

Review

Review of Ship Risk Analyses Through Deficiencies Found in Port State Inspections

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Abstract

This literature review examines the relationship between the number and type of deficiencies identified during Port State Control (PSC) inspections and a ship's overall risk. The main objective is to synthesise the current academic evidence, detailing the analytical methodologies employed and highlighting key research contributions. The selection of literature has focused on peer-reviewed articles and relevant doctoral theses addressing detention risk prediction, accident risk and ship risk profiling. The findings indicate a consistent correlation between PSC deficiencies and ship risk, although the nature and strength of this correlation may vary depending on the type of risk considered and the specific deficiencies. A methodological evolution is observed in the field, from descriptive statistical analyses and regressions towards more complex predictive models, such as Machine Learning (ML) and Bayesian Networks (BNs). This transition reflects a search for greater accuracy in risk assessment, going beyond simple numerical correlation to improve the selection of ships for inspection. Multivariate statistical techniques, on the other hand, focus on the identification of risk patterns and the evaluation of the PSC system. The conclusions underline the importance of deficiencies as indicators of risk, the need for differentiated inspection approaches and the persistent challenges related to data quality and model interpretability.

Keywords: ship's risk; maritime safety; Port State Control; Machine Learning; Bayesian Networks; multivariate statistical

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1. Introduction

Port State Control (PSC) is a fundamental pillar of international maritime security. It functions as a “safety net” to ensure that ships sailing around the world comply with international safety standards [1]. Its origins can be traced back to the need to complement the oversight exercised by flag states, some of which may lack the resources to ensure the regulatory compliance of ships under their flag [2]. This need led to the establishment of regional Memoranda of Understanding (MoUs), such as the Paris MoU and the Tokyo MoU, which coordinate inspection efforts between their constituent States. The Paris MoU is recognised as a pioneer in the implementation of structured PSC systems.

Historically, improvements in maritime safety have been driven by reactive approaches, where regulations were developed in response to serious accidents. However,

contemporary research and new regulations emphasise the adoption of proactive approaches, which seek to identify and mitigate risks before they materialise into incidents [3]. The PSC is an essential tool in this proactive strategy.

The shipping industry is characterised by remarkable heterogeneity, operating as a non-standardised international business, with a diversity of rules applicable to national and international traffic and an absence of common sources of information beyond the basic characteristics [3]. This lack of uniformity underlines the inherent complexity faced by the PSC and highlights the importance of coordinated regimes, such as MoUs, in their attempt to harmonise inspection practices and criteria for compliance with safety standards. This heterogeneity not only justifies the existence of MoUs but also poses significant challenges for research on PSC effectiveness and risk modelling, as comparability of data between different regions, or even within MoUs, can be compromised by variations in the practices of Port State Control Officers (PSCOs) and reporting systems [4]. Non-standardisation extends, for example, to the coding and reporting of deficiencies, which represents a key challenge for the quality of data used in risk modelling [5].

Problem Statement: The Relationship Between Deficiencies and Ship's Risk

A fundamental premise in the PSC field is the existence of a direct link between the deficiencies found on a ship and its risk level. Several studies have corroborated a strong link between the overall safety of a ship and the results of its PSC inspections. Deficiencies identified during these inspections are therefore considered key indicators of a ship's condition and its risk of failing to meet safety standards and being a hazard to shipping and the environment [6].

The central problem addressed by the academic literature in this context is to understand the nature and strength of this relationship. Specifically, it investigates whether the number and/or type of deficiencies can be used to reliably predict the risk associated with a vessel. This risk can manifest itself in various forms, including the likelihood of detention during a PSC inspection or the likelihood of being involved in future maritime accidents [7].

The relationship between deficiencies and risk is not limited to simple counting or basic statistical correlation. It involves a deeper understanding of the predictive power of deficiencies, the differential importance of different types of deficiencies and how this information can be used to optimise the selection of ships for inspection. For example, some studies investigate the “predictive power” of deficiencies for future accidents [7], while others analyse specific “deficiency patterns” for different types of ships [8] or focus on predicting the probability of detention or the number of deficiencies that will be found [9]. If this relationship is indeed predictive and specific—i.e., if certain deficiencies have a greater weight in determining risk—then systems for selecting ships for inspection, known as “targeting”, such as the Ship Risk Profile (SRP) used by the Paris MoU, can be significantly more efficient and effective. The research problem is therefore multi-faceted: it is not only about establishing the existence of a correlation, but also about quantifying its predictive power, identifying the strongest predictors, such as the total number of deficiencies versus specific types of deficiency and applying this knowledge to improve maritime safety through a more informed and proactive PSC.

The main objectives of this literature review are to systematically search for and analyse academic articles that investigate the correlation between deficiencies detected in PSC inspections and ship risk in its various manifestations. Then, we aim to identify, describe and analyse in detail the research methodologies employed in these studies, assessing their strengths and limitations in the context of maritime risk analysis, as well as

evaluate the consistency of the accumulated scientific evidence, identify the limitations of the current research and point out areas where further research is required.

This review focuses primarily on peer-reviewed academic literature, including original research articles and doctoral theses that make significant contributions to the topic. The scope covers various aspects of ship risk, such as the probability of detention, accident proneness and classification according to risk profiles such as SRP. Both the total number of deficiencies and the influence of specific types of deficiencies are considered.

Following this introduction, Section 2 sets out the conceptual framework, defining key terms such as PSC deficiencies and ship risk. Section 3 is devoted to the analysis of the predominant methodologies used in the literature. Section 4 presents a review of the empirical evidence on the correlation between deficiencies and risk. Section 5 provides an integrative discussion of the findings, methodologies and current challenges. Finally, Section 6 presents the main conclusions and proposes future lines of research. The article concludes with a comprehensive list of references.

2. Port State Control (PSC): Fundamentals, Regimes and Inspection Process

The rationale for the PSC lies in the right and obligation of port states to inspect foreign ships arriving in their ports for compliance with international conventions relating to maritime safety, pollution prevention and shipboard living and working conditions. Among the main conventions are SOLAS (Safety of Life at Sea), MARPOL (Prevention of Pollution from Ships) and STCW (Standards of Training, Certification and Watchkeeping for Seafarers).

To coordinate and harmonise these inspections at the global level, several regional PSC regimes have been established in the form of Memoranda of Understanding (MoU). The most frequently referenced in the scientific literature are the Paris MoU (covering Europe and the North Atlantic) and the Tokyo MoU (covering the Asia-Pacific region). These MoUs establish common procedures and shared databases, such as “The Hybrid European Targeting and Inspection System” (THETIS) [10] for the Paris MoU and ship selection systems for inspection. Data from these MoUs, especially the Paris MoU and Tokyo MoU, are the main sources for most of the studies analysed in this review.

The PSC inspection process generally starts with the selection of the ship to be inspected. This selection is often based on the ship’s risk profile, as implemented in the Paris MoU through the New Inspection Regime (NIR) [11] and referred to as SRP. The SRP classifies ships as low risk (LRS), standard risk (SRS) or high risk (HRS) based on a few historical and generic factors. Once a vessel has been selected, an initial inspection is carried out, usually focusing on a review of certificates and documentation. If, during this initial phase, the PSCO finds clear indications that the ship, its equipment or crew do not comply with the safety requirements of the various international conventions, a more detailed inspection is carried out [12]. If serious deficiencies are confirmed, the ship may be detained until these are rectified.

The effectiveness of the PSC system lies not only in the ability to detect deficiencies but also in the robustness, fairness and efficiency of the selection and inspection process. The introduction of the NIR in the Paris MoU in 2011 was a significant attempt to improve these aspects by implementing a more sophisticated ship selection system based on the risk profile of each ship [13]. Resources for inspections are limited, and not all ships arriving at a port can be inspected in detail. It is therefore essential to have a system in place to focus efforts on those ships that present the greatest potential risk. However, the very effectiveness of such targeting systems, such as VMS, is the subject of research and debate. Some studies have pointed out that the PRS may not be optimal for identifying those ships

with the highest number of deficiencies or the highest probability of detention [9]. In this context, research on the relationship between deficiencies and risk is essential to validate, calibrate and continuously improve these targeting systems, ensuring that they target the most problematic ships and effectively contribute to maritime safety.

2.1. Typologies, Coding and Implications of Deficiencies in PSC Inspections

PSC deficiencies are defined as non-compliant with the rules and regulations set out in international maritime conventions that are detected during an inspection. These deficiencies are recorded by PSCOs using harmonised code systems, developed by the MoUs to facilitate information exchange and data analysis. For example, the Paris MoU uses a list comprising 497 different deficiency codes [14]. Despite harmonisation efforts, there may be problems related to the universality of the application of these codes and their interpretation by inspectors in different ports or regions, which may affect the quality and comparability of data [4].

Deficiencies are grouped into various categories that reflect the areas covered by the international conventions. Some of the most commonly analysed categories in the literature include fire safety, life-saving appliances, safety of navigation, compliance with the International Safety Management Code (ISM Code), structural conditions, watertightness and weathertightness, emergency systems, radio communications, cargo operations, living and working conditions, pollution prevention, and compliance with the International Ship and Port Facility Security Code (ISPS Code) [8].

The consequences of identified deficiencies vary according to their severity. Some may simply require rectification before the ship's next departure from port, or within a certain timeframe. However, if the deficiencies are considered serious enough to compromise the safety of the ship, the crew or pose a threat to the marine environment, they may lead to the detention of the ship. Detention is the most severe measure that can be imposed by a PSC authority and means that the ship cannot sail until the deficiencies have been rectified.

It is crucial to recognise that not all deficiencies carry the same weight in terms of risk. Some deficiencies, which, by their nature, lead to immediate detention of the ship, indicate an unacceptable risk to the safety of navigation, human life at sea or the marine environment. For example, a deficiency in the main engine or critical fire-fighting equipment is likely to have a much greater impact on the ship's risk profile than a minor documentary deficiency. Many studies attempt to predict the probability of detention [9] or identify the specific types of deficiencies that most commonly lead to detention [15]. Therefore, a simple count of the total number of deficiencies may be less informative than a weighted analysis that considers the severity of each deficiency, or an approach that focuses on the presence of high-risk or critical deficiencies. This distinction is critical for accurate risk modelling and the development of effective inspection strategies.

2.2. Definitions and Indicators of Ship Risk

In the maritime context, "ship risk" generally refers to the likelihood of an adverse event, such as a PSC detention or a maritime accident, and the potential severity of its consequences. In the PSC framework, risk is often associated with a ship's substandard condition, i.e., its high degree of non-compliance with international safety and environmental standards [16].

Ship risk is a multi-faceted concept. The main dimensions analysed in the literature are as follows:

- Detention risk: Defined as the probability that a ship will be detained because of a PSC inspection due to the severity of deficiencies found.

- Accident risk: Represents the probability of a ship being involved in a marine casualty, such as a collision, grounding, fire, sinking or polluting spill. This dimension relates to the goal of maritime safety.
- SRP: An index or classification used by some PSC regimes, notably the Paris MoU, to categorise ships (e.g., into low risk, standard risk or high risk) to prioritise inspections. The SRP is calculated based on a few weighted factors, including the age of the ship, the flag, the historical performance of the management company under the ISM Code, the performance of the Recognised Organisation (classification society) and the ship's history of deficiencies and detentions in the last 36 months.

Various indicators are used to quantify and assess these dimensions of risk. Among the most common are the total number of deficiencies, the number of previous detentions, the presence of specific types of deficiencies (especially those considered serious or critical), the age of the ship, its type (e.g., tanker, bulk carrier, container ship), the flag under which it sails (some flags have worse compliance records than others), the performance of the ISM company responsible for the management of the ship and the accident history of the ship or the company's fleet.

A closer analysis of the relationship between these indicators and the dimension of risk reveals considerable complexity. There is, in some cases, a disconnect between 'arrest risk'—which is often the focus of PSC targeting systems—and 'accident risk'. Research such as Heij et al. (2019) has shown that the correlation between the probability of arrest and the probability of serious or very serious incidents is, in fact, "very low" [17]. This observation has profound implications: if PSC policies focus predominantly on detention risk (based, for example, on past deficiency and detention history), they may not optimally identify those vessels that, while perhaps not accumulating the kind of deficiencies that typically lead to detention, do present a high risk of being involved in future accidents. The factors driving the risk of detention may not be identical to those driving the risk of an accident. Therefore, to truly improve maritime safety, PSC risk models and inspection strategies should evolve to more explicitly integrate incident predictors, rather than assuming that detention risk is a sufficient proxy for accident risk. This may require access to different types of data, e.g., more detailed accident investigation data, information on operational or human factors and the use of more sophisticated analytical methodologies capable of modelling these different dimensions of risk together.

3. Predominant Methodologies in Deficiencies-Risk Relationship Research

Research on the relationship between PSC deficiencies and ship risk has employed a variety of methodological approaches, ranging from traditional statistical analysis to advanced machine learning techniques. The choice of methodology is often determined by the nature of the data available, the specific objectives of the study and the complexity of the relationships to be modelled.

3.1. Statistical and Econometric Approaches

Statistical and econometric models have been widely used to quantify the relationships between ship characteristics, inspection deficiencies and risk outcomes.

- Regression Analysis (Logit/Probit): These models are often employed when the variable is dichotomous, such as the detention of a vessel (yes/no) or the occurrence of an accident (yes/no). Predictor variables may include the number or type of deficiencies, age of the vessel, type of vessel and flag, among others. Heij and Knapp et al. (2018), for example, used logit models to establish a quantitative rela-

tionship between a deficiency index (derived from multiple deficiency codes) and a vessel's future accident risk [7].

- Correspondence Analysis: This statistical technique is particularly useful for exploring and identifying relationships and patterns between categorical variables. It has been used prominently by Prieto et al. to analyse large datasets from the Paris MoU to identify specific deficiency profiles associated with different ship types and visualise these associations [8]. This approach makes it possible to discover, for example, whether certain ship types tend to have more frequent occurrences of certain categories of deficiencies.
- Grey Relational Analysis (GRA) and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution): These are multi-criteria decision methods that have found application in PSC data analysis. GRA is used to analyse the degree of correlation or similarity between different factors or sequences of data, while TOPSIS is used to rank and select options based on their proximity to an ideal solution. These methods have been applied, for example, to analyse deficiency records and propose optimisations for the PSC's Concentrated Inspection Campaigns (CIC) [18]. Korkmaz et al. also used Entropy-based GRA to identify the most influential deficiency types in ship detentions in the Black Sea region [15].
- STATIS (Structuration des Tableaux à Trois Indices de la Statistique) and its variants (e.g., X-STATIS, CO-X-STATIS): These are multivariate techniques designed for the analysis of multiple data tables, such as PSC inspection data collected over several years, for different ports or for different groups of ships. Prieto et al. have made extensive use of STATIS to assess the temporal evolution of Paris MoU inspections, identify ship risk profiles, and analyse the performance of flag states and classification societies over time, as well as the impact of external events such as the COVID-19 pandemic [19].
- HJ-Biplot: Another exploratory multivariate technique that allows a reduction in the dimensionality of the data and the simultaneous graphical representation of the rows (individuals, e.g., ships or countries) and columns (variables, e.g., ship characteristics, number of deficiencies) of a data matrix. Almorza et al. have applied it to characterise different categories of qualitative variables (such as country of registry, ship type, inspection class and port of inspection) in relation to their values in quantitative variables, such as ship dimensions, number of deficiencies identified, inspection type and ship age [6].
- Principal Component Analysis (PCA): This technique is used to reduce the dimensionality of a dataset with multiple correlated variables by transforming them into a smaller set of uncorrelated variables called principal components, which retain most of the original variance. Heij and Knapp (2018) employed it to aggregate many individual impairment codes into a single overall impairment index, making it more tractable for inclusion in accident prediction models [7].
- Event Tree Analysis (ETA): A deductive method used to analyse the sequence of events that may follow an initiating event and calculate the probability of different final outcomes. It has been applied to the analysis of PSC inspection data from the Paris MoU to prioritise areas of risk of deficiency based on ship type and age [20].

The choice of a specific statistical methodology in PSC research is often guided by the intrinsic nature of the data (which may be categorical, continuous or time series) and by the objective of the study, be it the prediction of an event, classification of entities or identification of underlying patterns and relationships. PSC data are inherently multi-dimensional, involving multiple vessel characteristics, a variety of deficiency types and diverse inspection results. In this context, multivariate methods such as STATIS and HJ-

Biplot prove particularly valuable. These techniques allow complex interrelationships between numerous variables to be analysed jointly, offering a more structured view of the phenomenon under study, as opposed to approaches that isolate individual variables. This ability to handle and visualise complexity is crucial for extracting meaningful knowledge from the vast repositories of PSC data.

3.2. Machine Learning Models (Machine Learning) and Bayesian Networks in Risk Prediction

In recent years, there has been a growing interest in the application of Machine Learning (ML) and Bayesian Network (BN) models to address risk prediction in the context of PSC, given their ability to handle large volumes of data and model complex relationships. These are discussed in detail below.

- Machine Learning (ML) General: Refers to a set of algorithms that allow systems to learn from data without being explicitly programmed for each task. In the field of PSC, various ML models have been explored to predict inspection outcomes (such as the probability of detention or the number of deficiencies) and to classify the risk of ships. Among the models mentioned in the literature are Random Forests, Deep Learning [3], Support Vector Machines (SVMs), the k-Nearest Neighbour (kNN) algorithm, and XGBoost [9]. Advantages attributed to ML include its ability to model non-linear and complex relationships between variables, which may not be easily captured by traditional statistical models, and its potential to achieve greater predictive accuracy in certain contexts [21]. They have been applied to predict whether a PSC inspection will result in a detention [3] and to estimate the number of deficiencies a vessel might have.
- Bayesian Networks (BNs): These are probabilistic graphical models that represent a set of variables and their conditional dependencies by means of an acyclic directed graph. BNs are particularly suited to modelling uncertainty and interdependencies between multiple risk factors. In the context of PSC, they have been used to predict the SRP, the probability of identifying deficiencies and the probability of detention [22]. They have also been used to analyse the risk factors influencing PSC inspections and incorporate detailed deficiency records into the analysis of the probability of detention, overcoming the difficulties this poses for other methods due to the large volume of deficiency data [9]. The advantages of BNs include their ability to handle the uncertainty inherent in maritime data, the possibility to integrate expert knowledge, e.g., from experienced surveyors in the model structure or in the definition of a priori probabilities, and their potential to perform causal diagnostics and infer the probable causes of an observed event. Moreover, their efficiency can be improved by using Bayesian learning methods, especially when working with big data [23]. However, building the structure of a BN can be a complex task, and the accurate estimation of Conditional Probability Tables (CPTs) that define the relationships between variables often requires large amounts of data or reliable expert judgement [23]. The uncertainty associated with risk factor information can also present a barrier to Bayesian inference [24].
- A priori algorithm: This is a classical data mining algorithm used to discover frequent association rules in large datasets. In the context of PSC, it has been applied to identify correlations between different types of deficiencies, i.e., to find out which deficiencies tend to appear together in inspections [25].

While ML and BN models offer considerable potential for improving risk prediction in the PSC domain, it is important to consider their characteristics. An often-cited limitation of some ML models, especially deep learning models, is their “black box” nature, meaning that it can be difficult to understand how the model arrives at a particular prediction [21]. This lack of interpretability can be a drawback for their acceptance and use by regulatory authorities, who often need to justify their decisions based on transparent

and understandable criteria. Bayesian Networks, in this sense, may offer a better balance between predictive power and interpretability, as their graphical structure can provide a more intuitive representation of causal dependencies between risk factors [23] and allow for the incorporation of expert knowledge. Ultimately, the choice between different types of models (ML, BN or more traditional statistical) involves careful consideration of the trade-off between pure predictive accuracy and the need for transparency, especially in a regulatory context where decisions have significant consequences, such as the detention of a ship. Future research could benefit from exploring Explainable AI (XAI) techniques applied to the PSC domain.

A comparison of the methodological approaches discussed is presented in Table 1.

Table 1. Comparison of the methodological approaches.

Methodology	Description	Applications in PSC Risk Analysis	References
Regression Analysis (Logit/Probit)	Models the probability of a binary event (stop, accident) based on predictors.	Detention prediction, accident prediction.	[7]
Correspondence Analysis	Explores relationships between categorical variables, visualising patterns.	Identification of deficiency profiles by vessel type.	[8]
GRA TOPSIS	Multi-criteria decision methods to analyse correlations and rank options.	Optimisation of CICs, identification of influential deficiencies.	[15,18]
STATIS X-STATIS	Analyses multiple data tables over time or across groups.	MoU inspection evaluation, ward/society performance analysis.	[26]
HJ-Biplot	Exploratory technique for dimensionality reduction and simultaneous representation of individuals and variables.	Classification of flags/societies/ship/port types according to deficiencies and characteristics.	[6]
Bayesian Networks (BN)	Graphical probabilistic models representing dependencies and interdependencies.	Prediction of SRP/deficiencies/deterrence, analysis of interdependent risk factors.	[22,23]
Machine Learning (ML)	Algorithms that learn from data to make predictions or classifications.	Prediction of detention, prediction of number of deficiencies, ship risk classification.	[3,9]
A priori algorithm	Discover frequent association rules in large datasets.	Discovery of correlations between different types of deficiencies.	[25]
Event Tree Analysis (ETA)	Analyses sequences of events following an initiating event, calculating probabilities of outcomes.	Prioritisation of deficiency risk areas according to vessel type/age.	[20]

3.3. Specific Multivariate Methodologies Used in Risk and Ranking Studies

The research works of Prieto, J.M. and Almorza D. Amor, V., often in collaboration with other authors, made them pioneers in using multivariate techniques applied to PSC inspections and are characterised by a specific methodological approach and the use of Paris MoU data, mainly through the THETIS platform [26].

Their methodological contributions focus on the application of multivariate statistical techniques to analyse the complexity of PSC data. These techniques and published work are presented below.

- Correspondence Analysis: This technique is used to identify patterns of risk differentiated by ship type. By analysing large volumes of inspection data (for example, 186,255 Paris MoU inspections between 2018 and 2022 in one study), they establish relationships between ship types and the specific profiles of deficiencies they tend to exhibit. This allows the identification of whether certain ship types are more prone to certain categories of deficiencies, which has direct implications for the optimisation of inspection processes and the prioritisation of higher risk areas [8].

Correspondence analysis is a multivariate technique that allows the rows and columns of a contingency table to be represented as points in a low-dimensional vector space [27]. This representation facilitates the superposition of the corresponding spaces to obtain joint visualisation, where the proximity between points reflects the relationship between the categories of the analysed variables. This method, in its various variants, has been widely applied in research in different fields, such as circular economy [28], economics [29], nutrition [30], medicine [31] and business [32]. Moreover, it has multiple software implementations that facilitate its practical application [33].

- STATIS and CO-X-STATIS: These sophisticated multivariate techniques are used to analyse the evolution of PSC inspections over time, the comparative performance of flag states and classification societies and the impact of significant external factors, such as the COVID-19 pandemic, on inspection patterns and risk profiles [26]. For example, in a study that analysed 17,880 inspections in major EU ports between 2013 and 2018, they concluded that the risk ratings of countries of the registry obtained through STATIS were consistently aligned with the performance lists published annually by the Paris MoU, thus validating the methodology as a useful tool for maritime authorities [26].

STATIS methods [34,35] make up a family of multivariate techniques aimed at the joint analysis of multiple data tables, with the objective of obtaining a compromise representation that synthesises the shared information. Among them, the X-STATIS method [36] stands out for dispensing with the a priori-defined operator, constructing the commitment directly from the internal relationships between the matrices. The work of Abdi et al. [37] presents an exhaustive review of this methodology, highlighting both its mathematical foundation and its applicability in contexts where it is necessary to integrate information from different sources or observation conditions. Its application has been extended to various fields, such as sustainability [38], environmental sciences [39,40] or digital governance [41], among others.

Within the STATIS family of methods, COSTATIS [42,43] combines a STATIS analysis with a co-inertia analysis and is designed to identify common structure and variations between two sequences of tables. Its initial development focused on the ecological domain [44] to study the relationship between environmental and biological datasets that vary in time or space. Subsequently, its application has been extended to other fields such as education [45], sustainability [46] or social survey analysis [47].

- HJ-Biplot: This multivariate visualisation and analysis technique is used to simultaneously classify and characterise flags, classification societies, ship types and ports according to a set of descriptive variables such as ship characteristics and inspection results, including the number of deficiencies. Almorza et al. applied it to the analysis of Paris MoU inspections carried out between 2012 and 2019 in 10 major European

ports, providing an intuitive graphical representation of the complex interrelationships in the data [6].

The HJ-Biplot [48] is a technique that stands out for its versatility in the analysis of complex data and its applicability in multiple disciplines. In the systematic and empirical review of its 38 years of evolution (1986–2024), carried out by Cascante-Yarlequé et al. [49] on a corpus of 121 studies, its use is evident in numerous fields, with applications in health (14.9%), environmental sciences (12.4%) and sustainability (11.6%) being more frequent.

These papers are distinguished by a focus on exploratory and descriptive analysis of large and complex PSC datasets. They use the power of multivariate statistical techniques to uncover latent structures, identify meaningful patterns and follow temporal trends, rather than building predictive “black box” models aimed at predicting individual vessel events. Their contributions are fundamental to providing a solid and informed knowledge base on how risks and deficiencies are distributed within the PSC system. This detailed understanding of risk profiles and inspection system dynamics is an essential prerequisite for the development of more refined predictive models and the formulation of more informed and effective inspection policies.

4. Literature Review: Empirical Evidence of Correlation

4.1. Impact of the Number and Type of Deficiencies on the Risk of Vessel Detention

Predicting the detention of a ship is an important objective in PSC research since detention represents the most serious consequence of an inspection and has significant economic and reputational implications for all actors involved. Numerous studies have focused on identifying those ships with a higher number of deficiencies or a higher probability of being detained [16].

An important development in this area has been the incorporation of detailed deficiency records into models for predicting the probability of detention. Wang et al. (2021), for example, developed a model based on Bayesian Networks (BNs) that pioneered the integration of these records, finding that deficiencies related to the safety condition of the vessel and the technical characteristics of the inspected vessel itself are among the most influential factors in PSC inspections and detentions [23]. This approach suggests that models that go beyond general ship characteristics such as age, type or flag and consider the detailed history and nature of previous deficiencies may provide more accurate predictions.

Along these lines, Kindberg's thesis [3] investigated the applicability of machine learning models (Random Forests and Deep Learning) to predict the results of PSC inspections. Using a large dataset including Paris MoU protocols, Clarksons Research data, IHS databases and EU MRV emissions data, the study was able to predict with 72% accuracy whether the next PSC inspection of a ship would result in a detention [3].

The work of Prieto et al., although not primarily focused on the prediction of individual detentions, also provides relevant evidence. Using multivariate statistical techniques such as STATIS and HJ-Biplot, they have identified that a higher number of deficiencies is consistently associated with vessel profiles considered higher risk, such as those that are older or smaller or operate under flags or classification societies with poor performance records [26]. These findings, derived from the analysis of large volumes of Paris MoU inspection data, reinforce the idea that the history of deficiencies is a key component in the assessment of a ship's overall risk, which in turn correlates with the likelihood of detention.

Other studies also provide valuable insights. For example, Korkmaz et al., analysing survey data from the Black Sea region, used methods such as Entropy-based GRA to identify the types of deficiency that were found to be most crucial or influential in the detention of ships, both before and during the COVID-19 pandemic [15].

Overall, the literature suggests that, while predicting detention is a complex goal and the effectiveness of models may vary, incorporating detailed data on deficiencies—not only their number, but also their type, severity and history—is critical to improving the accuracy of these predictive models.

4.2. Predictive Capacity of PSC Deficiencies on Future Maritime Casualties

Beyond the risk of detention, an area of research of paramount importance is the ability of deficiencies detected during PSC inspections to predict the likelihood of a ship being involved in future maritime accidents. This link is crucial, as the goal of maritime safety is casualty prevention.

The work of Heij and Knapp (2018) is important in this respect. Their research directly addressed whether PSC deficiencies possess predictive power for future accident risk, even after controlling for other known ship risk factors such as type, age, size, flag and owner [7]. Using global accident data and deficiency information from various PSC regimes and employing a methodology that included aggregating deficiency codes into groups, with a focus on human factor aspects and creating an overall deficiency index using PCA, their logit models revealed a significant relationship. They concluded that ships with deficiency scores above average had a significantly higher future accident risk: the risk increase factor was about 6 for total losses, 2 for very severe accidents, 1.5 for severe and 1.3 for less severe.

Prieto et al. (2025), in their study on risk patterns by ship type, also state that their findings, by confirming that deficiencies found in PSC inspections are good indicators of maritime risk, provide a solid basis to support the connection between deficiencies and incident proneness [8].

However, the relationship between deficiencies and different types of risk (detention versus accident) is not straightforward. Heij et al. [17] further explored this issue, showing that the correlation between a vessel's probability of detention and its probability of being involved in incidents, especially serious and very serious ones, is in fact very low. This finding is of particular importance because it suggests that inspection policies and PSC targeting systems, if they focus excessively on predicting and preventing detentions based (for example, on the history of deficiencies that typically lead to detention), may not be optimal for preventing accidents. Proactive prevention of future incidents, according to these authors, is significantly improved when both dimensions of risk are considered, i.e., by combining information on past incidents with information on detentions and deficiency history [17].

This apparent disconnect between the predictors of detention and the predictors of accidents poses a fundamental challenge. If the goal of the PSC is the improvement of maritime safety through accident prevention, and if the factors driving accident risk differ substantially from those driving detention risk, then the PSC targeting systems need modification. It may be necessary to develop more sophisticated risk profiles that explicitly integrate accident-specific predictors, which may not be sufficiently weighted in current models that rely heavily on deficiency and detention history. This may imply the need to incorporate new types of data into PSC risk models, such as more detailed information from accident investigations [50], human factors data or operational variables, to achieve a more effective risk assessment for accident prevention.

4.3. Relevance of Specific Impairment Categories as Indicators of Risk

Research has convincingly demonstrated that not all deficiencies have the same impact on a ship's risk profile. Certain categories of deficiencies regularly emerge as particularly critical indicators, often suggesting deeper underlying problems than simply isolated

technical non-compliances. The following are the most important deficiencies that have been considered in the different papers:

1. International Safety Management (ISM) Code: Deficiencies related to the implementation and maintenance of the ISM Code are identified as problematic and predictive of increased risk. A general lack of on-board maintenance, which is often indicative of failures in the company's safety management system documented in the ISM Code, is a frequent cause of ship detentions [12]. In addition, a strong correlation has been observed between deficiencies in the ISM Code and deficiencies in Certificates and Documentation, especially during disruptive periods such as the COVID-19 pandemic [15]. Analysis of Paris MoU data has shown that ISM deficiencies are particularly prevalent on bulk carriers, chemical tankers and container ships [14]. The importance of these deficiencies lies in the fact that the ISM Code is designed to ensure the safe management of ship operations and the prevention of pollution; therefore, failures in its implementation point to systemic weaknesses in the safety culture and operational practices of the company and ship. A study by the International Maritime Organisation (IMO) on the effectiveness of the ISM Code seeks precisely to identify the factors contributing to serious marine casualties and their linkage to ISM-related provisions, which underlines the importance of this category of deficiencies [50].
2. Fire safety: This is another category of deficiencies that stands out for its importance. It figures significantly in the deficiency correlation analyses [25]. Specifically, deficiencies in fire doors and other openings in fire-resistant divisions have been identified as the most representative in Ro-Ro passenger ships and offshore supply vessels [14]. Research has revealed that deficiencies related to fire safety and emergency systems are crucial in determining the likelihood of a vessel's detention [15]. In fact, fire safety is one of the three most critical types of deficiency that impact the duration of a vessel's detention [51].
3. Safety of navigation: Deficiencies in this category, which covers aspects such as navigational equipment, nautical charts, publications and voyage planning, are also considered significant indicators of risk. Prieto et al. analysed this category in their studies on risk patterns [8]. Problems with nautical publications, charts and voyage or voyage planning have been found to constitute a very high proportion, more than half, of all deficiencies detected in tugboats [14].
4. Life-saving appliances: Like safety of navigation, this category is analysed by Prieto et al. as an important component of the risk profile [8]. Deficiencies in these appliances (lifeboats, lifejackets, rafts, etc.) have direct implications for survival in the event of casualty.
5. Structural conditions: Deficiencies related to the structural integrity of the ship are also mentioned as an area of concern and a risk factor [8].
6. Emergency systems: Along with fire safety, deficiencies in emergency systems in general have proven to be crucial for ship detentions [15].
7. Other relevant categories: Other areas that frequently emerge as problematic include propulsion and auxiliary machinery and pollution prevention, both identified as critical to detention duration [51], as well as ship and crew certificates and documentation [15].

The recurrent occurrence of deficiencies in these key categories—especially those related to safety management systems (ISM), emergency preparedness and response (fire, rescue, emergency systems) and functions critical to the safe operation of the ship (navigation, propulsion)—suggests that these are often not isolated or minor technical problems. Rather, they may be indicative of deeper systemic failures in the company's safety culture, crew training and competence, ship maintenance or the adequacy of operating procedures. Therefore, an effective risk analysis should not treat all deficiencies equally; those that point

to weaknesses in these critical safety or management systems deserve considerably more weight and attention.

4.4. Findings on Relevant Studies and Comparative Results

The literature on the relationship between PSC deficiencies and ship risk is diverse in its methodological approaches and the nuances of its findings, although there is a general convergence in certain aspects that are presented in this section.

The methodological approach of Prieto et al. is distinguished using tools such as Correspondence Analysis [8], STATIS and its variants such as X-STATIS and CO-X-STATIS [26], and HJ-Biplot [6]. These techniques allow them to explore the complex structure of PSC data, identify latent patterns, visualise multidimensional relationships and analyse the temporal evolution of various indicators.

Their main contributions to the field are as follows:

1. Identification of heterogeneous impairment profiles according to ship type: through correspondence analysis, they have shown that different ship types, e.g., container ships, tankers and bulk carriers, exhibit distinctive impairment profiles. This finding underlines the need for a more tailored and specific PSC inspection approach for each ship type, rather than a one-size-fits-all approach [8].
2. Confirmation that deficiencies are good indicators of maritime risk: Their studies reinforce the premise that deficiencies detected during PSC inspections serve as valid indicators of the level of risk associated with a ship [8].
3. Classification and performance assessment of flags and classification societies: Using STATIS and HJ-Biplot, they have developed classifications of flag states and classification societies based on the characteristics of the ships they certify and the results of their inspections. These classifications are aligned with the performance lists published annually by the Paris MoU, which validates their methodological approaches and provides additional tools for maritime authorities to assess risk. They have also identified profiles of substandard ships, typically characterised by being older, smaller in size and with a higher number of deficiencies [26].
4. Analysis of the impact of external factors on PSC inspection patterns: They have investigated how significant events, such as the COVID-19 pandemic, have affected PSC inspection practices and flag risk profiles. Their findings indicate, for example, a reduction in the total number of inspections during the pandemic and a change in the type of inspections performed, with a decrease in comprehensive inspections [19].
5. Rationale for PSC decision-making: Overall, their work provides a solid empirical basis that can inform decision-making in the field of PSC inspections, with the goal of improving maritime safety and marine pollution prevention [8].

Studies using Machine Learning (ML) to predict the results of PSC inspections, such as Kindberg's thesis (2023) [3], have shown accuracy in the order of 70–72% for the prediction of detentions. However, these same studies often point to difficulties in accurately predicting the specific number of deficiencies a particular ship will have, especially in atypical or extreme cases. This suggests that while ML can identify general patterns, prediction remains a challenge.

Research using Bayesian Networks (BN) [23] consistently highlights the importance of factors such as ISM company performance, RO performance and ship flag in determining the risk profile. A key strength of BNs is their ability to model the interdependencies between these and other risk factors, as well as to incorporate uncertainty.

In the field of Concentrated Inspection Campaigns (CIC), studies such as [18], using GRA and TOPSIS, have questioned the adequacy of the current CIC approach, which is often based on a single set of deficiencies identified as most frequent in the previous year.

These papers propose more dynamic and evolutionary CIC schemes, based on the analysis of deficiency data from the last three years, in order to more effectively identify significant deficiency codes and improve the selection of areas for inspections.

Research focusing on the correlation between specific deficiencies, such as that using the a priori algorithm [25], has confirmed that factors such as ship type, age, deadweight and gross tonnage are intrinsically related to the occurrence of deficiencies and the likelihood of detention. These studies help to understand which deficiencies tend to occur together, which may be indicative of common underlying problems.

Comparing these results reveals a complementarity. While Prieto et al. focused on identifying system-level patterns and characterising risk profiles using multivariate statistics, a more descriptive and exploratory approach, other researchers are more oriented towards predicting events at the individual vessel level using ML or BN tools. Despite these methodological differences, there is a remarkable convergence in the risk factors identified as crucial: the age of the ship, its type, the flag under which it operates, the history of deficiencies and detentions and, very significantly, compliance with and effectiveness of the ISM Code, as well as deficiencies in critical areas such as fire safety and navigational safety [12].

Notwithstanding this convergence in risk factors, the optimal way in which these factors should be weighted and combined to build a comprehensive risk assessment model remains an active area of research and debate. The Paris MoU's SRP represents a structured attempt to do so, but as some studies suggest, it may have limitations in its ability to identify all high-risk ships or to accurately predict the outcomes of inspections [9]. Research continues, therefore, in the search for risk models that are not only accurate and robust but also interpretable and practically implementable by PSC authorities.

Table 2 below contains the key studies where the most important findings are represented, together with the methodologies and databases used, including the different types of risk to which they apply.

Table 2. Summary of key deficiencies—risk relationship studies.

Reference	Primary Data Source	Primary Methodology	Risk Definition/Measurement Used	Key Findings on Deficiency-Risk Correlation
[7]	Global (PSC, Accidents, IHS Markit)	Logit models, PCA	Future accident risk (total loss, very severe, severe, severe, less severe)	PSC deficiencies predict future accidents; risk increases $\sim 6\times$ for total loss with deficiencies > average.
[23]	Tokyo MoU (2014–2017)	Bayesian Networks (BN)	Probability of detention	Deficiencies of safety condition and technical characteristics of the vessel are influential in detentions; BN incorporates big data of deficiencies.
[8]	Paris MoU (THETIS, 2018–2022).	Correspondence Analysis	Deficiency profiles as risk indicators	Heterogeneous deficiency profiles by ship type (container ships, tankers, bulk carriers); need for tailored inspection.
[3]	Paris MoU, Clarksons, IHS, MRV EU (2016–2020)	Random Forest, Deep Learning	Detention, Number of deficiencies	Detention prediction with 72% accuracy; difficulty in predicting exact number of individual deficiencies.
[22]	Paris MoU (THETIS, Portuguese Ports 2018–2021).	Bayesian Networks (BN)	Ship Risk Profile (SRP), Deficiencies, Detention	ISM company performance critical for SRP; RO, flag, age, ship type also influential.

Table 2. Cont.

Reference	Primary Data Source	Primary Methodology	Risk Definition/Measurement Used	Key Findings on Deficiency-Risk Correlation
[6]	Paris MoU (THETIS, 10 EU ports, 2012–2019)	HJ-Biplot	Ship risk profile (based on characteristics and impairments)	Positive age-impairment correlation; classification of flags/societies/ship types according to risk.
[26]	Paris MoU (THETIS, 10 EU ports, 2013–2018)	STATIS	Ship risk profile	Flag/company classifications match Paris MoU lists; identifies substandard ships (old, small, more deficiencies).
[18]	Paris MoU (2018–2021)	GRA, TOPSIS, Three-Sigma Rule	Effectiveness of CIC in detecting significant deficiencies	Current CIC (based on 1 year) is insufficient; proposes 3-year rolling CIC. Identifies priority deficiency codes and ship types.
[25]	Asia-Pacific PSC (2014–2018)	Improved A priori Algorithm (DQCPEA)	Correlations between deficiencies	Vessel type, age, DWT, GT related to deficiencies/detentions; reveals internal correlations between categories and subcategories of deficiencies.
[17]	Global (Inspections, Vessel Characteristics, Incidents)	Logit models	Detention Probability, Incident Probability (VSS)	Very low correlation between detention probability and incident; prevention is improved by combining both risk dimensions.

With regard to the main methodologies listed in Table 2, significant diversity can be observed. Logistic regression models (Logit) and Bayesian Networks (BNs) are recurrent for predicting the probability of stopping or accidents. For example, one study uses Logit models to show that PSC deficiencies can predict future accidents. On the other hand, Bayesian Networks are used to analyse the probability of detention and the performance of the ISM company, flag and age of the ship. Machine learning techniques such as Random Forest and Deep Learning are also employed, achieving 72% accuracy in predicting detentions, although with difficulties in predicting the exact number of deficiencies.

Multivariate techniques such as Correspondence Analysis are also used to identify specific deficiency profiles for different ship types, as well as HJ-Biplot and STATIS to classify flags and companies according to their risk. This demonstrates that the aim is not only to predict a binary outcome (detention/non-detention) but also to understand the underlying dimensions of maritime risk.

The main data sources vary, but the most common are MoU databases, especially THETIS for Paris MoUs, supplemented by accident data, ship registers and ship characteristics.

The definition of risk is a crucial point and is measured in various ways. While most studies focus on the probability of detention or the number of deficiencies, others take a broader approach, such as the risk of future accident (total loss, very serious, etc.) or the effectiveness of Concentrated Inspection Campaigns (CIC). This diversity in risk measurement underlines the complexity of the issue and the need to consider multiple factors.

Key findings reveal several important correlations, such as that PSC deficiencies are a significant predictor of future accidents, with one study indicating an approximately six-fold increased risk for total loss when a vessel has above-average deficiencies.

Factors such as ship age, flag, ship type and management company (ISM performance) are strongly correlated with the risk of deficiencies and detentions.

There is an internal correlation between categories and sub-categories of deficiencies, which allows identifying patterns of risk.

An interesting finding is the low correlation between the likelihood of detention and the likelihood of an incident. This suggests that inspections and incidents are distinct dimensions of risk and that prevention should be addressed in combination, not just on the basis of a single indicator.

In summary, academic research uses big data from PSC inspections to go beyond mere deficiency detection and build more sophisticated predictive models. Studies highlight the need for tailored inspection approaches for different ship types and the importance of considering multiple factors (ship characteristics, history, etc.) for a more accurate risk assessment.

5. Discussion

5.1. *Integration of Key Findings and Confirmation of the Evidence on the Deficiencies–Risk Relationship*

The review of academic literature consistently confirms the existence of a significant correlation between deficiencies detected during Port State Control (PSC) inspections and the level of risk associated with a ship. This general statement is supported by a wide range of studies, which, using various methodologies and data sources, conclude that a higher number and/or higher severity of deficiencies are associated with a higher likelihood of the ship being detained or involved in maritime accidents [16].

However, this general relationship becomes more complex when delving into the details. The evidence is strong that not only is the total number of deficiencies important, but also, and perhaps more critically, the type of deficiencies present. Categories such as those related to the International Safety Management (ISM) Code, fire safety, safety of navigation and life-saving appliances appear in the literature as particularly indicative of high risk [12]. This suggests that deficiencies in these areas may reflect systemic failures in the safety management or operational readiness of the ship, rather than isolated technical problems.

Another important aspect is the distinction between different dimensions of risk, primarily detention risk and accident risk. While both are related to the presence of deficiencies, studies such as Heij et al. (2019) have shown that the correlation between the likelihood of detention and the likelihood of a major accident can be low [17]. This finding is crucial because it implies that the factors that predict a stop, and that often inform PSC targeting systems, may not be the same, or carry the same weight, as the factors that predict a crash. Therefore, a risk assessment approach that relies predominantly on arrest history and the types of deficiencies that often lead to arrests may not be optimal for accident prevention.

In this context, the evidence is strong that there is a general correlation between deficiencies and risk. However, this consistency becomes more complex when broken down by risk type, stop versus accident or when analysing the predictive influence of specific types of deficiencies as opposed to simple total counts. This shift in focus drives the adoption of more sophisticated methodologies and the search for more comprehensive data to move from simply finding correlations to building predictive and explanatory models that can more effectively guide inspection policies and practices.

5.2. *Strengths and Limitations of the Methodologies Employed in the Literature*

The diversity of methodologies employed in investigating the relationship between PSC deficiencies and ship risk reflects the complexity of the problem and the different orientations from which it can be approached. Each approach has its own strengths and limitations:

1. Traditional statistical models (logistic regression, correspondence analysis).

Strengths: These methods, such as logistic regression, are well-established, relatively easy to implement and their results are often interpretable, making it easy to understand the influence of individual variables [7]. Correspondence analysis is excellent for visualising patterns in categorical data [8].

Limitations: Can have difficulty capturing complex non-linear relationships or interdependencies between multiple predictor variables, especially when working with large volumes of heterogeneous data, as is common in the PSC domain [23].

2. Machine Learning (ML)

Strengths: ML models, such as Random Forests or Deep Learning, could identify complex patterns and non-linear relationships in data, which can lead to high predictive power. They are suitable for handling large datasets (big data) [3].

Limitations: A frequent criticism is their “black box” nature, especially in more complex models such as deep neural networks, making it difficult to interpret how a prediction arrives at [21]. They can require large amounts of high-quality data for training and are susceptible to overfitting if not properly validated. In addition, creating a predictive PSC model that is sufficiently accurate at the individual sample level has proven to be challenging [3].

3. Bayesian Networks (BNs)

Strengths: BNs are explicit in modelling uncertainty and probabilistic dependencies between variables. They allow the integration of empirical data with expert domain knowledge and provide a framework for causal inference, which can be very valuable in understanding the underlying causes of risk [23].

Limitations: The construction of the network structure can be complex if not derived from the data. Estimation of conditional probability tables (CPTs) may require large amounts of data or expert judgement. In addition, the inherent uncertainty of risk factor information remains a challenge for accurate inference [23].

4. Multivariate Statistical Techniques (e.g., Correspondence Analysis, STATIS, HJ-Biplot)

Strengths: These techniques are excellent for exploring data analysis, identifying latent structures and patterns in complex datasets with multiple interrelated variables. They facilitate visualisation of these relationships and an understanding of system dynamics [26].

Limitations: They are primarily descriptive and exploratory in nature, rather than inherently predictive for future events at the individual level, although their findings can inform and enhance the development of predictive models.

There is no universal methodology for approaching research in this field. The optimal choice inherently depends on the specific objectives of the study, e.g., prediction of individual events versus explanation of system-level patterns, as well as on the availability, quality and nature of the data. If the primary goal is to achieve maximum predictive accuracy for individual vessel targeting, ML models may be preferable, provided that their interpretability limitations are addressed [21]. If, on the other hand, the goal is to achieve maximum predictive accuracy for individual vessel targeting, ML models may be preferable, provided that their interpretability limitations are addressed. If, on the other hand, the goal is to understand the structural relationships between (for example, vessel types and their characteristic deficiency profiles at the system level), correspondence analysis offers powerful tools [8]. For modelling causal interdependencies in an environment of uncertainty, Bayesian Networks are a robust option [23].

One perspective that emerges from this review is that a combination of methodological approaches may be most appropriate. Exploratory approaches, such as those employed by Prieto et al., can generate valuable hypotheses that, in turn, can feed into and refine more

focused predictive models, such as those based on ML or BN. For example, identifying which categories of deficiencies are particularly problematic for certain vessel types through correspondence analysis can help improve feature engineering or assign differential weights to variables in an ML model. Future research could benefit from mixed methodological approaches or triangulation of results obtained through different techniques to achieve a more complete understanding of the complex relationship between PSC deficiencies and ship risk.

5.3. Current Research Challenges: Data Quality, Standardisation, Access to Information and Limitations of Risk Models

Despite methodological advances, research on the relationship between PSC deficiencies and ship risk faces a few persistent challenges, many of which are related to the nature and availability of data.

5.3.1. Data Quality and Standardisation

One of the main obstacles is the lack of complete universal standardisation in the use of impairment codes and the wording of impairment descriptions by PSCOs. These inconsistencies can lead to incorrect entries in databases, making comparative analyses difficult and potentially leading to false alarms or erroneous conclusions [5].

Discrepancies in inspection procedures and actual PSC implementation exist not only between different MoUs but sometimes even between ports within the same MoU [4]. This variability can affect the consistency of the data collected and, thus, the reliability of the risk models built from it.

The subjectivity inherent in the inspection process also plays an important role. The experience, training and individual judgement of the PSCO can influence the detection, severity rating and recording of deficiencies [14], introducing an element of variability into the data.

5.3.2. Data Access and Transparency

The reluctance to share data by some shipping companies and other organisations in the maritime sector represents a significant problem. This lack of transparency hinders large-scale Big Data analyses that could lead to substantial improvements in maritime safety and operational efficiency [5].

Detailed information from maritime accident investigations, which could be crucial to understanding the root causes of casualties and their relationship to previous deficiencies, is often not publicly available or its disclosure is significantly delayed [7].

5.3.3. Limitations of Risk Models

Current risk models, despite their increasing sophistication, may not adequately capture all the complex interdependencies between the multiple risk factors affecting a ship [23].

The effective incorporation of the human factor, aspects such as crew competence, fatigue and safety culture on board, into risk models remains a considerable challenge, despite the recognition of its critical importance as a contributing cause of maritime accidents [52].

As discussed above, risk models that rely predominantly on historical data from PSC inspections, deficiencies and detentions may not be sufficient to predict the risk of future incidents if they do not also consider other factors or dimensions of risk [17].

The inherently dynamic nature of maritime risk, which may change due to variations in ship operation, crew changes, environmental conditions, etc. It is difficult to capture models that rely primarily on static or historical data.

Advances in risk modelling in the context of PSC are intrinsically linked to overcoming these fundamental data challenges. Without access to high-quality data that is standardised, comprehensive and includes relevant information on human and operational factors, even the most sophisticated analytical methodologies will be limited in their predictive power and practical utility. It is crucial to address the constraints of the PSC reporting system, as these prevent the shipping industry from leveraging Big Data to gain valuable insights [5]. This leads to a need for concerted efforts at the level of intergovernmental bodies to improve leadership, quality, standardisation and sharing of maritime data. Improving maritime safety through smarter, data-driven PSC is not only a technical challenge for researchers but also a policy and governance imperative for the entire maritime community.

Table 3 summarises the main challenges and constraints.

Table 3. Challenges and limitations in researching the deficiency–risk relationship in the PSC.

Challenge Area	Detailed Description of the Challenge/Constraint	Implications for PSC Research and Practice	Reference
Data Quality	Inconsistencies in coding and recording deficiencies; inspector subjectivity; incomplete or erroneous data.	Reduces reliability of analysis; makes comparisons difficult; may lead to suboptimal risk models.	[4]
Standardisation of Deficiencies	Lack of universality in codes/descriptions; differences in procedures between MoUs/ports.	Hinders aggregation of global data; affects comparability of studies; complicates development of universal risk models.	[4]
Access to information	Reluctance to share data by industry stakeholders; limited/delayed availability of accident investigation reports.	Limits scope and depth of analysis, especially Big Data, hinders validation of models and understanding of accident causation.	[5]
Human Factor Modelling	Difficult to quantify and integrate factors such as crew competence, fatigue, safety culture.	Potential underestimation of risk if a major accident causal factor is not adequately included.	[52]
Model Interpretability	Complex ML models (e.g., Deep Learning) can be “black boxes”, making their predictions difficult to understand.	Makes acceptance by regulatory authorities difficult; limits ability to draw lessons for safety improvement.	[21]
Detention vs. Accident Risk Differentiation.	Models optimised for predicting stops may not be optimal for predicting accidents due to low correlation and different causal factors.	PSC targeting strategies may not be fully effective in preventing accidents if they focus only on stopping risk.	[17]
Interdependencies of Risk Factors	Simplified models may not capture all the complex interactions between the various factors contributing to risk.	Incomplete risk assessment if synergies or combined effects of factors are not considered.	[23]

6. Conclusions

This literature review has led to several key conclusions on the relationship between deficiencies detected in PSC inspections and the risk associated with ships:

1. Confirmed correlation: There is robust and consistent academic evidence confirming a significant correlation between a higher number and/or severity of PSC deficiencies

and an increase in ship risk. This risk manifests itself in both an increased likelihood of detention and an increased propensity for maritime accidents.

2. Importance of the type of deficiency: Not all deficiencies carry equal weight. Certain categories, notably those related to the ISM Code, fire safety, safety of navigation and life-saving appliances, recurrently emerge as particularly critical indicators of risk, often suggesting systemic failures.
3. Evolution and methodological diversity: The field has seen an evolution in the methodologies employed, from descriptive statistical analysis and regression models to more sophisticated techniques such as Machine Learning (ML) and Bayesian Networks (BNs), seeking greater predictive accuracy. Multivariate statistical work (Correspondence Analysis, STATIS and HJ-Biplot) extends the methodologies used so far to analyse large Paris MoU databases, identifying risk patterns and assessing the PSC system from a structural perspective.
4. Distinction between stopping risk and accident risk: Crucially, detention risk and accident risk, although both influenced by deficiencies, are not perfectly interchangeable. The correlation between the likelihood of detention and the likelihood of serious incidents can be low, which implies that PSC targeting models must consider both dimensions to be fully effective in improving maritime safety.
5. Persistent challenges: Research in this area continues to face significant challenges related to quality, standardisation and access to PSC and accident data. Effective human factor modelling and the interpretability of more complex predictive models are also areas that require continued attention.

6.1. Implications for PSC Authorities, Shipowners and Other Stakeholders in the Sector

The findings of this review have practical implications relevant to various actors in the maritime sector.

6.1.1. PSC Authorities

There is a need to continue to improve systems for selecting ships for inspection, such as the SRP. These systems should incorporate findings on the types of deficiencies that are particularly critical and consider the distinction between factors that predict detention risk and those that predict accident risk.

Consideration should be given to optimising Concentrated Inspection Campaigns (CICs), possibly by adopting more dynamic approaches based on longer-term trend data analysis, as suggested by some studies [18]. Continuous improvement of training and education of trainers should be considered.

Continuous improvement of training and standardisation of procedures for PSCOs is essential to ensure the quality of inspections and thus of the data generated [4].

6.1.2. Shipowners and Ship Operators

Findings on high-risk deficiency categories (ISM, fire safety, navigation, etc.) can be used proactively by shipowners to focus on their own safety management systems, maintenance programmes and crew training. Paying special attention to these areas can help prevent deficiencies, avoid stoppages and, most importantly, reduce the risk of accidents.

6.1.3. Other Industry Actors: Insurers, Classification Societies and Charterers

Information on the risk profiles of ships, flags and management companies derived from these studies can be valuable for insurers in pricing premiums, classification societies in their own auditing and monitoring processes and charterers in ship selection.

6.2. Suggestions for Future Research

Research on the relationship between PSC deficiencies and ship risk is a dynamic field with numerous avenues for future research, such as:

Improving Predictive Models

1. Incorporate a wider range of data, including ship dynamic data and more detailed human factor information (e.g., crew fatigue, experience, specific training), as well as operational variables.
2. Develop and apply Explainable Artificial Intelligence (XAI) models that can provide accurate predictions together with an understandable justification of how that prediction was arrived at, facilitating their adoption by regulatory authorities.

Deeper Causality Analysis

Go beyond statistical correlations to investigate the root causes of recurring deficiencies and their direct causal link to maritime accidents. This could involve a more systematic analysis of maritime accident investigation reports and their integration with PSC data.

Impact of New Technologies and Regulations

Assess how increasing digitalisation in the maritime sector, the introduction of alternative fuels and new environmental regulations (e.g., EEXI, CII) are affecting existing vessel impairment profiles and risk models.

Data Quality Improvement and Standardisation

Promote initiatives to improve global standardisation of deficiency coding, inspection procedures and overall PSC data quality. Encourage greater data sharing between MoUs and with the research community.

Effectiveness of PSC Interventions:

Investigate the long-term effectiveness of different PSC intervention strategies, beyond simple deficiency detection and detention, in improving the safety performance of ships and companies

Comparative Studies between MoU Regimes

Conduct broader and more detailed comparative studies between different MoU regimes to analyse the consistency of inspection practices, detention criteria, deficiency profiles and overall maritime safety performance.

In conclusion, while research has firmly established that PSC deficiencies are important indicators of ship risk, the future challenge lies in refining the understanding of this complex relationship, improving data quality and access and developing more accurate, interpretable and operationally useful analytical and predictive tools. Addressing these challenges is critical if Port State Control continues to play its vital role in promoting a safer and more sustainable maritime industry. Future lines of research must therefore address not only the technical improvement of models but also systemic data issues and the need for a deeper understanding of accident causation, going beyond statistical correlations to inform more effective preventive interventions.

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Abbreviations

The following abbreviations are used in this manuscript:

PSC	Port State Control
MoU	Memoranda of Understanding
THETIS	The Hybrid European Targeting and Inspection System
NIR	New System of Inspections
SOLAS	The International Convention for the Safety of Life at Sea
MARPOL	The International Convention for the Prevention of Pollution from Ships
STCW	The International Convention on Standards of Training, Certification and Watchkeeping for Seafarers
PSCOs	Port State Control Officers
BN	Bayesian Networks
ML	Machine Learning
ETA	Event Tree Analysis
PCA	Principal Component Analysis

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