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Risk factors and navigation accidents: A historical analysis comparing accident-free and accident-prone vessels using indicators from AIS data and vessel databases

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ABSTRACT

This paper presents the results of an explorative analysis aiming to identify indicators and factors associated with navigation accidents (groundings and collisions). The analysis compares cargo vessels with at least one registered navigation accident (grounding or collision) within Norwegian waters with those that have none, in the period 2010–2019. The comparison is made using data based on automatic identification system (AIS) satellite data in combination with information from IHS Fairplay, to construct indicators that reflect different characteristics of the vessels. Hallmarks of vessels involved in navigation accidents have been identified using bivariate and multivariate statistical analysis. The multivariate model was a strong predictor of vessels' accident involvement with 44% of the variance explained. Indicators that predicted reported navigation accidents included: (1) vessel type, (2) higher age, (3) smaller size, (4) longer distance sailed, (5) higher average speed, (6) flying Norwegian flag, (7) gray or black Tokyo MoU rating, and 8) not on US Coast Guard target list. The results are discussed relative to their potential causes as well as limits and practical applications. The study shows the promising potential of utilizing AIS data combined with various data sets to obtain knowledge on risk factors and risk indicators.

1. Introduction

This article presents an explorative statistical analysis of factors associated with navigation accidents, based on AIS (automated identification system) data, vessel data from IHS Fairplay, and the accident database of the Norwegian Maritime Authority (NMA). The analysis has been initiated in order to provide evidence-based support for the development of risk models for Norwegian waters, as well as trying to identify variables that may be utilized as indicators of risk factors (c.f. Bye and Almklov, 2019; Bye and Aalberg, 2018; Haugen et al., 2012) for navigation accidents. The objective is not to develop a risk model for individual ships and events, but to establish an overall model for monitoring accident risk in Norwegian waters. Our approach is, in essence, to utilize some of the potential of the "big data" of satellite-based communication based on AIS transmitters when integrated with other data sources, to enhance our knowledge of risk factors and indicators to improve risk models.

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Table 1
Risk factors of navigation accidents identified in previous research.

Luo and Shin (2019)[(Literature review)	Bye and Aalberg (2018) (Literature review)	Publications 2018–2020
Environmental factors -Wind, -Current -Fog -Wave -Tough weather -Narrow channel	Ship behavior and external conditions -High speed -Impact area in collision -Weather and sea condition -Traffic in sea area -Area of navigation -Visibility -Darkness -Time of the day -Season -Involvement of fishing vessels (collisions) -Differences in risk factors related to sea areas	Environmental factors -Low visibility (Bye and Aalberg, 2018; Zhang et al., 2019b; Weng et al., 2019) -Good visibility (severity- Wang et al.,2021) -Darkness/daylight Bye and Aalberg, 2018; Uğurlu et al.,2020) -nighttime periods (Weng et al.,2018, 2019) -Area of accident (Xu et al. (2020) -Adverse weather (Weng et al.,2018) (severity - Wang et al. (2021) -Wind (Zhang et al., 2019b);(Weng et al.,2019); (severity - Wang et al., 2021) -Current (severity - Wang et al.,2021) -Season (Xu et al.,2020; Weng et al.,2019)
-Traffic factors -Dispersion of thousands of islands -Traffic congestion -Congested seaway -Narrowness		-Traffic factors -Fewer vessels in the area last hour (Bye and Aalberg, 2018) -Traffic volume – high (Li et al., 2019) -All vessels in the area: -Fewer hours of operation last hour -Fewer port calls last hour -Fewer port calls last day (Bye and Aalberg, 2018) -Location (Zhang et al., 2021; severity-Wang and Yang, 2018; severity Wang et al., 2021)
-Vessel and equipment factors -Insufficient stability -Insufficient ergonomic design -Radar failure -Structural failure -Leaks in hull -Auto pilot failure -Communication equipment failure	**-Ship conditions** -Vessel categories/characteristics -Different configuration s of relations between vessel type, accident types and risk factors -Age of vessel -Stability -Mechanical conditions -Equipment -Cargo/stow	**-Technical factors** -Vessel types (Bye and Aalberg 2018; Ventikos et al., 2018; Xu et al.,2020; Weng et al.,2019;severity-Wang et al.,2021) -Associations between certain vessel types and certain accident types (Navas de Maya et al., 2019) -Shorter length [Bye and Aalberg, 2018; Uğurlu et al.,2020) -Age of vessel (Bye and Aalberg, 2018; Fiskin et al. (2021); Uğurlu et al., 2020; severity- Wang and Yang, 2018; Navas de Maya et al., 2019) -Gross tonnage (Bye and Aalberg, 2018; Fiskin et al.,2021) -Propeller types (Fiskin et al.,2021)
-Navigation & operational factors -Poor level of maintenance -Poor bridge layout -Navigational error -Inadequate work planning -Inadequate vertical /horizontal -communication -Inadequate workplace condition -Inadequate task allocation		**-Operational factors** -Distance from shore/port/harbor (Ventikos et al.,2018; Xu et al.,2020; Weng et al.,2018; Fiskin et al.,2021) -Days in operation (Bye and Aalberg, 2018) -Speed (Bye and Aalberg, 2018) -Number of course alteration per nmi last hour (Bye and Aalberg, 2018) -Heading variance (Li et al.,2019) -Number of calls last day (Bye and Aalberg, 2018)
-Human factors -Careless navigation -Master asleep on watch -Health conditions -Excessive risk taking -Physical impairment -Smoking -Misuse of equipment -Wrong navigation process -Observation failure -Decision failure -unauthorized route -Violations -Mistake -Skill based errors -Memory and attention failure -Miscommunication -Physical stress, alcohol, fatigue -No licensed seaman -Incompetent Master/office -Lack of experience -Improper supervision -Inadequate team culture and safety culture	**-Human conditions** -Noncompliance with the safety management system -Procedures -Decision failures -Inappropriate planning -Failures related to supervision -Misuse or non-use of navigation instruments planning -Task error navigation "Inappropriate situational awareness"/ "Inadequate navigational -attention" -Pilot-related incidents -Communication and cooperation -Distractions -Confusion -Fatigue -Health **-Organizational conditions** -Education -Manning level -Heavy workload -Manning of the bridge -No dedicated lookout -Failures of "resource management" -Classification societies	**-Human factors** -Inadequate passage plan (groundings)(Yildirim et al.,2019) -Insufficient bridge communication (groundings) -Decision error (Collisions) -Inadequate resource planning (Collisions) -Violations (Collisions) -Miscommunication (Collisions) -Adverse mental state (Collisions) -Inadequate planning (Collisions) -Skill-based errors (Collisions) -Human error is associated with the accident types of contact, grounding and collision, certain vessel types (fishing boats and construction vessels), poor visibility (Zhang et al., 2019b) -Negligence and judgement error are associated with the season of spring, poor visibility, and night (Weng et al.,2019) -Certificate status (severity -Wang and Yang, 2018) -Poor theoretical knowledge (severity -Wang and Yang, 2018) -Less experience (severity-Wang and Yang, 2018) **-Organizational factors** -Insufficient safety management (Overlooked hazards, insufficient training, and insufficient feedback to the company) (Puisa et al., 2018) -Manning (Yildirim et al., 2019; Zhang et al., 2019b) -Flag state (Bye and Aalberg, 2018; Xu et al., 2020) -Flag of convenience (Bye and Aalberg, 2018)

(*continued on next page*)

Table 1 (*continued*)

Luo and Shin (2019)[(Literature review)	Bye and Aalberg (2018) (Literature review)	Publications 2018–2020
-Inadequate manning -Non-compliance with SMS -**Shipping market factors** -Low freight rate -Economic activity -High oil price	-Vessel register -ISM code	

AIS has not been fully utilized in statistical analysis of maritime accident data (Bye and Almklov, 2019; Svanberg et al., 2019). However, Kulkarni et al. (2020) assume that the use of AIS data in accident and risk analysis will be a future trend within the field of risk research. So far there are only a few publications that are based on data obtained from AIS, and the research has been limited to specific geographical areas, such as the Baltic Sea (e.g. Goerlandt et al., 2017a; Lensu and Goerlandt, 2019) the Strait of Singapore (e.g. Zhang et al., 2019a, 2019b), the Western port of Shenzhen City, China (Li et al., 2019), the coast of Portugal (e.g. Dinis et al., 2020), the Canary Islands (Talavera et al., 2013) and the coast of Norway (e.g. Bye and Almklov, 2019; Hassel et al., 2020).

Most statistical analyses of risk factors have, until now, been based on data related to the accidents and the ships involved, not including the total population of vessels (i.e., not having a "control group"). To the extent that population data has been used, it has mainly been limited to data obtained from vessel registers (number of vessels) (such as Alderton and Winchester, 2002; Nævestad et al., 2015) and port authorities (number of port calls) (Kujala et al., 2009; Sormunen et al., 2016). The use of AIS as a data source for statistical accident analysis makes it possible to obtain richer data related to the activity of a larger population of vessels in a specific sea area, not only of the vessels involved in accidents. By transforming position report data from each vessel, it is possible to construct indicators for sailing time, sailed distances, port calls, speed, navigation patterns, vessel density and various other aspects. AIS information regarding the identity of the vessels may also be used to obtain a wide range of vessel information by linking the data to other data sources (Bye and Aalberg, 2018). The originality of our study is the application of such data on the total population of defined vessel types, making it possible to compare vessels involved in accidents with those which have not been involved.

The paper is organized as follows. Section 2 gives an overview of previous exploratory empirical research on maritime accidents. Section 3 is an outline of the methods and research design used in our analysis, and the variables/indicators constructed by combining data from AIS, IHS Fairplay database, and the NMA accident database. Section 4 presents the results from bivariate and multivariate analyses. The findings are then discussed in Section 5. Sections 6 presents the final conclusions.

2. Previous research on maritime accidents and risk factors

In their extensive literature review of journal papers published from 1965 to 2014, Luo and Shin (2019) give an overview of identified causes of maritime accidents in previous research. They classified these causes into vessel and equipment factors, environmental factors, traffic factors, human factors, navigation and operational factors, and shipping market factors (Table 1). Bye and Aalberg (2018) carried out a literature review of publications between 2000 and 2017 that used historical data to identify risk factors associated with maritime accidents. They classified identified risk factors into ship behavior and external conditions, ship behavior, human conditions, and organizational conditions (Table 1). Building on this work, a review of journal articles, published during the last years (2018–2020) has been conducted, limited to publications based on statistical analysis of accident-related data. In the following, the findings of each article are described.

Bye and Aalberg (2018) compared navigation accidents (groundings and collisions) with other types of accidents (e.g., capsizing or fire). A multivariate logistic regression analysis showed that factors such as vessel types, the length of the vessel (shorter vessels), poor visibility, and flag of convenience were strong predictors for navigation related accidents. Puisa et al. (2018) analyzed 188 accidents and incidents using the inductive qualitative method CAST as a framework to identify contributing causes and interrelations. Most common causes that they identified include overlooked hazards in the safety management system (SMS), insufficient training, and insufficient feedback to the company. They also found that individual failures (human error and equipment failures) were marginal compared to organizational factors.

Ventikos et al. (2018) conducted a statistical analysis of navigation accidents ($N = 277$) that occurred in adverse weather. Calculation of accident frequencies (accidents per ship-year) showed that cruise, Ro-Ro ships, and general cargo ships had the highest accident frequency. The least accident-prone ships were tankers. Collision accidents occurred in milder weather conditions than groundings and contact accidents. Most of the groundings occurred en-route, whereas collisions and contact accidents occurred mainly in restricted waters and port areas. Analyses of maritime accidents in New Zealand from 2015 to 2018, conducted by Xu et al. (2020), showed that foreign non-passenger ships contributed more than other ships to accident occurrence. The most accident-prone ships among the domestic ones were fishing vessels, followed by non-passenger ships, passenger ships, and other ship types. Accidents were more likely to happen during the spring season, and more likely to happen in berth and harbor areas.

Yildirim et al. (2019) analyzed 257 groundings and collision accidents using the HFACS (Human Factors Analysis Classification System) framework as a tool for an inductive qualitative analysis. Parts of their HFACS data were then analyzed by using correspondence analysis. Regarding collisions, the most frequent contributing factors were decision error, inadequate resource management, violation, miscommunication, adverse mental state, inadequate planning, and skill-based errors. Further, the most frequent contributing factors to grounding were inadequate resource management (inadequate passage plan and insufficient internal bridge communication). Low manning of the bridge was also addressed as an important contributing factor. Chen et al. (2019) analyzed factors associated with total loss maritime accidents, finding that the accident types foundering, stranding and fire/explosions were the factors which contributed most to total loss accidents, when controlling for geographic regions and vessel types. Navas de Maya et al. (2019) analyzed 24,757 maritime accidents between 1990 and 2016, among ships registered by Marine Accident Investigation Branch (MAIB). Bivariate Correspondence analysis was used to explore possible relations between categorical variables. Their model of vessel types and accident types, with 89.5% explained variance, showed associations between passenger ships and fire/explosions, damage to ship or equipment, hull failure and contact. Chi-square tests revealed that there is a relationship between age of the vessels and total loss accidents (for which older ships were more prone). Zhang et al. (2019b) analyzed associations between causes/risk factors and consequences of different types of accidents, based on 477 ship accident reports world-wide. They found that crew size on vessels involved in grounding accidents was related to ship damage and cargo damage. However, this was not the case for collisions. Their analysis shows that both wind condition and visibility condition were positively related to ship damage and cargo damage, and that there was a strong link between poor visibility and fatality.

Weng et al. (2019) applied a multinominal logistic regression analysis of factors associated with different types of human error. Their analysis is based on 1248 records from accidents in the southeastern area of Chinese waters from 2000 to 2014. They found that poor visibility conditions, no strong wind/waves, accident types of contact, grounding and collision, involvement of fishing boats and work vessels such as e.g., construction vessel/sand dredger, were associated with a higher probability of human error. They find that negligence and judgment/operation error were associated with the season of spring, poor visibility, and night. An analysis shipping accidents word wide ($N = 23{,}029$), based on ZIND regression technique, showed that high human life loss was associated with sinking, fire/explosions and miscellaneous accidents under adverse weather, far from the coast/harbor/port during nighttime (Weng et al., 2018). Uğurlu et al. (2020) analyzed data from 226 fishing vessel accidents worldwide. Based on bivariate analyses they found relationships between type of accidents and length of vessel, the age of the vessel, and the presence of daylight/darkness.

Li et al. (2019) analyzed accidents in the Western port of Shenzhen, combining AIS and GIS data. By analyzing 95 accidents they found that relative consequences of regional hazards were successfully predicted by normalized ship heading variance, traffic speed and traffic volume. Fiskin et al. (2021) tried to identify factors associated with harbor tugboat accidents ($N = 496$) using data mining, followed by logistic regression and decision three analyses. A combination of vessel properties, such as propeller type, larger boats (gross tonnage), and age were identified as risk factors. Zhang et al. (2021) analyzed the geographical distribution of accidents worldwide—based on data from 2003 to 2018—and identified several "hot spots" with a high number of accidents. However, the number of accidents in these areas were not controlled for the activity, and it is therefore unclear whether one could conclude that these areas represent risk factors in terms of probability of accidents.

There have also been conducted several analyses of risk factors associated with accident severity. Based on data from 229 accident investigation reports from Chinese waterways and inland rivers, Wang and Yang (2018) identified accident type, vessel type, age, and location of the accident as risk factors. Wang et al. (2021) analyzed data from 1207 accidents worldwide that occurred in the period of 2000–2019. Using logistic regression—applying accident severity categories as dependent variables—they found that the most severe accidents were associated with accident types (sinking), location of the accident (far away from port), vessel types, incomplete or invalid ship and/or old certificates among the crew members, weather conditions, wind, current, visibility (good), poor theoretical knowledge, and less sea experience.

The literature review demonstrates that a wide range of factors have been identified as related to navigation accidents. Most of the studies were based on analyses of accident data primarily, and do not include non-events or vessels without accidents. The present study sought to address some of the gaps in current research by emphasizing the analysis of both vessels without any experienced/reported navigation accidents and vessels with at least one navigation accident.

3. Method

The research design consisted of five steps (Fig. 1): (1) define risk factor indicators, (2) obtain vessel data, (3) transform the data into indicators, (4) bivariate analysis, and (5) multivariate modeling. The first three steps were conducted in a cyclic process.

3.1. Define risk factor indicators based on available data

Previous literature reviews (Bye and Aalberg, 2018; Luo and Shin, 2019) combined with a literature search for the period 2018 to 2020, were used to obtain risk factors identified in previous research. The literature search was conducted through Web of Science and Google Scholar using the following search words: "accident data AND statistical analysis AND (maritime OR marine OR ship*)".

Operationalizing risk factors with a set of feasible risk factor indicators was conducted using available data from AIS, linked to IHS Fairplay (information about each vessel) and the Norwegian Maritime Authority (NMA) accident database. In addition, lists of port

Fig. 1. Steps in the research.

state control ratings, and the list of flags of convenience were considered as relevant frameworks for constructing variables. Paris MoU https://www.sdir.no/en/guides/guidance-note—notification-and-reporting-of-marine-casualties-and-incidents/.

Tokyo MoU Vessels belonging to the Norwegian Ordinary Ship Register (NOR) and the Norwegian International Ship Register (NIS) and US Coast Guard target list https://www.parismou.org/detentions-banning/white-gray-and-black-list are three different regional/ national regimes used by national authorities for verifying that a vessel visiting a port, along with its equipment and manning comply with international regulations. Port State Control (PSC) ratings for flag authorities are based on inspection reports carried out by authorities. Common parameters are numbers of detentions and numbers of inspections. The ratings for different flag states are used as one of several criteria for prioritizing inspections.

More specifically, the Tokyo MoU and Paris MoU operate with categories of flag states reflecting different performance scores: Flags administration with low detention ratio and classified as "white" whereas flags with high and very high detention ration are, respectively classified as "gray" and "black". US Coast Guards Port State control covers vessels visiting US waters. Flags on the target list comprises of flag administrations with a detention ratio higher than the overall average.

The list of "flag of convenience" (FOC) is issued by International Transport Workers' Federation. http://www.tokyo-mou.org/ and consist of administrations, judged by the trade unions, that are associated with ships with very poor working conditions (e.g. low wages, poor on-board conditions, inadequate food, long working hours and poor opportunities for rest).

The final set of risk indicators used in the analysis was the result of iterations between the risk factors in the preliminary BBN model (Haugen et al., 2016), findings from previous research, feasible variables for comparing vessels involved in accident with vessels not involved, the process of obtaining vessel data, and transforming them into variables. In this set, we divide between (1) technical, (2) operational, and (3) organizational risk factor indicators/variables. Technical risk factor indicators included vessel category, age, gross tonnage, and length. All variables have in previous research been associated with accidents; vessel category: e.g. Bye and Aalberg (2018); Goerlandt et al. (2017b), age: e.g., Ventikos et al. (2018) and vessel size (gross tonnage, length etc.): e.g. Jin (2014).

Operational risk factor indicators included nautical miles sailed, hours in operation, average knots, port calls, and port calls per nautical miles sailed. Previous findings have shown that the indicators are associated with accidents (e.g. Tirunagari et al., 2012), and proposed as suitable to reflect operational patterns (Bye and Almklov, 2019).

Organizational risk factor indicators included foreign vessel, Paris MoU black or gray list, Tokyo MoU black or gray list, US target list, classification society, and FOC. Previous research has shown association between accident and/or consequences of accidents and these indicators; vessel register and /or foreign vessels (e.g. Ventikos et al., 2018), port state control ratings, classification societies (e.g. Li et al., 2014) and FOC (e.g. Bye and Aalberg, 2018; Wang and Yang, 2018).

3.2. *Obtaining AIS vessel data*

The static AIS reports (message type 5) applied in our study include the combination of the International Maritime Organization (IMO) number and the Maritime Mobile Service Identity (MMSI) number in the period 01.01.2010 to 31.12.2019. This information was used to identify the unique vessels operating in the defined sea areas (Fig. 2). The IMO or MMSI-number information was linked with information obtained from the IHS Fairplay database, and included vessel type, year of build, length, gross tonnage, flag state, and classification society. Flag state information was then linked to information regarding rating/classification according to the PSC regimes lists as well as FOC lists by the ITF. The identifiers of the ship were also used to obtain accident history by connecting to the NMA accident database (see also Blix et al., 2015).

The AIS position reports (message type 1, 2 and 3) were used to calculate time in operation, nautical miles sailed, number of port calls, and average speed (several defined time periods) for each individual vessel.

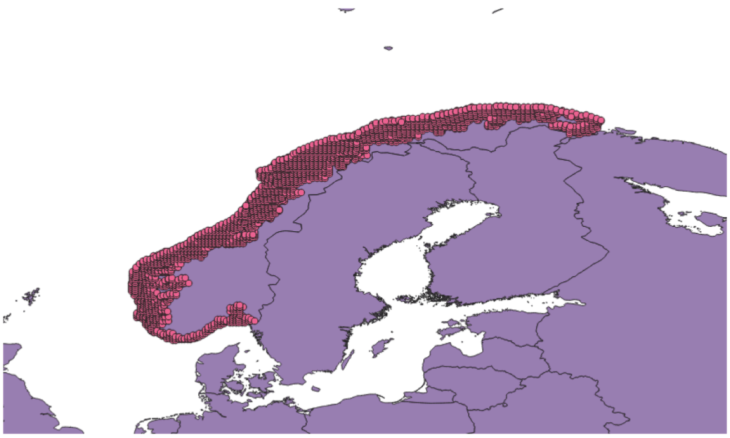

Fig. 2. Sea areas included in the analysis.

3.3. Transforming vessel data into indicators

The obtained data was transformed into 16 indicators to be utilized as variables for statistical analysis (see Table 2).

Accident involvement (1)

The dependent variable indicates whether a vessel has reported at least one grounding or collision (weighted equally) to the NMA database. Only accidents classified by the MNA as "Very serious marine casualty", "Serious causality with vessel,", and "Maritime accident" were included in the variables. http://www.tokyo-mou.org/ These categories correspond to IMO categories of casualties. Accidents classified as "other ship accidents" were excluded, due to indications of under-reporting (Bye and Almklov, 2019).

Vessel category (2)

Based on the ship taxonomy of National Ship Risk Model (NSRM) (Blix et al., 2015) and StatCode5 categories from HIS Fairplay, we included the following vessel types: (i) cargo carrying vessels (including tanker, bulk, dry goods), (ii) wellboats, (iii) work and service vessels, and (iv) offshore service vessels (including mainly standby & service vessels, anchor handling vessels, subsea/construction vessels).

Age, gross tonnage and length (3–5)

Data from IHS Fairplay for each identified vessel was used to construct continuous variables for age, gross tonnage, and length. Age is simply the year of build of the vessel. Due to non-normal distribution, length overall was recoded as a categorical variable in the bivariate analysis.

Nautical miles sailed (6)

Nautical miles sailed was calculated using the distance between two AIS reports, using the Haversine method. A similar filtering as for hours in operation was used (see next paragraph). Number of nautical miles sailed, as a parameter in the analysis, is the sum of all these calculations. In the regression analysis, for practical reasons, the number was divided by 1000.

Hours in operation (7)

Hours in operation was defined as the time between two AIS reports. A filtering was applied to remove faulty messages by applying a maximum allowable time, set to six hours. When two reports exceeded this time criterion, the time was set to 0.1 h if the estimated speed between the reports was acceptable. If the estimated speed was not acceptable (greater than 50 knots), the time was set to zero. The cut-off value of six is based on industry experience with AIS data, established in the NSRM project (see Kleiven, 2016). A value of 0.1 h is added to avoid discounting uncertain data yielding an underestimation of number of hours in operation. Lastly, we summarized the hours in operation for the period. In the regression analysis, for practical reasons, the number of hours was divided by 1000.

Average speed (8)

Speed was included as part of the AIS messages. If the given value was corrupt, for any reason, an estimation was made based on the sailed time and distance to the point. This value was also used to verify whether the given was real or an error. For example, if the coordinates of the data point are corrupted and the point is located very far from its neighbor, the resulting speed would be very high. In that case the point was dropped. The stored value for the speed of the vessel was given based on a pre-tabulated set of speeds, e.g. 0–1 knots, 1–2 knots etc. The average value of the sailing speed was then given as the average of this tabulated value.

Port calls (9–10)

The port calls algorithm was based on how close position points are located to each other. When a vessel is sailing, two neighboring

Table 2
Categorical and continuous variables used in the analysis.

No	Type	Unit	Indicators	Description	Data source
1	Cat.		Accident involvement (grounding & collision)	Yes/No	NMA
Technical					
2	Cat.		Vessel category	The NSRM taxonomy	AIS, IHS Fairplay, NSRM taxonomy list
3	Cont.	Years	Age	Year of build	IHS Fairplay
4	Cont.	Gt	Gross tonnage		IHS Fairplay
5	Cont. /Cat.	meters	Length overall		IHS Fairplay
Operational					
6	Cont.	Nmi	Nautical miles sailed	In transit last 10 years	AIS
7	Cont.	hours	Hours in operation	In transit last 10 years	AIS
8	Cont.	knots	Average speed	In transit last 10 years	AIS
9	Cont. /Cat.	frequency	Port calls	In transit last 10 years	AIS
10	Cont.	frequency	Port calls per nautical miles sailed	In transit last 10 years	AIS
Organizational					
11	Cat.		Flag state	NOR or Foreign	IHS Fairplay
12	Cat.		Paris MoU	“white”/ “gray”/ “black”	Paris MoU lists
13	Cat.		Tokyo MoU	Yes or No	Tokyo MoU lists
14	Cat.		US target list	Yes or No	US target list
15	Cat.		Flag of convenience	Yes or No	FOC list
16	Cat.		Classification society	Member of IACS or not	IHS Fairplay, Member list IACS

points forms the corners of a box without any other points within that box. As the vessel nears a point of interest, the box shrinks and may then contain other points. When the box is sufficiently small, it is defined as a visit to a point of interest. This is exemplified in Fig. 3. The points p1 and p2 forms a bounding box not containing any other points. The same is true for p4 and point A, but the square formed by these points is noticeably smaller. For the points 6 through 12, the bounding box shrinks even further indicating that the vessel is coming to a halt. Contrary, as the vessel sails from point D to p14, the bounding box increases in size again. The algorithm interprets point A and D as candidates for arrival and departure to a point of interest. Notice that the bounding box of A and D encompasses other points, also indicating that the vessel has stopped. See Kleiven (2016) for more details. The number of port calls per nautical mile is essentially number of port calls (variable 9) divided by sailed distance (variable 6).

Flag state (11)

Information regarding the flag state, obtained by IHS Fairplay, was coded into a dichotomous variable of foreign versus Norwegian vessels. https://www.dco.uscg.mil/Our-Organization/Assistant-Commandant-for-Prevention-Policy-CG-5P/Inspections-Compliance-CG-5PC-/Commercial-Vessel-Compliance/Foreign-Offshore-Compliance-Division/Port-State-Control/targetedflags/

Port state control regimes (12–14)

Flag state information obtained by IHS Fairplay was recoded into dichotomous variables, according to both Paris MoU and Tokyo MoU classification of vessels into white (coded as 0), and gray and black lists (coded as 1). A dichotomous variable was also coded based on the US Coast Guard́s Targeted Flag administrations. The categories of flag administrations are assumed to be relevant as indicators of the standard of the ships, in terms of compliance with international regulations.

Flag of convenience (FOC) (15)

This is a dichotomous variable, describing ships regarded as FOC and not FOC, based on flag state information and the International Transport Workers' Federation (ITF) list of "flag of convenience" .

Classification society (16)

Information regarding classification society was obtained from IHS Fairplay database. The categories of classification societies have been recoded into a dichotomous variable, according to whether the company is a member of the International Association of Classification Societies (IACS) https://www.itfglobal.org/en/sector/seafarers/flags-of-convenience or not. https://en.wikipedia.org/wiki/International_Association_of_Classification_Societies

Sample

The final data sample ($N = 9300$) for multivariate models consists of all cargo vessels sailing at least 24 h, and are at least 15 m of length, in Norwegian waters during the period 01.01.2010–31.12.2019, identified with AIS data registered to the Norwegian Coastal Authority. Bivariate analyses use n = 9300–9304 due to a few unknown/missing entries that are not excluded in these analyses. Further descriptions of the sample are presented along with the bivariate results.

Some ships (and thus accidents) were excluded from our analysis due to lack of data (see also discussion on missing AIS data in Section 3.5), but is regarded as not to affect the analysis with systematic bias (see also Bye and Aalberg, 2018).

3.4. Analysis

The objective of the statistical analysis was to explore differences in ship characteristics, ship behavior, and organizational conditions. In the analysis, we compared ships with accidents to ships without any such record. First, we describe bivariate analyses conducted, then multivariate modeling.

3.4.1. Bivariate analysis

The chi-square statistic (X^2) was the method applied for analyzing degree of association between distributions within different

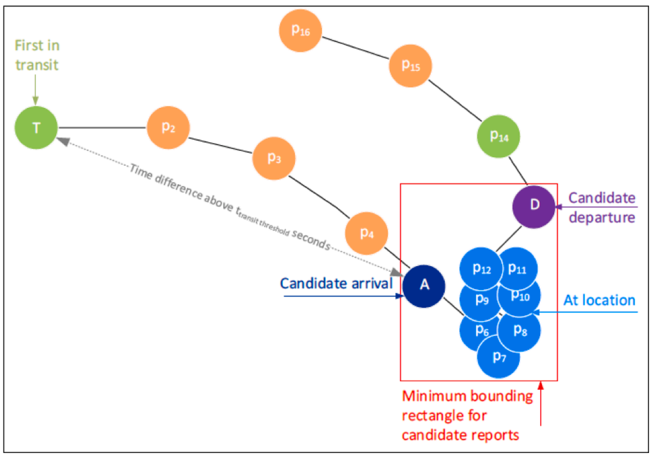

Fig. 3. Approach for identifying arrivals/departures from AIS position reports applied in the study.

categories (categorical variables). The chi-square analysis does not indicate the direction of the effects, only whether the distributions in total are significantly different from each other.X^2 indicates statistical significance (test statistic) and *phi* indicates effect size.

For investigating differences between averages of two groups (continuous variables) we used an ANOVA (Analysis of Variance) analysis. Several of the variables were analyzed using a logarithmic transformation due to violation of normality assumptions.

3.4.2. Logistic, multivariate analysis predicting vessels with accidents

To further analyze relative contributions of the different set of variables in predicting accident involvement, we applied a hierarchical multiple logistic regression procedure.

In logistic regression, the odds-ratio is calculated for each independent variable which describes how the likelihood changes under the different conditions of the variable of interest. Additionally, the total percentage explained by the model was measured by the Nagelkerke *R* squared (R^2).

3.5. Methodological limits

This study has several important limits to be discussed. For general issues, see Section 5.2. In the following, we discuss the specific technical and methodological issues of our study. First, there is a limit of that we extrapolate static data. If a ship changed MMSI number during the timeframe of the study, it was assigned a new ship id, and then was analyzed as a separate vessel, without any history. For all other types of changes, in order to keep vessel record history, and reduce complexity, we chose to generalize a snapshot at a random point in time. This means that this analysis does not capture changes in these variables during the time frame if the vessel did not change IMO. The variables are Paris MOU, US/Tokyo target list, class society, flag of convenience, and foreign ship.

A limitation is the potential of underreporting to the NMA's accident database, which is further discussed later in the article. Further, a limitation is the use of proxy data, like ship register data. It was difficult to gather concrete information about the total population, especially related to human and organizational factors (e.g., manning, nationality and so on). An important limit is the number of ships not identified in AIS data and/or accident data, although the diagnostics do not indicate that there is systematic bias in the sample. Fig. 4 shows the number of reported incidents per year (ID) and the number of reported incidents with a vessel identified from AIS (ship_id), where discrepancy between the two indicates a sample bias. There is a sharp increase from 2005, in AIS data, in number of accidents identified with a vessel. . In the period after 2010, the degree of identified vessels with accidents is seen to be around 70–80%. The high number of unidentified vessels before 2005 is most likely due to these vessels being decommissioned prior to 2009 when AIS usage was increased. When AIS data is obtained, it resembles a snap-shot at the time of collection. This does not directly portray the transient nature of this data. For example, if a vessel is sold it may change name and MMSI number. This means that vessels with changes to their particulars, that have occurred within the timeframe of this study (2010–2019), may not be correctly represented in the applied dataset. That is, if a vessel is registered with one name in 2014 and is involved in an accident, and later is assigned a new MMSI value, data will not be available at the time of the accident. Such accidents were therefore not included in this study.

We have not identified any circumstances that indicate that the missing sample constitutes any systematic error that influences the model.

4. Results

The results section consists of two main parts, namely the results of the bivariate analysis and the results of the multivariate logistic regression.

4.1. Bivariate analysis - categorical variables

In the following subsections, we will briefly present bivariate analyses between predictors and accident involvement. In total, 9304 ships were included in the analysis of bivariate analysis. Approximately 5.6% ($n = 517$) of these had reported at least one navigation accident (i.e., grounding and/or collision) to the NMA, while 94.4% had not ($n = 8787$), as seen in Table 3 below.

Ship type

The sample included 7569 (81.4%) cargo carrying vessels, 911 (9.8%) offshore service vessels, 77 (0.8%) wellboats and 747 (8.0%)

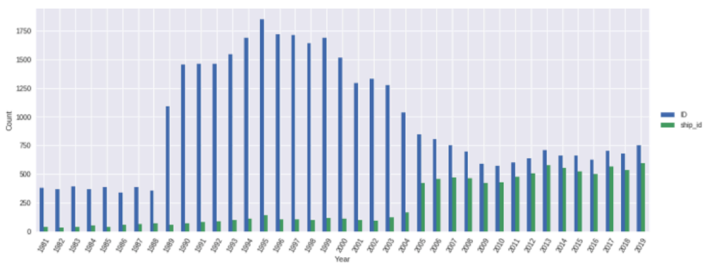

Fig. 4. Plot with mapping of ships and accident records.

Table 3
Descriptive statistics of accidents & vessels included in the study ($N = 9304$).

Navigation Accidents		Number of ships
No	*n*	8787
	%	94.4%
Yes	*n*	517
	%	5.6%
Total *N*		9304

work and service vessels. The relationship between type of ship and accident involvement was statistically significant ($X^2[3] = 446.169, p < .001$, phi = 0.22); see Table 4. Although the chi-square analysis does not indicate concretely *where* the significant effect lies, we see that there is an important overrepresentation of vessels with at least one reported accident within the category of wellboats (55.8% as opposed to the total 5.6%). Moreover, we see that both offshore service vessels and work and service vessels had slightly higher representation (5.9 and 11.8%) compared to cargo carrying (4.4%). The effect size was moderate.

US target list

The distribution of vessels included in the study was 3241 (34.8%) on US target list and 6060 (65.2%) not on the list. Table 5 shows that there was a higher percentage of vessels with at least one reported accident within ships not on US Target list (7.4% vs 2.1%). This difference was statistically significant, X2(1) = 115.5, $p < .001$, phi = −0.11. The effect size was small/moderate.

Class category

A total of 8341 (89.6%) vessels included in the study have been classed by a class society that is member of IACS, and 963 (10.4%) from other class societies. From Table 6 one can conclude that vessels classed by class societies that are not members of IACS had a higher percentage of vessels with at least one navigation accident (11.5%) compared to vessels classed by class societies in members (4.9%). This difference was statistically significant $X^2 = 72.945$, $p < .001$, phi = 0.09. The effect size was small/moderate.

Flag of convenience (FOC)

As for FOC, the descriptive statistics showed that 4687 out of 9304 (50.4%) ships were sailing under FOC) and 4617 (49.6%) were not. Table 7 shows that there was an underrepresentation of ships with accident(s) within ships recorded as FOC (2.4% as opposed to other ships 8.8%). This difference was statistically significant; $X^2(1) = 177.808$, $p < .001$, phi = −0.14. The effect size was moderate.

Paris MoU

Regarding Paris MOU classification list, only a minority of the vessels were classified as black or gray (250; 2.7%) as opposed to white (9054; 97.3%). The results of the chi-square analysis (see Table 8) showed an overrepresentation of ships on the black or gray list on Paris MOU (8.4% as opposed to white; 5.5%). The analysis was statistically significant; $X^2(1) = 3.957$, $p < .05$, phi = 0.02, however the effect size was small.

Tokyo MoU

The majority of the ships identified in the study were classified as white on the Tokyo MoU list (9014, 96.9%), and only 290 as black or gray (3.1%).The Tokyo MoU classification list was significantly related to whether ships have recorded a navigation accident or not, as described in Table 9; $X^2(1) = 8.036$, $p < .01$, Phi = −0.03. Approximately 8.4% of the vessels registered as black or gray had reported accidents, compared to 5.5% of the vessels registered as white. The effect size was small.

Norwegian or foreign flag

Vessels sailing under the Norwegian flag were a minority of the total number of cargo vessels in the study. Norwegian vessels constituted 10.2% of the sample ($n = 947$), while foreign flagged vessels constituted 89.8% ($n = 8357$). Ships sailing under Norwegian flag (NOR or NIS) had a much higher representation of reported accidents (31.3%) than ships sailing under foreign flags (2.6%), and this is statistically significant, $X^2(1) = 1326.902$, $p < .001$, Phi = −0.38 (Table 10). The strong effect size of −0.38 was apparent.

Bivariate chi-square analysis of navigation accidents and flag state ($N = 9304$)

Since there is reason to believe that foreign vessels sail predominantly in Norwegian waters to a lesser extent than Norwegian vessels, we further investigated the number of nautical miles sailed and hours in operation, which showed (Table 11) that indeed, vessels sailing under Norwegian flag had around 15 and 5 times higher hours in operation and nautical miles sailed, respectively, than foreign vessels. These findings clearly show the importance of multivariate modeling to (see Section 4.3.)

Length overall

The average length overall was 145 m ($SD = 69.67$). Due to non-normal distribution, the bivariate analysis was conducted in a categorical transformation based on quartiles. The analysis (see Table 12) showed that there was a tendency towards shorter ships

Table 4
Bivariate chi-square analysis of navigation accidents and vessel type ($N = 9304$).

			Cargo carrying vessel	Offshore service vessel	Wellboat	Work and service vessel	Total
Navigation accident	No	n	7237	857	34	659	8787
		%	95.6%	94.1%	44.2%	88.2%	94.4%
	Yes	n	332	54	43	88	517
		%	4.4%	5.9%	55.8%	11.8%	5.6%
Total		n	7569	911	77	747	9304
		%	100%	100%	100%	100%	100%

Table 5
Bivariate chi square analysis of navigation accidents and US Target list classification ($N = 9301$).

			Vessel on US target list		Total
			No	Yes	
Navigation accident	No	n	5610	3174	8784
		%	92.6%	97.9%	94.4%
	Yes	n	450	67	517
		%	7.4%	2.1%	5.6%
Total		n	6060	3241	9301
		%	100%	100%	100%

Table 6
Bivariate chi-square analysis of navigation accidents and class society ($N = 9304$).

			Class society member of IACS		Total
			No	Yes	
Navigation accident	No	n	7935	852	8787
		%	95,1%	88,5%	94,4%
	Yes	n	406	111	517
		%	4,9%	11,5%	5,6%
Total		n	8341	963	9304
		%	100%	100%	100%

Table 7
Bivariate chi-square analysis of navigation accidents and flag of convenience ($N = 9304$).

			No	FOC	Total
Navigation accident	0	n	4180	4604	8784
		%	91.2%	97.6%	94,4%
	1	n	402	115	517
		%	8.8%	2.4%	5,6%
Total		n	4582	4719	9301
		%	100%	100%	100%

Table 8
Bivariate chi-square analysis of navigation accidents and Paris MOU classification ($N = 9304$).

			White	Black or gray	Total
Navigation accident	0	n	8558	229	8787
		%	94.5%	91.6%	94.4%
	1	n	496	21	517
		%	5.5%	8.4%	5.6%
Total		n	9054	250	9304
		%	100%	100%	100%

Table 9
Bivariate chi-square analysis of navigation accidents and Tokyo MoU classification ($N = 9304$).

			White	Black or gray	Total
Navigation accident	0	n	8558	229	8787
		%	94.5%	91.6%	94.4%
	1	n	496	21	517
		%	5.5%	8.4%	5.6%
Total		n	9054	250	9304
		%	100%	100%	100%

having a higher degree of reported accidents than older ships. The analysis was statistically significant, $X^2(3) = 565.493$, $p < .001$, phi = 0.25. This effect (phi) is moderate.

Number of arrivals

The mean number of arrivals in the sample was 241.55 (SD = 1089.22). We dichotomized the continuous variable into a binary variable based on the bottom and top 50%, due to a non-normal distribution. The cross-tabulation (Table 13) showed a higher degree

Table 10
Bivariate chi-square analysis of navigation accidents and flag state ($N = 9304$).

			Norwegian flag	Foreign flag	Total
Navigation accident	0	n	651	8136	8787
		%	68.7%	97.4%	94.4%
	1	n	296	221	517
		%	31.3%	2.6%	5.6%
Total		n	947	8357	9304
		%	100%	100%	100%

Table 11
Exposure data of vessels sailing under Norwegian and foreign flags ($N = 9304$).

Flag state		1000 nautical miles sailed	1000 h in Operation
Norwegian flag	Mean	58.64	24.78
	N	947	947
	SD	101.89	25.34
Foreign flag	Mean	4.61	1.62
	N	8357	8357
	SD	21.38	5.05
Total	Mean	10.11	3.98
	N	9304	9304
	SD	41.63	11.72

Table 12
Bivariate chi-square analysis of navigation accidents and length of vessels ($N = 9304$).

			Bottom 25 percent	25–50 percent	50–75 percent	75–100 percent	Total
Navigation accident	0	n	1977	2221	2292	2297	8787
		%	85%	95.4%	98.6%	98.8%	94.4%
	1	n	350	108	32	27	517
		%	15%	4.6%	1.4%	1.2%	5.6%
Total		n	2327	2329	2324	2324	9304
		%	100%	100%	100%	100%	100%

Table 13
Bivariate chi-square analysis of navigation accidents and number of arrivals ($N = 9304$).

			Bottom 50%	Top 50%	Total
Navigation accident	0	n	4902	3885	8787
		%	98.7%	89.5%	94.4%
	1	n	63	454	517
		%	1.3%	10.5%	5.6%
Total		n	4965	4339	9304
		%	100%	100%	100%

of ships with reported accidents in the high amount of arrivals group (10.5% as opposed to 1.3% in the lower group), and the test was statistically significant, $X^2(1) = 372.84$, $p < 0.001$, phi = 0.20. The effect size was moderate.

4.2. Bivariate analysis - continuous variables

The sample descriptives as well as ANOVA test can be inspected in Table 14 below. The means of the continuous variables were: hours in operation ($M = 3978$), nautical miles sailed ($M = 10{,}107$), arrivals per nautical mile ($M = 2.8$), average knots ($M = 7.8$), gross tonnage ($M = 21{,}301$), and year of build ($M = 2004$).

For the continuous variables included in the study, we performed a series of ANOVA analyses. From the analysis, we found that, for ships with at least one reported accident, there were a higher average of hours in operation, nautical miles sailed, and average knots ($p < .001$). Further, a lower average of gross tonnage and year of build among the ships with at least one reported accident was observed ($p < .001$). The mean-difference was considerable in all significant tests. The effect size Eta^2 indicates that the strongest effects were for hours in operation, nautical miles sailed, and year of build.

Table 14
Bivariate analyses of variance (ANOVA) (N = 9303–9304).

Navigation accident		Hours in operation*	Nautical miles sailed*	Arrivals per nautical mile	Average knots*	Gross tonnage*	Year of build*
No	Mean	2559	5269	2.7	7.9	22,229	2005
	N	8787	8787	8787	8787	8786	8786
	SD	8326	25,696	16	1.9	26,806	10.1
	Min	24	0.0	≈ 0.00	≈0.00	85	1896
	Max	85,245	740,135	1203	21	404,458	2019
Yes	Mean	28,093	92,327	3.4	7.1	5518	1990
	N	517	517	517	517	517	517
	SD	26,036	113,276	5.3	2.1	12,435	16.2
	Min	26.7	0.3	≈0.00	≈0.00	86	1929
	Max	83,543	522,703	38,9	12.5	102,315	2017
Total	Mean	3978	10,107	2.8	7.8	21,301	2004
	N	9304	9304	9304	9304	9303	9303
	SD	11,717	41,631	15.9	1.9	26,493	11.0
	Min	24.0	≈0.0	≈0.00	≈0.00	85	1896
	Max	85,245	740,135	1203	21.1	404,458	2019
F[a]		1686.58	1671.65	73.33	588.86	588.86	988.07
Eta^2		.15	.15	.00	.01	.06	.10

Note. ANOVA is conducted with the natural logarithmic transformation of hours in operation, nautical miles sailed, gross tonnage, and year of build, due to non-normal distributions, but the numbers reported in the table are raw calculations.
* $p < .001$ [a] (df = 1; 9301–9303).

4.3. Multivariate analysis - logistic regression

To understand the relative contributions of these variables to the variation in vessel accidents, we wanted to control for each other's variance. This was done through a hierarchical multivariate logistic regression consisting of four steps. Step 1 was ship type. Then we included ship characteristics in step 2. These two steps constitute technical factors. Further, in step 3, we included information about the flag and class society which constitute organizational factors. In the fourth and final step, we included ship behavior (hours in operation, arrivals, nautical miles sailed, average speed and arrivals per nautical miles), which constitutes operational factors.

In this analysis we used original continuous variables, considering that in logistic regression, lack of normally distributed predictors is generally not of a high concern (Schreiber-Gregory, 2018). Moreover, some have been concerned about issues with a skewed/unequal sampling in the dependent variable in logistic regression. In this case, we have approximately 6 to 94% sample distribution within navigation accidents. The main argument is that the problem of unequal distribution is mainly when the model has few (absolute number of) events. This is not the case in our sample with 517 cases. However, the unequal sample hinders a separation of the

Table 15
Final model output of multivariate logistic regression predicting whether the ship has had a navigation accident or not in the time period 2010–2019 (N = 9300).

Indicators	**B**	**SE**	**Wald**	**Exp(B)**	**CI 95% Exp(B)**	R^2 (ΔR^2).
Technical – Ship type						
Offshore service vessel[c]	−0.49	0.19	6.35	0.62**	0.42 - 0.9	
Wellboat[c]	0.39	0.35	1.23	1.47	0.75 - 2.9	
Work and service vessel[c]	−0.64	0.21	9.53	0.53**	0.35 - 0.79	.06 (0.06)***
Technical – Age and size						
Gross tonnage	−0.02	0.01	17.63	0.98***	0.97 - 0.99	
Year of build	−0.06	0.01	188.13	0.94***	0.93 - 0.95	.26 (0.20)***
Organizational - Flag state and class information						
FOC[a]	0.28	0.16	2.93	1.32	0.96 - 1.81	
PARISMOU[a]	−0.27	0.32	0.74	0.76	0.41 - 1.42	
Tokyo[a]	0.86	0.28	9.25	2.36**	1.36 - 4.11	
US target[a]	−0.58	0.18	10.4	0.56**	0.39 - 0.8	
Class society - member[b]	0.32	0.16	3.85	1.37*	1 - 1.88	
Foreign flag	−2.05	0.18	130.15	0.13***	0.09 - 0.18	.40 (0.14)***
Operational – ship behavior						
Hours in operation (1 000)	0.01	0.01	3.16	1.01	1 - 1.02	
Nautical miles sailed (1000)	0.01	0	36.99	1.01***	1.01 - 1.01	
Arrivals (1 000)	−0.01	0.05	0.01	1	0.9 - 1.1	
Arrivals per nmi	0	0	0.23	1	1 - 1.01	
Average speed	0.08	0.04	5.6	1.09*	1.01 - 1.16	.44 (0.04)***[d]
Constant	*123.21*	*9.05*	*185.45*	*3.237E+53*		

*** $p < .001$,.
** $p < .01$,.
* $p < .05$. [a]1=On the list. [b]1=Not classed by member society of IACS or missing. [c]Reference category: Cargo carrying vessel. [d]When inserted in model 1, Ship behavior $R^2 = 0.26$.

data into a training set and a test set, which could be beneficial in testing of the predictive effect of the statistical model.

Length overall showed multicollinearity issues, leading to removal of this indicator in the analysis. Other variables also showed a high correlation (e.g. arrivals, hours in operations and nautical miles sailed, ranging from $r = 0.88$ to $r = 0.91$) but collinearity statistics were satisfactorily). The average VIF was 1.35 and no tolerance level was below 0.45 indicating no serious issues with multicollinearity overall.

The multivariate statistical model (Table 15) explained 44% of the variance in the dependent variable navigation accident ($X^2[5] = 1566.449$, $p < .001$), −2 Log likelihood = 2426.240, Nagelkerke $R^2 = .44$). The model correctly classified approximately 99% of the observed non-events and 36% of the events (ships with accidents), which equal a total percentage of 95.5% correct predictions. By using a hierarchical procedure, we see the respective increase of the total variance explained for each step. Model 1, consisting of vessel categories, explained 6% of the variance. In model 2, we inserted vessel characteristics in terms of age and size, which increased the variance explained by a further 20% to reach 26%. Thus, 26% was explained by technical factors. Further, in Model 3, we inserted various flag lists (organizational conditions), which increased the variance explained by 14%. An alternative regression model shows that model 2 increased by an extra 11% with the inclusion of the variable foreign flag. Lastly, we included operational ship behavior variables, which increased the variance explained by 4% for a final 44%. In an alternative model, where we included ship behavior variables in the first model, the predictors explained approximately 26% of the variance in the dependent variable. Thus, ship behavior has a strong effect on accident involvement, but a considerable amount of this variation is accounted for by the other variables.

The results for the logistic regression show that following conditions increase the probability that the vessel in question has reported at least one navigation accident; the vessel is or has:

(a) cargo carrying vessel (bulk, tanker, chemical)
(b) lower gross tonnage (size)
(c) older of age
(d) not on US target list
(e) on Tokyo black/gray list
(f) sailing under Norwegian flag
(g) more nautical miles sailed
(h) sailing with higher average speed (knots)

For determining individual indicators effect size, we interpreted the Exp(B) coefficient (odds-ratio). For example, for each 1000 nautical miles sailed, the odds that a vessel has reported an incident is increased by 1.01, when other variables are held constant. Similarly, for each knot in average speed increased, the odds that a vessel has reported an incident is increased by 1.09 times. As for the Tokyo MOU target list variable, a vessel on the Tokyo MOY list as black or gray has 2.36 times greater chance of having reported an incident than vessels regarded as white.

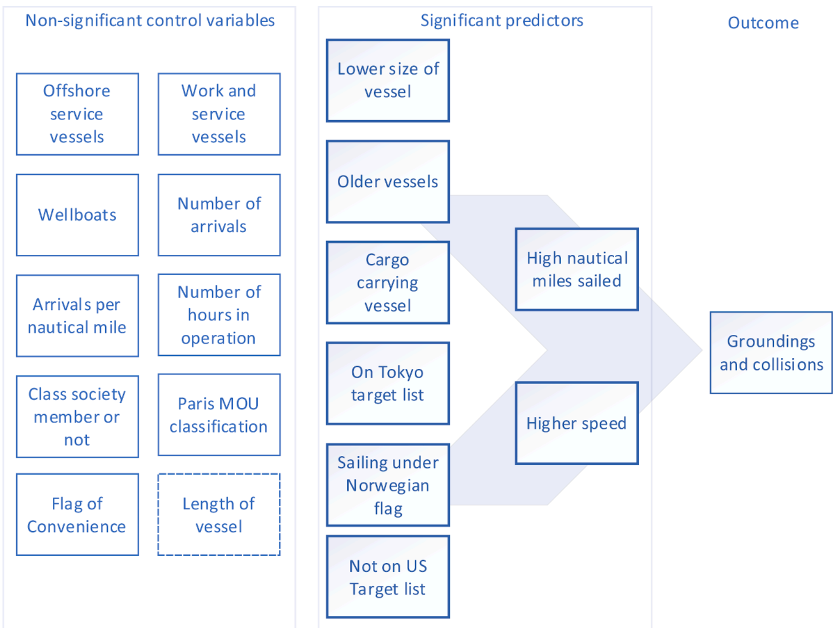

Fig. 5. Results from multivariate analysis predicting vessels with reported navigation accidents. Length of vessel was not included in multivariate analysis due to multicollinearity (high correlation) with gross tonnage.

5. Discussion

Considering the research problem, our aim was to explore what factors are associated with ship accidents (groundings and collisions) using indicators based on AIS data and vessel data. In this section we will first discuss the findings of our analyses, following by a reflective discussion on limitations and lastly describing possible practical application of our study.

5.1. Summary and discussion of findings

Considering our main research aim, we clearly see that the indicators that constitute the statistical model using AIS data and other parameters, collected from 9000 vessels for 10 years, have a strong relationship with vessels' accident records. The model explains approximately 44% of the variance. In essence, this shows that somewhat basic elements (like amount of sailing, vessel type and size) account for large amount of variation in complexity of (reported) accident frequency—at least when we flatten out over a large period like ten years. See Fig. 5 and Table 16 for an overview of the findings. Breaking down our results, approximately 26% of the variation is explained by technical factors, 14% by organizational factors, and 4% by operational factors. These numbers should be interpreted with some caution, due to the incremental nature of hierarchical regressions, where the chronology of a model influences the variance explained. Although operational factors explained only 4% in addition to the other predictors, it showed in fact 26% in an alternative model in which these factors were modelled in the first step. This further shows that operational factors, as measured by AIS parameters, are strong predictors of navigation accidents, but this effect is largely accounted for by technical and organizational factors.

Although the model overall was a good fit, several of the indicators involved were not significantly related to the outcome when controlled for all other parameters. This implies that several of the indicators to some degree share a lot of variation and that their individual contribution is not high.

There are numerous notable changes from the bivariate analysis to the multivariate analysis. First, the predictor wellboats was no longer significant in multivariate comparison despite an effect size that was considerable bivariately. This likely means that wellboats share some characteristics with other variables that inhibit the effect of the ship type, for example that wellboats tend to be of a certain size. Considering the low n of wellboats, there is a potential for a type II error (false negative). Cargo carrying vessels, on the other hand, have a higher degree of reported incidents in the multivariate model but not in the bivariate model. Length overall was removed in the multivariate analysis due to collinearity with gross tonnage. Number of arrivals was no longer significant in predicting ship incidents, and neither was hours in operations. This is probably caused by a high inter-correlation: if a ship has a high activity, it is likely to have both a high number of port calls, high number of operating hours and sailing considerably far. The analysis shows, however, that the most prominent factor of these in regards to accident involvement, is the number of nautical miles sailed, and that number of arrivals and operating hours are not adding incremental effect. The finding that more sailed nautical miles within the entire 10-year period makes being involved in an accident more likely, may simply reflect increased exposure (Bye and Almklov, 2019).

Age of ship, USCG Target list, Tokyo MoU, Norwegian flag, nautical miles sailed, and average speed remained significant in the multivariate analysis. This indicates that even when all other variables remained constant, these effects are still significantly related to whether a given ship has reported at least one navigation accident or not. Notably, average speed changed the direction of the effect in the multivariate analysis, indicating a moderator effect or suppressor effect. In the bivariate models, a higher speed was associated with less reported accidents, whereas in the multivariate models, lower speed was associated with less reported accidents. It is reasonable to assume that the average speed of the vessel is primarily determined by the ship type and size, which in turn reflects the type of operation. Thus, when these factors are controlled for, we see that a higher average speed increases the probability of reporting at least one navigation accident. That higher speed indicates higher risk of navigation accidents is rather intuitive since it lowers the response time for dealing with conflicts. Alternatively, lower average speed could be a proxy of sailing under complex traffic or fairways, leading to a higher exposure of conflicts. Thus, the relation is not perfectly clear.

The findings are partially in line with previous research on accidents data worldwide. Cargo vessels have previously also been identified to be more likely to be involved in navigation accidents, compared to other vessel types (e.g., Li et al., 2014). Rather common risk factors identified in several previous analysis include higher age (e.g., Li, 1999) and vessel size (e.g. Jin, 2014). Higher age of vessels is likely an indicator of the risk factor technical condition, thus indicating that older vessels have high probability of failure of equipment and machinery. Gross tonnage is interpreted as an indicator of vessel size. It is challenging to conclude on whether the fact that small vessels have had a higher risk of navigation accidents than large vessels should be attributed to their exposure as an effect of their operation (e.g. sailing relatively more inshore) or to their navigational features (e.g. maneuverability), although the former seems more plausible given that smaller vessels generally have faster response time for evasive maneuvers. Adequate control variables for traffic and characteristics of operating area might enable evidence for this issue.

The finding that vessels not on the US Coast Guard target list are more likely to be involved in a navigation accident is counter-intuitive in relation to the intention of port state control. The differences between black/gray and white on the Paris MoU is not significant in the final model, but the bivariate analysis showed that black and gray ships are also less likely to be involved in accidents. However, it is more likely that a vessel classified as gray or black by Tokyo MoU has reported a navigation accident compared to vessels classified as white. The bivariate analysis does also show that FOC vessels are less likely to be involved in a navigation accident compared to vessels not classified as FOC. This is not in line with previous findings (Bye and Aalberg, 2018). In the multivariate analysis, where ship type and other variables are taken into consideration, the effect size is in the opposite direction, and more in line with previous findings, namely that FOC constitutes a risk indicator for navigation accidents. However, the effect (odds-ratio 1.32) is not statistically significant ($p = .09$). Further, the finding that Norwegian vessels are more likely to be involved in an accident than foreign vessels is not in line with previous findings (Bye and Aalberg, 2018), and findings regarding foreign versus domestic vessels in

Table 16
Conditions associated with reported navigation accidents .

Bivariate analysis *Categorical variables*	**Logistic regression model**
Wellboats[b]	Cargo carrying vessel[a]
Work and service vessels	Lower gross tonnage
Not on US target list	Older age of ship
On Tokyo MoU list (Black/gray)	
Classification society not member of IACS	Not on US Coast Guard's target list
Not on flag of convenience	On Tokyo MoU list (black/gray)
Not on Paris MOU black/gray	Sailing under Norwegian flag
Sailing under Norwegian flag	More nautical miles sailed
Shorter length overall	Higher average speed
Higher number of arrivals	
Continuous variables	
Higher hours in operation	
More nautical miles sailed	
Lower average speed	
Lower gross tonnage	
Older age of ship (lower year of build)	

[a] Compared to offshore service vessel and work and service vessel.
[b] Compared to cargo carrying vessel.

other parts of the world (Ventikos et al., 2018).

The differences related to the flag authority indicators may be interpreted and attributed to a variety of factors such as ship standard, SMS, manning, accommodation, sailing period, sailing patterns etc. To interpret the results as a consequence of ship standard and SMS seems somewhat odd, taking into account that these are factors that are supposed to be reflected in the port state control regimes. It seems also rather counterintuitive that Norwegian ships are more accident-prone than foreign ships, taking into account their MoU ratings, a reasonable assumption that the navigators are more familiar with the fairways than foreign navigators, as well as results from previous research (Baniela and Ríos, 2011). An alternative interpretation may be that differences between Norwegian ships and foreign ships may also be attributed to manning level. NOR ships have in general a lower manning level than foreign ships (Størkersen et al., 2011; Bye and Røyrvik, 2015) which has been identified as risk factor in previous studies (e.g. Chauvin et al., 2013). Another possible interpretation is that it reflects differences in sailing patterns as well as differences in the distribution of Pilot Exemption Certificates and requirement of compulsory pilotage. This means that the variable in fact may be an indicator for multiple risk factors. However, regardless of what risk factor(s) they reflect, the variables might be used as an indicator for the probability of an accident. If the variable is used in this way, it will still be problematic if its validity is influenced by an uneven proportion of underreporting of accidents to the Norwegian Maritime Authorities (Hassel et al., 2011). This effect should, however, have been minimized by not including the less severe causality categories in the analysis. This issue needs further exploration to conclude.

The bivariate analysis shows that non-members of IACS are more likely to be involved in a navigation accident, compared to members, but this difference is not significant in the multivariate model. The findings from the bivariate analysis could be interpreted as a reflection of the differences in quality between the classification societies following the IACS standards and those which do not. However, the multivariate model does not indicate that this has any impact on the probability of accidents.

5.2. Limitations

Although our research has robust and novel analyses, there are important limits to be discussed. First, the choice of aggregation of data in a 10-year period yields opportunities and challenges. On the one hand, it enables the statistically robust analysis by accumulating a reasonable number of ships with accidents ($N = 517$). On the other hand, this procedure inherently involves significant data reduction. Further, a prominent weakness of the present analytical model is that it does not measure dynamic conditions such as weather, visibility, light conditions, fairway conditions at the location of the accident, wind, current, traffic density, or course alterations. (see Table 1). Operationalizing variations in environment and traffic conditions is challenging since this study is based on a comparison of aggregated data from ships that have been involved in a navigation accident, respectively, with ships that have not. Whereas accidents could be represented by spatial data (location and/or time) and linked to environmental and traffic conditions at this geographical area, "non-accidents" cannot. However, it is feasible to operationalize aggregated indicators that to some extent capture more dynamic conditions related to the environment and the traffic. For example, one could construct indicators that measure the central tendency or variation of exposure to for example traffic density or weather conditions, by the use of position data obtained from AIS. Alternatively, by changing the analytical object from *ship* to *area* (see e.g. Li et al., 2019) one could more easily integrate dynamic conditions of the traffic.

Another issue that represents a limitation of the research is the degree of theoretical assumptions regarding relationship between the operationalized indicators and the factor that we want to measure (i.e. a validity issue). For example, measuring the factor speed by an indicator based on the relation between position points extracted from AIS has a higher validity than measuring the more abstract factor working condition assuming that this is related to whether a ship is sailing under FOC or not.

Moreover, although our model showed a strong fit, a more robust method to assess the prediction effect is to generate separate datasets for training and for testing. This has been difficult in the present work, considering that test set would only include 129 accidents. The accumulation of data as the years passes would enable such approach with a larger dataset.

The aim for future research should be concerned with exploring new empirical sources and operationalizations towards a holistic integrated set of data encompassing static and dynamic parameters. This study has been limited to data from AIS, IHS Fairplay and NMA accident databases, but a wide range of other sources could also be included, using the IMO or MMSI number as a connection between databases.

5.3. Practical application

The knowledge obtained in this study facilitates maritime authorities and other stakeholders to establish leading indicators for monitoring risk in specific sea areas, not only relying on lagging indicators (number of accidents/accident frequencies). This study has shown that there is a relation between accidents and vessel types, age of vessel, vessel size, speed, nautical miles sailed. Changes in average speed and the composition of vessel types, age and gross tonnage of the vessels operating in a specified sea area, may therefore be used as leading indicators of risk. In theory, a similar approach could be feasible for shipping companies monitoring their fleet.

The different operationalizations of indicators based on flag authority identity appear to be somewhat contra-intuitive and dubious in terms of validity. Furthermore, the observed differences in bivariate and multivariate analyses of indicators implicate those stakeholders seeking to obtain knowledge on risk level through indicators should be careful of monitoring specific indicators in isolation.

6. Conclusions

The aim of our research was to provide an empirical basis for the identification of risk factors and indicators for navigation accidents, and through this aim, providing insight into the development of generalized risk models of maritime activity in Norwegian waters.

We have conducted an analysis of risk indicators associated with navigation accidents involving different types of cargo vessels in Norwegian waters. The findings show that specific vessel types (cargo carrying vessels), lower gross tonnage, older ship, not on US target list, on Tokyo target list (black or gray), Norwegian flag, more nautical miles sailed, and higher average speed make it more likely that a ship is involved in, or at least reports, a navigation accident. A logistic regression showed a strong prediction with 44% of variance explained. The novelty of this work is that we have been able to compare ships involved in reported navigation accident with those which have not reported such accidents during a period of 10 years. Relatively rich data from the total population of vessels has been obtained using historical recorded AIS data and information regarding vessel identity. This study demonstrates the potential for using recorded AIS data in statistical analysis related to measuring indicators of maritime risk factors. The operationalizations of the data sets combined in the study give directions for potential monitoring of the risk factors through risk indicators.

Declaration of Competing Interest

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

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References

Alderton, T., Winchester, N., 2002. Flag states and safety: 1997-1999. Marit. Policy Manag. 29 (2), 151–162.

Baniela, S.I., Ríos, J.V., 2011. Maritime safety standards and the seriousness of shipping accidents. J. Navig. 64 (3), 495–520.

Blix, E., Bye, R., Kleiven, E., Almklov, P., Kongsvik, T., Gåseidnes, H., Berntsen, V., 2015. What is a ship? Ship categories and application of AIS data and accident statistics for the normalization of ship risk. Safety and Reliability of Complex Engineered Systems: Proceedings of the 25th European Safety and Reliability Conference. Boca Raton London CRC Press, London, pp. 315–322.

Bye, R.J., Almklov, P.G., 2019. Normalization of maritime accident data using AIS. Mar. Policy 109, 103675.

Bye, R.J., Aalberg, A.L., 2018. Maritime navigation accidents and risk indicators: an exploratory statistical analysis using AIS data and accident reports. Reliab. Eng. Syst. Saf. 176, 174–186.

Chen, J., Bian, W., Wan, Z., Yang, Z., Zheng, H., Wang, P., 2019. Identifying factors influencing total-loss marine accidents in the world: analysis and evaluation based on ship types and sea regions. Ocean Eng. 191, 106495.

Chauvin, C., Lardjane, S., Morel, G., Clostermann, J.P., Langard, B., 2013. Human and organisational factors in maritime accidents: analysis of collisions at sea using the HFACS. Accid. Anal. Prev. 59, 26–37.

Dinis, D., Teixeira, A.P., Soares, C.G., 2020. Probabilistic approach for characterising the static risk of ships using Bayesian networks. Reliab. Eng. Syst. Saf. 203, 107073.

Fiskin, R., Cakir, E., Sevgili, C., 2021. Decision tree and logistic regression analysis to explore factors contributing to harbour tugboat accidents. J. Navig. 74 (1), 79–104.

Goerlandt, F., Goite, H., Banda, O.A.V., Höglund, A., Ahonen-Rainio, P., Lensu, M., 2017a. An analysis of wintertime navigational accidents in the Northern Baltic Sea. Saf. Sci. 92, 66–84.

Goerlandt, F., Hänninen, M., Ståhlberg, K., Montewka, J., Kujala, P., 2017b. Simplified risk analysis of tanker collisions in the gulf of Finland. Misc. Probl. Marit. Navig. Transp. Shipp. 25, 181.
Haugen, S., Almklov, P.G., Nilsen, M., Bye, R.J., 2016. Norwegian national ship risk model. In: Proceedings of the 3rd International Conference on Maritime Technology and Engineering-MARTECH. CRC Press.
Haugen, S., Seljelid, J., Nyheim, O.M., Sklet, S., Jahnsen, E., 2012. A generic method for identifying major accident risk indicators. In: Proceedings of the *11th International Probabilistic Safety Assessment and Management Conference and the Annual European Safety and Reliability Conference*, pp. 5643–5652.
Hassel, M., Grossmann, M., Aalberg, A.L., Arntsen, R., 2020. Identification of near-miss situations between ships using AIS data analysis and risk indicators. In: E-proceedings of the 30th European Safety and Reliability Conference and 15th Probabilistic Safety Assessment and Management Conference. Venice. Nov 01-05.
Hassel, M., Asbjørnslett, B.E., Hole, L.P., 2011. Underreporting of maritime accidents to vessel accident databases. Accid. Anal. Prev. 43 (6), 2053–2063.
Jin, D., 2014. The determinants of fishing vessel accident severity. Accid. Anal. Prev. 66, 1–7.
Kleiven E. (2016). Application of AIS data to accident statistics normalization. Technical Note Safetec Nordic/NTNU Social Research. https://samforsk.no/Publikasjoner/ST-10310-2%20Application%20of%20AIS%20data%20to%20accident%20statistics%20normalization.pdf, Accessed data: 22 august 2021.
Kujala, P., Hänninen, M., Arola, T., Ylitalo, J., 2009. Analysis of the marine traffic safety in the Gulf of Finland. Reliab. Eng. Syst. Saf. 94 (8), 1349–1357.
Kulkarni, K., Goerlandt, F., Li, J., Banda, O.V., Kujala, P., 2020. Preventing shipping accidents: past, present, and future of waterway risk management with Baltic Sea focus. Saf. Sci. 129, 104798.
Lensu, M., Goerlandt, F., 2019. Big maritime data for the Baltic Sea with a focus on the winter navigation system. Mar. Policy 104, 53–65.
Li, K.X., 1999. The safety and quality of open registers and a new approach for classifying risky ships. Transportation Research Part E: Logistics and Transportation Review 35 (2), 135–143.
Li, M., Mou, J., Liu, R., Chen, P., Dong, Z., He, Y., 2019. Relational model of accidents and vessel traffic using AIS data and GIS: a case study of the Western Port of Shenzhen City. J. Mar. Sci. Eng. 7 (6), 163.
Li, K.X., Yin, J., Fan, L., 2014. Ship safety index. Transp. Res. Part A Policy Pract. 66, 75–87.
Luo, M., Shin, S.H., 2019. Half-century research developments in maritime accidents: future directions. Accid. Anal. Prev. 123, 448–460.
Navas de Maya, B., Ahn, S.I., & Kurt, R.E. (2019). Statistical analysis of MAIB database for the period 1990-2016. In Proceedings of the 18th International Congress of the Maritime Association of the Mediterranean 2019 Aug 22.
Nævestad, T.O., Phillips, R., Elvebakk, B., Bye, R.J., & Antonsen, S. (2015). Work-related accidents in Norwegian road, sea and air transport: prevalence and risk factors. TØI report, 1428.
Puisa, R., Lin, L., Bolbot, V., Vassalos, D., 2018. Unravelling causal factors of maritime incidents and accidents. Saf. Sci. 110, 124–141.
Schreiber-Gregory, D., 2018. Logistic and linear regression assumptions: violation recognition and control. Paper presented at. In: Proceedings of the 26th SESUG Conference. St. Pete Beach, FL, USA, pp. 14–17 (paper 247)October.
Sormunen, O.V., Hänninen, M., & Kujala, P. (2016). Marine traffic, accidents, and underreporting in the Baltic Sea. Zeszyty Naukowe Akademii Morskiej w Szczecinie.
Størkersen, K.V., Bye, R.J., Røyrvik, J.O., 2011. Sikkerhet i fraktefarten. Analyse av Drifts-Og Arbeidsmessige Forhold På Fraktefartøy. NTNU Samfunnsforskning AS, Studio AperturaNTNU, Trondheim.
Bye, R., Røyrvik, J.O., 2015. Internasjonalisering av norsk innenriksfart. Sikkerhet i Norske Farvann. Gyldendal Akademiske, Oslo.
Svanberg, M., Santén, V., Hörteborn, A., Holm, H., Finnsgård, C., 2019. AIS in maritime research. Marine Policy 106, 103520.
Talavera, A., Aguasca, R., Galván, B., Cacereño, A., 2013. Application of Dempster–Shafer theory for the quantification and propagation of the uncertainty caused by the use of AIS data. Reliab. Eng. Syst. Saf. 111, 95–105.
Tirunagari, S, Hanninen, M, Stanhlberg, K, Kujala, P, 2012. Mining causal relations and concepts in maritime accidents investigation reports. International Journal of Innovative Research and Development 1 (10), 548–566.
Uğurlu, F., Yıldız, S., Boran, M., Uğurlu, Ö., Wang, J., 2020. Analysis of fishing vessel accidents with Bayesian network and Chi-square methods. Ocean Eng. 198, 106956.
Ventikos, N.P., Papanikolaou, A.D., Louzis, K., Koimtzoglou, A.J.O.E., 2018. Statistical analysis and critical review of navigational accidents in adverse weather conditions. Ocean Eng. 163, 502–517.
Wang, H., Liu, Z., Wang, X., Graham, T., Wang, J., 2021. An analysis of factors affecting the severity of marine accidents. Reliab. Eng. Syst. Saf. 210, 107513.
Wang, L., Yang, Z., 2018. Bayesian network modelling and analysis of accident severity in waterborne transportation: a case study in China. Reliab. Eng. Syst. Saf. 180, 277–289.
Weng, J., Yang, D., Chai, T., Fu, S., 2019. Investigation of occurrence likelihood of human errors in shipping operations. Ocean Eng. 182, 28–37.
Weng, J., Yang, D., Qian, T., Huang, Z., 2018. Combining zero-inflated negative binomial regression with MLRT techniques: an approach to evaluating shipping accident casualties. Ocean Eng. 166, 135–144.
Xu, T., Liu, X., Hu, S., 2020. Maritime accidents in New Zealand from 2015 to 2018: revealing recommendations from statistical review. J. R. Soc. N. Z. 50 (4), 509–522.
Yıldırım, U., Başar, E., Uğurlu, Ö., 2019. Assessment of collisions and grounding accidents with human factors analysis and classification system (HFACS) and statistical methods. Saf. Sci. 119, 412–425.
Zhang, L., Meng, Q., Fwa, T.F., 2019a. Big AIS data based spatial-temporal analyses of ship traffic in Singapore port waters. Transp. Res. Part E Logist. Transp. Rev. 129, 287–304.
Zhang, L., Wang, H., Meng, Q., Xie, H., 2019b. Ship accident consequences and contributing factors analyses using ship accident investigation reports. Proc. Inst. Mech. Eng. Part O J. Risk Reliab. 233 (1), 35–47.
Zhang, Y., Sun, X., Chen, J., Cheng, C., 2021. Spatial patterns and characteristics of global maritime accidents. Reliab. Eng. Syst. Saf. 206, 107310.