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Uncovering the determinants of ship detention duration in the Black Sea Region: a hybrid Bayesian and association rule mining perspective

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This study examines the key determinants of ship detention duration under Port State Control (PSC) within the Black Sea Memorandum of Understanding (MoU) region, comparing pre-pandemic and pandemic inspection outcomes. Using 756 PSC detention cases retrieved from the Black Sea Information System, a Tree-Augmented Naïve Bayesian Network (TAN) and Association Rule Mining (ARM) were applied to identify both probabilistic dependencies and frequent co-occurrence patterns. The TAN analysis revealed that PSC Authority exerted the strongest influence on detention duration, with its impact increasing notably during the pandemic. ISM Code-related deficiencies also became more critical, while traditional technical deficiencies such as Fire Safety and Life-Saving Appliances declined in significance. ARM results further highlighted that ISM non-compliance on older Ro-Ro vessels, were closely associated with detentions longer than two days in Russian and Romanian ports. These findings underline the necessity of authority-specific, risk-based inspection strategies and improved standardisation of ISM audits to minimise operational disruptions. This study is the first duration-focused analysis for the Black Sea MoU using an integrated TAN + ARM framework.

Keywords Port state control, Deficiency types, Ship detention duration, The Black Sea MOU, Maritime safety, Bayesian network

Port State Control (PSC) is one of the most crucial inspection mechanisms in the maritime industry. PSC aims to ensure safety at sea and protect the marine environment. It verifies that foreign ships comply with international maritime regulations by conducting inspections in national ports. The International Maritime Organization (IMO) encouraged the establishment of regional PSC regimes worldwide to combat substandard vessels, as formalised in Resolution A.682 (17)[1].

PSC serves as a complementary measure to flag state control, allowing port states to inspect foreign ships visiting their ports and ensure that any deficiencies are rectified before departure. At present, several regional PSC regimes operate globally, including the Paris MoU (Europe and North Atlantic), Tokyo MoU (Asia–Pacific), Indian Ocean MoU, Mediterranean MoU, Black Sea MoU, and others[2]. In these regimes, PSC inspections typically begin with an initial on-board check of certificates and documents, by the PSC Officers (PSCO). If PSCO detects serious deficiencies, detention measures are imposed and the ship remains detained until all deficiencies are rectified[3]. The period during which the ship remains detained is referred to as the detention duration.

The detention duration has significant operational, financial, and reputational implications for various stakeholders, including shipowners, management companies, flag states, and port authorities. Prolonged detention can lead to increased operational costs (e.g., fuel, port charges), disruption of cargo delivery schedules, and reputational damage to the ship operator, flag state, and recognised organisations[4]. Moreover, frequent or long detentions may increase the likelihood of future PSC inspections, as detention is often considered an indicator of substandard vessel condition. Thus, identifying the factors influencing detention duration and minimising this period is of considerable importance for maritime stakeholders.

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Despite its importance, the duration of PSC detentions has received limited attention in the academic literature until recently. Research interest in this area has grown only after 2024, with studies analysing detention duration in the Paris MoU[5,6] and Tokyo MoU[7]. Although a study focusing on deficiency types during the pre- and post-pandemic periods in the Black Sea MoU region has been conducted[8], no research has specifically examined detention duration in this region. The Black Sea MoU, with its smaller yet high-risk maritime traffic, provides a unique environment for analysing detention duration dynamics. The COVID-19 pandemic altered PSC practices, such as inspection frequency and enforcement priorities, which may have significantly affected detention duration. The Black Sea MoU is a particularly relevant case due to its distinctive regional characteristics, operational practices, and the potential effects of the COVID-19 pandemic on PSC inspections.

Although recent studies have applied advanced methods such as Bayesian modelling and machine learning to analyse detention duration in the Paris and Tokyo MoU regions[5–7] these studies mainly focused on global patterns and have not considered regional differences in PSC enforcement practices. Moreover, they rarely addressed the potential impact of extraordinary events, such as the COVID-19 pandemic, on detention procedures. The Black Sea MoU, with its specific regional practices and comparatively smaller but strategically important maritime traffic, represents an underexplored area where detention duration dynamics might significantly differ from those in larger MoU regions. Addressing this gap is essential to enhance regional PSC effectiveness and to provide practical recommendations for stakeholders operating in this region. For this purpose, the following research questions are to be addressed in this study:

(1) Which factors significantly affect detention duration before and during the COVID-19 pandemic in the Black Sea MoU region?
(2) What are the most influential factors prolonging detention duration in the Black Sea region during the pre-pandemic and pandemic period?
(3) Does the PSC Authority (where PSC inspection is carried out) have an effect on the duration of ship detention? If it does, did the influence of PSC authorities on detention duration change between the pre-pandemic and pandemic periods?
(4) Which PSC Authority-related factors contribute most to prolonged detentions (≥ 2 days)?

In the light of the above research questions, it is aimed to find the factors influencing detention duration both before and during the pandemic with the data-driven based Bayesian method and ARM in the Black Sea MoU region.

Literature

Since the early 2000s, academic discussions on *PSC* have expanded significantly due to the need to enhance maritime safety and minimise the operation of substandard vessels. Early works primarily examined detention probability and causal factors, focusing on global datasets and simple regression-based methods. For instance, econometric methods were used to analyse the impact of vessel-specific characteristics, such as early-stage age and type, on the risk of detention across various MoUs[9,10]. These studies found that older general cargo vessels flying non-IACS flags were most susceptible to detention, providing the empirical basis for subsequent probabilistic modelling.

Since 2015, the focus of research has shifted towards data-driven and predictive analyses that incorporate Bayesian networks and machine learning algorithms. The application of association rule mining (ARM) and grey relational analysis was investigated in the identification of patterns among various deficiency types[11,12]. The research consistently highlighted deficiencies in the ISM Code, Fire Safety, and Emergency Systems as significant predictors of detention, thereby suggesting that managerial factors often have a greater impact than technical faults.

Parallel developments occurred in risk-based inspection optimisation. Bayesian networks and multi-criteria decision-making (TOPSIS) were integrated to model inspection scenarios under uncertainty in the Paris MoU, while big-data-trained BNs were employed to improve the probabilistic prediction of detention outcomes[13,14]. Machine learning techniques such as random forests and support vector machines (SVMs) were subsequently introduced, achieving higher classification accuracy and highlighting the importance of deficiency clustering for inspection prioritisation[15,16]. These contributions collectively demonstrate a clear methodological evolution from static regression models to dynamic, inference-based frameworks capable of quantifying the interplay among multiple inspection variables.

Nevertheless, three significant research limitations persist. Firstly, the majority of studies have concentrated on identifying detention occurrence, rather than detention duration. Only recently has the temporal dimension of ship detentions been integrated into probabilistic modelling frameworks[5,6,17]. These models have applied Bayesian and generalised linear methods to PSC data from the Paris and Tokyo MoU regions. Their analyses revealed *that the inspecting PSC Authority,* deficiency type, and ship age collectively determine how long a ship remains detained. Nevertheless, the relative influence of these variables varies across different regions.

Secondly, research remains geographically concentrated in Paris and Tokyo MoUs, which represent mature inspection regimes with extensive data availability. In contrast, smaller regional regimes such as the Black Sea MoU – comprising Bulgaria, Georgia, Romania, Russia, Turkey, and Ukraine – have received minimal empirical attention despite their distinct enforcement characteristics[2]. The Black Sea MoU has been examined by a limited number of studies[18,198]. Previous studies approached ship detentions from different analytical perspectives. Some studies have examined detention practices from a strategic management perspective, while others have focused on the overall distribution of deficiencies or on changes in deficiency patterns during the COVID-19 pandemic. Collectively, these studies indicate that inspection behaviour varies significantly across *PSC* Authorities.

Thirdly, there is a lack of research examining how extraordinary disruptions such as the pandemic have altered the performance of PSCs. In the context of pandemic-related restrictions, the time allocated to onboard inspections has decreased, and there has been a shift towards prioritising documentary verification. This situation may lead to a shift from technical deficiencies towards managerial deficiencies. It was observed that during the pandemic, PSC inspections under the Tokyo MoU showed shorter inspection scopes but longer detention periods for ISM-related non-conformities[17]. This observation needs to be verified in other regions. Furthermore, an overview of changes in the professional judgements of PSC Officers (PSCOs) in the Paris MoU has also been documented in recent literature[21].

Given these research gaps, the Black Sea MoU offers a unique context for empirical exploration. It encompasses diverse maritime governance structures, variable enforcement capacity, and mixed inspection experience among PSCOs, all of which can significantly affect detention practices. Moreover, its strategic yet modest shipping volume makes it ideal for controlled statistical modelling without the confounding effects of large-scale, multi-regime variability.

Building on these considerations, this study contributes to the literature in three principal ways:

- It provides the first quantitative analysis of detention duration in the Black Sea MoU region, filling a geographic and thematic void in PSC research.
- It applies an integrated TAN + ARM framework, combining probabilistic inference with pattern discovery.
- It incorporates pre-pandemic and pandemic phases, offering comparative insights into how PSC Authority inspection behaviour and deficiency composition evolved under unprecedented global constraints.

Collectively, these contributions position the present work within a new generation of PSC analytics that emphasises regional heterogeneity, data fusion, and governance interpretation. Bayesian models quantify uncertainty and identify dominant causal factors, while ARM reveals the co-occurrence structures among deficiencies that probabilistic inferences may overlook. This dual-method approach enables a deeper understanding of why detention periods differ between authorities and provides evidence-based recommendations for improving control standards, reducing operational disruptions, and strengthening maritime safety management.

Material and methods

This study employs an integrated analytical framework combining TAN and ARM to identify the determinants of ship detention duration in the Black Sea MoU region. The dual-method design enables complementary insights: TAN captures conditional dependencies among inspection variables, while ARM reveals frequent co-occurrence patterns of deficiencies contributing to prolonged detentions.

The adoption of this dual-method framework aligns directly with a recent paradigm shift in maritime safety and PSC analyses (2024–2026). Contemporary research underscores that integrating ARM with data-driven BN, such as the TAN classifier, effectively overcomes the limitations inherent in isolated frequentist or probabilistic models. By simultaneously mapping hierarchical conditional dependencies and extracting complex co-occurrence rules, these hybrid methodologies provide a robust epistemological foundation for systemic risk evaluation. For instance, Nurduhan and Kamal (2026) demonstrated the efficacy of coupling ARM with data-driven BNs to evaluate certificate and documentation deficiencies dictating ship detentions within the Black Sea MoU[22]. Similarly, a TAN-ARM architecture was recently deployed to uncover systemic risk drivers and deficiency accumulation trajectories within private vetting regimes, specifically SIRE and CDI inspections[23]. Expanding beyond compliance frameworks into advanced accident forensics, this hybrid approach has also been utilized to model the multifaceted interactions between human factors and operating conditions in determining maritime collision severity[24]. Consequently, the deployment of the TAN-BN and ARM methodology in this study not only substantiates the multidimensional mechanism of prolonged detentions but also positions the analytical framework at the forefront of maritime safety research.

Bayesian network (BN)

A BN is a probabilistic graphical model. It represents a set of variables and their conditional dependencies through a Directed Acyclic Graph (DAG)[25]. BNs are widely used in causal modelling, prediction under uncertainty, decision-making, risk level on the consequences of the accident, and classification tasks[25,26]. The probabilistic relationships in a BN are expressed through Conditional Probability Tables (CPTs). Equations (1) and (2) define the joint and conditional probability distributions, respectively. U is the set of all possible variables, represented as $U = \{X_1, X_2, \ldots, X_n\}$. The conditional probability of U is described by Eq. (1). The overall joint probability distribution of the network is calculated as follows:

$$P(U/x) = \prod_{1}^{n} P(X/x) \tag{1}$$

We subsequently specify the joint probability of U by equation (2).

$$P(U) = \prod_{1}^{n} P(X_i/Parent(X_i))(i = 1,2,\ldots..n) \tag{2}$$

where $X = \{X_1, X_2, \ldots, X_n\}$ is the set of all variables, and Parents(X_i) denotes the parent set of variable X_i in the BN structure[26,27].

There are usually two main stages involved in the construction of the BN: structure learning and parameter learning. These two phases are considered the most fundamental steps in BN development, followed by model validation and sensitivity analysis[28,29].

In this study, a BN was applied to Black Sea MoU detention data to determine the key factors influencing detention duration and to evaluate the influence of PSC authorities before and during the pandemic. Specifically, the TAN algorithm was used for structure learning due to its ability to model interdependencies between variables while maintaining computational efficiency. The version 6.07 of the Netica software was utilised in the study. The Netica provides a user-friendly interface for BN construction and employs efficient inference algorithms to perform probabilistic reasoning[30].This tool is commonly used in studies involving BN[27,31,32].

BN structure learning

The Tree-Augmented Naive Bayes (TAN) algorithm was adopted in the study for data-driven structure learning. TAN extends the conventional Naive Bayes classifier by allowing limited dependencies between attributes, thereby improving prediction accuracy while preserving computational efficiency. This approach is widely accepted in PSC-related studies for detention prediction, as demonstrated by Yang[33] significantly improving BNs. The Naive Bayes classifier, as a basis for TAN, is one of the most commonly used and effective classifiers in prediction problems due to its simplicity and efficiency.

This algorithm effectively models interdependencies among ship-related factors and deficiency types, making it suitable for predicting and analysing detention duration in PSC inspections. In this study, the TAN-based BN was trained using Black Sea MoU detention data to uncover the probabilistic relationships between ship characteristics, PSC Authority practices, deficiency types, and detention duration. The TAN algorithm was selected for this study because it maintains the simplicity and computational efficiency of the Naïve Bayes classifier while allowing dependencies between attributes to be represented. This makes TAN particularly suitable for analysing PSC data, where multiple interdependent factors such as ship age, deficiency type, and inspection authority interact in complex ways[34].

BN monitoring and analysis

Once the *BN* structure and parameters were established, the model was used for monitoring and probabilistic analysis to identify the most influential factors affecting detention duration. BN monitoring refers to the process of updating the probabilities of certain variables when new evidence (observed data) is introduced into the network, thereby enabling inference about unobserved variables [27,28].

In this study, monitoring was performed by entering different evidence scenarios (e.g., specific deficiency types, PSC Authority, ship age) into the network, allowing the conditional probabilities of detention duration to be updated accordingly. This process made it possible to examine how each variable, individually or in combination with others, influenced detention duration.

The analysis involved two key steps:

Probabilistic Inference: Using Netica's built-in inference engine, the posterior probabilities of detention duration were calculated for various evidence combinations. Netica employs efficient inference algorithms, including message-passing and state-of-the-art junction tree methods, to ensure computational accuracy and speed[31,32].

Sensitivity Analysis: The analysis was carried out with the objective of determining the relative importance of each variable in the process of predicting detention duration. This approach quantifies how changes in the probability distribution of input variables affect the probability of the target variable, is conducive to the identification of the most critical factors[29,30].

The outcomes of this monitoring and analysis step were used to interpret the probabilistic associations between ship-related factors, deficiency types, PSC authorities, and detention duration in the Black Sea MoU region.

Association rule mining

While Bayesian analysis uncovers causal relationships, it does not fully reveal frequent co-occurrence patterns among deficiencies or authorities. To complement TAN findings, ARM, was applied to explore combinations of variables associated with long detentions (≥ 2 days).

ARM, as initially proposed by Agrawal[35,36]. is one of the most significant techniques in data mining. It facilitates the transformation of large datasets into actionable knowledge. ARM is used to identify frequent co-occurring patterns, i.e., to discover associations between different elements within the same dataset[35]. The Apriori algorithm was selected due to its ability to efficiently identify hidden and interpretable associations among inspection deficiency areas. The primary goal of ARM is to reveal hidden relationships and patterns within data sets[37].

Formally, $I = \{i_1, i_2, \ldots, i_n\}$ is a set of items. $D = \{U_1, U_2, \ldots, U_m\}$ represents a transaction database. Each transaction t is a non-empty subset of I. The association rule is written as $X \rightarrow Y$, where $X \subset I$, $Y \subset I$, $X \cap Y = \varnothing$. The quality of a rule is evaluated using three key metrics: support, confidence, and lift. These are defined as follows [38]:

$$\text{Support}\,(X \rightarrow Y) = \frac{Supp(X \bigcup Y)}{Supp(D)} \tag{3}$$

$$\text{Confidence}\,(X \rightarrow Y) = \frac{Supp(X \bigcup Y)}{Supp(X)} \tag{4}$$

$$\text{Lift}\,(\text{X} \rightarrow \text{Y}) = \frac{Supp(X \bigcup Y)}{Supp\,(X) * Supp(Y)} \tag{5}$$

The association rule for an item set I can be expressed as follows: It is clear that {A→B} (A⊂I, B⊂I, A⋂B=∅), where A and B represent the antecedent and consequent (target) of the rule, respectively. The evaluation of association rules is based on two key parameters: minimum support *(minsup)* and minimum confidence *(minconf)*. The support term is defined in the text as the joint probability of the antecedent and target, which is expressed in Eq. (3). The rule that demonstrates high support value shows frequent occurrence. In contrast, a low value assigned to support indicates a lower frequency of usage. The confidence of a rule is match with the conditional probability of the target, given the antecedent, as expressed in Eq. (4). This measure indicates the strength of association within the discovered rule.

During the ARM process, only rules that satisfy both the *minsup* and *minconf* thresholds are generated and taken into account as meaningful[39]. There is no standard criterion in the literature for defining these thresholds. These values are typically determined empirically based on the dataset and the objective of generating strong and interpretable rules[40,41]. In this study, *minsup* was set to 0.03 and *minconf* to 0.75, respectively after preliminary testing.

The ARM process was carried out in RStudio. The aim is to identify the antecedents of deficiency combinations associated with ships detained for more than two days (+2 days) at PSC authorities. The Apriori algorithm follows a bottom-up approach, beginning with frequent 1-itemsets that meet the minimum support *(minsup)* threshold. These itemsets are iteratively extended by adding one item at a time (a process known as candidate generation). Then, we test the candidate itemsets against the dataset, and only the ones that meet the minimum confidence (*minconf*) threshold are kept. The process continues until no more frequent itemsets can be generated. The resulting association rules provide insight into which deficiency types and PSC Authority practices most strongly contribute to prolonged detentions, complementing the findings from the BN analysis.

Model construction

Data acquisition and pre-processing

The Black Sea Information System (BSIS) database was the source of the data used in this study. The dataset covers the period from October 2017 to March 2022, during which 756 ship inspections resulted in detention. Table 1 presents the types of deficiencies used in the model.

The foundational procedures for establishing the qualitative architecture of the TAN network specifically applied for the probabilistic estimation of detention duration states utilizing the Construct-TAN algorithm[42] are systematically delineated in Table 2.

The fundamental assumption of standard Naïve Bayes models is strict conditional independence among attributes[34]. However, this assumption is frequently violated in complex real-world scenarios such as maritime safety inspections. Therefore, the TAN architecture was specifically adopted because it relaxes this restrictive assumption, allowing for conditional dependencies among deficiency variables, thereby capturing the systemic risk profile more realistically [22–24].

The following data was included in the study: Ship flag, ship age, gross registered tonnage (GRT), ship type, detention history, casualty history, last inspection, classification society, PSC Authority, and detention duration. Through the TAN analysis, a total of ten variables were selected. In addition, each deficiency type shown in Table 1 was included separately into the model by '*yes*' and '*no*' categories. The details of other variables, along with the class variable utilized in the TAN model, as well as the states assigned to each variable, are outlined below:

(1) Ship flag

Deficiency Type	Description of the deficiencies
Certificates and Documentation (CD)	Lacking or invalid documents required for the vessel or crew, including essential ship and personnel certifications
Structural Conditions (SC)	Structural issues involving key components like the hull, rudder systems, ballast tanks, and fuel compartments
Water/Watertight Conditions (WC)	Problems in watertight elements such as doors, hatches, covers, portholes, and ventilation units
Emergency Systems (ES)	Malfunctions or deficiencies in critical emergency tools, including fire pumps, backup power systems, lighting, and safety drills
Radio Communications (RC)	Failures in radio systems, equipment compliance with technical standards, and proper maintenance of communication logs
Fire Safety (FS)	Defects in fire detection and alarm mechanisms, fire suppression systems, hoses, valves, and related firefighting infrastructure
Safety of Navigation (SN)	Gaps in navigation safety equipment, like nautical charts, radar devices, voyage data systems, electronic chart displays, and compasses
Life-Saving Appliances (LSA)	Issues affecting life-saving equipment such as lifeboats, rescue boats, onboard safety drills, and maintenance of survival tools
Propulsion and Auxiliary Machinery (PAM)	Technical or maintenance-related faults in main propulsion systems, auxiliary machinery, indicators, and gas-related installations
Pollution Prevention (PP)	Non-compliance with MARPOL standards, including failures in antifouling systems and ballast water treatment operations
ISM	Breaches in safety and management protocols as outlined by the ISM Code, covering operations, equipment upkeep, and environmental safeguards
Working, Living and Labour Conditions (WLL)	Inadequacies in crew welfare and work conditions, such as workspace arrangements, hygiene facilities, access gear, and recreation areas

Table 1. Summary of deficiency types used in this study and their definitions.

Step No	Detail
Step 1	Select detention duration category as the class variable, and Ship flag, Ship age, GRT, Ship type, Ship detention history, Ship casualty history, Ship last inspection, Classification society, and PSC Authority as attributes
Step 2	Compute the conditional mutual information between each pair of attributes, given the class variable, to define their relationship strengths
Step 3	Construct an undirected graph with attributes and the conditional mutual information
Step 4	Construct a maximum weighted spanning tree considering the weights of edges ordered from large to small, then select the largest weights between all pairs of attributes
Step 5	Convert the undirected tree into a directed tree by selecting an attribute variable (such as "PSC Authority") as the root attribute variable and setting the directions of all arcs to other attributes to be outward from it
Step 6	Complete the TAN model by superimposing the class variable (i.e., detention duration) onto the network and drawing a directed arc from the class variable to each individual attribute node

Table 2. TAN network construction steps.

The ship flag variable included in the dataset are categorized as *Panama, Comoros, Liberia, Malta, Marshall Islands, Moldova, Tanzania, Togo,* and *Other*.

(2) Ship age

Ship age is a significant factor influencing the ship risk profile for the PSC. The Black Sea MoU New Inspection Regime, fundamentally classifies ship age into *0–24* and *25+* years[43]. The structural subdivision of the *0–24* range into two sub-intervals captures mid-life-cycle degradation. This tripartite partitioning *(0–12, 13–24*, and *25+* years) methodologically supported by Fan44, who validated dividing ship age into three macro-stages (young, middle, and old) based on an approximate 30-year commercial service life.

(3) GRT

The GRT variable was discretized into three distinct states: *Small (<500), Medium (500–25,000*), and *Large (>25,000)*. Specifically, the 500 GRT threshold aligns with the fundamental SOLAS and ISM Code applicability limits for commercial vessels[44,45,46].

(4) Ship type

This classification follows the framework established by Yang et al. (2024). Accordingly, the variable is categorized into distinct states: *Bulk carrier* (including combination carriers), *Container ship*, *General cargo/multipurpose*, *Ro-Ro cargo*, *Tankers,* and *Other* (comprising livestock carriers, vehicle carriers, and specialized hulls).

(5) Ship detention history

This variable is categorized as *Yes* or *No* based on whether the ship has had any "detentions within previous 36 months" by the Authorities [43].

(6) Ship casualty history

This variable indicates whether the ship has previously been involved in a marine casualty, and is categorized as either *Yes* or *No*.

(7) Ship last inspection

Accordingly, the variable was categorized into two distinct states: *(0to3)* and *(3 +)*. The threshold of 3 deficiencies was adopted from validated parameters in the established PSC risk literature by the study of Yang[33]. It represents a critical operational inflection point where isolated technical faults transition into systemic maintenance neglect**.**

(8) Classification society

The variable is divided into two categories: The distinction is between *IACS* and *non-IACS*. The *IACS* category comprises classification societies that are members of the International Association of Classification Societies (IACS) [47]. The *non-IACS* category refers to societies that are not affiliated with IACS.

(9) PSC Authority

This variable includes the PSC authorities of *Bulgaria*, *Georgia*, *Romania*, *Russian Federation*, *Turkey*, and *Ukraine*.

(10) Detention duration (class variable)

This variable is classified into two categories: *(0to2)* indicates that the ship was detained for a period of between 0 and 2 days, while the *(2+)* category denotes ships that have been detained for a period exceeding two days. While detention duration is fundamentally a non-negative, continuous, and non-linear outcome where dichotomisation

	Predicted positive	Predicted negative
Real positive	T_p	F_n
Real negative	F_p	T_n

Table 3. Meaning of the parameters of the evaluation index. True positive (T_p), True negative (T_n), False positive (F_p), False negative (F_n).

	Predicted (0to2)	Predicted (2+)
Real (0to2)	$T_{(0to2)}$	$F_{(2+)}$
Real (2+)	$F_{(0to2)}$	$T_{(2+)}$

Table 4. Confusion matrix.

may theoretically lead to information loss, this operationally defined binary threshold was intentionally adopted for three compelling reasons. First, from a methodological perspective, the Tree-Augmented Naïve Bayes (TAN) classifier requires discrete states for its root and attribute nodes to construct reliable Conditional Probability Tables (CPTs) without facing the curse of dimensionality or data sparsity issues often encountered with continuous variants. Second, exploratory data analysis indicated a natural concentration of cases around the 48-hour mark, rendering a balanced target variable profile (47.2% before COVID and 35.4% during COVID for the 2+ days state) that significantly enhances the classification accuracy and statistical stability of both the TAN and Apriori algorithms. Third, from a practical Port State Control (PSC) perspective, the 2-day threshold represents a critical operational line of demarcation. Detentions lasting 0–2 days are typically associated with routine, easily rectifiable technical deficiencies or minor certificate renewals. In contrast, detentions exceeding 2 days routinely signal deep-seated systemic failures (such as complex ISM breakdowns or structural integrity issues) that necessitate extensive multi-party coordination among ship managers, classification societies, and flag states before vessel clearance can be granted.

Furthermore, to avoid ambiguity regarding the inclusion of '0-day detentions' within a dataset exclusively composed of officially detained vessels, a technical clarification is warranted. In Port State Control database architectures (such as the BSIS), detention duration is automatically computed as the integer difference between the official date of detention release and the date of detention imposition. Consequently, a '0-day detention' denotes a case where a vessel was officially issued a detention order by the PSC Authority due to serious non-compliances, but the ship operator successfully rectified all detaining deficiencies, passed the re-inspection, and secured the official release order on the exact same calendar day. These cases represent highly efficient, rapid-rectification scenarios where operational disruptions were minimized to less than 24 hours. Therefore, the *(0to2)* category comprehensively encompasses these same-day releases ('0 days'), 1-day, and up to 2-day routine detentions, clearly distinguishing them from prolonged systemic detentions exceeding two days.

TAN model selection and evaluation

The subsequent methodology is employed to facilitate an evaluation of the classification accuracy and reliability of the TAN model. Initially, a training dataset is selected for the construction of the model. Subsequently, the efficacy of the constructed model is appraised on a test dataset (unseen data) [28,48]. The *overall accuracy* (Eq. 6) is the most commonly used and effective metric with which to evaluate the accuracy of model predictions. In this study, *precision* (Eq. (7)), *recall* (Eq. (8)) and *F-measure* (Eq. (9)) metrics were utilised to evaluate the reliability of the TAN model, as well. Precision is a measure of the accuracy of the classifier's performance, whereas recall is a measure of the classifier's integrity or completeness. However, it should be noted that both precision and recall are mutually restrictive. The F-measure, defined as the harmonic mean of precision and recall, is widely regarded as a more reliable metric for evaluating classification performance, as it provides a balanced assessment of both precision and recall. Moreover, an alternative metric was utilised for the purpose of evaluating the reliability of the model. This metric was the *Area Under the Curve* (AUC), which was based on the *ROC* (Receiver Operating Characteristics) curve. The ROC curve is plotted with sensitivity (also known as recall) on the y-axis against 1- specificity (Eq. 10) on the x-axis. The AUC value is typically between 0.5 and 1, with an approaching value of 1 indicating an enhancement in the model's capacity to differentiate between classes. The above parameters, as shown in Eqs. (6) through (10), are derived from the confusion matrix presented in Tables 3 and 4.

$$overallaccuracy = \frac{T_P + T_N}{T_P + F_P + F_N + T_N} \tag{6}$$

$$precision = T_P/\left(T_P + F_P\right) \tag{7}$$

$$recall/sensitivity = T_P/(T_P + F_N) \tag{8}$$

$$F - measure = \frac{2 * precision * recall}{precision + recall} \tag{9}$$

$$specificity = T_N/(T_N + F_P) \tag{10}$$

Model	Train/test	Accuracy		AUC		Detention duration	Precision		Recall		F-measure	
		BC	DC	BC	DC		BC	DC	BC	DC	BC	DC
1	50/50	**76.1**	74.2	0.82	0.80	(0to2)	0.74	0.81	0.84	0.79	0.79	0.80
						(2 +)	0.80	0.52	0.66	0.72	0.72	0.60
2	60/40	75.5	71.8	0.82	0.79	(0to2)	0.72	0.79	0.86	0.77	0.78	0.77
						(2 +)	0.80	0.58	0.65	0.60	0.72	0.59
3	70/30	73.5	73.8	0.82	0.80	(0to2)	0.80	0.88	0.86	0.83	0.83	0.85
						(2 +)	0.78	0.55	0.58	0.65	0.66	0.59
4	80/20	74	**75**	0.84	0.84	(0to2)	0.70	0.86	0.84	0.78	0.76	0.82
						(2 +)	0.80	0.54	0.64	0.68	0.71	0.60

Table 5. Comparison of the accuracy and reliability of different BN models. Note: BC denotes "before COVID; DC denotes "during COVID". Significant values are in bold.

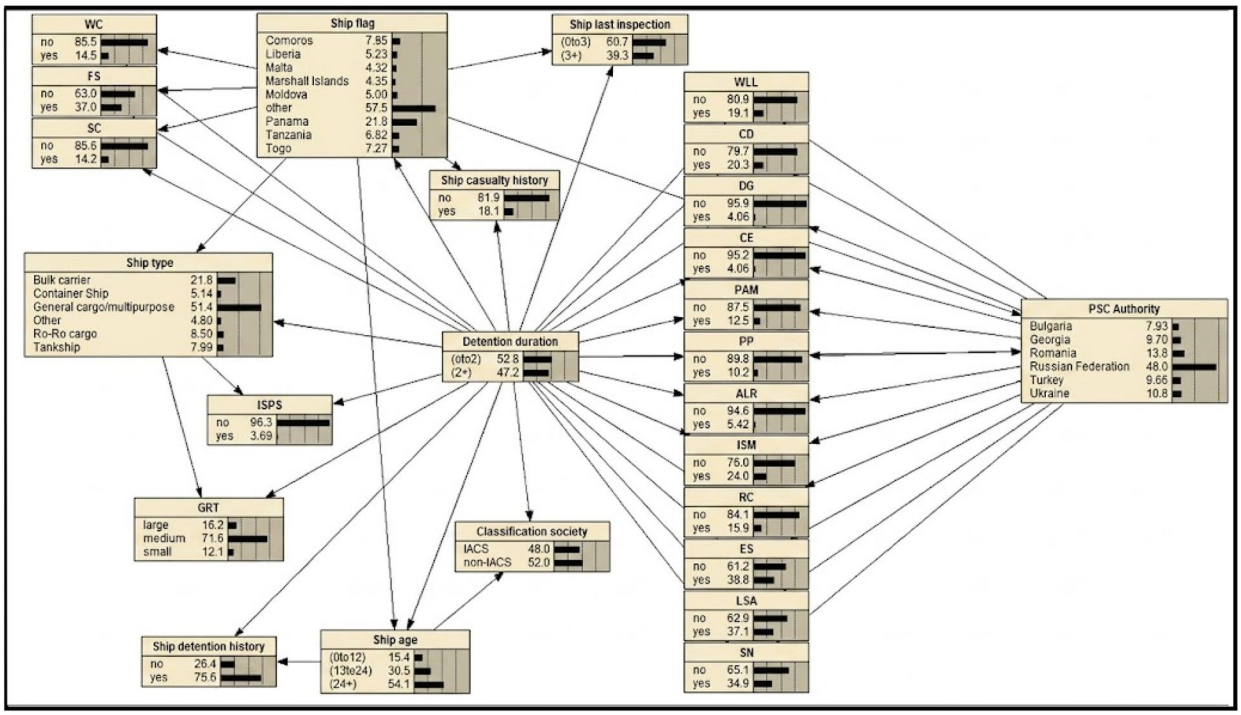


Fig. 1. TAN model with marginal probabilities for before COVID period.

The classification performance results of the TAN models created using different training-to-test data ratios are presented in Table 5. The evaluation results show that Model 1, which was trained using 50% of the data, achieved the highest classification accuracy for pre-COVID PSC inspections. Meanwhile, Model 4, which achieved an overall accuracy of 75%, was selected to analyse the data for PSC inspections during the COVID. Consequently, Model 1 was chosen for pre-pandemic data and Model 4 for pandemic-related data for further analysis.

Results

TAN implementation findings

The marginal probability distribution of the BN models

Following the development of the final TAN model with 50% of the PSC inspection data prior to the onset of the COVID, the marginal probabilities of the states associated with each variable were obtained, as illustrated in Fig. 1. Subsequent analysis of detention data revealed that 47.2% of detentions prior to the emergence of COVID involved detention duration of more than two days. It is evident that approximately half of the detentions that transpired during this period occurred in Russian Federation ports. Once more, upon examination of the vessel types, it is noteworthy that general cargo/multipurpose ships account for 51.8% of the total, with more than half (54.1%) of the detained ships being over 24 years of age. Furthermore, it has been determined that 73.6% of the ships that had been detained during this particular period were detained on prior occasions. An analysis of the types of deficiencies that led to detention reveals that those related to ES (38.8%), LSA (37.1%), and FS (37%)

are the most prevalent. These distributions indicate that authority-specific operational differences largely explain prolonged detentions across the region.

Conversely, an examination of the ship detentions that occurred during the period of the pandemic reveals a decline in the percentage of detentions lasting more than two days (35.4%) in comparison to the pre-pandemic era (Fig. 2). As was the case in the period prior to the pandemic, it has been observed that general cargo/multipurpose ships and ships with an age in excess of 24 years are the most frequently detained. Analysis of the past PSC records of detained ships reveals a striking correlation: 59.9% of these ships were detained as a result of previous PSC inspections. A detailed examination of the deficiencies that resulted in detention indicated that those related to ISM (32.4%), ES (32%) and FS (30.1%) were the most frequently encountered.

Sensitivity analysis

In order to ascertain the extent to which each variable affects the class variable: a sensitivity analysis was conducted. As illustrated in Fig. 3 the influence of variables during the pre-pandemic and pandemic periods was compared using mutual information. The results of the sensitivity analysis are presented in Table 6. The second column of the table displays the percentage of entropy reduction. Increased entropy is indicative of greater data uncertainty. Consequently, variables with the greatest potential for entropy reduction exert the strongest influence on the class variable. The "PSC Authority" variable exerts the most significant influence on prolonged detention duration, both prior to and during the pandemic period with reduction of 4.43% and 12.2%, respectively. The "CD" deficiency type has been identified as the second most significant variable influencing pre-pandemic period ship detentions, while it emerges as the third most important variable during the pandemic period. Furthermore, the variables of "ISM" and "Ship type" exhibited one of the most significant entropy reduction percentages during the pandemic period, while the impact of these variables on the pre-pandemic period was found to be limited.

Effects of attributes on class variable

The effect of each state of the attribute variables on the class variable is illustrated in Fig. 4 for pre-pandemic detentions. The initial column of each figure, designated as "average", signifies the class variable with the marginal probability. The subsequent columns represent the conditions under which each state of the attribute variable has a 100% occurrence probability, respectively. Figure 4(a) indicates that ship detentions which occurred in "Ukraine", "Bulgaria" and "Romania" increase the probability of a detention duration exceeding 2 days. Figure 4(b) illustrates that the presence of "CD" deficiency has been demonstrated to increase the probability of a detention duration exceeding two days from 47.2% to 68.2%. It is imperative to note that another salient attribute exerting a significant influence on the duration of detention during the pre-pandemic period is designated *"Ship detention history"*. The presence of a detention history record in previous PSC inspections has been demonstrated to increase the risk of durations exceeding two days from 47.2% to 51.1% (Fig. 4(c)). Conversely, if the detained ship has a "*Class society"* of IACS members, the probability of duration of detention exceeding two days decreased from 47.2% to 40.3%. (Fig. 4(d)). Finally, an analysis of the effect of the presence

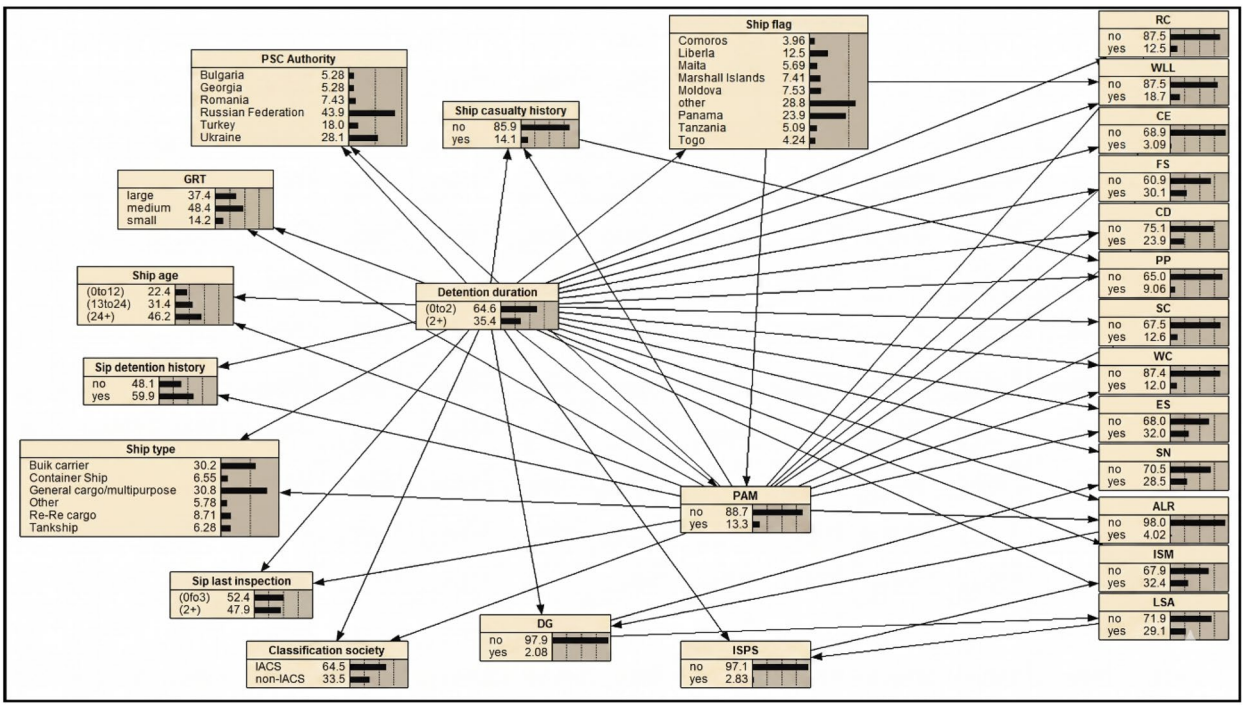


Fig. 2. TAN model with marginal probabilities for during COVID period.

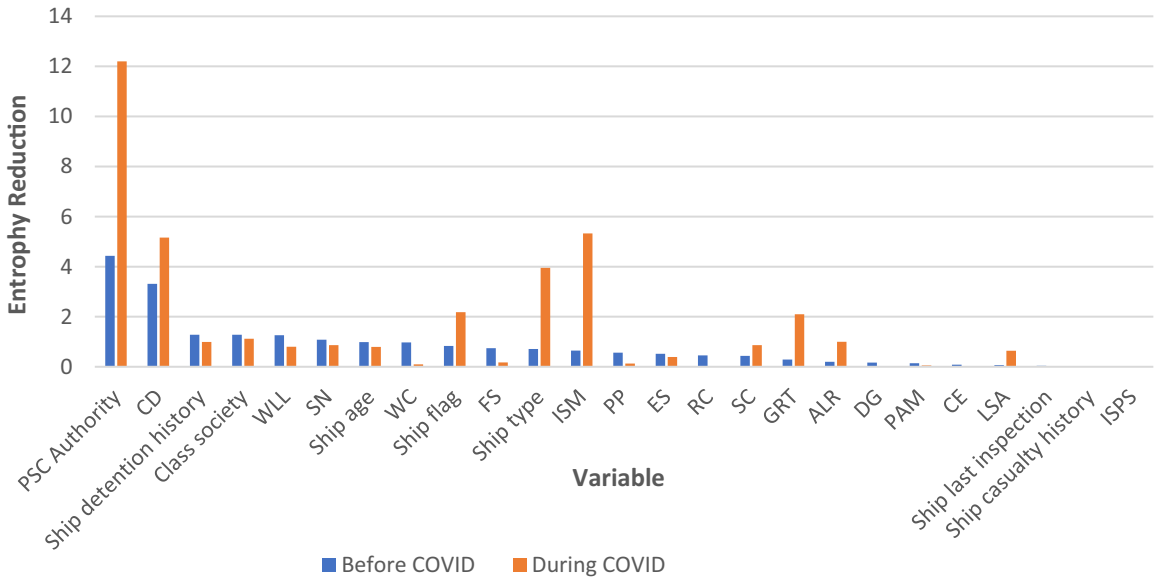


Fig. 3. Sensitivity analysis comparison of pre-pandemic and pandemic period.

Node	Entropy reduction (%)	
	Before COVID	During COVID
Detention Duration	100	100
PSC Authority	**4.43**	**12.2**
CD	**3.31**	**5.16**
Ship detention history	**1.28**	0.989
Class society	**1.28**	**1.12**
WLL	**1.26**	0.799
SN	**1.08**	0.861
Ship age	0.986	0.791
WC	0.974	0.099
Ship flag	0.829	**2.18**
FS	0.741	0.174
Ship type	0.709	**3.95**
ISM	0.645	**5.33**
PP	0.566	0.128
ES	0.516	0.393
RC	0.452	0.01
SC	0.433	0.862
GRT	0.287	**2.1**
ALR	0.197	**1**
DG	0.167	0.029
PAM	0.142	0.05
CE	0.086	0.01
LSA	0.068	0.638
Ship last inspection	0.038	0.02
Ship casualty history	0.002	0.002
ISPS	0.001	0.003

Table 6. The sensitivity of the node "Detention duration". Significant values are in bold.

of 'WLL' and 'SN' deficiency types on detention duration reveals that the "WLL" and 'SN' deficiency types which found during PSC inspections, significantly increases the detention duration risk exceeding 2 days.

In accordance with the findings observed prior to the advent of the pandemic, the attribute exerting the most significant influence on the duration of detention during the pandemic period is that of *PSC Authority*. As

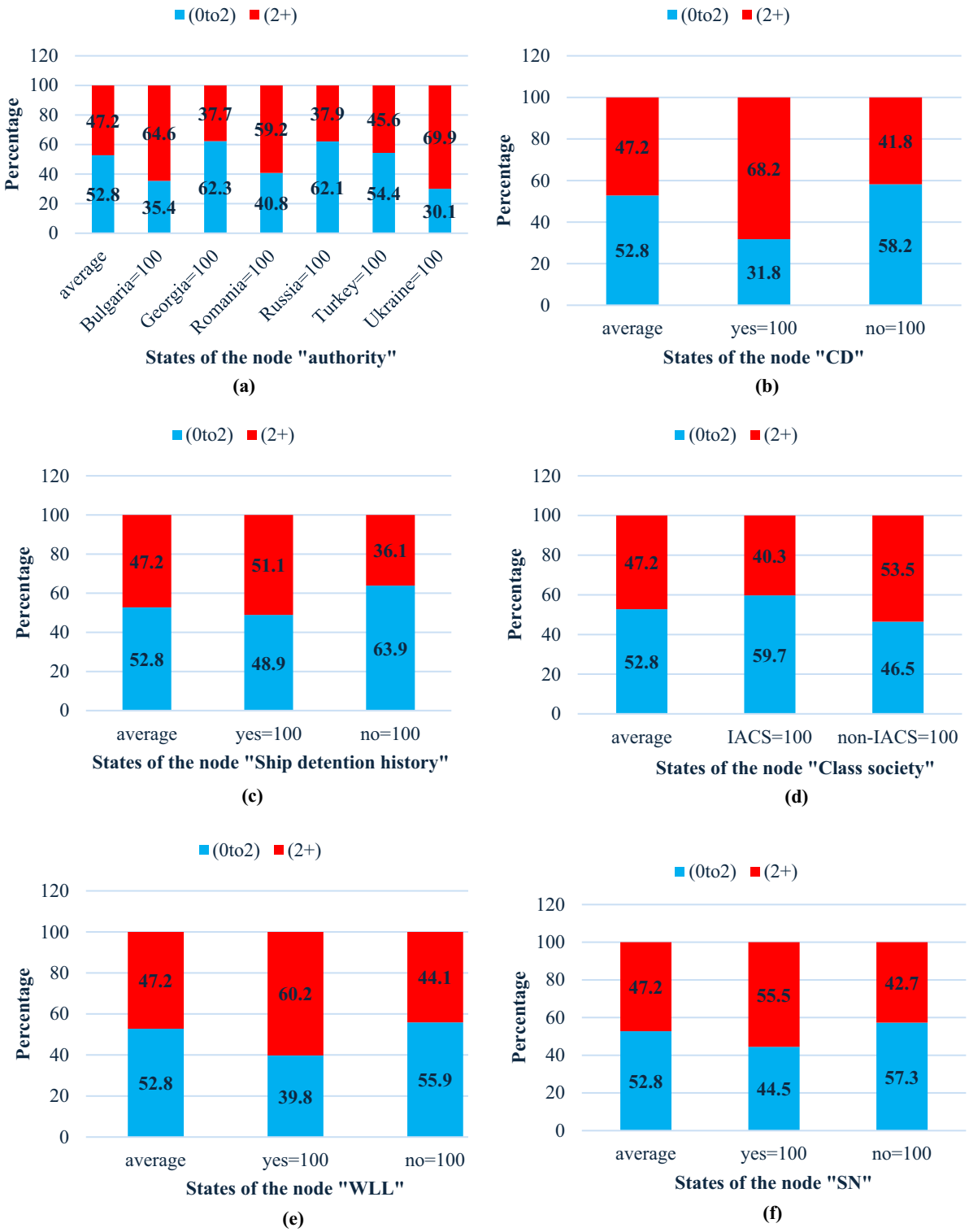


Fig. 4. Effects of different states of variables on the detention duration before COVID. (**a**) Effect of different states of "PSC Authority" on "duration" (**b**) Effect of different states of "CD" on "detention duration" (**c**) Effect of different states of "Ship detention history" on "detention duration" (**d**) Effect of different states of "Class society" on "detention duration" (**e**) Effect of different states of "WLL" on "detention duration (**f**) Effect of different states of "SN" on "detention duration".

illustrated in Fig. 5(a), the probability of detention duration exceeding 2 days from *35.4%* to 77.3%, 67.7% and 62.4%, respectively. Another significant attribute that is classified as an "ISM" has been shown to increase the risk of prolonged detentions. In more precise terms, the probability of detention exceeding two days increases from 35.4% to 53.8% in cases where ISM-type deficiency is present (Fig. 5(b)). The "CD" deficiency type has been shown to exert a similar effect on ship detentions during the pandemic period to that of the "ISM". The presence of the "CD" deficiency type in all detentions has been demonstrated to increase the risk of prolonged detention days from 35.4% to 57.9% (Fig. 5(c)). An analysis of the impact of ship type on the duration of detention reveals that vessels categorised as 'other' exhibit a marked increase in the risk of detention exceeding two days (Fig. 5(d)). The other variable affecting the number of days of detention, "*Ship flag",* shows that ships flying the flags of *Tanzania, Togo and Comoros* are more likely to be detained for more than two days (Fig. 5(e)).

ARM implementation findings

Following the implementation of a TAN analysis for the duration of PSC inspections, it was determined that the attribute of *"PSC Authority"* was the most significant for both pre-pandemic and pandemic detentions. Consequently, an ARM analysis is scheduled for detentions exceeding two days, with the objective of identifying associations between other variables and *"PSC Authority"*. For the purposes of this study, the Right-Hand Side (RHS) was designated as the *"PSC Authority"*, while the Left-Hand Side (LHS) was incorporated into the study as all variables.

The Apriori algorithm is utilised to identify the fundamental rules that contribute to detention time. In this study, the *minsup* and *minconf* thresholds were determined through a preliminary sensitivity analysis. Different parameter combinations were tested by gradually varying *minsup* between 0.01 and 0.15 and *minconf* between 0.60 and 0.85. The analysis showed that lower threshold values generated an excessive number of weak and redundant rules, reducing interpretability, whereas higher threshold values produced only a limited number of highly specific rules with insufficient coverage. The selected thresholds (*minsup* = 0.03 and *minconf* = 0.75) provided the most balanced outcome in terms of rule interpretability, statistical relevance, and practical significance for PSC detention analysis. Consequently, as illustrated in Table 7, the twenty rules with the highest confidence values that provide minimum support for class attribute are highlighted. As demonstrated in Table 7, rules that stipulate minimum support and confidence values were identified exclusively for the *PSC Authority* of the *Russian Federation, Romania*, and *Ukraine*.

A thorough examination of PSC inspection results in Russian ports has revealed that circumstances resulting in detentions lasting more than two days are considerably prevalent among Ro-Ro vessels that are over 24 years of age. It is also apparent that the non-compliance with the "ISM" is prevalent among this ship type. This phenomenon contributes to an elevated probability of prolonged detention (exceeding two days) once a ship is detained. In addition, the rules reveal that ships of this type have been detained in ports in the past and classified by a classification society that is not a member of IACS. On the other hand, in the cases of detention resulting from PSC inspections by the Romanian authorities, it is seen that the "ES", "SN" and "ISM" types are more commonly found in the rules. These types of deficiencies are frequently found together as a result of PSC inspections in Romanian ports, but they are also frequently encountered in older general cargo/multipurpose ships. Furthermore, in accordance with the findings observed in the context of detentions at ports within the Russian Federation, it has been noted that a presence of detention history and an absence of IACS membership for ships, significantly increases the probability of protracted detention periods in Romanian ports. Lastly, another examination of the rules concerning the detention of ships in Ukrainian ports reveals a unifying element: the identification of three or more deficiencies during a preceding inspection.

In this study, we utilize scatter plots to illustrate the relationship between the support, confidence, and lift values of the selected rules created with the Apriori Algorithm, as demonstrated in Fig. 6. Upon thorough examination of Fig. 6, it becomes apparent that the rules pertaining to detention duration exceeding two days are predominantly concentrated within the range of 0.03 to 0.06 of the support value, 2 to 6 of the lift value, and confidence values that exceed 0.7.

Group matrix-based visuals are also created using the arulesViz library in RStudio. As illustrated in Fig. 7, the figure delineates the relationship between the grouped antecedents (LHS) and consequences (RHS) of all rules pertaining to detention periods in excess of two days. In the figure, the columns represent the most common elements of the grouped antecedents, while the rows represent the consequences. The size of the bubbles is indicative of the magnitude of the support value. The darker color of the bubbles is indicative of the set of rules with high lift values. Furthermore, it is notable that the rules with the highest lift value are located in the upper left corner of the figure. It is notable that the highest lift and support values are to be found in the rules created for the *PSC Authority* of *Romania*. Moreover, an analysis of the rules with high support values found for Romania reveals a concentration in detentions involving the deficiency types of "ES", "SN"' and "CD".

Beyond the extraction of the explicit structural rules presented in Fig. 7, the relative predictive efficacy of the proposed architecture was validated against four standard supervised learning algorithms (Logistic Regression, Random Forest, Naïve Bayes, and CART) using tenfold stratified cross-validation. As reported in Table 7, predictive performance remained moderate across all baselines, with classification accuracy ranging from 57.07% to 70.70% and AUC values spanning 0.569 to 0.728 across both datasets.

As Table 8 indicates, although ensemble methods like Random Forest achieved competitive AUC scores, they operate as "black boxes," optimizing for global accuracy without providing the interpretable conditional dependency structures required by maritime regulators[49]. The rationale for implementing the TAN-ARM framework is rooted in its structural interpretability and inferential flexibility [50]. Methodologically, the TAN algorithm relaxes the strict conditional independence assumption of Naïve Bayes. This allows it to capture critical operational interactions, such as the systemic link between ISM non-compliance and technical faults without the high computational burden of fully unrestricted Bayesian Networks[34]. Moreover, compared to static baseline

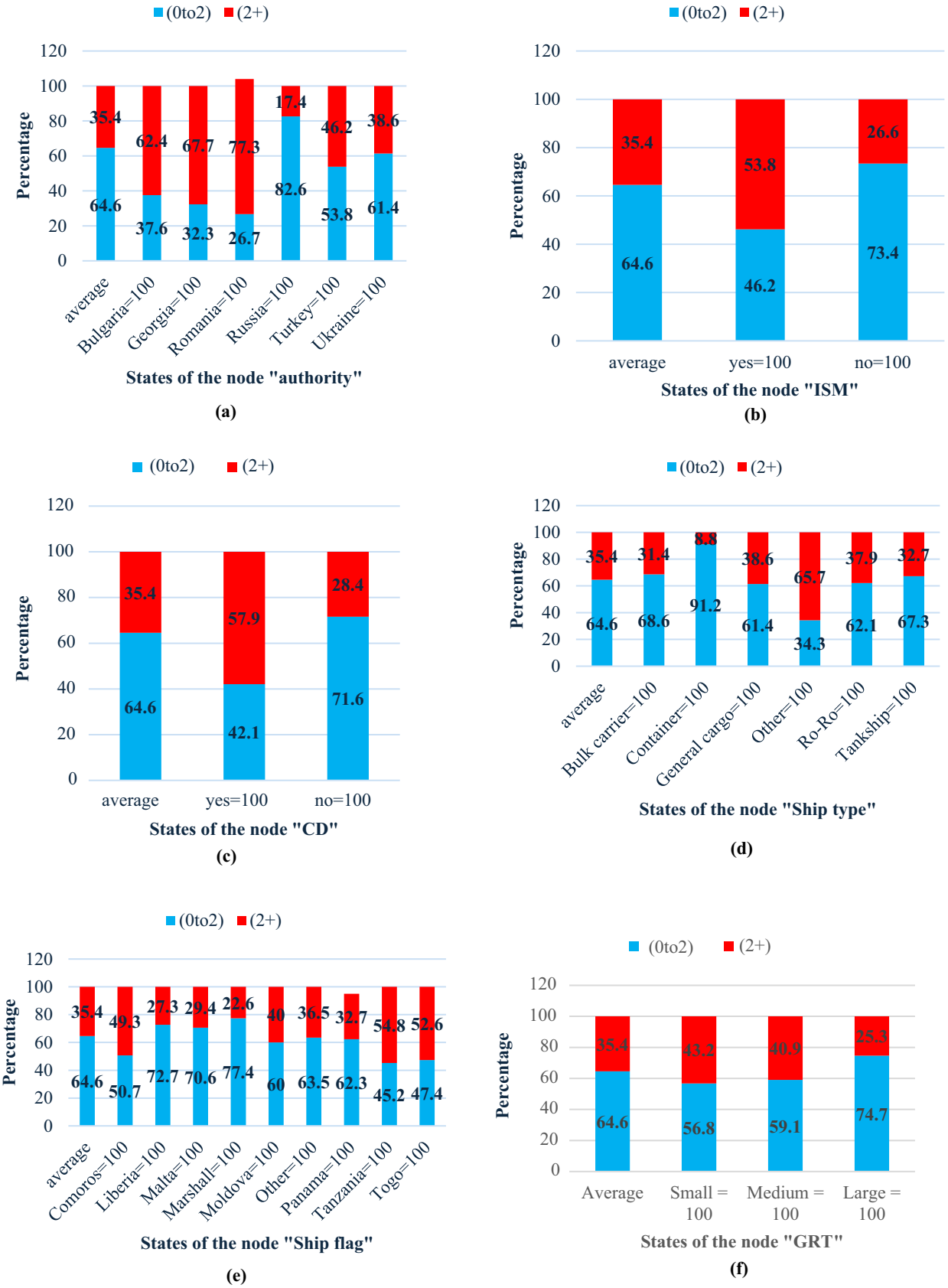


Fig. 5. Effects of different states of variables on the detention duration during COVID. Effect of different states of "PSC Authority" on "duration" (b) Effect of different states of "ISM" on "detention duration" (c) Effect of different states of "CD" on "detention duration" (d) Effect of different states of "Ship type" on "detention duration" (e) Effect of different states of "Ship flag" on "detention duration"5(f) Effect of different states of "GRT" on "detention duration".

Rule no	LHS	RHS = "PSC Authority"	Conf	Support	Lift
1	{Ship type = Ro-Ro cargo, ISM = yes} = >	Russian Federation	1	0.034	2.756
2	{Ship type = Ro-Ro cargo, Classification society = non-IACS, ISM = yes} = >	Russian Federation	1	0.034	2.756
3	{Ship age = (24 +), Ship type = Ro-Ro cargo, ISM = yes} = >	Russian Federation	1	0.034	2.756
4	{Ship type = Ro-Ro cargo, Ship detention history = yes, ISM = yes} = >	Russian Federation	1	0.034	2.756
5	{Ship flag = other, SN = yes, ISM = yes} = >	Romania	0.875	0.044	5.334
6	{Ship detention history = yes, ES = yes, SN = yes, ISM = yes} = >	Romania	0.826	0.060	5.035
7	{Ship age = (24 +), Ship type = Ro-Ro cargo} = >	Russian Federation	0.818	0.056	2.255
8	{Ship age = (24 +), Ship type = Ro-Ro cargo, Classification society = non-IACS} = >	Russian Federation	0.818	0.056	2.255
9	{Ship type = Ro-Ro cargo, Classification society = non-IACS} = >	Russian Federation	0.818	0.056	2.255
10	{Ship age = (0to12), Ship type = Bulk carrier, Ship last inspection = (3 +)} = >	Ukraine	0.800	0.037	3.622
11	{Classification society = non-IACS, ES = yes, SN = yes, ISM = yes} = >	Romania	0.790	0.047	4.812
12	{Ship type = Ro-Ro cargo, Ship detention history = yes} = >	Russian Federation	0.790	0.047	2.176
13	{Ship age = (0to12), ISM = yes} = >	Ukraine	0.790	0.047	3.575
14	{Ship detention history = yes, ES = yes, ISM = yes} = >	Romania	0.790	0.091	4.778
15	{Ship age = (24 +), Ship detention history = yes, ES = yes, ISM = yes} = >	Romania	0.790	0.063	4.689
16	{Ship type = General cargo/multipurpose, ES = yes, ISM = yes} = >	Romania	0.777	0.066	4.741
17	{CD = yes, ES = yes, ISM = yes} = >	Romania	0.761	0.050	4.644
18	{Ship age = (24 +), Classification society = non-IACS, ES = yes, ISM = yes} = >	Romania	0.750	0.056	4.572
19	{Ship age = (0to12), Ship detention history = yes, Ship last inspection = (3 +)} = >	Ukraine	0.750	0.031	3.483
20	{ES = yes, ISM = yes} = >	Romania	0.750	0.104	4.572

Table 7. Rule extraction for detention duration exceeding 2 days.

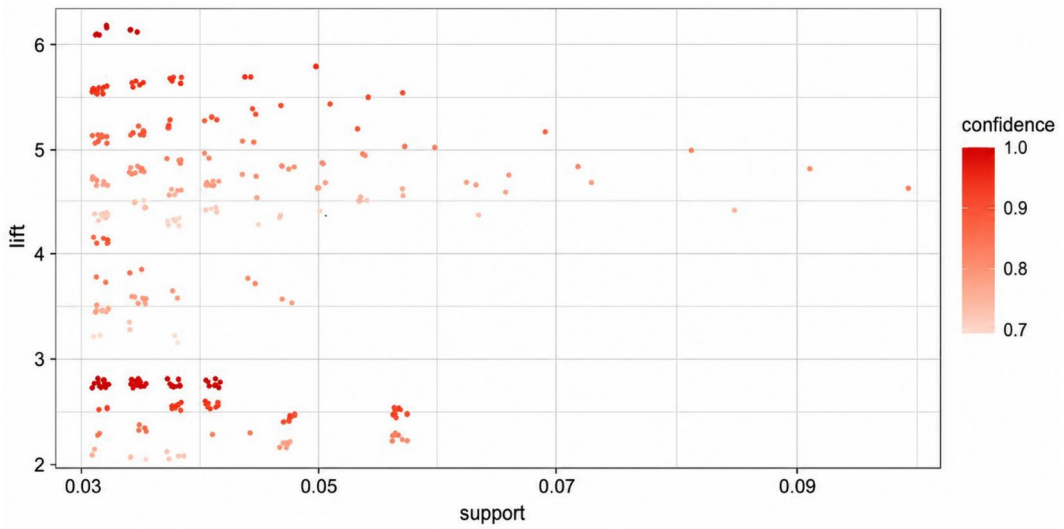


Fig. 6. Scatter plots for association rules.

classifiers, the TAN architecture allows for dynamic probabilistic inference. This capability enables authorities to conduct real-time 'what-if' analyses, updating the likelihood of prolonged detentions as new deficiencies are sequentially observed during an inspection [51].

Ultimately, while baseline models excel in global classification accuracy, the integrated TAN-ARM approach graphically maps probabilistic dependencies and extracts explicit targeting rules. This inherent transparency bridges the critical gap between predictive analytics and practical implementation.

To translate these probabilistic methodologies into actionable maritime safety strategies, the TAN-ARM framework serves as a dynamic risk-profiling tool. For PSC authorities, the conditional dependencies identified via TAN allow for the real-time adjustment of inspection priorities based on the declared PSC Authority and vessel age. Instead of relying on static, uniform checklists, authorities can utilize the ARM-derived rules to implement 'cluster-based' targeting; for instance, the identification of an Emergency System (ES) deficiency should immediately trigger a targeted audit of Safety of Navigation (SN) protocols and ISM compliance. For ship operators and maritime administrations, these findings dictate a necessary paradigm shift from isolated

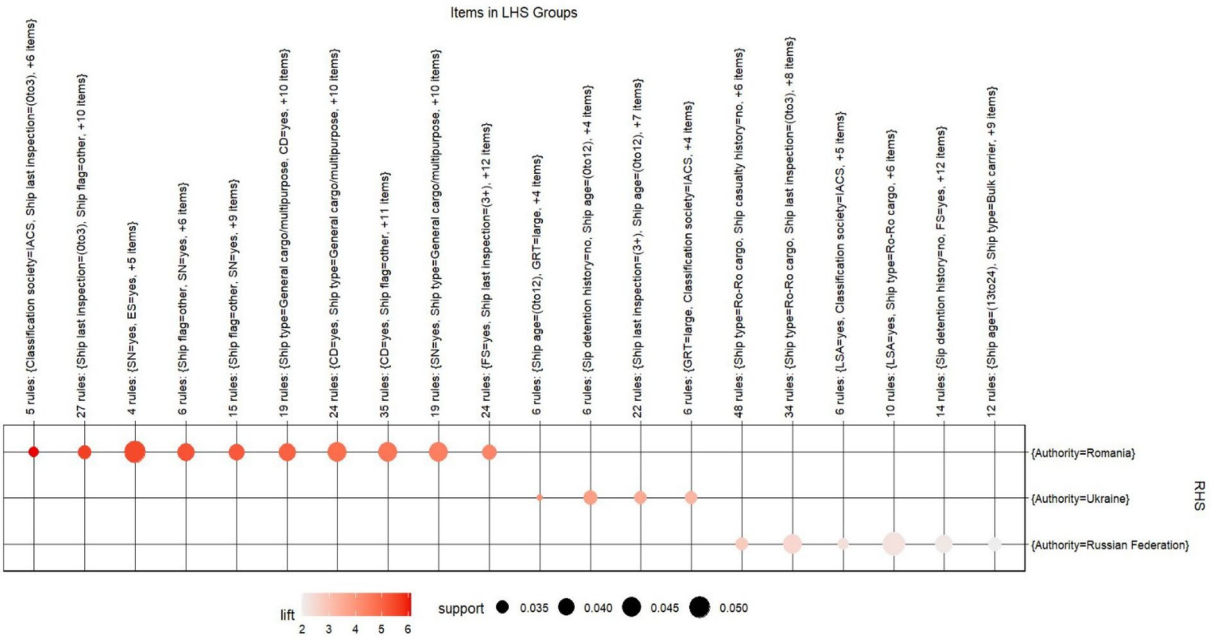


Fig. 7. Group matrix of association rules.

Model	Dataset 1 — Pre-Pandemic (n = 422)			Dataset 2 — Pandemic (n = 334)		
	Accuracy (%)		AUC	Accuracy (%)		AUC
	Mean ± SD	95% CI	Mean ± SD [95% CI]	Mean ± SD	95% CI	Mean ± SD [95% CI]
Logistic Regression	64.93 ± 7.85	[59.01, 70.85]	0.6841 ± 0.1102 [0.6010, 0.7672]	70.37 ± 4.68	[66.83, 73.90]	0.7081 ± 0.0856 [0.6435, 0.7726]
Random Forest	63.25 ± 7.69	[57.45, 69.05]	0.6787 ± 0.0908 [0.6102, 0.7471]	69.50 ± 5.54	[65.33, 73.68]	0.7282 ± 0.0713 [0.6744, 0.7820]
Naïve Bayes	65.38 ± 8.38	[59.06, 71.69]	0.6870 ± 0.1001 [0.6115, 0.7625]	70.70 ± 7.63	[64.94, 76.45]	0.7266 ± 0.1024 [0.6494, 0.8038]
CART (Decision Tree)	57.07 ± 7.96	[51.06, 63.07]	0.5689 ± 0.0795 [0.5090, 0.6289]	64.11 ± 5.41	[60.03, 68.19]	0.6118 ± 0.0626 [0.5646, 0.6591]
TAN	65.14 ± 9.03	[58.33, 71.96]	0.6647 ± 0.0882 [0.5983, 0.7312]	64.79 ± 12.05	[55.70, 73.87]	0.6761 ± 0.1171 [0.5879, 0.7644]

Table 8. Baseline models performance comparison.

equipment maintenance to systemic safety management, where internal audits proactively target these high-confidence deficiency co-occurrences to mitigate severe detention risks.

Discussion

The present study employs Bayesian modelling and ARM to provide a comprehensive analysis of ship detention durations during PSC inspections within the Black Sea MoU region. A fundamental objective of our research endeavours is to examine the impact of the various variables such as *ship age*, *PSC Authority, ship type*, *deficiency* type etc. on the duration of detention. A salient finding of this study, derived from Bayesian analysis, is that the inspecting *PSC Authority* is the most significant variable on detention duration for both pre-pandemic and pandemic period. This emphasizes a pivotal, albeit frequently unexplored, dimension of PSC effectiveness: the practical implementation of inspections and the management of deficiencies can exhibit substantially variations across diverse authorities within a specified MoU region.

A detailed sensitivity analysis of the study demonstrates that the PSC Authority is the strongest factor in reducing uncertainty in detention duration. It is evident from the data that there was a decrease in entropy of 4.43% before the pandemic and 12.2% during the pandemic. This indicates that the PSC Authority exerts a greater influence on detention duration during the pandemic. The significant influence of PSC authorities on detention duration within the Black Sea region can be empirically supported by the structural and operational disparities documented in the Black Sea MoU (2023) annual reports[52]. For instance, the uneven distribution of inspection resources and the varying number of qualified PSCOs across member states ranging from extensive technical teams in the Russian Federation and Türkiye to more limited personnel in other member jurisdictions create inherent discrepancies in inspection depth and the subsequent time required for deficiency verification. In

addition, Knapp and Franses[9] further validate the 'human element' in PSC, suggesting that a PSCO's professional profile such as the distinction between a former master mariner and a technical engineer leads to varying priorities during inspections. In the specific context of the Black Sea, the absence of a centralized, mandatory training framework (unlike the EMSA framework for the Paris MoU) means that PSCO qualifications are largely governed by diverse national standards. These results are consistent with the prevailing view in the literature that PSC inspections are not applied uniformly. For instance, Deng[17] examined the impact of *PSC Authorities* on ship detentions in the Tokyo MoU region, noting that *PSC Authorities* affected detentions across ship categories, with the scope of deficiencies and detention duration varying according to port state practices [7]. In a similar vein, Akyurek and Bolat[53] found that each EU15 country in the Paris MoU region has its own unique country characteristics for ship detentions. The extant literature supports the notion that PSC authorities exert a significant influence on inspection decisions and, consequently, detention durations.

The finding that ISM-related deficiencies became particularly problematic during the pandemic warrants a more nuanced interpretation through the lens of ARM results. Rather than treating ISM failures as isolated events, our analysis reveals that they often co-occur with specific technical deficiency clusters, providing targeted intervention directions for shipowners and PSCOs. For instance, the high-confidence rules identified in this study indicate that ISM deficiencies frequently serve as a root cause for clusters involving LSA and FS systems, especially during the pandemic period when maintenance schedules were disrupted. To enhance the practical value of these findings, we propose targeted countermeasures: shipowners should prioritize remote internal audits that specifically verify the interface between ISM documentation and the operational readiness of emergency equipment. Simultaneously, for PSCOs, the detection of a technical failure in navigation or emergency systems should be treated as a 'red flag' for a broader ISM breakdown, necessitating a more comprehensive audit of the vessel's safety management culture. By focusing on these specific deficiency combinations rather than individual faults, maritime stakeholders can implement more effective resource allocation and preventative maintenance strategies to mitigate the risks associated with prolonged detentions.

Some deficiency combinations identified in Romania and Ukraine may reflect regional differences in inspection focus and vessel traffic structure. Ships operating in these ports are often composed of older bulk carriers, general cargo vessels, and regionally operating fleets with relatively high technical wear and maintenance requirements. Deficiency combinations involving certificates, safety management, navigational safety, and fire safety systems may therefore indicate broader organisational and operational weaknesses rather than isolated technical failures. From a PSC perspective, multiple interconnected deficiencies may increase the perceived probability of systemic non-compliance, thereby requiring more extensive corrective actions before vessel release. In addition, PSC inspection procedures themselves may contribute to the observed regional variation in deficiency combinations. Although Black Sea MoU inspections are conducted under harmonised international frameworks, PSCOs may still demonstrate differences in inspection emphasis depending on local operational experience, port traffic characteristics, and historical detention patterns. Similar regional variations in PSC inspection outcomes and detention practices were also discussed by Heij and Knapp (2018) and Yang[5] who highlighted that detention decisions are often shaped not only by individual deficiencies but also by the combined operational risk profile presented during inspections.

The high frequency of "ES" and "FS" deficiencies observed during the pandemic period can be associated with operational and maintenance disruptions caused by COVID-19 restrictions. Emergency systems and fire safety equipment require periodic onboard testing, drills, calibration, and maintenance in accordance with SOLAS requirements. However, pandemic-related travel restrictions, reduced shipyard accessibility, limited availability of technical service personnel, and extended crew contracts likely delayed routine maintenance and inspections of emergency generators, fire pumps, detection systems, and firefighting appliances. As a result, PSC inspections during the pandemic increasingly identified deficiencies related to emergency preparedness and onboard safety systems. Similar operational disruptions during COVID-19 were also reported by Yan[54], who noted that pandemic conditions significantly affected PSC inspection practices and onboard operational compliance, and by Deng[17] who highlighted the growing importance of management- and safety-related deficiencies during the pandemic period. In addition, "CD" deficiencies emerged as one of the most influential factors affecting prolonged detention duration, particularly during the pre-pandemic period. Documentary deficiencies often require verification and coordination between ship operators, flag administrations, classification societies, and PSC authorities before a vessel can be released. During the pandemic, administrative delays associated with remote working practices, restricted physical access to offices, and disruptions in international communication processes may have further prolonged the rectification of certification-related deficiencies. Similar findings were reported by Akyurek and Bolat[21] who discussed how pandemic conditions altered PSC inspection practices and increased reliance on documentary verification procedures.

The findings also indicate that ships classified by non-IACS classification societies were associated with a higher probability of prolonged detention. This result may reflect differences in inspection quality, survey consistency, and technical oversight between *IACS* and *non-IACS* organisations. IACS member societies generally apply more standardised survey procedures and stricter compliance controls under internationally recognised quality systems. Therefore, vessels operating under non-IACS societies may face a higher likelihood of accumulated deficiencies and delayed corrective actions during PSC inspections. Similar relationships between classification society quality and detention-related outcomes were also discussed by Knapp and Franses[9] and Chen[12], who found that ships operating under weaker compliance structures tend to exhibit higher detention risks.

Beyond these general observations, the ARM results of this study provide a data-driven framework for jurisdiction-specific policy recommendations. Instead of broad administrative improvements, our findings advocate for targeted inspections based on identified deficiency clusters. For instance, the "ES" "SN" "ISM" combination identified specifically for Romania suggests that in this jurisdiction, technical failures in emergency and navigation equipment are systematically linked to management lapses under the ISM Code. Consequently,

it is recommended that the Romanian PSC Authority strengthen joint inspection protocols that concurrently evaluate navigation and emergency systems to identify these recurring patterns. Such a targeted approach would allow PSCOs to focus on the most probable combinations of deficiencies, thereby optimizing inspection resources and reducing the subjectivity of detention durations. Recognizing these specific links allows PSCOs to focus on the most probable combinations of deficiencies during the rectification process, thereby optimizing inspection resources and reducing the subjectivity of detention durations**.** For vessel operators, these findings imply that internal audits should be restructured to prioritize these high-risk 'deficiency patterns' rather than treating each category in isolation.

The disparities observed among PSC authorities can be ascribed to a range of factors. Firstly, it should be noted that the educational levels and experience of PSCOs may vary from country to country[55]. It is acknowledged that discrepancies may arise in the application of inspection protocols, with certain authorities exhibiting a propensity to adopt a more stringent approach than their counterparts. Secondly, it should be noted that each PSC Authority's national legislation and inspection procedures may include their own interpretations and priorities in addition to international standards. This discrepancy can result in different authorities making different decisions regarding the same deficiency. Thirdly, the effectiveness of information sharing and coordination mechanisms within regional memoranda of understanding (MoUs) may also vary. Finally, political and economic factors may also influence PSC authorities' inspection practices; for example, a particular country's emphasis on maritime safety or environmental protection may increase the frequency and severity of inspections[56,57]. These institutional disparities underscore the need for harmonised PSCO training and consistent implementation of inspection protocols within the Black Sea MoU.

The findings of our study indicate that these regional disparities are also evident in the Black Sea MoU region, and that this effect has been further exacerbated during the pandemic period (as evidenced by the increase in entropy reduction). The increased influence of the PSC Authority during the pandemic can be explained by the transformative effects of COVID-19 on inspection practices[58]. Travel restrictions, quarantine measures, and staffing shortages may have affected the frequency and scope of inspections. While some authorities may have been forced to reduce their inspections or focus on specific types of ships, others may have continued to conduct more intensive inspections with their existing resources[54]. This situation may have further deepened inconsistencies among authorities and led to longer detention durations at certain ports. The statistical dominance of ISM and specific technical deficiencies during the COVID-19 pandemic necessitates a critical operational interpretation. The surge in ISM-related detentions reflects the profound disruption of the maritime human element; extended crew contracts, severe psychological fatigue, and the suspension of routine superintendent visits systematically degraded safety management cultures onboard. Concurrently, the prominence of Emergency Systems (ES) and Fire Safety (FS) deficiencies was not merely a mechanical failure but a regulatory side-effect of pandemic-induced supply chain disruptions, delayed dry-docking, and the widespread application of remote surveys, which ultimately postponed critical maintenance. Furthermore, the amplified variance among PSC Authorities during this period highlights an inherent lack of regulatory harmonization; while some authorities adopted pragmatic leniency, others intensified enforcement to compensate for reduced inspection scopes, thereby skewing the detention duration distributions**.**

It is imperative to eliminate observed discrepancies between PSC authorities and enhance the efficacy of inspections during global crises, such as pandemics, to ensure maritime safety and operational efficiency. In order to surmount these issues, measures must firstly be implemented to reduce subjectivity arising from differences in the training and experience of inspectors (PSCOs). This objective can be realized through the development of internationally standardized training programs and certification processes, thereby increasing consistency in the identification and assessment of deficiencies while encouraging inspection decisions to be based on objective criteria[59]. Secondly, the national legislation of each PSC Authority should be brought into full compliance with international conventions, and common interpretation guidelines should be established within the framework of regional MoUs; this will minimize inconsistencies in detention decisions issued by different authorities for the same deficiencies. Thirdly, information sharing and coordination mechanisms within regional MoUs should be further strengthened; joint inspection databases and regular cooperation platforms will enable more consistent evaluation of high-risk deficiency clusters on detained vessels and efficient use of resources during the rectification process[56,59].

The study found that ship detention periods were affected by different deficiencies before and during the pandemic. "ES", "LSA" and "FS" were the most common before the pandemic, but "CD" was the second most significant after the PSC Authority. "CD" deficiencies increased the probability of detention by 68.2% and the duration of detention by more than two days. "WLL" and "SN" deficiencies also had a significant impact. During the pandemic, "ISM" deficiencies became particularly problematic, affecting detention duration. The study also found that "ISM" deficiencies had a substantial impact on detention duration, while the effect of "CD" deficiencies diminished. The study's findings are consistent with those of Deng[7] who also found that "ISM" deficiencies significantly impact pandemic detention periods. It is acknowledged that pandemic conditions have resulted in disruptions to ship management systems and ISM Code compliance. This may have led inspection authorities to focus more on ISM documents and practices that demonstrate the soundness of a ship's management processes in an environment where physical inspections are restricted. It is anticipated that the rectification of management deficiencies will require a greater temporal investment and coordination than the resolution of technical issues. This is due to the fact that, in general, the rectification of management deficiencies necessitates a more protracted duration. Moreover, ARM findings of this study provide a deeper understanding of the relationship between certain types of deficiencies and other factors. For example, ISM non-compliance contributing to long-term detentions on Ro-Ro ships over 24 years old in Russian Federation ports indicates that these types of ships and operational conditions carry specific risk factors. This may be associated with the operational characteristics of ageing Ro-Ro fleets operating on short-sea and regional trade routes. Ro-Ro vessels generally operate under

intensive cargo turnover schedules and tight port rotation cycles, which may increase operational pressure on both crews and ship management systems. In older vessels, these operational pressures may contribute to weaknesses in safety management implementation, maintenance planning, and procedural compliance under the ISM Code. Previous studies have also shown that ageing ships are more likely to accumulate managerial and technical deficiencies due to deferred maintenance and organisational limitations[9,12]. Consequently, PSCOs may perceive the coexistence of advanced ship age and ISM-related deficiencies as an indicator of elevated operational risk, leading to more cautious detention decisions and longer detention durations.

A multifaceted and integrated approach should be adopted in order to reduce ship detention durations and to reduce ISM deficiencies and other common types of deficiencies. Firstly, it is vital that PSC authorities continuously develop and update their risk-based inspection strategies. This approach entails the identification of management deficiencies, such as ISM, and the proactive management of novel risk factors that emerge during crises, including pandemics[5,7]. Secondly, the integration of technological solutions into inspection processes is of great importance. The utilization of remote inspection technologies, artificial intelligence, and machine learning models has been demonstrated to facilitate the expeditious and effective identification of deficiencies, the estimation of detention periods, and the optimization of inspection resources[6]. Thirdly, ship owners and operators should continuously educate their crews and raise their awareness about the types of deficiencies commonly encountered in PSC inspections that affect detention periods. It is imperative to adhere to the stipulated requirements of the ISM Code to ensure enhanced operational resilience and to avert protracted detentions. These comprehensive strategies will elevate safety standards in the maritime sector while improving operational efficiency and minimizing the negative impacts of ship detentions.

The Bayesian analysis conducted indicates that the age of a ship exerts a moderate influence on its detention period. It is particularly noteworthy that ships over 24 years of age were among the most frequently detained ship types both before and during the pandemic, thus underscoring the heightened risk factors associated with older ships. Furthermore, ARM findings reveal the correlations between ship age and other factors, thereby providing a more in-depth perspective on the impact of age on detention periods. The ISM non-compliance of ships over 24 years old in Russian Federation and Romanian ports contributes to long-term detentions, indicating that the risk increases significantly when older ships are combined with certain operational conditions and management deficiencies. The aforementioned correlation rules underscore the notion that ship age does not function as an independent factor; rather, it interacts with other deficiencies and operational contexts to influence detention duration. This finding is consistent with the general trend evidenced in extant literature. The studies on detention duration suggest that the direct effect of ship age may be less pronounced than that of other variables, such as the severity of deficiencies or managerial factors[17]. For instance, in the Bayesian-based models conducted by Yang[5,6] it was observed that factors such as deficiency types and PSC Authority, in addition to internal characteristics like vessel age, exert a more pronounced influence on detention duration[5,6]. This suggests that the type and severity of deficiencies identified in older ships may be more determinative of detention duration than ship age alone.

Despite its contributions, this study has certain limitations that should be acknowledged. *Regarding* limitations, the regional specificity of the Black Sea MoU database must be explicitly acknowledged. Unlike the highly harmonized Paris or Tokyo MoUs, the Black Sea regime encompasses a higher proportion of older, non-IACS certified tonnage operating on short-sea routes, which inherently skews the baseline risk profile. Additionally, the analysis is constrained by potential reporting inconsistencies and subjective discretions inherent to individual PSCOs across different member states, given the absence of a centralized, stringent quality-assurance mechanism akin to EMSA. Consequently, while the proposed TAN-ARM methodological framework is universally robust and fully transferable to other PSC regimes, the specific deficiency clusters and authority-driven dependencies identified herein are highly contextual. Therefore, these empirical findings should not be directly extrapolated to the operational dynamics of the Paris or Tokyo MoUs without prior regional recalibration.

Conclusion

This present study uses Bayesian modelling and *ARM* to investigate the key factors influencing ship detention duration in the Black Sea MoU region. The analysis is based on PSC inspection data collected between October 2017 and March 2022. The study focuses on changes in inspection outcomes before and during the pandemic, emphasising the role of PSC authorities, deficiency types, and ship-related characteristics. To address these objectives, the study explores four research questions concerning variables affecting detention duration, the influence of PSC authorities, and deficiency types contributing to prolonged detentions.

The findings of this study demonstrate that the PSC Authority is the most influential factor affecting detention duration in both pre-pandemic and pandemic periods. This result underscores persistent regional disparities in inspection practices within the Black Sea MoU region. Ship age alone has a moderate influence on detention duration. However, when combined with managerial deficiencies such as ISM non-compliance, the risk of extended detention increases substantially. ARM further identified specific high-risk patterns, reinforcing the value of targeted, risk-based inspection strategies. These findings provide practical insights for PSC authorities and ship operators, highlighting the importance of harmonising inspection procedures, strengthening ISM compliance, and employing data-driven decision-making to enhance maritime safety. Methodologically, the study demonstrates that integrating probabilistic TAN structures with ARM overcomes the 'black-box' limitations of standard predictive algorithms, offering the structural transparency required for high-stakes regulatory environments. Future research should consider expanding the geographical scope to other MoU regions and exploring the use of advanced analytical techniques to deepen understanding of detention dynamics.

Some potential limitations of this study are discussed below. The dataset used in this study is based on data retrieved from the Black Sea MoU Information System. In order to enable a consistent and comparable temporal

analysis between the pre-pandemic and pandemic periods, the timeframe was deliberately restricted to cover the period from October 2017 to March 2022. This approach ensured that corresponding months across multiple years could be evaluated in parallel, reducing potential seasonal biases. However, this temporal limitation inherently reduced the number of observations, particularly for the pandemic period, which constitutes a relatively shorter timeframe within the selected range. As a result, the sample size for the pandemic period remained limited, potentially affecting the robustness of statistical comparisons and the generalizability of the findings. Despite these limitations, the consistency of findings across models supports the reliability of the conclusions.

Moreover, during the COVID-19 pandemic, the implementation of health and safety measures,such as the use of masks and gloves, social distancing, and efforts to minimise physical contact,led to a reduction in the time spent onboard during inspections. Consequently, the scope of inspections was narrowed, and inspectors' ability to identify deficiencies was diminished. In some cases, this may have resulted in overlooked deficiencies or postponed detention decisions. These circumstances were not solely a consequence of health protocols, but they were also shaped by the professional judgment of the inspectors.

Data availability

Data will be made available on request.

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References

1. IMO. Regional Co-Operation in the Control of Ships and Discharges-IMO Resolution A.682 (17). vol. 682 https://wwwcdn.imo.org/localresources/en/KnowledgeCentre/IndexofIMOResolutions/AssemblyDocuments/A.682(17).pdf (1991).
2. Black Sea MoU. About PSC. *About Us* 20–22 https://bsmou.org/about/ (2021).
3. International Maritime Organization. *Procedures for Port State Control Resolution A.1119(30)*. 92–105 (2017).
4. Yan, R., Wang, S. & Peng, C. An artificial intelligence model considering data imbalance for ship selection in port state control based on detention probabilities. *J. Comput. Sci.* **48**, 101257 (2021). https://doi.org/10.1016/j.jocs.2020.101257
5. Yang, Z., Yu, Q., Yang, Z. & Wan, C. A data-driven Bayesian model for evaluating the duration of detention of ships in PSC inspections. Transp. Res. Part E Logist. Transp. Rev. **181**,(2024). https://doi.org/10.1016/j.tre.2023.103371
6. Yang, Z., Wan, C., Yu, Q., Yin, J. & Yang, Z. A machine learning-based Bayesian model for predicting the duration of ship detention in PSC inspection. *Transp. Res. Part E Logist. Transp. Rev*. **180**, 103331 (2023). https://doi.org/10.1016/j.tre.2023.103331
7. Deng, Q., Wan, Z. & Chen, J. Factors influencing ship detentions: Pre- and post-pandemic analysis. *Ocean Coast. Manag.* **257**, 107344 (2024). https://doi.org/10.1016/j.ocecoaman.2024.107344
8. Çelik Maşalacı, B. & Çakır, E. Differences in deficiency types causing ship detentions at the Black Sea Region during the Covid-19 pandemic and pre-pandemic. *Mar. Policy* **151**, 1–11 (2023). https://doi.org/10.1016/j.marpol.2023.105553
9. Knapp, S. & Franses, P. H. Econometric analysis to differentiate effects of various ship safety inspections. *Mar. Policy* **32**, 653–662 (2008). https://doi.org/10.1016/j.marpol.2007.11.006
10. Graziano, A. *et al. Port State Control Inspections in the European Union : Do Inspector ' s Number and Background Matter?* https://shs.hal.science/halshs-01649418 (2017) https://doi.org/10.1016/j.marpol.2017.11.031.
11. Tsou, M. C. (2019). Big data analysis of port state control ship detention database. *Journal of Marine Engineering and Technology*. **18** 113–121 https://doi.org/10.1080/20464177.2018.1505029
12. Chen, J. et al. Identification of key factors of ship detention under port state control. *Mar. Policy* **102**, 21–27 (2019). https://doi.org/10.1016/j.marpol.2018.12.020
13. Yang, Z., Wan, C., Yang, Z. & Yu, Q. Using Bayesian network-based TOPSIS to aid dynamic port state control detention risk control decision. *Reliab. Eng. Syst. Saf.* **213**, 10–12 (2021). https://doi.org/10.1016/j.ress.2021.107784
14. Liu, K., Yang, Z., Yu, Q., Wan, C. & Yang, Z. BN-based port state control inspection for Paris MoU : New risk factors and probability training using big data. *Reliab. Eng. Syst. Saf.* https://doi.org/10.1016/j.ress.2022.108530 (2022).
15. Wu, S. et al. Ship detention prediction via feature selection scheme and support vector machine (SVM). *Marit. Policy Manag.* **00**, 1–14 (2021). https://doi.org/10.1080/03088839.2021.1875141
16. Xiao, Y. et al. Interpreting the influential factors in ship detention using a novel random forest algorithm considering dataset imbalance and uncertainty. *Eng. Appl. Artif. Intell.* **133**, 108369 (2024). https://doi.org/10.1016/j.engappai.2024.108369
17. Deng, Q. & Wan, Z. Long-term or short-term? Prediction of ship detention duration based on machine learning. *J. Mar. Sci. Eng.* **12**, 2220 (2024). https://doi.org/10.3390/jmse12122220
18. Akpinar, H. & Sahin, B. Strategic management approach for port state control: The Black Sea Memorandum of Understanding detention analysis. *Marit. Bus. Rev.* **5**, 281–293 (2020). https://doi.org/10.1108/MABR-10-2019-0043
19. Şanlıer, Ş. Analysis of port state control inspection data: The Black Sea Region. *Mar. Policy* https://doi.org/10.1016/j.marpol.2019.103757 (2020).
21. Akyurek, E. & Bolat, P. Port state control at European Union under pandemic outbreak. *Eur. Transp. Res. Rev.* https://doi.org/10.1186/s12544-020-00460-4 (2020).
22. Nurduhan, M. & Kamal, B. Data-driven analysis of Black Sea MoU detentions considering certificate and documentation deficiencies using Bayesian networks and association rule mining. *Transp. Policy* **176**, 103903 (2026). https://doi.org/10.1016/j.tranpol.2025.103903
23. Genis, T. T., Aydin, M., Uçak, ŞŞ, Fıskın, R. & Çakır, E. Uncovering systemic risk drivers in SIRE and CDI inspections: A hybrid TAN–ARM approach. *Ocean Eng.* https://doi.org/10.1016/j.oceaneng.2026.125238 (2026).
24. Ma, L., Ma, X., Du, Q. & Zhang, R. Investigation of the severity of maritime accidents considering the interaction between human factors and operating conditions: A case study on collision accidents in China. *Reliab. Eng. Syst. Saf.* **265**, 111533 (2026). https://doi.org/10.1016/j.ress.2025.111533
25. Pearl, J. Chapter 2 - Bayesian inference. In *Probabilistic Reasoning in Intelligent Systems* (ed. Pearl, J.) 29–75 (Morgan Kaufmann, 1988). https://doi.org/10.1016/B978-0-08-051489-5.50008-4.
26. Sevgili, C. Analysis of Ship Inspection Results using Data Mining Methods: An Application on Turkish Flagged Ships. (Order No. 32259308, Dokuz Eylul Universitesi (Turkey)). PQDT - Global. Retrieved from https://www.proquest.com/dissertations-theses/gemi-denetim-sonuçlarının-veri-madenciliği/docview/3250851838/se-2
27. Zou, X. & Yue, W. L. A Bayesian Network Approach to Causation Analysis of Road Accidents Using Netica. *J. Adv. Transp.* **2017**, 2525481, 18 pages, 2017. https://doi.org/10.1155/2017/2525481
28. Cakir, E., Sevgili, C. & Fiskin, R. An analysis of severity of oil spill caused by vessel accidents. *Transp. Res. Part D Transp. Environ.* **90**, 102662 (2021). https://doi.org/10.1016/j.trd.2020.10266

29. Zhang, D., Yan, X. P., Yang, Z. L., Wall, A. & Wang, J. Incorporation of formal safety assessment and Bayesian network in navigational risk estimation of the Yangtze River. *Reliab. Eng. Syst. Saf.* **118**, 93–105 (2013). http://dx.doi.org/10.1016/j.ress.2013.04.006
30. Norsys Software Corp. Netica Application. 85–133 (2011).
31. Fan, S., Blanco-Davis, E., Yang, Z., Zhang, J. & Yan, X. Incorporation of human factors into maritime accident analysis using a data-driven Bayesian network. *Reliab. Eng. Syst. Saf.* **203**, 107070 (2020). https://doi.org/10.1016/j.ress.2020.107070
32. Fan, S., Zhang, J., Blanco-Davis, E., Yang, Z. & Yan, X. Maritime accident prevention strategy formulation from a human factor perspective using Bayesian networks and TOPSIS. *Ocean Eng.* **210**, 107544 (2020). https://doi.org/10.1016/j.oceaneng.2020.107544
33. Yang, Z., Yang, Z. & Yin, J. Realising advanced risk-based port state control inspection using data-driven Bayesian networks. *Transp. Res. Part A Policy Pract.* **110**, 38–56 (2018). https://doi.org/10.1016/j.tra.2018.01.033
34. Freidman, N., Geiger, D. & Goldszmidt, M. Bayesian network classifiers. *Mach. Learn.* https://doi.org/10.1023/A:1007465528199 (1997).
35. Han, J., Kamber, M. & Pei, J. *Data Mining: Concepts and Techniques. Data Mining: Concepts and Techniques* (Elsevier, Waltham, USA, 2011). https://doi.org/10.1016/C2009-0-61819-5.
36. Agrawal, R., Imielinski, T. & Swami, A. Database mining- A performance perspective. *IEEE Trans. Knowl. Data Eng.* **5**, 914–925 (1993).
37. Wu, Y. & Zhang, J. Building the electronic evidence analysis model based on association rule mining and FP-growth algorithm. *Soft Comput.* **24**, 7925–7936. https://doi.org/10.1007/s00500-019-04032-0 (2020).
38. Agrawal, R. & Srikant., R. (1994). A fast algorithm for mining association rules in image. *Proc. 20th Int. Conf. Very Large Data Bases.* **1215**, 487–499
39. Liu, J. et al. Data-driven and association rule mining-based fault diagnosis and action mechanism analysis for building chillers. *Energy Build.* **216**, 109957 (2020). https://doi.org/10.1016/j.enbuild.2020.109957
40. Jia, X. & Zhang, D. Prediction of maritime logistics service risks applying soft set based association rule: An early warning model. *Reliab. Eng. Syst. Saf.* **207**, 107339 (2021). https://doi.org/10.1016/j.ress.2020.107339
41. Li, X., Chen, C., Hong, Y. & Yang, F. Exploring hazardous chemical explosion accidents with association rules and Bayesian networks. *Reliab. Eng. Syst. Saf.* **233**, 109099 (2023). https://doi.org/10.1016/j.ress.2023.109099
42. Wang, S., Yan, R. & Qu, X. Development of a non-parametric classifier: Effective identification, algorithm, and applications in port state control for maritime transportation. *Transp. Res. Part B Methodol.* **128**, 129–157 (2019). https://doi.org/10.1016/j.trb.2019.07.017
43. Mou, B. S. Informatin Sheet of the Bs Mou New Inspection Regime. 1–6 https://bsmou.org/downloads/info-sheets/InfoSheetBSMoUNewInspectionRegime.pdf (2016).
44. Fan, L., Wang, M. & Yin, J. The impacts of risk level based on PSC inspection deficiencies on ship accident consequences. *Res. Transp. Bus. Manag.* **33**, 100464 (2019). https://doi.org/10.1016/j.rtbm.2020.100464
45. International Maritime Organization. *SOLAS, Consolidated Edition, 2009: Consolidated Text of the International Convention for the Safety of Life at Sea, 1974, and Its Protocol of 1988: Articles, Annexes and Certificates* (International Maritime Organization, 2009).
46. Merchant, W., Statistics, F. & Equasis, E. The 2022 World Merchant Fleet Statistics from Equasis. *Electron. Qual. Shipp. Inf. Syst.* 110 (2022).
47. IACS. IACS Members. https://iacs.org.uk/membership/iacs-members (2025).
48. Sun, J. & Sun, J. A dynamic Bayesian network model for real-time crash prediction using traffic speed conditions data. *Transp. Res. Part C Emerg. Technol.* **54**, 176–186 (2015). https://doi.org/10.1016/j.trc.2015.03.006
49. Rudin, C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nat. Mach. Intell.* **1**, 206–215 (2019). https://doi.org/10.48550/arXiv.1811.10154
50. Freitas, A. A. Comprehensible Classification Models – a position paper. *C. SIGKDD Explor. Newsl.* **15**, 1–10 (2014).
51. Fenton, N. & Neil, M. *Risk Assessment and Decision Analysis with Bayesian Networks* (Chapman and Hall/CRC., 2018). https://doi.org/10.1201/b21982.
52. Black Sea MoU. *Port State Control in the Black Sea Region Annual Report 2022*. https://share.google/usuKkRLTHwyeKCoxk (2023).
53. Akyurek, E. & Bolat, P. Ranking port state control detention remarks: Professional judgement and spatial overview. *Eur. Transp. Res. Rev.* https://doi.org/10.1186/s12544-021-00480-8 (2021).
54. Yan, R., Mo, H., Guo, X., Yang, Y. & Wang, S. Is port state control influenced by the COVID-19? Evidence from inspection data. *Transp. Policy* **123**, 82–103 (2022). https://doi.org/10.1016/j.tranpol.2022.04.002
55. Ravira, F. J. & Piniella, F. Evaluating the impact of PSC inspectors' professional profile: a case study of the Spanish Maritime Administration. *WMU J. Marit. Aff.* **15**, 221–236 (2016). https://doi.org/10.1007/s13437-015-0096-y
56. Chuah, L. F. et al. Analyzing the influencing factors of Port State Control for a cleaner environment via Bayesian network model. *Cleaner Eng. Technol.* https://doi.org/10.1016/j.clet.2023.100636 (2023).
57. Yuan, C. C., Chiu, R. H. & Cai, C. Important factors influencing the implementation of independent port state control regimes. *J. Marine Sci. Eng.* https://doi.org/10.3390/JMSE8090641 (2020).
58. DNV. PSC inspections during COVID-19: Are we back to normal? 9 https://www.dnv.com/news/2020/psc-inspections-during-covid-19-are-we-back-to-normal--188091/ (2020).
59. IMO. Procedures For Port State Control. vol. 3 1–167 https://wwwcdn.imo.org/localresources/en/OurWork/IIIS/Documents/A33-Res.1185 - PROCEDURES FOR PORT STATE CONTROL, 2023 (Secretariat) (1).pdf (2023).

Author contributions

Erkan Çakır: Conceptualization, Data curation, Methodology, Validation, Writing – review & editing. **Burcu Çelik Maşalacı:** Investigation, Data curation, Methodology, Visualization, Writing– original draft, Writing – review & editing.

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Declarations

Competing interests

The authors declare no competing interests.

Additional information

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