perspective of the macro shipping market, the direct impact of strict restrictions is the reduction of maritime traffic (Chinazzi et al., 2020). The global maritime traffic density map based on AIS data shows that 70.2% of global ship activities are analyzed, reflecting the impact of COVID-19. The port congestion caused by COVID-19 is quantified by accounting for the number of visiting ships and their residence time. Finally, a case study is carried out on vessels in the Beibu Gulf, China, operating from 2019 to 2020. The results show that the average anchoring time and berthing time increase by 62% and 11% for cargo ships and by 112% and 63% for oil tankers after the outbreak of COVID-19 compared with that before COVID-19. And the density of ships increases in the port area in 2020. Accordingly, the relevant improvements and countermeasures are proposed to reduce the adverse impact of the pandemic on the port navigation system. The paper has the potential to provide a reference for port management and improving port navigation efficiency in the post-pandemic era.
decrease in passenger ship traffic (March et al., 2021). AIS data from the Veneto region show a 69% decrease in vessel activity, an 84% decrease in fishing activity, and a 78% decrease in passenger traffic in the region during the March–April 2020 lockdown compared to the same period in 2017 (Depellegrin et al., 2020). The reduction in maritime traffic causes a significant blow to shipping networks, particularly the security and stability of the global supply chain system (Jiang et al., 2021). Specific manifestations include declining shipping capacity, port congestion, lower container turnover, soaring freight rates, and container shortages. By December 2020, the global schedule reliability of shipping has hit the lowest point of 44.6% since 2011 (Jin et al., 2022).

Specific to the port and supply chain, in the context of globalization of supply chains, ports as nodes and shipping services as links play an important role in global supply chains (Wan et al., 2021). COVID-19 exposes the efficiency and supply chain deficiencies of some ports in response to the crisis, such as the closure of warehouses, the inability of suppliers to pick up goods at the ports, and the reduction of the labor force at the ports, further aggravating cargo congestion, among others (Menhat et al., 2021). The import and export data of ports show that the severity of the epidemic, government restrictions, and macroeconomic indicators will significantly impact port operations (Xu et al., 2021a,b). The increase of some port restrictions, such as the compulsory isolation of entry seafarers or passengers with virus risks for 14 days, has a direct impact on the decline of port workers’ efficiency, the decrease of wharf turnover rate, and the significant increase in the time of ships in ports and anchorages (Yazir et al., 2020). This not only leads to the increase of the risk of navigation and the difficulty of maritime supervision of ships piling up in anchorages, but also may bring some long-term problems such as the decrease in port revenue, the increase of debt risk and the decline of port competitiveness (Saeed et al., 2018; Su et al., 2022).

Moreover, the negative impact of the COVID-19 pandemic on ports is multifaceted and interrelated, and some negative effects are also reflected in port state control and port environment. Peng et al. (2022) used AIS data to analyze the failure of important nodes in the international liner network caused by COVID-19, which will cause container traffic fluctuation and ship freight supply mismatch. Fluctuations in the number of port ships have affected the number and results of inspections undertaken by the International Maritime Organization and the special inspection arrangements for port state control agreed in the Memorandum of Understanding (MoUs) worldwide. At the same time, the discharge of air pollutants in port waters has also changed due to the extension of ship port turnover time. Compared with February 2019, the emissions of cargo ships decreased significantly in February 2020, while the emissions of container ships and tankers decreased slightly (Shi and Weng, 2021). And since the prevalence of COVID-19, the utilization rate of disposable plastic waste is expected to increase due to the use of personal protective equipment as health care measures, which makes white marine pollution more serious (Alfonso et al., 2021; Varkey et al., 2021).

Research has been carried out on how to deal with a series of threats and challenges brought by COVID-19, especially port congestion. Gut et al. (2022) proposed a port congestion risk assessment method based on fuzzy Bayesian reasoning, Analytic Hierarchy Process (AHP), and the variation coefficient method. The data obtained through expert consultation were used to analyze the congestion of the Los Angeles port, and it was found that supply chain disruption and shortage of human resources were the key factors causing the congestion of the port. Guerrero et al. (2022) used complex network analysis methods to analyze changes in maritime networks before and after the COVID-19 outbreak. They found that mitigation measures taken by the government have different effects on different levels of ports, very large ports and small but densely inter-connected ones resisted better than others, while small transshipment hubs and bridges. AbuAlbaqal et al. (2018) mined spatial complexity, spatial density, and temporal criticality of port waters from AIS data as evaluation indexes to measure port congestion. Peng et al. (2022) constructed a port congestion prediction model based on Long Short-Term Memory (LSTM) to provide a comprehensive review of port congestion. At the same time, some studies have pointed out a positive correlation between port congestion and shipping prices and provided trend forecasts for freight change directions (Bai et al., 2021). In summary, a lot of research on COVID-19 in maritime transport, port transport, and environmental protection have been carried out. However, there are few studies on quantify the changes in ship behavior before and after the outbreak of COVID-19. This paper quantitatively analyzes port congestion through changes in ship behavior. A data-driven ship behavior recognition and classification method is proposed. The changes in ship stay behavior in time and space before and after the COVID-19 outbreak are analyzed with a large amount of AIS data. The discovered knowledge could help shipping companies, port operators, and the government to change the strategy to cope with the effect of the COVID-19 pandemic, which has a positive significance for alleviating the pressure on port ships.

2. Framework

The framework comprises of three stages, as shown in Fig. 1. The details of the stages are specified in each sub-section.

- **Stage I - The AIS data pre-processing is introduced.** This section includes AIS data parsing and matching, ship trajectory data segmentation, error data rejection, and correction.
- **Stage II - Ship behaviors extraction.** The model contains ship stay behavior identification and the stay-track identification and classification obtained by comparing the different patterns between ship stay behavior and normal navigation.
- **Stage III - The statistics analysis of the impacts of COVID-19 on ship visiting behaviors to ports.** The experiment is conducted at the waters of Qinzhou Port in Beibu Gulf. Two sets of data, ship data before and after COVID-19, are used in a comparative analysis. The possible causes of port congestion are identified, and feasible countermeasures for the government and port management are proposed.

Further details associated with each of these stages are outlined in the following sections.

2.1. Step I: data pre-processing

The AIS is an auxiliary navigation system for maritime safety and communication among ships and shores. With the wide application of AIS equipment, massive AIS data provides a new marine traffic research method. The AIS data contain rich characteristics of maritime traffic flow, which makes it widely used in maritime supervision, risk control, maritime trade, ship pollution prevention, and other fields (Zhang et al., 2016; Yang et al., 2019; Zhang et al., 2022b; Zhang et al., 2021a,b). However, AIS data may cause missing, erroneous, and redundant problems during collection and transmission due to equipment failure, signal delay, and obstacle interference, so the noise contained in them needs to be cleaned to reduce experimental errors before using AIS data for analysis.

AIS data includes dynamic and static data. Static AIS data contains information related to ship characters, such as ship draft, ship name, ship type, ship length, etc. (Shu et al., 2022; Zhang et al., 2022c). These static data are input manually by the pilot. The information contained in dynamic AIS data is related to the ship’s current position and motion status, including spatial coordinates, course of ground, speed of ground, navigation status, etc. (Zhen et al., 2022). Both static AIS data and dynamic AIS data contain Maritime Mobile Service Identity (MMSI) and the timestamp, enabling the combination of the two types of AIS data.

In the first step of data pre-processing, the dynamic information with the same MMSI is sorted in ascending order by the timestamp to get the ship track with time sequence, and at the same time, unnecessary information such as device type, positioning, accuracy, etc. is removed. In
In the second step, the static AIS data of the same MMSI are filtered to retain the most complete and reasonable information. The filtering method is to select the data with the most frequent occurrence. Because the static data of the ship is input manually, the static information of the same MMSI may be different at different times. In the third step, the ship type obtained in the second step is added to the ship trajectory sequence obtained in the first step to obtain a trajectory sequence containing a timestamp, MMSI, latitude, longitude, speed, heading, and ship type.

\[
p_i = \{\text{mmsi}, \text{timestamp}_j, x_j, y_j, v_j, c_j, \text{type}_j\} \quad (1)
\]

\[
T_{ri} = \{p_{i1}, p_{i2}, p_{i3}, ..., p_{ij}, ..., p_{in}\}, \quad (1 \leq j \leq n) \quad (2)
\]

where \(p_{ij}\) denotes a point of ship trajectory \(T_{ri}\); \(x\) stands for the longitude of the position; \(y\) stands for a latitude of the position; \(v\) stands for speed over ground; \(c\) stands for the course; \(\text{type}\) stands for ship type; \(i\) stands for a trajectory number; \(T_{ri}\) denotes a ship trajectory.

The core content of AIS data pre-processing is to eliminate the abnormal data in the obtained ship trajectory sequence data, including deleting AIS data error values, duplicate values, outliers, and repairing missing values. The flow chart of AIS data processing is shown in Fig. 2. The process of AIS data preprocessing is summarized as shown in Appendix A.

### 2.2 Step II: Ship behaviors identification and classification

The ship trajectory is a direct representation of ship behavior. Ship activities can be effectively identified through the feature extraction and analysis of ship trajectory data (Xiao et al., 2022). For example, AIS data can effectively identify ship navigation, steering, anchoring, and other behaviors. The “stay” behavior of the ship is an important sign of the navigation state change. When being “stay”, the ship could be in a state of anchored, docked, collided, or grounded and there will stay trajectory. Thus, to identify the change in the navigation status, the key is to identify the ship stay behavior among the ship trajectory data. The logic to identify a ship’s “stay” behavior is deduced from the following facts:

- Import historical AIS data
- Matching static and dynamic data based on MMSI
- Remove abnormal data
- Constructing spatio-temporal trajectory sequence
- Segmenting trajectories
- Delete outlier data
- Data quality satisfied?
  - No → Exclude
  - Yes → Triplet spline interpolation
  - Processed ship trajectories
1. The vessel speed will not change significantly when it is sailing outside the port and there is no ship around (Zheng et al., 2021); 2. When the ship approaches the stopping area, it will decelerate significantly and keep a low speed for a while until it is anchored for berthing or berthing and loading. Then, it will start to accelerate and leave the area. Thus, the “stay” behavior of a ship can be indicated when the speed is very low for a while, and the spatial position of the ship is rarely changed. In the meantime, the distance between the ship trajectory points has a decreasing trend, maintaining a small variation during the stay, and then gradually increases when it starts leaving the port. The ship decelerates from a normal travel to stay and then accelerates to a normal travel from a complete stay trajectory. An example of the extraction steps of a stay trajectory is shown in Fig. 3.

Because of the low speed of the ship’s stay trajectory, most of the trajectories of moving ships can be screened out by speed. Firstly, the velocity sequence in the trajectory sequence \( \text{Tr} \) is processed by moving average to eliminate the fluctuation error of velocity change and highlight the trend of velocity change. The ship speed in anchoring or berthing is generally lower than 2 knots (Fu et al., 2022; Millefiori et al., 2021; Sheng and Yin, 2018), and the trajectory segments with speed less than 2 knots and the number of trajectory points greater than 20 are obtained by filtering the speed sequence. But these tracks may contain tracks where the ship is sailing at a slow speed, which need to be further filtered by the farthest distance of track points in track duration, as shown in Eq. (3).

\[
N(\text{Tr}) > 20 \\
2R \arcsin\left(\sqrt{\frac{\sin\left(\frac{\theta_{m} - \theta_{c}}{2}\right)}{2}} \cos\left(\cos(\cos(\sin(\frac{\theta_{m} - \theta_{c}}{2}))\right)\right) \leq D_{\text{max}} \\
\text{timestamp}_{i} - \text{timestamp}_{i-1} \geq T_{\text{max}}
\]

Where \( N(\text{Tr}) \) denotes the number of trajectory points contained in the trajectory segment; \( D_{\text{max}} \) denotes the longest distance of trajectory points in stay trajectory.

The maximum distance \( D_{\text{max}} \) of the trajectory can be determined by statistical analysis of the maximum distance of the trajectory after velocity screening. Trajectories that stay for a long time may have thousands of trajectory points and finding the farthest distance from thousands of points by conventional methods requires a lot of time and resources. The solution is to first calculate the convex hull of the set of stay trajectory points, and then calculate the furthest distance between the points on the convex hull by pairwise calculation.

The obtained trajectory contains the deceleration and acceleration segments before and after the ship’s stay. Further filtering is required to extract the ship stay trajectory without these segments. We construct a feature space using the velocity, absolute value of acceleration, and distance between trajectory points, and then use K-means methods to cluster them for analysis (Likas et al., 2003). The feature matrix \( C_{\text{tr}} \) of the trajectory \( \text{Tr} \) can be expressed as

\[
C_{\text{tr}} = [v_{\text{tr}}, a_{\text{tr}}, d_{\text{tr}}]
\]

where \( v_{\text{tr}} \) stands for the speed sequence of the trajectory \( \text{Tr} \), \( a_{\text{tr}} \) denotes the acceleration sequence of trajectory \( \text{Tr} \), and \( d_{\text{tr}} \) denotes the trajectory point spacing sequence of trajectory \( \text{Tr} \).

In the clustering results, points with smaller feature values are considered the stay trajectory points, and the larger ones are considered the trajectory points in ship navigation. After the trajectory of the ship is obtained, the distribution of the change of the ship’s interest area and the residence time before and after the occurrence of COVID-19 can be found.

There are two main reasons for the occurrence of the stay trajectory in the port. One is that the trajectory generated by the ship loading and unloading operations at the wharf berth is called the berthing trajectory. And the other is that the trajectory generated by the ship waiting to enter the port or avoiding a typhoon in anchorage is called the anchoring trajectory. The impact of COVID-19 on the two types of stay behavior is not the same. The impact on berthing ships is due to the reduced efficiency of port operations and prolonged loading and unloading time caused by COVID-19, resulting in long-term berthing of ships. The impact on the anchoring ship is due to the lack of berths at the wharf, and the ship needs to queue for berth allocation to prolong the residence time. Therefore, it is necessary to analyze berthing and anchoring ships separately to determine the different effects of COVID-19 on them.

By analyzing and comparing the berthing and anchoring states, the berthing ships are usually tied with multiple cables to prevent the ship from colliding with the quay due to the wind and waves, which puts the ship at berth in a fixed state without large movement. The anchoring ship is only subject to the pulling force of the anchor chain, and the ship will drift and move within a certain range under the action of wind and current. Compared to the anchoring ship, the berthing ship has more spatial constraints, so the spatial aggregation of the berthing trajectory is more obvious, the course change is smaller, and the berthing trajectory is closer to the shoreline in the spatial distribution. Therefore, the ship stay trajectory can be classified according to these characteristics, including the distance from the shoreline, and the concentration of track points, the change of course.

The method to calculate the distance between the stay trajectory and coastline is shown in Fig. 4. The essence of the stay trajectory and shoreline is a curve, and the distance between the two curves is difficult to measure. However, the stay trajectory moves in a small range. We select a center point \( P_{k} \) that can represent the trajectory and use the shortest distance from the center \( P_{k} \) to the shoreline as the distance from the trajectory to the shoreline. The center point of the stay trajectory and the distance from the stay trajectory to the shoreline were calculated as:

\[
p_{k} = \frac{1}{n} \sum_{i=1}^{n} x_{i} - \frac{1}{n} \sum_{i=1}^{n} y_{i}
\]

\[
D_{a} = \min \left( \sum_{i=0}^{n} d(p_{k}, p_{i}) \right)
\]

Where \( p_{k} \) stands for the center point of stay trajectory; \( D_{a} \) denotes the distance between the stay trajectories and coastline.

The coastline data contains a series of latitude and longitude points that can be extracted from the basic geographic framework data obtained through the China National Geographic Information Public Service Platform\(^1\), and the position of certain points can be manually adjusted by comparing with the actual satellite map to make the coastline data closer to the port terminal. Thus, the data obtained by interpolation is more accurate.

The berthing and anchoring trajectories are distinguished by the distance from each stay trajectory to the shoreline and the longest distance from the trajectory point. The stay trajectory with the distance to the shoreline less than 500 m and the longest distance between the trajectory points less than 50 m is considered the berthing trajectory. On the contrary, the stay trajectory with the distance to the shoreline beyond 500 m is considered an anchoring trajectory.

### 2.3. Step III: Ship behaviors analysis of port dwell time statistics

The actual anchoring of ships, due to the psychological factors of the ship’s pilot and the complicated actual navigation situation, as well as the many types and different scales of anchoring ships, the required anchorage area and the actual occupied area of the ship do not match. Usually, the actual anchorage area of the ship will exceed the designated anchorage area. If only the anchorage time in the planned anchorage

\(^1\) https://www.tianditu.gov.cn/.
To quantitatively analyze the influence of COVID-19 on ship anchoring time, it is necessary to determine the actual ship anchoring area improving the accuracy and reliability of the analysis results. In this study, the DBSCAN algorithm is implemented (Fig. 5). It is a clustering algorithm based on density that finds clusters of arbitrary shapes in noisy spatial databases (Birant and Kut, 2007), as presented in Table 1. The core of the algorithm is two parameters, namely the eps field and the minimum number of points, MinPts. By performing DBSCAN clustering analysis on the anchor trajectory points near the anchorage, the area with a high density of the stay trajectory points is obtained, which is regarded as the actual anchoring area of the ship. The choice of parameters eps and MinPts directly determines the reasonableness of the clustering results. Calculate the distance from each point to its nearest point and sort it to get the curve of the nearest distance. And the optimal value eps will be found at the point of maximum curvature. The Minpts selection method is to calculate the number of average trajectory points in the eps field in the planning anchorage. Finally, the clustering results are measured by the number of clusters and silhouette coefficient, and the optimal parameters are determined by iteration. In this paper, several groups of Minpts (15000–30000) were compared with ε between 0.01 and 0.03. The experiences show that when the Minpts and eps are determined as 20000 and 0.015, the number of clusters is equal to the number of planned anchorages, showing that the performance of DBSCAN clustering is the best.

After determining the actual anchoring area of the ship, the ship stay time in the actual anchoring area is obtained by the timestamp in the anchoring trajectory. The stay time of the trajectory \( T_r \) is calculated as

\[
\text{Staytime} = \text{timestamp}_n - \text{timestamp}_1
\]  

(7)

where \( \text{timestamp}_n \) stands for the timestamp of the last point of stay trajectory, \( \text{timestamp}_1 \) denotes the timestamp of the first point of stay trajectory.

3. Case study

In this section, a case study area in the Beibu Gulf is selected to analyze the impact of COVID-19 on ship visiting behaviors to ports using the proposed framework. The Beibu Gulf is an essential node of maritime transportation routes, see Fig. 6.

3.1. The study area and experimental data

The study area selected in this experiment is Qinzhou Port in Beibu Gulf, located in the coastal area of southern China of Guangxi. The AIS data was collected from January 2019 to December 2020 in the range of 20.961°N to 21.843°N and 109.211°E to 107.961°E. In this study, cargo ships and tankers are the main focus. Cargo ships include container ships and bulk carriers, and tankers include liquefied natural gas ships and liquefied petroleum gas ships. The visualization of the 2019 cargo ship trajectories before and after cleaning is shown in Fig. 7. There are obvious drift points and wrong trajectories of cross-domain land before cleaning. The above errors are eliminated by using the preprocessing method described in Section 1.2, presenting the correct historical trajectories of the ship traffic flow in the region.

3.2. Stay trajectories extraction

In this paper, the ship with MMSI 212091000 is selected to validate the method of identifying and classifying the stay trajectory. After the pre-processing of AIS data, it can be found that the ship’s trajectory contains 3548 points, which completely shows the whole process of the ship from anchoring in the anchorage, entering the port, berthing, and leaving the port. Its trajectory is shown in Fig. 8. It shows a significant difference between the trajectory formed in the anchorage and the berth. The trajectory formed by the ship in the anchorage can be approximated as a circle, but the trajectory of the ship in the berth is more like a point, which is identical to our expectation.

In this case study, a total of three trajectories are obtained by filtering the ship speed. two of them contain the ship at anchor or berth in the anchorage, and one is the trajectory of the ship in the channel. Since this trajectory of the ship sailing at slow speed in the harbor exists for only 800 s, this trajectory is ignored in the subsequent analysis. The obtained trajectory in the anchorage has 578 trajectory points, and the trajectory in the berth includes 1896 trajectory points.
The K-means clustering method is used to cluster each segment of the stay trajectory points, and the obtained is visualized as shown in Fig. 9. The blue dots and lines in the figure are the dwell trajectories initially obtained after the speed threshold, and the red represents the dwell trajectory points obtained after classification. The experimental results show that the proposed method can effectively identify and classify the

### Table 1

| Algorithm 1: DBSCAN algorithm |
|-------------------------------|
| **Input:** Anchoring trajectories $T = \{ T_1, T_2, \ldots, T_n \}$, radius $\epsilon ps$, minimum number of points in radius $Minpts$ |
| **Output:** Clustering division $C = \{ c_1, c_2, \ldots, c_k \}$ |
| **Process:** |
| 1. Get the points of anchoring trajectories $P = \{ p_1, p_2, \ldots, p_k \}$ |
| 2. Make all the points in $P$ as the unvisited. |
| 3. Randomly select an unvisited point $p_i$ and mark it’s visited. |
| 4. Check the neighborhood $\epsilon (x_i)$. |
| 5. If $\epsilon (x_i) < Minpts$, mark $p_i$ as noise. |
| 6. Elseif $\epsilon (x_i) \geq Minpts$, mark $x_i$ as core point and set up a new class $c$ and add objects in $\epsilon (x_i)$ to $N$; |
| 7. For $p$ in $N$ |
| 8. Check the neighborhood $\epsilon (p)$. |
| 9. If the number of objects in $\epsilon (p) \geq Minpts$; |
| 10. Add objects are not classified in $\epsilon (x_i)$ to $N$ and add $p$ to $c$; |
| 11. Else: |
| 12. Add $p$ to $c$; |
| 13. End if |
| 14. End for |
| 15. End if |
| 16. Output $C = \{ c_1, c_2, \ldots, c_k \}$ |
| 17. End procedure |

![Fig. 6. International shipping routes linked to the Beibu Gulf.](image-url)
stay trajectories of ships entering the port.

The method is then used to identify all the stay trajectories in the study area. 12343 stay trajectories of cargo ships in 2019 are obtained. The visualization of the results is shown in Fig. 10. It can be found that most of the stay trajectories are located around the anchorage or near the wharf. The stay trajectories far from the shoreline is usually a circular or semicircular shape, which matches the pattern that the mooring ship always moves around the anchor point under the influence of wind. The stay trajectories close to the shoreline is more like a point because of the closer distance between the trajectory points.

After getting the stay trajectories of the ships, we calculate the distance between each trajectory and the coastline and visualize the result after sorting them as shown in Fig. 11(a). It is found that half of the obtained stay trajectories are within 500 m from the shoreline, and the rest stay trajectories are between 1 km and 20 km from the coastline. This is because the berths are generally close to the shoreline, but the anchorage is far away from the shoreline. The distance from different anchorages to the shoreline varies greatly. Therefore, the stay trajectories can be effectively divided into anchoring trajectories and berthing trajectories by the distance from the mooring trajectory to the shoreline. After the classification of the ship stay trajectories, 6667 ship berthing trajectories and 5676 ship anchoring trajectories are obtained. The visualization results are shown in Fig. 11(b).

3.3. Data statistics and analysis

To quantitatively analyze the changes in ship number and stay time in the port anchorage before and after the outbreak, the cluster analysis of the ship trajectory points in three anchorages is carried out. It is necessary to obtain the statistical range by using cluster analysis method to calculate the number and residence time of ships in port anchorage. The obtained ship anchoring trajectories have a clear trend of aggregation as shown in Fig. 12(a), where the ship anchoring trajectories are clustered in three blocks. Fig. 12(b) shows the clustering results obtained by using DBSCAN. The blue rectangular area is the planned mooring area of the port, and the red rectangular area is the actual mooring area of the ship detected from the AIS data. It can be seen that there is a significant difference between the actual planned area and the actual area, and the actual mooring area of the ship is larger than the planned mooring area.

The number of anchor ships per day in the region is counted as shown in Fig. 13. The number of cargo ships and oil tankers in anchorage increased in 2020 compared with 2019. In 2019, the average daily number of cargo ships was 15, and in 2020 it increased to 24. The average daily number of ships in anchorage increased by 60%. The number of ships in anchorage reached 34 and 51 at most on the 313rd day of 19 and the 363rd day of 20. Before and after the outbreak, the average daily number of oil tankers in the anchorage was 9 and 12, respectively. The average daily number of ships in anchorage increased by 33%, and the maximum number of ships in the anchorage was 20 on day 303 and day 93, respectively. The figure shows that the number of anchor ships on the 201th – 203rd day of 2019 is 0, which is caused by the lack of AIS data.

We count the stay time at anchor and berth in 2019 and 2020 in Table 2. It shows that for cargo ships the annually average anchoring time increased from 15.92 h in 2019 to 25.83 h in 2020, and the annual average dwell time at the berth increased from 24.13 h in 2019 to 26.78 h in 2020. The median and third quartile of anchorage time and dwell time both increase in 2020. Tankers appear to be more severely affected, with the annually average anchoring time for tankers increasing from 15.63 h in 2019 to 33.04 h in 2020; and the annual average berth dwell time increasing from 22.4 h in 2019 to 36.26 h in 2020. All indicators show longer vessel dwell time in 2020.

The anchoring time and berthing time of the freighter at the first point in 2020 are smaller than those in 2019. The reason for this anomaly is because of the low-quality AIS data. This may lead to wrongly dividing a trajectory into several segments, causing some trajectories attributed to shorter residence time. It is worth noting that the maximum value of ship anchoring time and anchoring time in 2020 has
increased significantly, which is verified by the stay trajectory. Maximum residence time in berths and anchorages increased significantly in 2020, and a detailed analysis of the stay trajectory found that the cargo ship MMSI 248904000 anchored from July 31, 2020 to November 8, 2020.

The comparison of vessel anchoring time in the three anchorages in 2019 and 2020 is shown in Fig. 14, where the blue area on the right side represents 2020 and the red area on the left side is 2019. It can be seen that the blue area in the upper part of the figure is significantly more redundant than the red, and the red area is also the year 2019 lasts up to 40 h, while the year 2020 reaches up to 80 h. And the three horizontal lines in the graph represent the quartile points, respectively, and they all show that the berthing time and anchoring time of 2020 are all longer than that of 2019. Fig. 15 shows the visualization of the ship track density from AIS data. It can be found that compared with 2019, the density of AIS data points in the same region in 2020 has increased significantly, and the red area near the port waters has increased significantly.

However, the trajectory density of ships within the route is only slightly increased, and there are few differences in the number of ships sending AIS data in the study waters of concern in 2019 and 2020, which may be due to the long stay of ships in anchorages and ports and the continuous transmission of AIS data. From the density distribution map of ship AIS data, it can be seen that the amount of ship AIS data in 2020 is significantly increased compared with that in 2019. The ship density is higher in the area near the port and anchorage, while the ship density does not change greatly along the route. It shows that AIS data has changed greatly in this area. The possible reason is that the ship stays in the area for a long time, resulting in the continuous transmission of data.
and increasing the density of ships in the area.

4. Discussion

The experimental results show that after the prevalence of COVID-19, the level of port congestion has increased, which is manifested in the increase in the number of anchor ships and the prolongation of ship waiting time. Port congestion is usually caused by an increase in the number of ships arriving at the port in a short time or a decrease in the efficiency of port operations (Zhen, 2016). And experimental results show that there is no significant change in the number of ships arriving at Qinzhou port before and after the outbreak of the epidemic. So, we infer that the reduction of port operating efficiency during COVID-19 to some extent exacerbated the congestion of Qinzhou Port.

By analyzing the reports of port congestion around the country, we summarize the direct causes of port efficiency reduction are as follows: 1) Strict anti-epidemic measures taken to prevent the spread of COVID-19, on the one hand, have reduced the efficiency of port staff and extended the ship’s handling time in port; on the other hand, have led to the need for ships to wait for nucleic acid testing reports after berthing and not to be carried out at the first time (Xu et al., 2021a,b). 2) Due to the high infectivity of COVID-19, local governments restrict population mobility, which leads to the problem of manpower shortage at port and that shippers unable to clear customs in time, and the slow delivery speed also leads to insufficient yards in the port area (Liu et al., 2020). 3) The disruption of the supply chain caused by the epidemic, the lack of infrastructure for port-rail intermodal transport and port-road intermodal transport, and the congestion of the multimodal transport network led to the increase in the density of ship dump yards and cargo ballast (Russell et al., 2022).

In the post-epidemic era, human resistance to the virus will be a long process. New infections may lead to sudden closure of the port, which further blocks logistics transportation. This situation is particularly evident in China, because under the strict epidemic prevention policy, even a very small infection can paralyze the entire port area. On the one hand, port operators need to spend extra time and experience on their own protection, which reduces the efficiency of human resources. The shortage of manpower on the shoreline has also had a negative impact. According to government policies in different countries, dock workers can be sick or quarantined because of the outbreak. On the other hand, the disruption of the supply chain requires additional time to recover, and the trade impact varies greatly between different geographical
regions and product categories. To reduce the economic slowdown and increase the risk of ship navigation caused by port congestion, the government and port management departments can take the following measures to alleviate the problem of port ship congestion.

- The government and port management departments should accelerate the construction of digitalization and automation of ports, and enhance the level of port unmanned to mitigate the impact caused by major public health emergencies in order to improve the efficiency of port handling and service capacity (Xie et al., 2021). 1) Combined with 5G technology, it enables operators to remotely control the loading and unloading operations of the shore bridge, thus improving the efficiency of port operations. 2) Blockchain technology is applied to unify the management of cargo and related certificates and electronic bills of lading, thus reducing the face-to-face communication between port staff and crew members to reduce the spread of epidemics and enhance the efficiency of related paperwork processing (Ahmad et al., 2021). 3) Real-time monitoring of port operation equipment through Internet of Things (IoT) technology, early warning positioning of equipment that breaks down, guaranteeing the health of port equipment and maintaining the orderly

![Fig. 13. Daily number of anchorage ships in 2019 and 2020.](image1)

![Fig. 14. Distribution of cargo and oil tanker anchoring time in 2019 and 2020.](image2)

### Table 2

| Ship type   | Status     | Year | First quartile | Median | Third quartile | Average | Maximum |
|-------------|------------|------|----------------|--------|----------------|---------|---------|
| Cargo ship  | Anchoring  | 2019 | 4.05           | 7.89   | 16.22          | 15.92   | 256.26  |
|             |            | 2020 | 3.30           | 8.37   | 25.51          | 25.83   | 2379.63 |
| Berthing    | 2019       | 5.15 | 12.21          | 28.96  | 24.13          | 381.69  |
|             |            | 2020 | 3.64           | 12.27  | 34.21          | 26.78   | 1253.88 |
| Oil tanker  | Anchoring  | 2019 | 4.40           | 8.66   | 18.03          | 15.63   | 272.00  |
|             |            | 2020 | 5.39           | 16.28  | 41.26          | 33.04   | 1149.52 |
| Berthing    | 2019       | 6.18 | 14.55          | 26.43  | 22.40          | 36.26   | 430.79  |
|             |            | 2020 | 9.39           | 22.49  | 40.36          | 1090.41 |
operation scheduling (Muñozri et al., 2020). 4) Apply artificial intelligence algorithms to analyze and mine ship arrival data to predict the number and time of arriving ships, and dispatch port resources more scientifically and effectively based on the results of mining and prediction (Chen et al., 2022).

- The construction of multimodal transport systems should be accelerated to integrate port transport with roads, railroads, pipelines and other modes of transport (Chen et al., 2022a; Chen et al., 2022b). 1) Enhance the level of connectivity between ports and railroads and land routes to enable the direct transfer of cargo from ships to railroads or highways. Such as transferring containers directly from ships to trucks or trains via shore bridges to reduce logistics and transfer links (Tsao and Linh, 2018). 2) Establish the container exclusive transport corridor to connect the nearby logistics center to realize the rapid transfer of containers and improve the turnover efficiency of port cargo (Li et al., 2021). 3) Create a functional and information-rich multimodal transport information system. Promote the interconnection of information between ports and railroads, shipping companies, freight forwarders, customs and other relevant subjects in the whole chain of multimodal transport and management departments, realize the barrier-free circulation and sharing of information in the whole process of transport organization (Shaw et al., 2017).

- Governments should promote and dominate the development of port clusters, strengthen the interconnection between ports, and realize the complementary advantages and division of labor between ports (Guo et al., 2021). This will strengthen the resilience of ports in the face of major emergencies. 1) Strengthen the information sharing between ports and ports, through the information-sharing platform to obtain port cargo, port logistics, port trade information, so that ships can reasonably choose ports of call and avoid the situation that some ports are congested while others are vacant. 2) According to the functions and development positioning of the ports, the ports give priority to the development of transit business suitable for itself and realize the division of labor and cooperation between ports and complementary advantages, so as to improve the operational efficiency of the ports (Yu et al., 2021).

- Port management departments carry out port operation training under the COVID-19 epidemic, strengthens personnel management and safety protection measures during operations, reduces the risk of

Fig. 15. Trajectory density maps of cargo and oil tankers in 2019 and 2020.

(a) Trajectory density of cargo ship in 2019

(b) Trajectory density of cargo ship in 2020

(c) Trajectory density of tanker in 2019

(d) Trajectory density of tanker in 2020
virus transmission, overcome the negative impact of COVID-19 in the short term, and ensure the normal operation of the port.

5. Conclusion

The outbreak and spread of COVID-19 had a negative impact on the global shipping trade network, reducing the mobility of the global supply network and slowing down the progress of globalization at the macro level, and causing port congestion and a substantial increase in the number of ships at anchor at the micro level. Given the question of how to quantify the increased number of ships in ports and longer berthing times caused by COVID-19, this paper proposes a stay trajectory recognition and classification model considering the spatial distribution and motion characteristics of ship trajectory. The changes in the number of ships in port anchorage and ships’ anchoring time and berthing time are obtained from AIS data to quantify port congestion. The main research contents include: A stay trajectory identification and classification model considering ship trajectory features and geospatial features is proposed to mine historical AIS data to obtain the changes in port ship visiting behavior before and after COVID-19, and quantify the port congestion caused by COVID-19 from the changes in the number of ships and stopover time. The proposed method was also validated using cargo ships and tankers in Qinzhou port, and the experimental results show that the proposed model can effectively achieve the distinction between the mooring trajectory and the stay trajectory of ships. And the average daily number of anchorages increased by 60% for cargo ships and 33% for tankers after the COVID-19 pandemic. The average time at anchor and berthing time for cargo ships increased by 62% and 11%, respectively. The average time at anchor and berthing time for oil tankers increased by 112% and 63% respectively. In the end, we analyze the direct cause of ports congestion: the blockade and restrictions brought by COVID-19 reduce staff efficiency, the goods in the yard cannot be cleared in time, and the lack of port transit capacity due to supply chain disruptions. In this regard, we put forward relevant measures for the port management department and the government to alleviate port congestion. It is necessary to accelerate the port’s digital construction, build a multimodal transport system, develop port industrial clusters, and carry out special training for port operators on epidemic prevention.

However, the limitation of this study is that only oil tankers and cargo ships in the waters of the Beibu Gulf, China. In the future, this paper can be expanded in several directions. Firstly, the AIS data can be extended to analyze the statistics of dry bulk, liquid bulk, tankers, rolling ships and other types of ships. The impact of COVID-19 on port production and operation can be more comprehensively assessed by analyzing changes in ship behavior at ports in several different regions. Secondly, a port throughput estimation model based on AIS big data can be proposed according to ship type, draft change, and other information contained in AIS data. A more objective and accurate statistical model of port cargo throughput can be constructed to analyze the impact of emergencies on global port production from multiple dimensions.

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.

Data availability

Data will be made available on request.

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Appendix A. The process of the AIS data preprocessing

- An error value is a value that is contrary to the facts in AIS data, which will greatly affect the accuracy of subsequent data mining and must be eliminated. Error data to be eliminated mainly include: 1). MMSI coding less than nine-bit data. 2). The longitude and latitude information does not represent longitude and latitude.
- Repeated values refer to the data in which time series coincide while other values are identical in AIS data. Duplicated data is meaningless to AIS data transmission, a single message can be repeatedly identified and stored, resulting in data duplication. Duplicated data is meaningless to the experimental accuracy while taking up a lot of space and resources in subsequent model training. Thus, if the timestamp of the experimental point is the same as that of the previous track point and the other values keep unchanged, it is then considered to be repeated data.
- The trajectory segmentation divides the trajectory sequence into multiple sub-trajectories to prevent the discontinuity of the trajectory. Because the trajectory sequence \( T_i \) obtained in the previous stage may contain a ship with different voyages, these trajectories are very different in spatial locations and cannot be regarded as the same trajectory. The reason for this phenomenon may be that the ship shuts down AIS equipment during navigation. According to the Technical Requirements of Shipboard Automatic Identification System, the minimum frequency of sending messages of Class A and Class B AIS equipment is 3 min when the ship speed is less than 2 knots. If the time interval between the forward and backward trajectory points in the trajectory sequence exceeds 900 s, it is considered to be composed of two sub-trajectories with different voyage times.
- Outlier value refers to the situation where the ship position changes greatly in a short time. It is usually caused by the error of information recording of a single point. The outliers in AIS data will affect data analysis and have a negative impact on the final results. Due to the ship motion characteristics, the change of ship trajectory should be continuous and smooth. When a feature in the trajectory changes abruptly, it means that the data is wrong. If the distance between the trajectory points is much greater than the distance that the ship speed can move, the point is considered an outlier value. The distance between trajectory points can be calculated by Eq. (A1).

\[
\begin{align*}
S_{i+1} &= 2R \arcsin \left( \sqrt{\sin^2 \left( \frac{y_{i+1} - y_i}{2} \right) + \cos(y_i) \cos(y_{i+1}) \sin^2 \left( \frac{x_{i+1} - x_i}{2} \right)} \right) \\
S_{i+1} &> \int_{t_i}^{t_{i+1}} w_v \max dt
\end{align*}
\]

where \( S_{i+1} \) means the space distance between trajectory point \( P_i \) and \( P_{i+1} \); \( R \) is the radius of the earth; \( x \) and \( y \) represent longitude and latitude. \( w_v \) denotes the gain coefficient (related to AIS data quality, usually taken as 1–2); \( R \) denotes the radius of the earth.

\[
\int_{t_i}^{t_{i+1}} w_v \max dt
\]
A complete ship trajectory sequence is composed of multiple continuous trajectory points in the ship voyage. However, due to the limitations of equipment, technology, or other factors, there are often some missing parts in the navigation data. Fitting data by cubic spline interpolation can help to recover missing data by inserting AIS data at equal intervals (McKinley and Levine, 1998). For the ship trajectory with the time interval, spline functions \( C(x) \) are shown in Eq. (A2), and the undetermined coefficients in the equation can be obtained by adjacent data.

\[
C(x) = ax^3 + bx^2 + cx + d,
\]

where \( a, b, c, \) and \( d \) are undetermined coefficients.

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